Proceedings of the 2024 Winter Simulation Conference
H. Lam, E. Azar, D. Batur, S. Gao, W. Xie, S. R. Hunter, and M. D. Rossetti, eds.

CYBER-PHYSICAL PRODUCTION SYSTEM FRAMEWORK FOR PRODUCTION SCHEDULING IN SMART FACTORIES

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ABSTRACT

Smart manufacturing refers to manufacturing systems composed of automatic processes interconnected through the internet of things. Likewise, a smart factory is a core concept of smart manufacturing that refers to an automatic production system that is fully connected, where data is collected and analyzed to make informed decisions. Moreover, smart factories are based on the coexistence of a physical and virtual factory. Hence, the development of a cyber-physical production system framework to merge the physical and virtual factory is motivated. This manuscript describes the integration of a supervisory control and data acquisition system with a factory digital twin, which allows production floor remote data gathering, scheduling optimization, and production floor machines remote control. A scenario of a painting shop is presented to illustrate the performance of the cyber-physical production systems framework. The results exemplify the potential benefits to the decision-making process when implementing the proposed framework.

1 INTRODUCTION

Smart manufacturing, also called industry 4.0, is a term used to describe the vision of a manufacturing system mainly composed of automatic processes, where the multiple sub-systems are interconnected and share information through the internet of things. The information of these sub-systems is processed in a central unit, and the system has the capacity to make decisions with little or no intervention (Marr 2018). The technologies encompassed by smart manufacturing include programmable logic controllers (PLCs), industrial robots, sensors, supervisory control and data acquisition (SCADA), simulation and modeling, artificial intelligence, cyber-physical production systems, digital twins, additive manufacturing, energy monitoring systems, internet of things, cloud computing, big data analytics, and augmented reality (Frank et al. 2019; Ryalat 2023). Furthermore, smart factory is a core concept for smart manufacturing. A smart factory is the conceptual model of a fully connected production system constituted by automated processes, where large data amounts are collected, stored, and analyzed to make informed decisions with little or no human intervention (Osterrieder et al. 2020).

The smart factory concept implies the coexistence of a physical and virtual factory. Hence, researchers and practitioners introduced the concept of the cyber-physical system (CPS) to bridge the gap between physical and virtual factories. Monostori (2014) reports that cyber-physical systems (CPS) are one of the most important future directions of computer science, information, and communication technologies, which are called cyber-physical production systems (CPPS) when applied in the manufacturing sector. Moreover, CPPS is the system of system components of all production levels (e.g., device, control, and information levels) interconnected through the industrial internet of things (IIoT). These CPPSs can monitor the entire system, improve the decision-making processes, and respond accordingly (Frank et al. 2019).

Furthermore, the cyber component of a CPPS is denominated factory digital twin (FDT). A FDT is a virtual representation of a production system that can mimic the behavior of the physical asset. Moreover, a FDT must have synchronization with its physical twin (i.e., production floor), active monitoring to detect significant events in its physical twin, and the capability to simulate what-if scenarios (Renteria-Marquez et al. 2020). In 2012, NASA introduced the general digital twin concept (Shafto et al. 2012), which surged with the need to have on earth an accurate representation of a vehicle in space. Initially, the digital twin was defined as the integration of multi-physics, multi-scale, probabilistic simulations, and physical models of a space vehicle that receives information collected by sensors located in the actual vehicle during its expedition in space.

Smart manufacturing implementations require efficient methodologies for integrating and controlling individual system components, like robots, CNC machines, VLS machines, and mobile platforms. Such systems benefit from incorporating a CPPS, which facilitates keeping track of the production floor's current state, and incorporating methodologies and algorithms that optimize them. Hence, the main objective of the presented manuscript is to propose a CPPS framework that would allow one to collect data from the production floor, optimize the production schedule, and control floor equipment according to the schedule requirements. The literature contains previous attempts to integrate CPPS with FDT (Bracho et al. 2018; Lin et al. 2020; Lin 2022; Monostori et al. 2016). However, these approaches do not incorporate remote control of production floor equipment.

