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ARTICLE

A digital twin-driven approach towards smart manufacturing: reduced energy consumption for a robotic cellular

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ABSTRACT
One of the significant trends in smart manufacturing is the idea of industrial digitalization, which is enabled through the use of new information technologies, such as the Internet of Things, big data, cloud computing, and artificial intelligence. However, manufacturing industries can only be achieved by combining the physical manufacturing world and digital world, to realize a series of smart manufacturing activities, such as active perception, real-time interaction, automatic processing, intelligent control, and real-time optimization, etc. In this paper, a digital twin-driven approach combines with agent-based decision-making for real-time optimization of motion planning in robotic cellular is proposed, with optimizing the physical and virtual layer at the manufacturing facility. Accordingly, an architecture of the digital twin-driven facility is design, and its operational mechanisms and implementation methods are explained in detail. Moreover, qualitative analysis and a quantitative comparison based on a real robotic cell are provided. Several key findings and observations are generated relating to managerial implications, which are valuable for various users to make manufacturing decisions under the digital twin-driven environment.

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Digital twin; smart manufacturing; robotic cell; energy consumption

1. Introduction

Smart manufacturing refers to the intensified and pervasive application of networked information-based technologies, such as computing platforms, communication technology, data modeling, and predictive engineering, throughout the manufacturing enterprise (Kusiak 2018; Li, Barenji, and Huang 2018). There are five typical features for recognizing a manufacturing system as 'smart'; this includes context awareness, modularity, heterogeneity, interoperability, and compositionality (Barenji 2018). It utilizes cutting-edge technologies, such as the Internet of Things, big data, cloud computing, and artificial intelligence (AI), etc., to facilitate the entire manufacturing system, and increase the overall profits (Park et al. 2019). Based on the research of the Gartner group, there will be more than 20 billion internet-connected devices for transforming the manufacturing enterprise into a digital business by 2020 (Vermesan and Friess 2013). Therefore, to head towards smart manufacturing, digitalization is the highest priority in the manufacturing workshop.

Manufacturing workshop refers to the shop floor, which provides both production machines and low-level software to produce a specific product and delivering customized services. The activities in the manufacturing workshop cover various manufacturing operations, internal logistics, quality checks, and maintenance, etc. In the view of low-level software, it mainly consists of production machinery software such as CNC machine, robotic system, data acquisition devices and software, production control systems and manufacturing execution systems, etc. They aim to realize the informatization and automation in production activities. This level of the manufacturing system is a highly heterarchical and hyperconnected environment because the software level directly or indirectly works with hardware-level to product-specific production (Li et al. 2019). The main challenges of this level are: (1) Most manufacturing decisions are made by the manufacturing experts, while the software systems only play an assistant role in the manufacturing decision-making process. (2) Production plans are often made at the pre-manufacturing stage, which is mostly static and lacks the consideration of the disturbance factors in the physical manufacturing space. (3) The current physical space and information space in the

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workshop lack of connectivity, resulting in the incapability of real-time interaction as well as fusion. The smart manufacturing workshop requires that the manufacturing activities become more intelligent, digitalized and have optimized energy consumption(W. Wang et al. 2018). Therefore, there are some gaps between the traditional manufacturing workshop and the smart manufacturing workshop, such as the autonomous decision-making mechanism and the real-time energy optimization as well as rareness in the interaction and integration that takes place between the physical and virtual workshop.

Recently, digital twin, as a paradigm for realizing the interaction and integration between the physical space and the virtual space, has attracted full attention from the relevant academic circles and enterprises (Boschert and Rosen 2016). The digital twin is composed of three components, which include the physical entities in the physical space, the virtual models in the virtual space, and the data connection between the two spaces. Additionally, in the manufacturing domain, it serves as a bridge that connects the physical space with the virtual space; this provides the manufacturers with a new solution for implementing smart manufacturing, accurate management & real-time optimization. Therefore, it offers the promise and potential to revolutionize the manufacturing workshop to achieve smart manufacturing. At present, most digital twin-based approaches mainly focus on theoretical models, frameworks, and enterprise-level (Haag and Anderl 2018; Tavares et al. 2017; X. V. Wang and Wang 2019). As the workshop level, especially robotic cellular mentioned, is the main section in the smart manufacturing industry, which is connected physical level and software level directly. This connection plays a crucial rule in the virtualization of physical to the virtual space. And it is the most critical part of the digital twin. Therefore, there is a need for a framework and use case-based experimental digital twin-driven for robotic cellular by considering real-time optimization and decision making realistically.

In this respect, the aim is to provide a digital twin-driven approach with detail implementation of the virtual environment for converging, analyzing, and optimizing the performance in the physical and virtual robotic cellular. A robotic cellular to cover smart manufacturing thoroughly is selected. To achieve this goal, a novel framework of the digital twin-driven approach is proposed as well as its operational mechanisms and implementation method, which are studied in detail in this paper besides real-time motion planning decision-making agents developed. Moreover, qualitative analysis and a quantitative comparison are carried out on the case study, based on the energy consumption data from the robot cell in physical and virtual aspects, respectively. The results show that the proposed digital-twin driven approach is useful in saving energy consumption in real-time for robotic cellular. A framework based on a mathematical model of the inverse and forward kinematics is proposed for developing digital twins. Finally, several key findings and observations are generated into the managerial implications, which are useful for various users to make manufacturing decisions under the digital twin-driven approach.

The main contributions of this paper include the following: 1) Compared with other researches about digital twin in manufacturing, this paper focused on the implementation of the digital twins in existing robotic cellular, rather than concentrating on enterprise-level. A framework to develop a digital twin-driven approach for robotic cellular is proposed. The mechanism of how to build a digital twin based on the parameters of the existing physical twin in a real robotic cellular is presented. 2) Existing researches were mainly focusing on the development of theoretical models and frameworks. But in this research, a specific implementation of the digital twin in the robotic cellular is explained. A real-time agent-based optimization motion planning for energy consumption is proposed. This planning can support both virtual and physical twins. 3) There are only a few efforts have been made on the experimental-based of the digital twin in existing studies. The research not only proposes a framework construction method, a qualitative analysis, and a quantitative comparison based on energy consumption in a robotic experiment case are explained. The results prove that the solution of the digital twin-driven approach is feasible and has significant improvements by the autonomous decision-making mechanism.

The rest of this paper is organized as follows: Section 2 provides a review of the computer-based simulation technologies, virtual reality, and digital twins in manufacturing. The architecture of the digital twin-based workshop is proposed in Section 3. To illustrate the effectiveness of this proposed solution, Section 4 describes an experiment-based robot case by using the digital twin simulation solution. Finally, the conclusion and further research are summarized in Section 5.

2. Literature review

In this section, the development of simulation technologies, which include computer simulation (computer-aided design, computer-aided engineering, and computer-aided manufacturing), virtual reality and digital twin in the manufacturing industry, is briefly reviewed.

