Reports in Mechanical Engineering
Vol. 4, No. 1, 2023, pp. 161-174
ISSN: 2683-5894, DOI: https://doi.org/10.31181/rme040115092023m

DES and IIoT fusion approach towards real-time synchronization of physical and digital components in manufacturing processes

Gergő Dávid Monek, Szabolcs Fischer
Széchenyi István University, Győr, Hungary

Article Info

Article history:

Received August 05, 2023
Revised September 09, 2023
Accepted September 12, 2023

Keywords:

Digital Twin,
IMU,
Discrete Event Simulation,
Smart Manufacturing.

ABSTRACT

Today's manufacturing systems offer more products to meet specific needs. Complex production systems in rapidly changing environments result from product variation, shorter product life cycles, and supply chain expansion. A cyber-physical production system (CPPS) can use manufacturing and logistics data to plan, monitor, and control production. Discrete event simulation (DES) and digital twin (DT) technology can model and evaluate manufacturing and logistics processes using high-level decision support and process monitoring. The cost of collecting input data from different enterprise data sources and mapping it into models and the lack of qualified experts prevent the widespread use of these methods in industry, especially in small and medium-sized enterprises and larger multinational companies. This research aims to create a modular digital twin framework for manufacturing process optimization and real-time monitoring in an industrial environment with few components. The system can identify and track the product through the manufacturing cycle while updating the DT in real-time and can be used independently to collect input parameters for discrete event-driven simulations and even for automatic simulation building in the future. The framework's operation will be shown through an example. With the proposed IIoT (industrial internet of things) system integration, it can detect faults and warn of deviations from normal operation, and DT can drastically reduce data collection and model building and support model reusability, increasing sustainability.

Corresponding Author:

Szabolcs Fischer,
Széchenyi István University
Email: fischersz@sze.hu

1. Introduction

Manufacturing companies must improve their production monitoring and forecasting to be flexible and reconfigurable. To that end, the digitalization of the manufacturing environment is a crucial issue. Several research and academic journals have used the discrete event simulation (DES) environment as a digital twin (DT) environment. However, only a few of the articles reviewed in this study went into detail about the design, and in most cases, complex, if not multiple, software and communication solutions were used to achieve the desired results. When considering their industrial applicability, such systems raise several concerns. One of these concerns is information security and the system's robustness, or its long-term stability and failure-free operation. The second factor is the non-industrial nature of the devices used; for example, a RaspberryPI in an industrial environment may not meet either the mechanical or potential protection against external network attacks. Finally, and perhaps most importantly, the complexity of the systems presented necessitates a high level of programming as well as specialized skills and experience to design and use. Schluse and Rossmann, for example, defined the digital twin as a virtual substitute for real world objects, while Latif et al. argue that the definition of the digital twin for manufacturing plants should be self-evident and simpler. The starting points were this assumption, the often-cited arguments against traditional DES systems, the lack of accurate input data, and time and cost-intensive model building.

The current research started by approaching several industrial partners, mainly target machine manufacturers. The target machine manufacturers interviewed mainly see the potential for providing extra services by incorporating DES and DT methodologies into their products. However, the current survey also confirmed the need for a solution that requires moderate additional effort, programming skills, and time, considering the price sensitivity caused by the intense price competition. Based on these criteria, the authors formulated the following criteria for our framework: no interference with the PLC program (supplementary use), no need to modify the current automation program, minimum system complexity, simplified usability even without programming knowledge, and user interface suitable for data visualization and process monitoring, debugging. The further direction is twofold: on the one hand, to create a relatively quickly deployable DES-based DT framework, and on the other hand, to investigate the usability of additional data available through an IIoT device that can be used independently but can also be integrated into the framework. Data will be more accurate and easier to access using the proposed system, as it will be collected contextualized rather than in isolation. The aim was to develop a framework and guidelines that can be adopted modularly by small and medium-sized enterprises while remaining relevant for large enterprises. This paper is organized as follows: Section 2 is formulated as an international literature review, Section 3 deals with the test environments and methods, Section 4 presents the results and discussion, and Section 5 summarizes the main results in short formats.

