A Conceptual Digital Twin for Cost-Effective Development of a Welding Robotic System for Smart Manufacturing

Minh Duc Vu[1], Chu Anh My[2(✉)], The Nguyen Nguyen[2], Anh Le[2], Minh Thanh Ta[3], Xuan Bien Duong[4], Tien Anh Nguyen[5], Chi Hieu Le[6], and Duc Hoang Chu[7]

[1] Department of Aerospace Engineering, Le Quy Don Technical University, Hanoi, Vietnam

[2] Institute of Simulation Technology, Le Quy Don Technical University, Hanoi, Vietnam
myca@lqdtu.edu.vn

[3] Deparment of Information Technology, Le Quy Don Technical University, Hanoi, Vietnam

[4] Center of Advanced Technology, Le Quy Don Technical University, Hanoi, Vietnam

[5] Department of Physics, Le Quy Don Technical University, Hanoi, Vietnam

[6] Faculty of Engineering and Science, University of Greenwich, London, UK

[7] Ministry of Science and Technology, Hanoi, Vietnam

Abstract. With rapid technology advancements and impacts of digital transformation technologies, there have been a lot of efforts in recent years at the global and national scope to develop technology eco-systems moving toward Industry 4.0. There has also been a growing number of studies about optimization of process parameters based on AI, IoT and Bigdata analytics, including CNC machining, additive manufacturing, as well as industrial welding with robots, for development of Smart Manufacturing (SM), which is one of the key elements of Industry 4.0. However, there are challenges to fully develop and apply in industrial practices the ideal SM models in the next 5 to 10 years. It is necessary to develop the cost-effective SM models that are easy to understand with a high level of applicability in practice and adoptability for SMEs. In this paper , a conceptual digital twin is proposed, with the focus on cost-effective design and development of a welding robotic system for smart manufacturing.

Keywords: Welding robot · Digital twin · Smart manufacturing

1 Introduction

Manufacturing is becoming smarter and smarter at all levels based on these core advancements, especially digital transformation technologies, AI and bigdata analytics, and abilities to learn, configure and execute with cognitive intelligence, leading to the concept of Smart Manufacturing (SM) and Smart Factory (SF) [1].

There has been a growing number of studies about optimization of process parameters based on AI, IoT and Bigdata analytics, including CNC machining, additive manufacturing, as well as industrial welding with robots, for development of SM, which is one of the key elements of Industry 4.0. Development of cost-effective digital twin models for optimization of smart manufacturing shop floors has also obtained growing attentions.

In the welding process with robots, a digital twin model includes not only a digital kinematic model of a robot arm, but also other signal processing layers which constructed with sensors, actuators, data acquisition systems integrated on a robotic system. Specifically, for a smart manufacturing system with welding robots, the signals in the signal processing layers include the following ones: welding voltage, current, weld tip position, seam profile, weld pool, bead dimension.

There are solutions that can be utilized to measure, analyse, monitor and control an integrated welding robotic system. In [2], a sonar sensor was used to estimate the quality of weld bead, together with voltage sensor, current sensor which gathered by a DAQ card and sent to a computer. Force/torque sensor on tool tip was employed in [3] to determine the point on unknow workpiece surface. For recognizing the weld path, a pair of sound microphone set up at two ends of path in [4]. Recently, due to the increasing ability of camera systems with high speed processor and new image recognition algorithm, several parameters of a welding robotic system can be measured without particular sensor. In [5, 6], a camera capturing 2D welding pool shape was integrated with a computation module for calculating the pool shape dimensions to give feedback signals to the controller. 3D images were processed in [7, 9]. A common hardware structure including a robot, a welding machine, sensors, cameras, a control software on PC was demonstrated in [4–6].

There have also been some research works focusing on digital twin model for a robotic system [8–11]. A Kuka robot and the Microsoft Kinetic to integrate a HIRIT platform was investigated in [8]. The work [10] takes into account a 3D digital robot, camera images, ROS to study a digital twin model. Based on the PLM platform, the authors in [11] attempted to a robotic digital twin with a Hybrid 6 DOFs cutting system connected to Labview and Matlab softwares.