2.1. Computer simulation in manufacturing

Early in the 1960 s, the concept of computer simulation was proposed. It refers to the dynamic and realistic imitation of the structure, function, and behavior of the system as well as the thinking process and behavior of the people involved in the system control. It is a comprehensive technology-based on similar principles, information technology, system technology and corresponding fields of expertise by using a computer and various physical effect devices such as tools, using system models to conduct experimental research on the actual or envisioned systems. Computer simulation has been widely used in different fields including military, transportation, energy, etc. In the manufacturing industry, the utilization of computer simulation mainly includes 1) applications based on the product model (Abdulmalek & Rajgopal, 2007); 2) applications based on the manufacturing system models (Barenji, Barenji, and Hashemipour 2016), 3) applications based on the process model.

Different researchers have proposed the application of simulation in manufacturing. For example, applications based on the product model, (Kwon and Kwon 2019) utilized computer-aided engineering (CAE); this is one of the kinds of computer simulation methods for optimizing the gate and runner design of an automobile part. This method is well-known and does well in analyzing intricate parts. Moreover, it is used for achieving a good casting layout. This method replaces the traditional way of repeated testing. The simulation saves time and reduces the cost of the casting layout design. As for the applications based on the manufacturing model,(Herrmann et al. 2011) proposed an innovative energy-oriented simulation approach for planning the manufacturing systems. This model aims to identify and select the measures for improving the relevant energy flows. Besides, (Thiede et al. 2016) introduced a multi-level simulation framework and recommendations for choosing the coupling concepts. This model aims to analyze the connection between water resources and energy as well as establish a dynamic connection.

Furthermore, the application of this simulation proved the importance of gaining a holistic factory perspective. Also, some researchers have focused on the simulation of a manufacturing process environment. As for the applications based on the development process model, Parteli and Pöschel (Parteli and Pöschel 2016) developed a particle-based numerical tool for the simulation of the powder application in additive manufacturing. The mathematical tool investigates the characteristics of the powder layer, which is deposited onto the part by using a roller as the coating system and optimizes the processing parameters. Besides, Barenji et al. (Barenji et al. 2017) proposed a platform for simulating and validating the distributed manufacturing system based on agent technology. Based on this study, a multi-agent-based dynamic scheduling system is introduced, and the results of its simulation indicate that the proposed method could simulate a distributed manufacturing system by considering the new technologies available (Vatankhah Barenji and Vatankhah Barenji 2017).

Those computer simulation technologies have great merits in carrying out a virtual process simulation. Moreover, it provides practical manufacturing activities with a useful guideline. However, it lacks interactions and fusions between the physical manufacturing resources and virtual simulation. Additionally, as enabled by cutting-edge technologies, such as IoT, cloud computing, etc., there is an intense desire, in the manufacturing industry, to combine the physical space and the virtual space.

2.2. Virtual reality in manufacturing

Virtual reality (VR) technology is one of the essential branches in a computer simulation system, which is capable of creating and immersing a user in a virtual world. It carries this out with the use of a computer for generating the simulation environment. It is a multi-source information fusion, interactive 3D dynamic vision and system simulation with an entity behavior.

The application of VR is a hot topic in these years, and this includes medicine, entertainment, and military aerospace, industrial simulation and so on.

Furthermore, (Council 1995) presents a low-cost telerobotic system, which utilizes VR technology for integrating existing robotic control infrastructure. The core control part constructs are the dynamic mapping between users and robots, also allowing for multiple sensor displays in its structure. The proposed system showed better performance when compared with the automation or the direct telepresence system so that it can be used for the assembly or the manufacturing task. (Matsas and Vosniakos 2017) proposed a system that can simulate in real-time the cooperation between the robotic manipulators and humans as well as work on simple manufacturing tasks. The proposed method can test users' enhanced experience and behavior inside the virtual world while operating the robot. Matsas and Vosniakos (2017) utilized VR technology to test two types of techniques for safe collaboration, which is both proactive and adaptive. These two technologies are evaluation indicators in Human-Robot Interaction. The above technologies' effectiveness, as well as the activation criteria, were investigated to avoid possible pointless or premature activation while running. According to the above studies, the application of virtual reality in manufacturing mainly focuses on the human-computer interaction and robot operational test.

Moreover, it shows that virtual reality has excellent advantages, such as achieving real-time interaction and feedback between the human-machine interfaces. However, the manufacturing environment has various as well as sophisticated manufacturing resources, which doesn't just involve staff and equipment information, but also process information and internal logistics, etc. As a matter of fact, it needs a more comprehensive as well as a general method for simulating the whole workshop performance.

2.3. *Digital twin in manufacturing*

The concept of Digital Twin has been proposed for the next-generation fighter aircraft and NASA vehicles (Grieves and Vickers 2017). It refers to the process or method of describing and modeling a physical entity's characteristics, behavior and performance with the use of digital technology. Additionally, it is an effective way to realize the interaction and integration of both the physical space and information space (Leng et al. 2019). It consists of three parts: the physical layer in the real space, the virtual product in the information space and finally, the connected virtual product with the physical product.

Since its conception, the idea of a digital twin has continued to attract more and more attention globally. During the phase of design and manufacturing, for example, (Schleich et al. 2017) studied the origin and application trend of the digital twin technology, and indeed introduced the comprehensive reference model of the digital twin to the product design and manufacturing structure. Similarly, (Tao et al. 2018) proposed a new method for product design, manufacturing, and service-driven by the digital twin. It aimed to generate and use converged cyber-physical data to serve the product lifecycle better, actualize the product design, and execute manufacturing, and delivery service, to be more efficient and sustainable. Tao and Zhang (2017) designed the reference system architecture of the digital twin workshop. The basic theory and key technology of realizing the integration of the digital twin workshop were systematically discussed, which provided a reference for the enterprises to understand the digital twin workshop. On this basis, (Tao and Zhang 2017) proposed a novel concept of the digital twin shop-floor (DTS) based on the digital twin. Its operational mechanisms and implementation methods for the DTS.

Moreover, challenges ahead were investigated, which was not only limited to the urgent demand for smart manufacturing but was also linked to the evolving trend of itself. Similarly, (Zheng, Yang, and Cheng 2019) analyzed the main problems that exist in the satellite assembly workshop and studied the application mode of the digital twin technology in a satellite assembly. The concept of a living workshop and its system composition, as well as operational mechanisms, were analyzed. It is provided theoretical support for running the digital twin technology in the studio. In order to optimize the planning and commissioning of human-based production processes, Nikolakis et al. (2019) proposed the implementation of the digital twin approach as part of a more comprehensive cyber-physical system (CPS) by using simulation-based strategies. This was achieved through the use of sensor data fusion, motion recognition, and a knowledge management mechanism. The case of intra-factory logistics operations in the white goods industry demonstrated the feasibility of the proposed approach, which enriched the simulation of the manual assembly operations with the incorporation of the operator's knowledge in the form of spatiotemporal constraints. Through a digital twin-based model, Álvares et al. (José Álvares, Oliveira, and Ferreira 2018) presented the architecture of a framework that was implemented in the way of an Internet-based client-server model, for the monitoring and teleoperation of CNC machine tools. The computational implementation was based on the integration of servers in the form of services through the proposed Cyber DNC web system.