2. Literature review

The authors compiled a concise international literature review on digital twins based on significant publications. Obviously, this summary cannot cover the literature in its entirety. Nonetheless, the key literature findings are summarized in the following sections.

The arrival of the Fourth Industrial Revolution (I4.0) has produced an enormous number of new possibilities and demands in industries. Companies want to be able to regulate, monitor, and forecast the performance of their equipment in order to be flexible enough to fulfill market needs. Among the most potential enabling technologies for I4.0 are big data, predictive maintenance, and the Internet of Things (IoT). These technologies, however, do not yet cross the gap between the physical and digital worlds. The cyber-physical system (CPS) and the cyber-physical production system (CPPS) are two essential ideas that link the two layers.

A simulation is often used to create the digital twin (DT), particularly in virtual manufacturing environments (Tao & Zhang, 2017). As a result, it should be able to update itself when the actual system changes automatically. Furthermore, it should be capable of doing real-time simulations in proactive and reactive modes in case of a deviation or perturbation from the plan (Ladj et al., 2021; Monostori et al., 2016).

The term digital twin has several interpretations in the literature, but in this study, (Kritzinger et al., 2018) defined the approach based on the directions and modes of communication between the physical and virtual worlds. According to this approach, a digital twin is defined as a two-way communication link between a physical object and a virtual object, where information flows as close to real-time as possible. Furthermore, in this paper, "DT" is defined as "simulation DT," which means that the behavior of the manufacturing system under study is represented by a discrete event simulation (DES). This solution is primarily concerned with the workpiece flow in the observed system. Changes in the model are triggered by discrete events, such as the need for operations, and the model operates on an abstraction level that ignores the physical and mechanical complexities of the system under investigation (Ding et al., 2019; Garrido & Sáez, 2019). Thus, except for the properties of interest for investigation, this type of simulation modeling leaves out the rest in favor of simplifications. Such simulations are primarily used to answer various "what if?" questions or to optimize processes. They are primarily offline simulations in this approach. However, online models that function as digital twins can be created with the proper communication channels. In this case, the factory's virtual model (simulation) is actively connected in real-time to the physical manufacturing system (at the shop floor level), allowing DT to act as a monitor (Feng et al., 2023; Hughes et al., 2014; Ruppert & Abonyi, 2018), identifying problems or deviant behavior. Furthermore, it can virtually (within the simulation) re-optimize the manufacturing process within certain limits and, once approved, feed these changes back to the physical factory via the connected control systems (e.g., MES (manufacturing execution system) (Barlas & Heavey, 2016; Prat et al., 2017; Reinhardt et al., 2019)).

Despite the growing interest in digital twins, little consensus exists on what constitutes a twin. The situation is complicated by using terms such as digital model, digital shadow, etc., which in practice may simply refer to the stages in the life cycle of a digital twin as a physical entity evolves from conception through design to operation. Without a framework of the type proposed by Boyes and Watson (2022), it is not easy to establish digital twins' capabilities or to conduct a comparative analysis. Given the diversity of capabilities referred to as digital twins, this poses a problem for academia when trying to study their use and evolution and for the industry when comparing claims from different solution providers. Their functional analysis has broken down the concept of digital twins into sixteen components, starting from a sector- and domain-independent definition of digital twins. For each component, they identified characteristics that can be used to describe the functional capabilities of the twin and facilitate architecture and operational analysis. Their contribution is an analytical framework that can be used to characterize digital twins when comparing abilities or selecting twins similar to those in the study. Their research identified four areas where further work is needed: information management, architecture and design, lifecycle, as well as security and safety.