The rest of the paper is organized as follows: Section 2 presents the proposed CPPS approach. Section 3 describes the SCADA system implementation in detail. In section 4, the FDT approach is described. Section 5 introduces a case study and the numerical results. Finally, section 6 presents the conclusions and future work.

2 CYBER-PHYSICAL PRODUCTION SYSTEM APPROACH

As previously mentioned, the proposed CPPS framework can gather and analyze production floor equipment data, optimize the production schedule, and control floor equipment according to the system requirements. Furthermore, the foundation of this framework is a SCADA system integrated with a FDT that allows the administrator to gather data remotely from the production floor (e.g., the number of active machines and machine breakdowns). Subsequently, the collected data feeds the FDT, composed of a genetic algorithm (GA) and a discrete-event simulation. As a result, this CPPS framework provides a scheduling optimization approach and remote control (i.e., on or off) of production floor machines.

Figure 1 shows the entire proposed CPPS framework. The CPPS comprises four levels: (1) Device level. The production floor equipment of interest, such as industrial robots, CNC machines, and PCB assembly machines, forms this level. (2) Control level. Client PLCs controlling production floor equipment belong to this second level. (3). Information level. The information level is composed of server PLCs and Admin PCs. (4). Optimization level. The optimization level is the FDT, composed of a GA and a discrete-event simulation. It is essential to mention that a code was programmed in MATLAB to serve as the interface that retrieves production floor data from the SCADA system. On top of that, the optimization GA is also contained in MATLAB. Additionally, an interface between MATLAB and the discrete-event simulation software is required. Microsoft Excel spreadsheets were implemented to communicate MATLAB and the simulation software.

Figure 2 shows the data flow starting at the device level and ending at the optimization level, and vice versa. The sequence of data gathering flow and its processing is as follows: (1) AC current sensors connected to production floor machines monitor and determine the machine's status. (2) The client PLCs located in the control level receive and interpret the data. (3) Then, server PLCs communicate with client PLCs to exchange data. (4) Subsequently, the admin PC requests data retrieved by server PLCs. (5) Then, data is imported into the optimization level through MATLAB, and the production sequence is optimized with the GA and exported to an Excel file. (6) The optimized production sequence and machine's status are imported into the discrete-event simulation. (7) The FDT obtains the optimal production schedule at the information level. (8) Finally, the production machines are turned on or off, depending on the scenario.

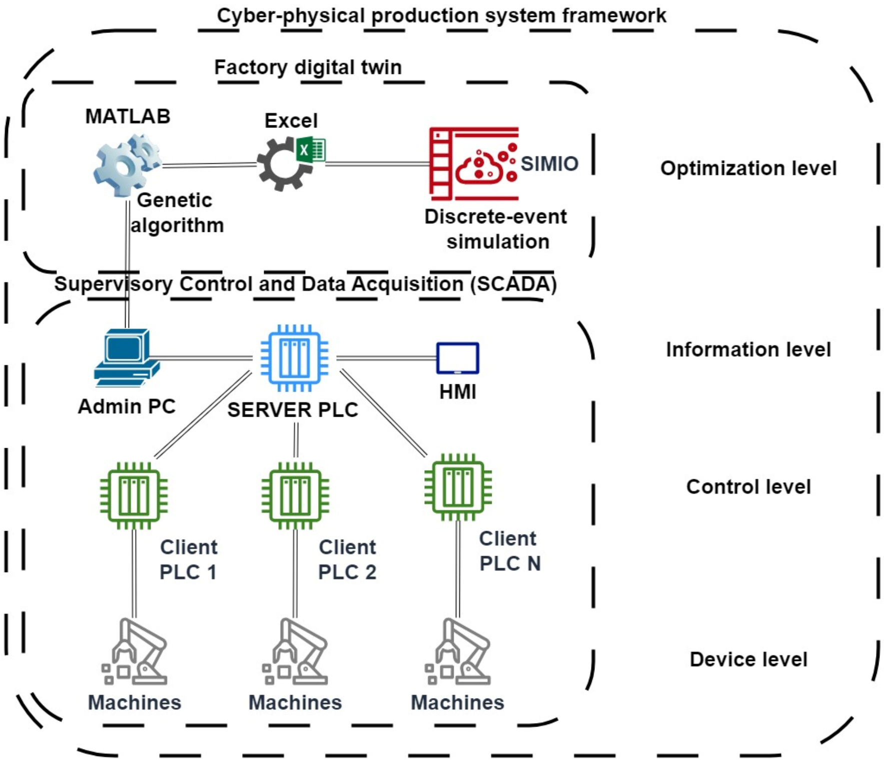

Figure 1: Cyber-physical production system framework.