To conclude, digital twin technology shows real promise and is an excellent approach to revolutionizing the manufacturing industry. It can optimize manufacturing performance by converging, interacting, and analyzing the physical manufacturing world and the digital world. A lot of studies about researching the architecture level of DT have been conducted. However, a few efforts have been made on the experimental-based of digital twin and optimization for smart manufacturing robot cellular. And so, a practical and standard-based pragmatic solution is still needed to implement and used DT in the robotic cellular with emphasizing energy consumption in the robotic cellular.

3. The architecture of the proposed digital twin-driven approach

In this section, the architecture of the proposed digital twin-driven plan is presented. It includes three parts: the physical layer, digital data exchange, and the virtual layer.

The physical layer refers to the real production environment. It has various manufacturing resources, including production machinery, robotic arm, perception devices, control devices, workers as well as the enterprise's information systems, such as ERP, and MES. Secondly, the virtual layer has the digital model of the physical resources for carrying out both the manufacturing simulation and real-time optimization of the systems. Those simulation analysis systems are divided into three categories i.e. energy consumption simulation, process simulation, production system simulation, etc. Product process simulation mainly simulates the processing technology, including the selection of the manufacturing tools, the planning of the processing flow and the setting of processing the optimization algorithm. On the other hand, the production system simulation mainly focuses on the product manufacturing process simulation, such as the delivery date, planning, quality, material supply, etc. The control simulation is mostly for equipment processing capacity, processing accuracy, rhythm, human-computer interaction and other aspects of the simulation. Energy consumption simulation is primarily for carrying out an estimate and optimizing the energy for each section. Thirdly, digital data exchange refers to the data interaction between the physical layer and the virtual layer. It contains the real-time data from the physical layer and the feedback from the virtual layer and vice versa, and most researchers used a cyber-physical based communication system for this communication (Vatankhah Barenji et al. 2019). However, this paper mainly studies the application of digital twin-driven workshop management and real-time energy consumption. Hence, it involves both the production process simulation and energy consumption simulation.

The proposed platform follows the standard of ANSI/ISA-95, and it divides the manufacturing enterprises into five levels, as shown in Figure 1. Level 0 refers to the implementation of the actual process, namely the Device-level; Level 1 refers to the measurement and control of operation, namely the Perception-level; Level 2 refers to the detection, monitoring and automatic control of process, namely the Beltline-level; Level 3 refers to the workflow control/process control of system, namely the Workshop-level; Level 4 refers to the main plan and transportation plan of system, namely the Enterprise-level. Although the digital twin-driven approach studied in this paper focuses on the workshop-level, which ranges from Level 0 to Level 3, the digital twin-driven strategy covers five levels of manufacturing enterprises. For example, the product design and process simulation systems include Level 3 to Level 4, and the production simulation system refers to Level 0 to Level 3. Product research & development and integrated business management system of the physical factory/workshop are located at Level 4. Manufacturing execution system and logistics warehousing system cover Level 2 to Level 3. Manufacturing control system and monitoring system cover Level 0 to Level 1.

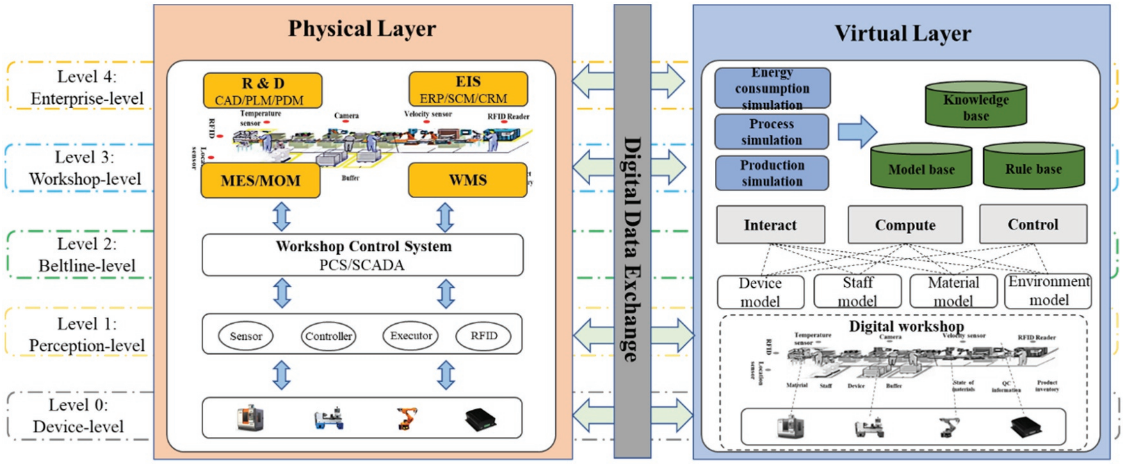


Figure 1. The proposed architecture of the digital twins-driven approach.

The proposed architecture will be explained using a use case robotic cellular which is located in the GDUT. It has a mini ARISTO industrial robotic arm which is used for assembly purposes, to develop a digital twin. The following section explains step by step mechanism to achieve digital twin.

4. The mechanism of building a digital twin

To illustrate the mechanism of a digital twin-driven approach, this section discusses the particular method of developing a digital twin, the comparison and analysis of the physical and virtual layers, and the optimization process of energy consumption.

4.1. Framework for building a digital twin

In order to develop the virtual layer, CAD software (SolidWork) and MATLAB software were utilized to create a virtual prototype. In Figure 2, a framework for developing the virtual twin based on an existing physical twin is provided. It consists of detail information for developed VR models and decision-making