In a comprehensive literature review on I4.0, Vieira et al. found that DES solutions are contributing to this industrial revolution, in particular concerning the following aspects:

- automated data exchange: taking data from real systems (e.g., machines, sensors, etc.) and translating this data into simulations in an automated way;
- automatic model generation: the possibility of automatic simulation building, which is essential in the context of I4.0, as the basic assumption is that an I4.0 production unit is very dynamic; thus, the need to keep simulation models up-to-date is a frequent requirement;
- visualization: the ability to visualize complex systems, allowing the user to immerse and/or extend the virtual environment into augmented reality. (Vieira et al., 2018)

Manufacturing system adaptability is recognized as a key competitive factor in the manufacturing industry. Material flow simulation is frequently used to design and validate production system modifications to reduce response times and increase cost-effectiveness. On the other hand, the repeated manual synchronization of the simulation model with the real-world production environment is time-consuming and potentially error-prone. Automatic simulation model generation, or ASMG method for short, may eliminate these and has been identified as a significant gap and research area (Reinhardt et al., 2019). Based on their literature review, they classified information decomposition as follows (Table 1).

Table 1. Information decomposition methods

Explicit methods	Implicit methods
Direct	Code Inspection
Indirect	Geospatial Analysis
	Inference
	Machine Learning
	Machine Vision
	Pattern Recognition
	Statistical Evaluation

As seen from Table 1, various methods and approaches are being experimented with to extract the information needed for model building, but no universally applicable, standardized method is currently known.

Focusing on logistics processes, a literature review on DES and DT integration identified trends and challenges in the field (Agalianos et al., 2020). CPSs can be based on simulation environments capable of receiving and processing data from IoT devices in real-time. If "sensing shop-floor data" becomes readily available soon, these real-time connected simulations could significantly improve the efficacy of manufacturing and logistics systems (Agalianos et al., 2020).

A long-standing rule of thumb in simulation projects is the so-called "40-20-40 rule". This rule is based on the observation that a simulation project can be divided into three main parts in proportion to their time requirements:

- gathering the information needed for the modeling (40%);
- building the model (20%);
- experiments and evaluations (40%).

Several previous studies have aimed to reduce the time required for the information-gathering phase of a manufacturing system simulation project, highlighting the topic's importance. This time-consuming phase includes the collection and preparation of input data. Significant design time reductions can be achieved by automating data collection and preparation. (Pfeiffer et al., 2012)

Haraszkó and Németh (2015) developed a configurator to speed up the modeling process, which generates a DES model after defining the necessary input parameters such as product mix, processing flow, layout, etc.

The model allows the user to explore different cases to help optimization. The developed tool is under continuous development and enhancement, and at the time of writing, it was still in prototype form. Limitations of their solution are the ability to map more complex production logic and the fact that the model is entirely offline (Haraszkó & Németh, 2015)

Dafflon et al. (2021) have formulated the following requirements for a well-functioning cyber-physical system: a simple user interface, appropriate human-machine interface (HMI), data collection, storage and management, appropriate service architecture, reconfigurable error and repair management, efficient machine-to-machine communication secure and seamless communication technology, and last but not least efficient interfaces between the different system components (Dafflon et al., 2021).

The development and use of sensing and on-board and peripheral data processing tools have revolutionized how production lines are monitored. This change has come in parallel with the communication protocols and semantic tagging of the parameters to be analyzed. However, challenges still remain, in particular for generic data specifications and their adoption by machine and IoT manufacturers; the future goal is still a plug-and-play environment where known sets of parameters are identified and secured for use by artificial intelligence (Turner & Garn, 2022).

The proposed configuration demonstrates the implementation and verification of DT, using a simulation program to visualize the data, and future research will focus on building a more complex DT structure (Delgado Sobrino et al., 2022).

Several approaches have been used to automate the simulation model construction by automatic input data collection and processing. Park et al. (2010) propose a naming convention for automatically identifying objects in PLC (programmable logic controller) programs and the control logic in the code that provides a basic data set for building the simulation model. If the proposed naming rule is not applied, this approach requires a renaming process in PLC programs.