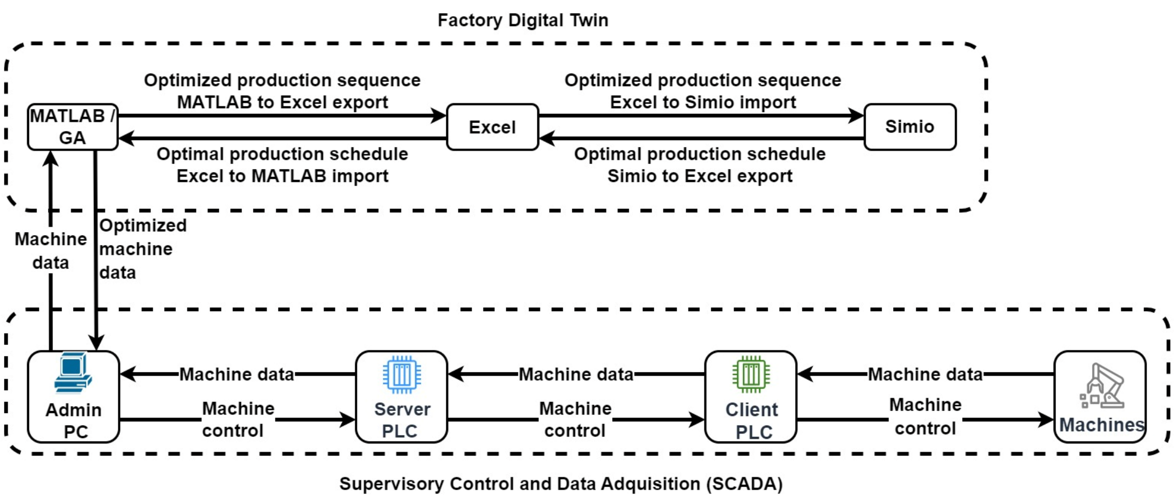

Figure 2: Data flow diagram.

3 SUPERVISORY CONTROL AND DATA ACQUISITION APPROACH

An industrial set-up was built in a laboratory to experiment and test the proposed CPPS framework. The main components of the physical system are AC current sensors, relays, server and client PLCs, an Admin PC, and a HMI. This framework proposes AC current sensors to check production equipment's status (i.e., on and off). Client PLCs are dedicated to monitoring and controlling production equipment. Conversely, server PLC manages communication between client PLCs and the Admin PC. Furthermore, an HMI was designed and integrated to facilitate system operation. Figure 3 shows the proposed SCADA system network connection diagram. Siemens PLCs SIMATIC S7-1200 and a HMI KTP700 were chosen to develop the proposed framework, which were programmed in TIA portal software. The rest of this section summarizes the programming strategies implemented for the SCADA system.

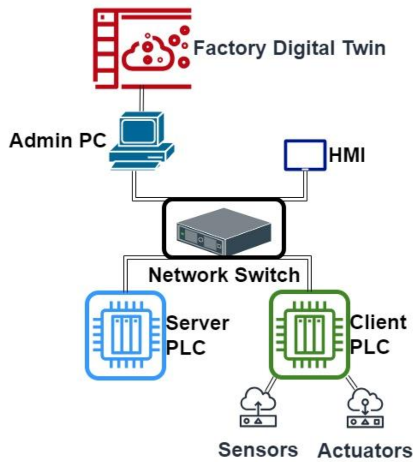

Figure 3: SCADA system network connection diagram.