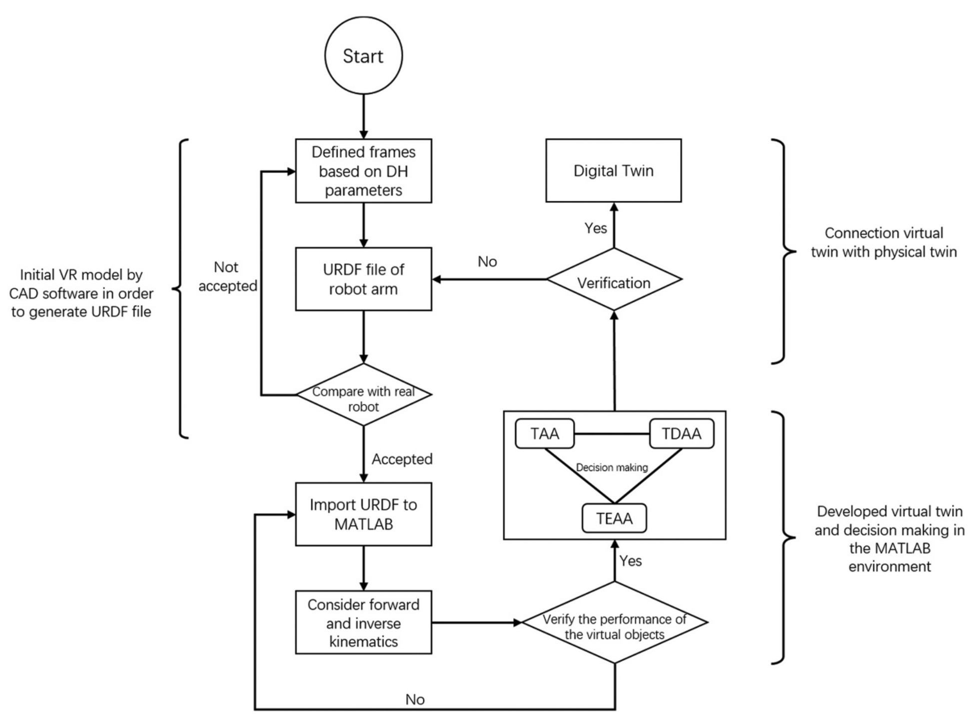


Figure 2. The mechanism of the building a digital prototype.

agents to optimized energy consumption in the cellular. This framework consists of four sections.

Firstly, a 3D model of the physical objects built in the CAD software with detail information such as joint variables of the robotic arm which are provided by Denavit-hartenberg parameters, then generates a URDF file simultaneously. Here, a sample of this code for a base link, as illustrated in Figure 3.

Secondly, digital twin initialized by developed URDF file in the MATLAB environment with considerable the mathematical model of forward and inverse kinematics for providing workspace. Thirdly, the decision-making agent develops in the MATLAB environment, which is consists of three agents, to real-time decision-making purposes. Following this, the developed digital twin with the decision-making unit connects with the physical twin for real-time communication and verification. If accepted, it communicates with the digital data exchange and establishes a real-time combination with the real robotic arm. The details information for each process explained as follows.

```
<! -- Base Link -->
 <link name="base_link">
  <visual>
   <origin xyz="0 0 ${height1/2}" rpy="0 0 0"/>
   <geometry>
   <box size="${width} ${width} ${height1}"/>
   </geometry>
  </visual>
  <collision>
   <origin xyz="0 0 ${height1/2}" rpy="0 0 0"/>
   <geometry>
   <box size="${width} ${width} ${height1}"/>
   </geometry>
  </collision>
  <inertial>
   <origin xyz="0 0 ${height1/2}" rpy="0 0 0"/>
   <mass value="1"/>
   <inertia
    ixx="1.0" ixy="0.0" ixz="0.0"
    iyy="1.0" iyz="0.0"
    izz="1.0"/>
  </inertial>
 </link>
 <!-- Joint between Base Link and Middle Link -->
 <joint name="joint_base_mid" type="revolute">
  <parent link="base_link"/>
  <child link="mid_link"/>
  <origin xyz="0 ${width} ${height1 - axle_offset}" rpy="0 0 0"/>
  <axis xyz="0 1 0"/>
  <dynamics damping="${damp}"/>
  <limit effort="100.0" velocity="0.5" lower="-3.14" upper="3.14" />
 </joint>
```

Figure 3. Example of a URDF file for a base link.

4.2. Developed VR model of robotic cellular in CAD and MATLAB environment

A robotic arm sample is presented here to study to develop VR based on the existing physical resource. The information, such as the available resources, control logic, process flow, products, and the information flow, have been collected in order to construct the virtual factory model. They are collected from the analyst and the user about the physical structure of the robotics cellular.

The cell consists of the robotic arm, storage, and a set of sensors to sense and integrate. Moreover, the 3-D model of this robotic cellular has been developed by combining the 3-D CAD data with MATLAB software and a robotic toolbox. To create the virtual twin, each part was obtained using the model number on the Aristo robot website. In Figure 4, an illustration of a virtual model with the physical model is presented. ARISTO is a 6-axis articulated robotic arm of industrial design; it is usually integrated for robotic cellular in conjunction with a CNC machine. The objective diagram of the virtual layer at level 0 and 1 is also illustrated in Figure 4. It contains an object diagram for step by step development of VR based on the existing robotic arm.

(1) In order to consider the workspace of robotic cellular, the Denavit-hartenberg convention is used to identify the kinematic coefficients and joints frames of the robotic arm. Based on the DH parameters forward and the inverse kinematics are possible to calculate the virtual model. Table 1 shows this parameter for this robotic arm. Following the rules that applied for assigning frames:: The z_i-axis is aligned with the $i + 1$ joint axis.
(2) :The x_i-axis is defined along the common normal between the z_{i-1} and z_i axes, pointing from the z_{i-1} to the z_i-axis.
(3) :The y_i-axis is determined by the right-hand rule, $y_i = z_i \times x_i$.

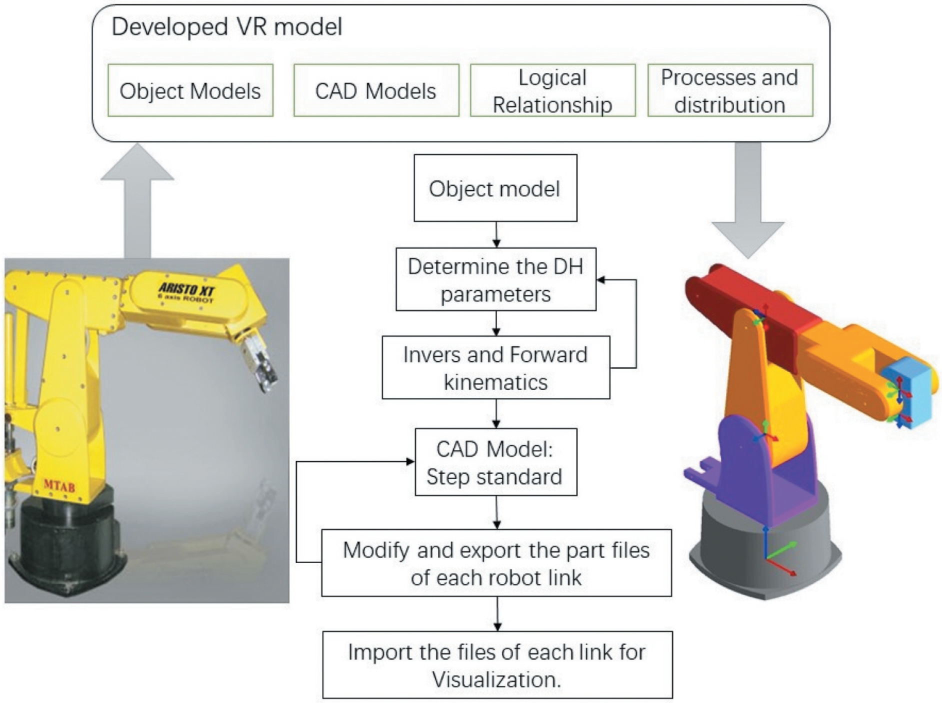


Figure 4. The method of simulating the robotic arm.