The applications of SM in practice are still in the early stage, and there have been a lot of proposed SF conceptualisations with different degree of automation and absence of human workforce [1, 12]. Therefore, there are challenges to fully develop and apply in industrial practices the ideal SF models.

There are challenges to fully develop and apply in industrial practices the ideal SM models in the next 5 to 10 years. It is necessary to develop the cost-effective SM models that are easy to under-stand with a high level of applicability in practice and adoptability for SMEs.

This paper proposes a framework and a case study for cost-effective design and development of a welding robotic system for smart manufacturing. A proposed case study of a digital twin model includes a robot arm and smart elements, for cost-effective development of a smart welding robotic system, with the focus on digital twin model for optimization of welding parameters and robot control, to increase the welding productivity and the welding accuracy.

The rest of the paper is presented as follows. Section 2 presents the materials and methods of a study, with the details about development of the conceptual digital twin for a smart welding robotic system for smart manufacturing. Section 3 presents discussions and conclusions.

2 Materials and Methods

2.1 Hardware and Software for a Smart Welding Robot System

A physical-digital structure of a smart welding robotic system, in which measurement functions, control features and data communication channels, were developed based on the integration of the following functional elements: A robot arm Mitsubishi RV-12SD, welding hardware devices, sensors, data acquisition cards. The following tools and software are used for 3D design and analysis: SolidWorks, LabVIEW and MatLab/SIMULINK.

2.1.1 Industrial Robot Arm

The robot arm Mitsubishi RV-12SD is shown in Fig. 1. The robot arm has 6 Degrees of Freedom (DOF), dedicated by Mitsubishi servo technology plus a high-performance controller CR3D-700 working for high speed (0.66 s cycle time) and accuracy. The robot controller is compatible with not only Mitsubishi's family of automation products, but also other standard devices from other suppliers. This makes the robot arm flexible and durable for industrial applications. The tool head can carry a maximum 12 kg load, moving in 1086 mm radius reach at a top speed of 9600 m/s with 0.05 mm position accuracy.

Fig. 1. Standard Robot hardware components for a smart welding system.

The robot controller, CR3D controller, supports the PTP and CP path control methods with the MELFA-BASIC language, which instructions could be sent from the computer. Remote command devices connect to the CR3D controller via either RS 232C or Ethernet ports. Additional teaching pedant R32TB is attached to Improved display performance and operability.

The 3D CAD models of the robot arm Mitsubishi RV-12SD was built in SOLIDWORKS for analysis and simulations.

2.1.2 The Welding Components

The high duty cycle Jasic Mig 250 welding hardware for the integration is used. The supply welding current is from 25 to 250 A at voltage range 11–29 V and wire feeding adjustable 2–15 m/min. The compact accessory set including a welding gun and a pressure air connector are provided to be attached on the robot arm.

2.1.3 Sensors

The voltage sensor module B25, current sensor module Qi-300-I (QEED), encoder Autonics E50S8-100-3-V-5 and air pressure sensor Autonics TPS30-G4KAR2-00 are selected and integrated to measure actual values of the welding voltage, current and wire feed speed respectively.

2.1.4 Data Acquisition Module

The NI USB 6001 module is used which provides functions to measure analog/digital signal from sensors with 8 AI (14-Bit, 20 kS/s), 2 AO (5 kS/s/ch), and 13 DIO. The amplified signal then be given into Labview environment for processing. Simulink model is designed to receive processed data to calculate and simulate the states of the welding robot. The Simulink module also sends separated data back to the robot via Labview/USB 6001.

2.1.5 Camera

In order to determine the dimensions of seam gap, weld bead, torch, etc., the robot is equipped a CCD camera with light filter attached beside the welding tip. The images from camera are transferred to a computer through USB port. In particular cases, it also used to estimate the welding point or path.