Server PLC was programmed through several function blocks that belong to the S7 communication protocol, allowing monitoring, data acquisition, and control of client PLC. Client PLCs contain two data blocks in their program that capture and store the production floor machines' status. The two main blocks of the S7 communication protocol are the PUT and GET blocks, which allow one to store and acquire data from client PLCs. Server PLC incorporates the capacity to communicate with the admin PC. The TCON, TDISCON, and TSEND blocks were implemented to establish open user communication, terminate transmission, and transmit data between the server PLC and the admin PC. Furthermore, the CPPS proposed here incorporates the capability to send data back to the client PLC, allowing remote control of the production floor equipment. This functionality was accomplished by enabling MATLAB software running on the admin PC to send data to the server PLC through TRCV block implementation. On the other hand, the purpose of the HMI is to oversee and manage the facility remotely from a central office. Hence, this HMI's communication interface was designed to enable communication between the different system components and activate blocks such as TCON, TDISCON, TSEND, TRCV, and GET/PUT.

Furthermore, a code formed by MATLAB scripts was developed to serve as the interface between the information and optimization levels. Hence, the FDT communicates to the SCADA system through a MATLAB-Admin PC interface, allowing the status of production floor equipment to be requested. MATLAB Instrument Control Toolbox, a collection of functions that enable IP/TCP communication and control capabilities of external instrumentation and devices, was incorporated to achieve this communication capability. In addition to that, it is required to interface MATLAB and the simulation software. Simio Simulation, Production Planning, and Scheduling software was chosen for this project. This simulation software offers an application programming interface (API) and a collection of API functionalities stored in the Simio LLC GitHub repository. In this work, Microsoft Excel served as an interface to communicate MATLAB and Simio software by incorporating the API ImportObjectsFromExcelUsingEPPlus.

4 FACTORY DIGITAL TWIN APPROACH

The proposed FDT will allow one to generate optimal production schedules and quantify risk. First, production floor status is obtained through the SCADA system, and manufacturing orders are input into the GA, which searches for the optimal production sequence. After that, this sequence will be input into the simulation model, which will run a certain number of replications and generate a production schedule. Subsequently, the associated risk will be calculated. Lastly, this information will be analyzed, the optimal number of required resources will be obtained, and control signals to production floor equipment will be sent as needed.

As mentioned previously, a GA was developed and programmed in MATLAB to optimize the production sequence. A GA is a metaheuristic evolutionary algorithm commonly used to generate good-quality solutions to complex optimization problems. GAs are inspired by how biological evolution works and use evolution concepts such as survival of the fittest to solve a variety of optimization problems. In other words, a GA generates several possible solutions, and only the strongest solutions will survive to the next generation. The main steps of the GA are the following: Generation of the initial population, selection of parents, reproduction, and generation of a new population. Figure 4 shows the general phases of the GA, which are briefly described in the following paragraphs (Srinivas and Patnaik 1994).

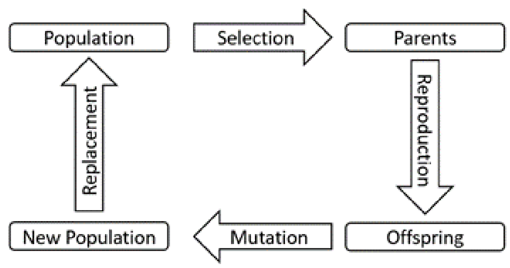

Figure 4: General GA flowchart.

Population: The population contains a set of possible solutions, each of which is called a chromosome of the GA. Moreover, the initial solution set is generated randomly to create the first generation.

Selection: Each possible solution is evaluated here. For instance, job shop problems aim to find the production sequence that minimizes makespan. Hence, each chromosome in the population has a specific makespan value. This makespan is the fitness value used in the selection process. Through tournament selection, chromosomes will be selected to become parents. This process involves selecting two chromosomes from the population and making them fight. Consequently, the chromosomes with a better fitness value will become parents.

Parents: Parents will recombine to reproduce and generate new chromosomes called children. These new chromosomes are solutions with some characteristics from the parents. This principle is based on the belief that combining the strongest parents will produce the strongest child.