Table 1. The parameters of the robotic arm.

Joint No	Joint type	d_i (Joint distance)	θ_i (Joint angle)	α_i (Link twist)	a_i (Link length)
1	Revolute	320 cm	θ_1	90	0
2	Revolute	0	θ_2	0	30 cm
3	Revolute	0	θ_3	90	0
4	Revolute	370 cm	θ_4	90	0
5	Revolute	0	θ_5	90	0
6	Revolute	63 cm	θ_6	0	0

4.2.1. Forward kinematics

The forward or direct kinematics is the transformation of kinematic information from the robot joint variable space to the Cartesian coordinate space. Finding the end-effector position and orientation for a given set of joint variables is the main problem behind forwarding kinematics. This problem can be solved by determining the transformation matrices to describe the kinematic information of the link (i) in the base link coordinate frame. The traditional way of producing forward kinematic equations for robotic manipulators is to carry it out link by link; this is accomplished by using the DH notations and frames. For a 6 DOF robot, six DH transformation matrices exist, with one for each link, which is required for the transformation of the final coordinates to the base coordinates. Equation (1) provided forward kinematics of the robotic arm.

$$T_i = \begin{bmatrix} \cos\theta_i & -\sin\theta_i\cos\alpha_i & \sin\theta_i\sin\alpha_i & a_i\cos\theta_i \\ \sin\theta_i & \cos\theta_i\cos\alpha & -\cos\theta_i\sin\alpha_i & a_i\sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} T_6^1 = T_1^0 T_2^1 T_3^2 T_4^3 T_5^4 T_6^5 \tag{1}$$

4.2.2. Inverse kinematics

Determination of the joint variables in terms of the end-effector position and the orientation is called inverse kinematics. Mathematically, inverse kinematics is carried out by searching for the elements of vector q, as shown in equation (2);

$$q = \begin{bmatrix} q_1 & q_2 & q_3 & \ldots & q_n \end{bmatrix}^T \tag{2}$$

Where a transformation T_n^0 is given as a function of the joint variables $q_1, q_2, q_3, \because, q_n$.

$$T_n^0 = T_1^0(q_1)T_2^1(q_2)T_3^2\ldots T_n^{n-1} \tag{3}$$

Inverse kinematics has multiple solutions because the trigonometric functions inherently provide various solutions. Therefore, multiple configurations of the robot are expected when the six equations are solved for the unknown joint variables. In this study, the inverse kinematics problem is decoupled into two subproblems, namely inverse position and inverse orientation kinematics (Mohammed et al. 2014).

$$T_6^0 = \begin{bmatrix} R_6^0 & d_6^0 \\ 0 & 1 \end{bmatrix} = D_6^0 R_6^0 = \begin{bmatrix} I & d_6^0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} R_6^0 & 0 \\ 0 & 1 \end{bmatrix} \tag{4}$$

D_6^0 is the position of the end-effector which involves only three joint variables of the manipulator. d_6^0 can be used to solve the variables that control the wrist position. The rotation matrix R_6^0 indicates the orientation of the end-effector, which involves three joint variables of the wrist.

Therefore, the wrist orientation matrix is:

$$R_6^3 = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \tag{5}$$

and the wrist position vector is:

$$d_6^0 = d_3^0 = \begin{bmatrix} r_{14} \\ r_{24} \\ r_{34} \end{bmatrix} \tag{6}$$

Therefore, is calculated by solving the following equation;

$$\theta_1 = \mathrm{Arctan2}\left(\frac{r_{14} - a_5 r_{11}}{\sqrt{(1 - (\frac{d_4}{\sqrt{(r_{14}-a_5r_{11})^2+(r_{24}-a_5r_{21})^2}})^2)}}\right) + \mathrm{Arctan2}(\frac{r_{24} - a_5 r_{21}}{r_{14} - a_5 r_{11}}) \tag{7}$$

Using the above value θ_1, θ_5 can be calculated by solving the following equation:

$$\theta_5 = \mathrm{Arctan2}(\frac{r_{11}\sin\theta_1 - r_{12}\cos\theta_1}{\sqrt{(1 - (r_{11}\sin\theta_1 - r_{12}\cos\theta_1)^2)}}) \tag{8}$$

Besides, the sum of them $\sum_{i=2}^{4}\theta_i$ is equal to the following equation:

$$\beta = \sum_{i=2}^{4}\theta_i = \mathrm{Arctan2}(\frac{r_{13}\cos\theta_1 + r_{23}\sin\theta_1}{r_{33}}) \tag{9}$$

Following this θ_3 can be found by solving the following equation by taking into consideration the DH parameters from Table 1;

$$\theta_3 = \mathrm{Arctan2}(\frac{\sqrt{1 - (\frac{(r_{14}\cos\theta_1+r_{24}\sin\theta_1)^2+(r_{34}-d_1)^2-a_2^2-a_3^2}{2a_2a_3})^2}}{\frac{(r_{14}\cos\theta_1+r_{24}\sin\theta_1)^2+(r_{34}-d_1)^2-a_2^2-a_3^2}{2a_2a_3}}) \tag{10}$$

Based on the, two value θ_2 can be calculated;

$$\theta_2 = \mathrm{Arctan2}(\frac{(a_2 + a_3\cos\theta_3)(r_{34} - d_1) - (a_3\sin\theta_3)(r_{14}\cos\theta_1 + r_{24}\sin\theta_1 - a_1)}{(a_2 + a_3\cos\theta_3)(r_{14}\cos\theta_1 + r_{24}\sin\theta_1 - a_1) - (a_3\sin\theta_3)(r_{34} - d_1)}) \tag{11}$$

Finally, θ_4 can be calculated by subtraction β, θ_2 and θ_3. Therefore, the mathematical solution applied for the inverse kinematic problem in the virtual model is provided to calculate the joint variables based on the end target. The Object diagram of the virtual model is illustrated in Figure 2. Moreover, DH parameters and inverse, as well as forward kinematics, play a crucial role in the virtual model.

4.3. Developed agent-based decision-making process

Real-time optimization of motion planning is the primary goal of this proposed digital twin-driven approach. This paper focused on the analysis and optimization of the energy consumption of the auxiliary robotic assembly processes. It contributes to the identification of sustainable smart manufacturing strategies for the robotic cellular. Moreover, it is responsible for the automatic generation of robotic trajectories and the sequencing of the robotic task by minimizing energy consumption. The motion planning agent is responsible for solving motion planning for a robot arm in a complex environment through the employment of probabilistic roadmaps and the execution of an energy consumption minimization criterion. The developed energy-saving agent has three sub-agents (check Figure 2), namely the trajectory generation agent (TAA), the trajectory dynamic assessment agent (TDAA) and the trajectory energy assessment agent (TEAA); each one defined as follows.