A strategy for reducing the time necessary to construct simulation models is being researched – a suggested generic simulation modeling framework to reduce the time required to build simulation models. The suggested framework comprised numerous pieces of software that provided layout and control logic information for the modeled items. According to this technique, the layout and control logic of the manufacturing system must be designed with suitable software (Kassen et al., 2021).

As previously stated, numerous developed systems use PLC program processing to facilitate automatic simulation model building, with some of them including reviewing PLC programs. In contrast, the authors of this work offer a PLC program process approach for analyzing the effects of modifying PLC programs on the overall system (Lee & Park, 2014).

Popovics and Monostory (2013) extend their previous investigation by automatically producing an ISA-95 standard simulation model via PLC code processing. They used this method on a huge car production factory conveyor system.

Examples can be found in the international literature from other disciplines where the addition of a digital twin to manufacturing could be important and useful. Two examples are given below, but of course this is only a small sample and thus not a complete list, but it may be of interest for the discussion of digital twins. Németh and Fischer (2021) dealt with glued insulated rail joints which can be manufactured not only at the field but in factory. Szalai et al.'s research (2022) is about deformation analysis of 18650 type batteries. In both cases, the digital twin model can be created and the production and deformation analysis can be tracked in the digital model. The production of glued insulated rail joints (Németh & Fischer, 2021) is an activity requiring a very high level of precision. Particular control and attention is required to ensure material qualities, preparation of the required number of parts, precise adherence to process times (e.g. importance of cut sizes, process sequence of assembly, consideration of glue open time, control of torque of bolts, etc.). Checking the charge and discharge levels of the batteries and the parallel spatial deformation measurements (Szalai et al., 2022) – like factory production control – can be the last step in the manufacturing process. Digital twinning of this process can bring huge benefits. Battery heat management was investigated in Kocsis Szürke et al. (2023), they prepared finite element simulation of 18650 batteries considering different state of charge and state of health. In all the examples, it is important to produce as accurate a digital replica of the production control process as possible: this means that both spatial structure and sequence are essential, as well as the recognition of technological steps and detailed knowledge of technological processes. In both of the above examples, the realistic model can be supplemented with acceleration sensors (IMUs) or with similar methodologies to refine the operation of the digital twin.

Zdravković and Korunović (2023) present a novel product design methodology that proposes an innovative approach to conducting structural analysis in the customization of products, with a specific focus on the realms of digitization and mass customization. The authors put forward a computational tool for real-time structural analysis, referred to as a "compiled finite element analysis (FEA) model". The construction of this model is based on a dataset consisting of distinct product parameters and their corresponding physical properties. The model utilizes Machine Learning (ML) algorithms and hyperparameters to enhance its performance. The proposed solution addresses common design obstacles by enabling real-time validation of product design, thereby enhancing decision-making efficacy and achieving a harmonious equilibrium between customer-specific demands and product functionality. While the paper does not explicitly state it, the concept described in the paper is consistent with the principles of a digital twin. In this context, a digital twin refers to a simulated model that offers valuable insights into the performance of real-world products. The utilization of Machine Learning and digitalization has led to the emergence of advancements that are facilitating a more streamlined and analytical methodology towards product design and mass customization.

In contrast to the methods presented so far, we are working on a solution that requires minimal hardware and software and no advanced programming skills, such as app development. By using an additional smart device to retrieve data on its own or a combination of data from a PLC controlling the manufacturing cell under test, we can gather more accurate information about the monitored system or align the digital and physical systems. A working DT is created, where a two-way data link between the physical system and the digital twin can intervene in the real system, providing valuable information about the system's state to the user decision-maker.

3. Material and methods

In order to carry out the experiments, a test environment was needed that could substitute a modern industrial environment, thus ensuring that the results of the tests could be relatively easily implemented in a real production environment. The test environment was the custom-developed Cyber-Physics training and demonstration platform at the Széchenyi István University in Győr (Hungary). The platform was designed and developed in a two-year development project. It was designed to provide an up-to-date, hands-on teaching and demonstration environment for students on industrial digitalization processes and Industry 4.0 and a testbed for research in CPS and Digital Twin.