Reproduction: Combining two or more chromosomes to produce one or more new chromosomes is called crossover, and several options exist. The most common are one-point, two-point, and uniform crossover (Kumar and Panneerselvam 2017). In this work, uniform crossover was selected to perform the reproduction process.

Mutation: Commonly, all the chromosomes are similar or alike after several generations. This situation allows the solution to lock in a local optimum, making it impossible to produce a new child different enough to avoid it because all the parents are very similar. Mutation addresses this problem by adding a random disturbance in the chromosome that allows it to generate a child that otherwise will not be possible with simple crossover.

New population: A new population will be formed by offspring and elite parents from the current generation. Elite parents are the top chromosomes for the current generation (i.e., solutions with the best fitness value).

Replacement: Lastly, a new population will replace the previous one. The entire GA will be repeated to allow several generations and will end after obtaining a good solution.

As previously indicated, Simio Simulation, Production Planning, and Scheduling is the software chosen to model the manufacturing system. This software is a multi-paradigm modeling tool that integrates the four discrete modeling paradigms developed for simulation: Events, processes, objects, and agent-based modeling (Renteria-Marquez et al. 2020). This software offers an object-oriented modeling technique where users can create new objects by changing base objects through processes. Moreover, an entire model is created graphically by combining base objects, derived, and composite objects that model physical elements of the real system (e.g., workstations, workers, robots, tools, etc.) (Pegden 2012; Smith et al. 2018). In this manuscript, the paradigms used to develop the simulation of the job shop are events, processes, and objects. Events are used to model the system's arrival of new manufacturing orders. Processes are used to model the different industrial processes that compose the system. At the workstation level, objects are used to model them.

The risk associated with each schedule is determined by calculating the average of the makespan delays for a given number of simulation replications implementing the Monte Carlo approach (Wu et al. 2018),

$$S_R = \frac{1}{N}\sum_{k=1}^{N}(M_k - M_0), \tag{1}$$

where S_R, M_k, M_0, and N denote schedule risk, makespan of stochastic schedule replication k, makespan of deterministic schedule, and number of simulation replications.

5 NUMERICAL RESULTS

A painting shop was selected as the scenario to demonstrate the proposed FDT. This scenario is a flexible job shop composed of four workcenters, each containing two identical machines (MA_i) placed in parallel, which means that each workcenter can process up to two jobs at a time. Each machine comprises a spray-painting robot controlled by a PLC and a HMI. Moreover, each workcenter has an area allocated for the work in progress to wait for a specific cure time, refer to Figure 5. A total of ten different job types are considered in this scenario. Table 1 shows the routing sequencing by job type.

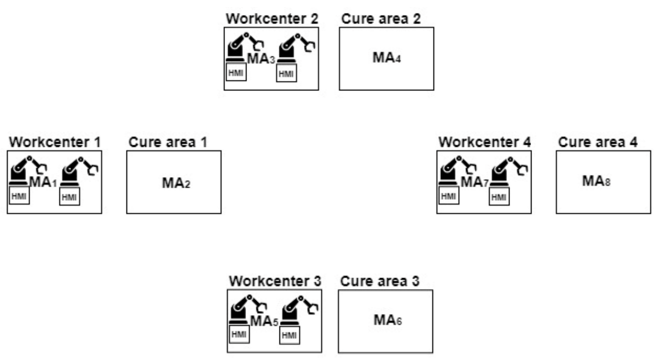

Figure 5: Painting shop layout.

In this scenario, the objective is to obtain the optimal production schedule, quantify the risk, and select the workcenters (i.e., number of robots per workcenter) capacity that allows a makespan of ten hours or less. Hence, the GA was implemented first to obtain the optimal production sequence. The best solution that allows the minimal makespan is MA_1[7,3,8,6,10,1], MA_2[7,3,8,6,10,1], MA_3[2,9,4,7,3,5,6,8,10,1], MA_4[2,9,4,7,3,5,6,8,10,1], MA_5[2,9,4,7,5,3,8,10], MA_6[2,9,4,7,5,3,8,10], MA_7[2,9,6,7,5,4,1,8,10], and MA_8[2,9,6,7,5,4,1,8,10]. After the optimal production sequence was obtained, its performance was quantified, and the schedule was generated using the discrete-event simulation model developed in Simio. First, a deterministic schedule was generated considering average processing times only, and makespans of 7.51 and 8.56 hours were obtained for workstations capacity of two and one robots, respectively. Subsequently, a total number of 100 replications of the schedules were stochastically simulated considering the system variability (i.e., variable processing times), and the obtained makespans were used to quantify the risk associated with the schedules. Figure 6 shows box plots of the makespan replications of the schedule. After that, through equation (1), schedule risks of 0.50 and 0.32 hours were obtained for workstations capacity of one and two robots, respectively.