Figure 5 shows how this approach optimizes the working path and then obtains the optimized energy consumption solution. TAA is responsible for generating the trajectory path; this is accomplished by calculating the collision-free path within the robot family of

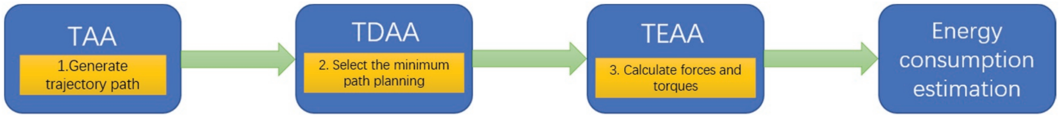


Figure 5. Process of obtaining the optimized energy consumption solution.

the assigned task. This agent considers three main factors, namely the degrees of freedom, the complexity of the environment, and criterion, which are concerning the path that is generated and optimized. TAA collaborates with the TDAA to choose the minimum path planning based on the probabilistic roadmap technique and Dijkstra algorithm(Kang, Lee, and Kim 2008). So, based on these, the optimal trajectory can be found. In this respect, TEAA is responsible for evaluating the energy consumption for generated trajectories based on the information acquired from the TAA and TDAA. TEAA calculates the estimated motor torque based on the robot's motor characteristics, in order to estimate the energy consumption. Therefore, the forces and torques affected by the joints of the robot are calculated in the TEAA. The process starts from the last link and ends up at the first link. Following this, the angular velocity and acceleration values are obtained from the forward recursion (Naudet et al. 2003). After that, the gravity vector g_0 is expressed in the frame for each link using equation (12).

$$g_i = (R_i^0)^T g_0 \tag{12}$$

Then, the force f_i and torque τ_i of link i are obtained by equation (13) at this point, and following this, the external force and torque applied at the robot's end-effector are considered implicitly.

$$\begin{aligned} f_i &= R_{i+1}^i f_{i+1} + m_i(a_{ci} - g) \\ \tau_i &= R_{i+1}^i \tau_{i+1} \times r_{i-1,ci} + R_{i+1}^i f_{i+1} \times r_{i.ci} + \omega_i \times (I_i\omega_i) + I_i a_{ci} \end{aligned} \tag{13}$$

Therefore, the energy consumption of the robot is calculated by TEAA based on two-step. In the first step, the energy is calculated for each joint, while in the second step, energy consumptions of all joints are accumulated to obtain the total energy consumption by robot arm for the specific trajectory.

The decision-making process in the proposed platform is illustrated in Figure 6; this decision-making process is performed based on the negotiation that exists between three agents.

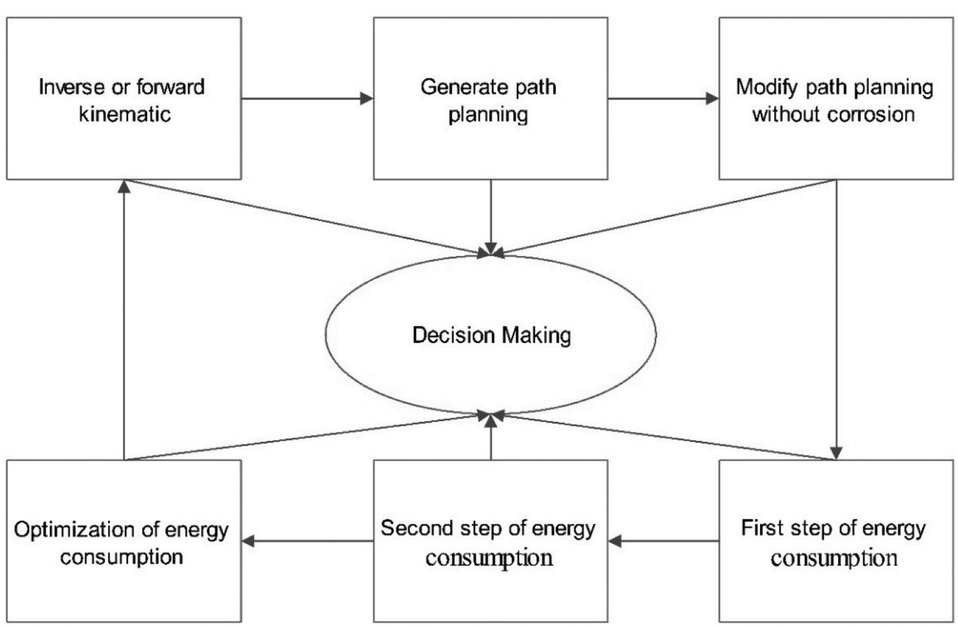


Figure 6. Decision-making in energy consumption based on TAA, TDAA, and TEAA.

5. An experimental robotic cellular case

5.1. Scenario description

A robotic assembly cellular is considered for the evaluation of the effectiveness of the proposed digital twin-driven approach in order to optimize energy consumption. Figure 7 shows this case study, including two buffers. The first one is the full buffer and consists of eight parts having different weights, while the second is an empty buffer. The objective is to pick and place each piece from the first buffer to the second empty buffer. Figure 7 illustrates this scenario by considering the new position and orientation for each piece. To compare the result of an old system without decision making RobotAnlayzer software was utilized and two types of scenarios were used first full part transfer to empty buffer with the fixed speed, which is the 15% of the maximum speed and then four different speeds for part 'A' are considered, namely 25% speed, 50% speed, 75% speed, and 100% speed, in order to arrive at their respective energy consumption. The developed system result was compared with the simulation software.

5.2. Result analysis and evaluation

This case aims to prove that the digital twin based approach has an excellent performance in energy consumption saving. A comparison analysis is utilized in this case. The analytical framework is shown in Figure 8. This case study was conducted based on eight different scenarios. Moreover, it was based on the eight peises presented in the full buffer and the empty buffer. Therefore, the performance of the approach was evaluated with different weights of pay-loading as well as different final orientations and positions. A comparison of energy consumption using RobotAnalyzer software was made. The comparison objects are the digital twin-based implementation and the traditional simulation platform illustrated in Figure 8. By calculating the energy consumption of moving 8 parts from full buffer to the specified position in the empty buffer, the consumption performance can be obtained. And based on these experiment results, our proposed platform improved the energy consumption of the case, with