2.1.6 Melfa-Basic Remote Command Set

In order to control the robot, the users need programming. For this robot, the commands via RS232C port are accepted. A command usually contains a frame of characters. The movement commands run in either PTP and CP types. The commands could be edited with various software (C#, Matlab, Visual Basic, etc.) to execute the desired tasks. In addition, it helps to set up angle, position or load during operation together with giving the dynamic parameters to remote controller. Remote control ability could change the strategy of movement online, suitable for adaptive welding movement.

Example of commands:

CNTLON set the Robot controller to On for operation.
SRVON to set all the servo a On ready to run all joints.
EXECP1 = (232.00,3.00,400.00,0.00,45.00,0.00)(6,0) set the position 6 DOF.

Figure 2 presents an integration of smart elements for a mart welding system, including the robot arm and controller, welding tool, camera, sensors, and data acquisition module.

Fig. 2. An integration of smart elements for a mart welding system. (1–3): Robot arm and controller. (4): Welding tool. (5): Camera. (6–9): Sensors, Data acquisition module.

2.2 Integration of a Digital and Communication Model

Figure 3 presents the link between the CAD software and Matlab platform. The robot arm RV-12SD was digitalized with respect to the definition of joints and interfaces, the dimensions of arm bodies, the limit position of the tool head, the range of speed and acceleration of each axis and home position. The 3D CAD model of the robot was built in Solidworks and converted into the Xml format, which is then embedded into the Matlab/Simulink work space with the kinematic features of the physical model.

Figure 4 present the Simulink block diagram of the RV-12SD robot model, a block diagram presents the kinematic features of a robot, in which J1, J2, J3, J4, J5 and J6 are respectively related to the Base, Shoulder, Upper, Elbow, Fore and Wrist of the robot.

The Labview program was built on a PC to read data from NI USB 6001, processes images from the camera to calculate the welding parameters and transfer all the data to Matlab/Simulink work space. In this manner, the states of the physical and digital models can be synchronized. The designed Simulink module also makes tasks and sends Melfa basic commands back to physical robot to make the bidirectional communication. This is an important part of the digital twin creation for the real time parameters updating. In addition, the sensor data, images can be stored in a bigdata platform for smart solution such as IoT and Machine learning.