Table 1: Routing sequencing by product type.

Jobs	**Machines**							
	MA_1	MA_2	MA_3	MA_4	MA_5	MA_6	MA_7	MA_8
1	X	X	X	X			X	X
2			X	X	X	X	X	X
3	X	X	X	X	X	X		
4			X	X	X	X	X	X
5			X	X	X	X	X	X
6	X	X	X	X			X	X
7	X	X	X	X	X	X	X	X
8	X	X	X	X	X	X	X	X
9			X	X	X	X	X	X
10	X	X	X	X	X	X	X	X

On top of that, the system administrator can use this information to determine the best option for each scenario, which, in this case, may opt for a workstation capacity of one robot because the stochastic average makespan for this scenario is 9.06 hours and the schedule risk is 0.5 hours. Moreover, the system administrator can use the CPPS remote control to turn off one robot of each workstation to reduce energy consumption.

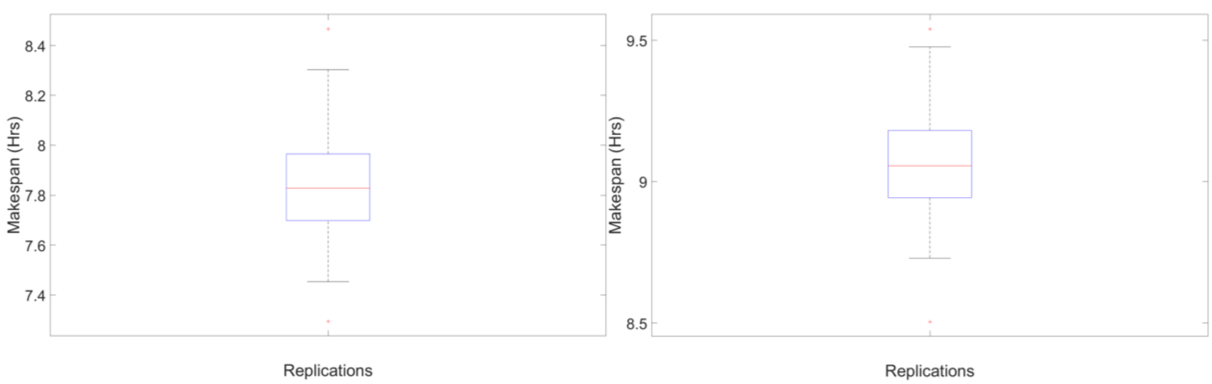

Figure 6: Makespan replications of stochastic schedule. (a) Two robots per workstation (b) One robot per workstation.

6 CONCLUSION

This manuscript presents a novel CPPS framework that allows remote data collection, optimization of production schedules and quantification of its risk, and remote control of production floor equipment. The CPPS framework proposed here is composed of a SCADA system and a FDT. Moreover, the FDT comprises a genetic algorithm that optimizes the production sequence and a discrete-event simulation that models the dynamics of the manufacturing environment.

An industry case study of a painting shop composed of four workcenters operated by painting robots is presented to illustrate the proposed CPPS framework. The results demonstrated the advantages and potential benefits of implementing the proposed framework in the manufacturing industry. Particularly, advantages to the decision-making process in smart factories were exemplified.

On top of that, the remote control of production floor equipment facilitates its operation and offers a pathway to integrate energy savings strategies. Hence, future work includes the study of methodologies to optimize energy consumption on the production floor and its implementation through this CPPS framework.

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