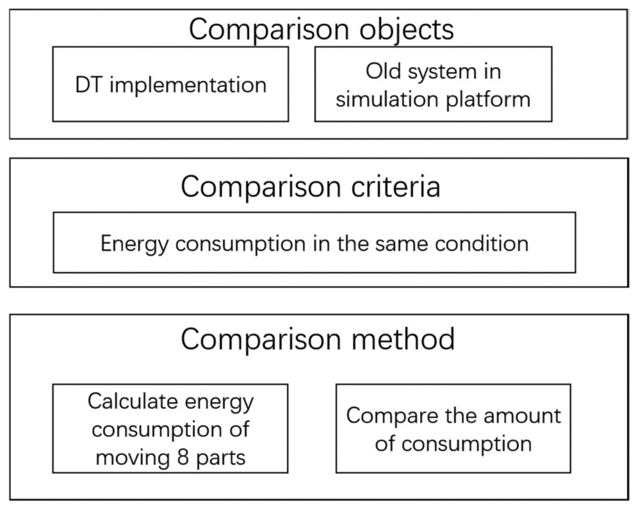
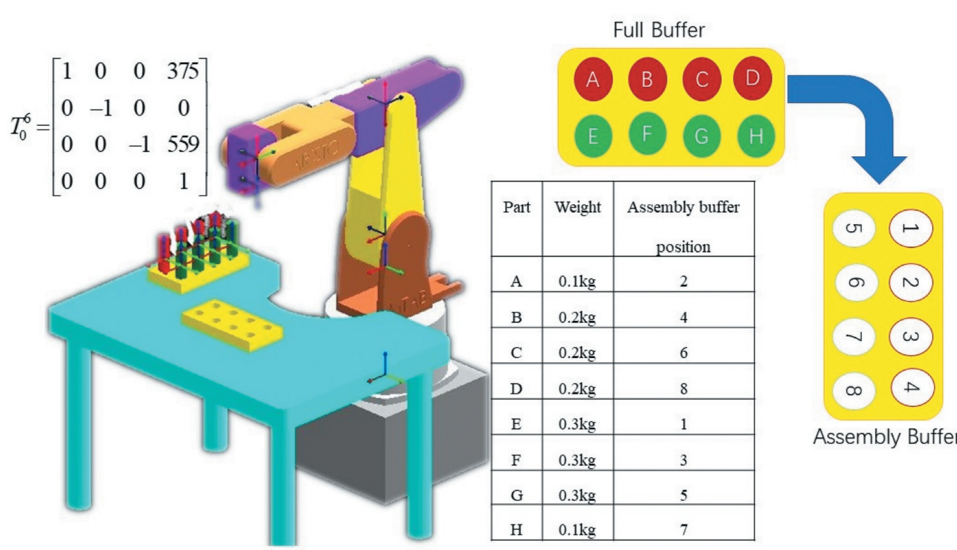


Figure 8. Analytical frameworks of the case.



$$T_0^6 = \begin{bmatrix} 1 & 0 & 0 & 375 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & -1 & 559 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Part	Weight	Assembly buffer position
A	0.1kg	2
B	0.2kg	4
C	0.2kg	6
D	0.2kg	8
E	0.3kg	1
F	0.3kg	3
G	0.3kg	5
H	0.1kg	7

Figure 7. The sample of a robotic assembly cellular.

an impressive total cut in energy consumption of 675 kW in the robotic cellular because of the developed digital twin system with the help of real-time decision making can select less energy consumption motion planning. It is an acceptable value for digital twin-based implementation in the real manufacturing industry. Therefore, it has an optimized effect on consumption results. Table 2 illustrated the results of this implementation. Energy consumption in all parts reduced by the developed system; however, time is not considered in this case study. For example, for part 'A' developed DT needs 2223 w but the simulation platform which used standard motion planning needs 2271 w. Of course, with increasing payload by part, the percentage of saving energy consumption improved. For example, in the piece 'A' pay leading is 0.1 kg and the percentage of saving is 3.8% but piece 'B' pay loading is 0.2 kg and the percentage of saving is 5.8%. It means that developed DT for the robotic arm with the help of real-time decision making can react in the different types of scenarios.

Also, four different speeds for part A are considered to carry out the pick and place operation to position 2. The result of this implementation is highlighted in Table 3 and Figure 9. Based on the results, three points need to be noted. Firstly, it is clear that the higher the speed, the higher the power. It explains the high accelerations that the machine makes to reach its maximum speed as quick as possible, therefore increasing speed needs more energy to consume. Secondly, there are very few differences in energy consumption i.e. between a speed of 50% and 75%. Amongst them, the most significant difference that occurs at the maximal speed in Joint 5. Thirdly, the gap that exists between the two extreme speeds (25% and 100%) is incredibly large. The energy consumption at a speed of 100% is more than twice the energy consumption at a speed of 25%. It is because the higher the speed gets, the higher the acceleration it climbs to in order to quickly change the state of the speed. However, automation helps in regulating this with an override. There is a perfect chance that the engines can never remain at its maximum power long enough due to various irregularities. The real-time data of energy consumption are presented in Figure 9. By using this data on DT implementation, the performance of this robotic cellular can be understood, so that the decision-maker can have a better operation plan to make robotic cellular more energy efficient and achieve energy consumption optimization.

Table 3. Maximal power for each speed.

Joint Velocity	Joint 1	Joint 2	Joint 3	Joint 4	Joint 5	Joint 6
Speed 25%	1245	1296	1219	146	289	181
Speed 50%	2861	2458	1803	187	404	285
Speed 75%	2891	2778	1831	171	502	351
Speed 100%	3024	3100	1961	178	541	391

The column chart presents the daily energy consumption of the case study, as shown in Figure 10. In order to increase the practicality and authenticity of the results, a pause time of 0.2 [s] has been added between the beginning and the ending of the cycle. The difference is not glaring. However, there is a more than 10 [%] difference between the speed of 25 and 50 [%]. Subsequently, the differences fall below 10 [%]. It can still be useful considering the long-time utilization of the single robotic cellular and massive numbers of applications of the robots in the future manufacturing workshop.

6. Managerial implications

The comparison and analysis of the energy consumption between the physical and virtual layers provide

Table 2. The energy consumption of the digital twin-based platform and simulation platform under different pay-loading.

Part	Energy Consumption: Digital twin-based implementation	Energy Consumption: Simulation platform	Pay-loading (Kg)	Save EC by the digital twin-based implementation	Percentage of saving EC (%)
A	2223	2271	0.1	48	3.8%
B	2289	2368	0.2	79	5.8%
C	2291	2375	0.2	84	6.1%
D	2291	2374	0.2	83	6.0%
E	2322	2431	0.3	109	7.6%
F	2321	2431	0.3	110	7.7%
G	2321	2431	0.3	110	7.7%
H	2223	2275	0.1	52	4.1%