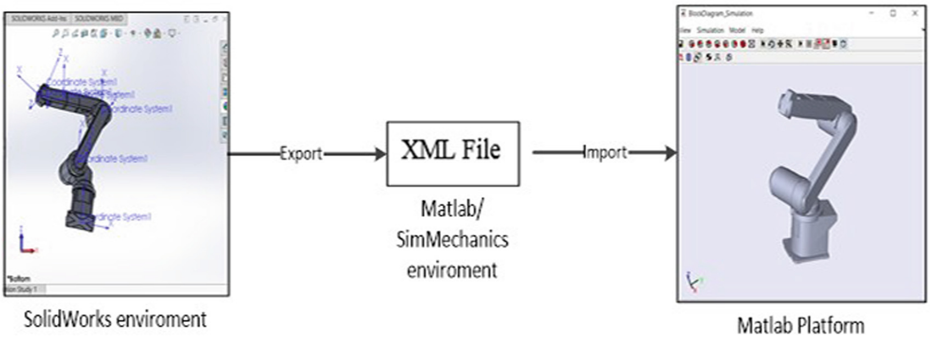

Fig. 3. CAD model to.XML file extension

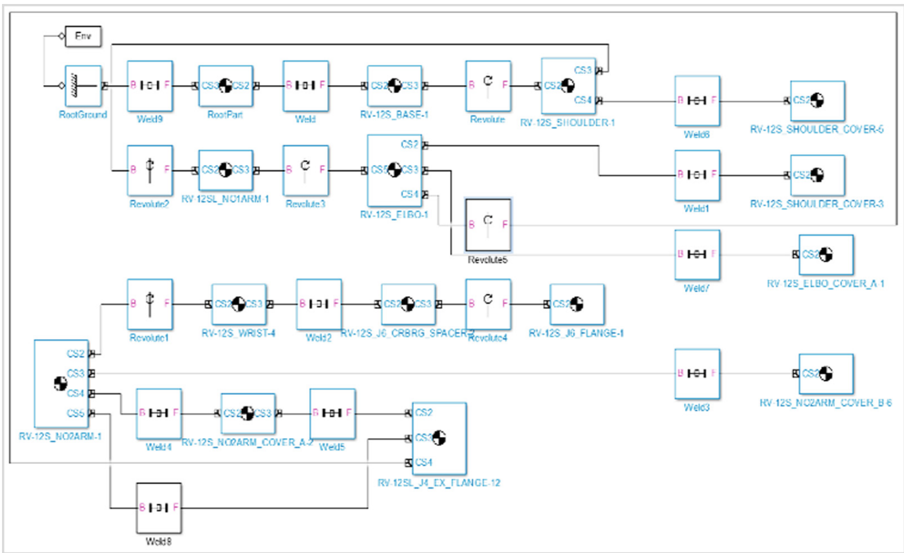

Fig. 4. Simulink block diagram of RV-12SD model

3 Discussions and Conclusions

A conceptual framework for cost-effective development of a smart manufacturing system is presented in Fig. 5, it is aimed to demonstrate the cost-effective digital twin model for a smart manufacturing system, with welding robots.

With the proposed digital twin model, it was successfully demonstrated that the proposed conceptual framework can be extended with additional physical and digital modules, based on the original model, with integration of additional smart elements. The sensor data captured during the operation of the digital-physical system can be stored for related bigdata analytics, from which the machine learning algorithms are applied to optimize the performance of the smart welding robotic system.

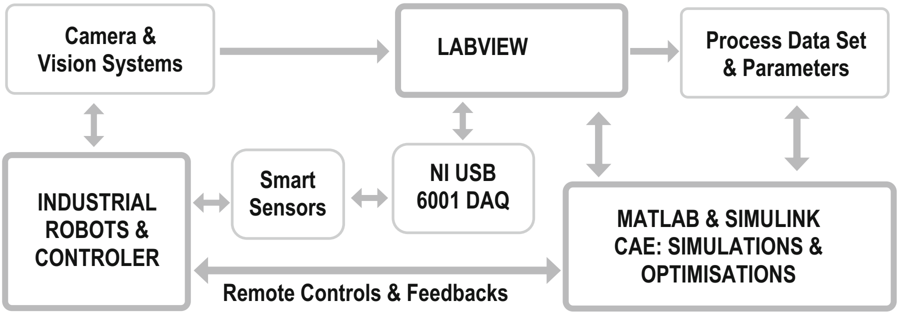

Fig. 5. A conceptual framework for development of a smart manufacturing system with robots.

In conclusion, there have been a lot of efforts in recent years at the global and national scope to develop technology eco-systems moving toward Industry 4.0. However, the manufacturing industry is more vulnerable compared to the service one due to the constraints related to human workforces and manufacturing resources as well as the economic fluctuations and recessions. In addition, applications in practice of SM are still in the early stage. There are challenges to fully develop and apply in industrial practices the ideal SM models in the next 5 to 10 years [1]. In addition, there is also the lack of skilled workforce and financial resources, standardization problems and cybersecurity issues related to development of SM solutions for industrial applications. Therefore, it is necessary to develop the cost-effective SM models that are easy to under-stand with a high level of applicability in practice and adoptability for SMEs. In this study, a conceptual digital twin for cost-effective design and development of a welding robotic system for smart manufacturing is proposed and demonstrated. The study is a foundation for further development of a smart manufacturing system, with a full integration of smart elements, including robots, CNC machines and additive manufacturing systems, collaborative robots, automated guided vehicles (AGVs) and smart sensors.

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