The main functional elements and topological model of the platform are shown in Figure 1. An important aspect in the technical and technological design of the platform was to have a full-function, control infrastructure, so the following elements were incorporated:

- a Siemens S7-1500 PLC (Programmable Logic Controller) controller;
- a Siemens KTP700 HMI (Human-Machine Interface) touchscreen control panel;
- a Siemens RF240 RFID (Radio Frequency Identification) identification system;
- a Siemens SCALANCE MUM856 5G router, and
- a monitor and a built-in PC (Intel NUC 11 i5, 16 GB DDR4-3200MHz) with the necessary peripherals to run the digital twin software in the future.

The table provides space for the infrastructure needed for the operation, which requires only electricity. A grooved base plate with milling on the table's surface allows the assembly of the process from conveyor belts.

The hardware components on the base plate are fixed using quick connectors, and the wires are connected using standardized connectors, which ensures modularity, free positioning, and easy assembly.

Figure 1. Cyber physics education and research platform

A modular process is set up in the work area of the table, currently consisting of a feeder and conveyors from a hardware element set. The product that moves on the hardware elements is an M5Stack Core2 type ESP-32 based microcontroller with touch screen display, WiFi, 6-axis IMU (Inertial Measurement Unit) (MPU6886), and a built-in 500 mAh battery. Each workpiece contains an RFID tag. Identification of the products is ensured by the RFID reader built into the feeder. Multiple real-time and near real-time data links are established between the PC and the PLC. The workpiece moving belts are driven by one stepper motor per conveyor. The speed of the belts is controlled by a frequency converter, allowing tests to be carried out at different control frequencies, i.e., different speed settings. The belts are also equipped with built-in sensors, and these sensor positions (two endpoints and center) can be assigned to a workstation or working position. The belts can be rotated and fixed at 90° using the quick connect coupling. This feature will be important in the future, as it allows the construction of multiple layouts simply. The test environment has been extended with a tripod fixed to the workbench for video recordings for reference video analysis.

The operation of the demonstration and research CPS (Cyber-Physical System) system described above is as follows. The feeder station delivers the smart workpieces one by one to a production line made up of conveyor belts, which simulate the production process. The workpiece stops at dedicated positions on the conveyors and undergoes various processing steps. By reducing the number of actuators and thus increasing the mappable possibilities, the actual process is only performed in the digital space, but changes to the product can be monitored via the smart product display. Workpieces are identified via an RFID chip. All necessary and available data from sensors, drives, RFID, HMI, and PLC are published to the client via the PLC's OPC-UA (OPC Unified Architecture) server during the process. OPC-UA is a widely used communication protocol in industrial automation and research of CPS and DT systems. This type of communication is also built into most modern PLCs. The OPC-UA is an advanced M2M (machine-to-machine) communication, which in the architecture developed implements the requirement for DT as defined by Kritzinger, i.e., it offers the possibility of bidirectional communication. The data to be shared was configured using the Siemens OPC-UA Modeling Editor software. The editor supports importing project files created with the Totally Integrated Automation Portal (TIA Portal) and editing the OPC-UA information model. During the editing process, the influencing factors were observed in the context of the MESS and OPC-UA integration project implemented by Szántó et al. (2023).