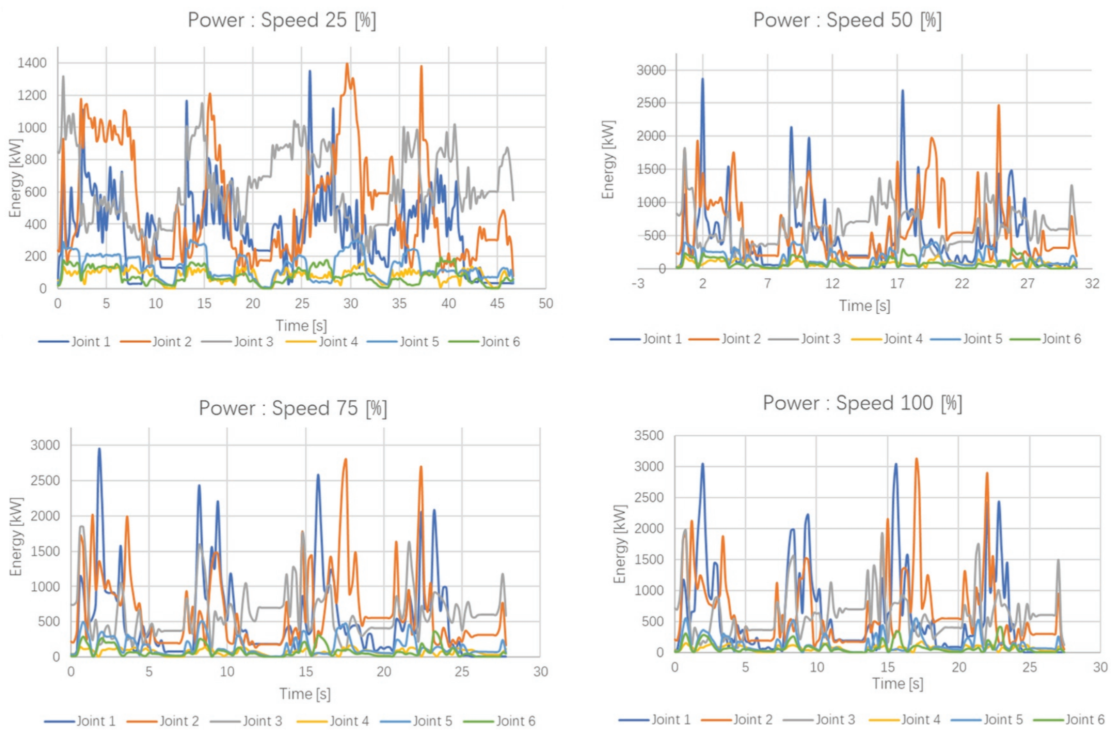


Figure 9. Power trend chart under four types of speeds for part A.

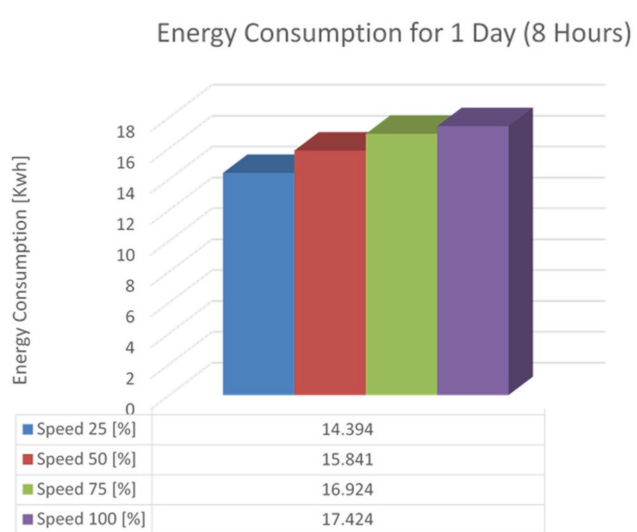


Figure 10. Energy consumption in physical prototype per day.

standards and suggestions for the smart workshop to make appropriate strategies for robotic operations as well as maximize the operating efficiency.

In the first place, the built-in digital-twin-based solution has the merits of saving the energy consumption of the robotic cellular. Based on Table 2, the total energy consumption saving of the robotic cellular operations is 675 kW. Moreover, the maximal saving percentage of energy consumption is 7.7%. In the long-run, not only can use for the single utilization of the robotic cellular, but it can also be profitable for the massive numbers of the robot's application in the future manufacturing workshop.

Moreover, the proposed digital twin-driven approach can digitally define, converge, and optimize the production process of the factory. For instance, it supports the configuration of the production lines so that the smart factories can achieve their optimal productivity. In the presented case, it can help the manufacturing workshop to achieve better energy consumption performance. With digital and intelligent production, the manufacturing enterpriser needs to acquire solutions to quickly address different challenges such as process optimization, raw material selection, and production live configuration and energy consumption, etc. The digital twin can help enterprises provide a variety of optimized solutions and then increase production efficiency as well as product quality.

Finally, the built mathematical models provide a standardized formula for digitalizing the robotic cellular. It not only helps to quantify the energy consumption of the robotic arm but also provides a generalizable method for application of more robot-related optimizations, such as the motion path optimization of the robots, the robot location configuration, etc.

However, some challenges need to be addressed. On the one hand, the cost of the digital twin-based solution is comparatively hard to afford, especially for small and medium enterprises. For instance, the application of digital twin needs professional knowledge and experts, which is a huge setback for small-scale manufacturing enterprises. On the other hand, the realization of a digital twin-driven approach requires upgrading or replacing physical manufacturing resources and production systems in traditional production, which will inevitably delay the production schedule and cause an inevitable loss of profits. Therefore, the implementation of a digital twin-driven workshop still needs more effort. Besides, in the developed decision-making agent, minimization of time-based on motion planning was not considered, and in this research, only energy consumption is focused. However, to improve the productivity of system minimization of time is significant.

7. Conclusion

In this paper, a digital twin-driven approach for robotic cellular with considering real-time motion planning decision-making agent was proposed. On the one hand, the proposed method establishes a connection between the physical and virtual space in the manufacturing workshop to achieve an autonomous decision-making mechanism and simulation analysis. On the other hand, it integrates, analyzes and optimizes the physical items as well as virtual items in the manufacturing workshop, and then improves the performance of the energy consumption in the manufacturing workshop. Besides, based on the proposed approach, a general mechanism for building a virtual twin was proposed. Moreover, the qualitative analysis and quantitative comparison in the case study is based on a realistic data energy consumption from the physical layer and virtual layer, respectively. It proves that the digital twin-driven approach helps support enterprise for effectively making a decision.

However, there are still some gaps in this paper. One of the main differences is how to implement this concept in small and medium-sized enterprises (SMEs) because as a SMEs, the application of digital twins and the realization of smart manufacturing requires upgrading or replacing the physical workshops and production systems under the traditional production, which will inevitably delay the production schedule and cause a loss in profit. Besides, the new development of technologies and systems need professional knowledge and experts, which usually cost a lot of money. Therefore, the implementation of a digital twin-driven approach is still risky for most SMEs. In the future, authors may concentrate on creating a new mechanism for establishing collaboration between the large enterprises and SMEs, to build the digital twin-driven workshop. Also, this paper focuses on constructing a digital robot arm prototype and analyzing energy consumption. However, a robot arm is just one of the constituent elements. There are a lot of more complex features in the manufacturing workshop that are of enormous importance, such as the human resource, logistics mechanism, and the raw material, etc. In subsequent research, this approach will be performed at different elements of the workshop and analyze them from various aspects in order to achieve the full-scale digital twin-driven workshop.

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