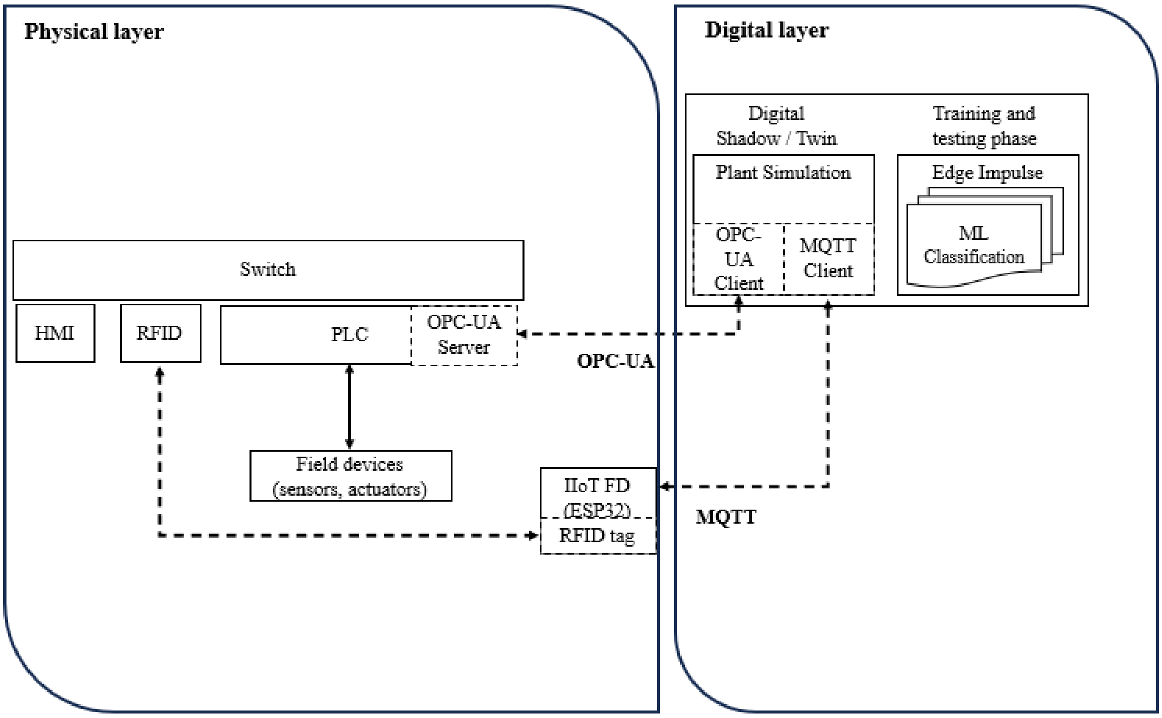

Figure 2. Proposed DES-based DT framework extended with a smart workpiece

4. Results and discussion

The experiments have shown that anomalies and faulty situations can occur under normal operating conditions using only the PLC data, which is exponentially worse when faulty operating conditions occur between the real and digital layers. To improve these, as well as the robustness of the system and the synchronization of the physical and digital systems, data from the IMU sensor embedded in the smart device is coupled into the framework. In a previous paper, the authors discussed tracking material flow that can be improved with an IMU sensor (Monek & Fischer, 2023). However, the method presented there needed further development. The code running on a smart device was written in an Arduino IDE 2.0 software environment. During the programming, extracting the IMU sensor data was critical so that the time between the two measurements remained constant. This was a problem at first because the target was set to acquire data at 500-1000 Hz, which is already the limit of the microcontroller. The microcontroller has two separate cores and divides the necessary calculation tasks between these cores automatically by default. During the evaluation of the measurements, it was found by comparing the time tags associated with each measurement that gaps of orders of magnitude larger than 1-2 ms on average between two measurements could be detected by chance. These gaps and outliers could have arisen because the module is concerned with retrieving the IMU data and transmitting them. This causes gaps of small and large size to occur during the transmission of the data (i.e., the delay in computation time is the cause of the delay). Due to the randomness, it was possible that data valuable for the computation algorithm could be lost or misplaced, and therefore, the program had to be optimized. Instead of automatic allocation between the two cores, tasks are delegated to the processor cores in a dedicated way, with one core being responsible only for measurements and the other for data transfer.

Implementing permanent, frequent sampling has made it possible to use the data collected. A digital layer representing the real system assisted the tagging process (Table 2). In the digital simulation environment, due to the communications established, information was available from both the smart products and the PLC. Thus, the parameter currently logged by the PLC and specific to the drive was added as a "new column" to the measurement data. This parameter is "waiting" if the PLC is not controlling the drive at that time and "moving" if it is.

For universal usability, the fusion of the smart product and PLC data with machine learning support allows the state of the workpiece to be determined with high accuracy. On the training data set (see Figure 3) automatically tagged by the PLC, the method's accuracy is 98.7% for determining the given motion characteristics.

An accuracy of 98.45% was achieved on the test datasets (see Figure 4). Due to the frequent sampling (exactly 500 Hz), the amount of data needed for teaching was available after only one test run. Thus, with this machine learning method, the workpieces' motion state (moving, standing) could be determined in near real-time, and potential anomalies due to stuckness or hardware failures could be detected. This information can be helpful to both the user and the proposed framework.

Table 2. Detail of the fusion of IMU and PLC data

time (ms)	acc. (m/s^2)	pitch (deg)	state
2	–0.0120	–0.8567	waiting
4	–0.0146	–0.8293	waiting
6	–0.0288	–0.8185	waiting
8	–0.0194	–0.7215	waiting
10	–0.0356	–0.6163	waiting
12	–0.2251	–2.2342	moving
14	–0.5083	–7.4176	moving

The next efficiency-enhancing feature is the extraction (save) of length-oriented objects, such as the conveyors necessary for the simulation model and DT. From the variation of the distances between the sensors on the conveyors and the sensor data, the travel distance of the workpieces can be calculated, but this method requires the user to specify the exact distance between the sensors and to take care when recording the data only to calculate the time required to travel when the conveyor is on. In contrast to this approach, the potential of using a state estimation solution inferred from IMU data was investigated by further applying the potential of the smart meter.

Figure 3. Model training output

Figure 4. Model testing output

The main advantage of MEMS IMU sensors is that they can be manufactured in minimal dimensions and have low power consumption. The price is about 10 US dollars. However, the compact size and low power consumption mean that the data measured by the sensor is "noisy". The gyroscope drifts can be greater than

60°/h, and the accelerometer module exhibits 0.01-1.0 mg of bias. As stated by James H. Kepper et al. (Kepper et al., 2019), a wide variety of methods and algorithms are available to reduce or eliminate noise, i.e., to improve the accuracy of the measurement data. Based on their literature review, methods with acceptable accuracy for linear acceleration tasks exist, but the accuracy of these methods can only be maintained over short intervals of about 10 seconds. The noise, error, bias, and drift of the accelerometer sensor in the integration operations for speed calculation increase the position estimation error exponentially from time to time. The IMU data for the experiments run on the platform are illustrated in the figure below (Figure 5).

The acceleration data plot shows that even with a workpiece moving smoothly, the noise is high, about ±0.1...0.2 m/s^2. The longer the process is observed, the more incorrect data (noise) accumulates, thus degrading the calculated value. It was necessary to reduce the observed period to improve the results; however, if shorter intervals of about 0.2-0.5 s are randomly sampled on the test data set, the result is still inaccurate. The solution is to find the acceleration time and calculate the speed parameter for uniform motion, assuming that the drive and gearing of the belt allow a nearly uniform motion. The exciting part of the speed calculation is the angular displacement measured on the transverse axis (pitch) derived from the fusion of the gyroscope and the accelerometer. Figure 5 shows the pitch angle diagram below the raw acceleration data. Observing the pitch angle's continuous monotonicity makes it possible to determine the acceleration phase relevant to the speed calculation, the dominant axis, and hence the direction of motion in near real-time. The dominant axis provides data for deriving the layout (see Figure 6), as the displacement in the x and y dimensions is well differentiated when the connected belt elements are connected perpendicularly, and the intermediate orientations due to different rotations of the conveyor belt and the smart product design did not need to be addressed.

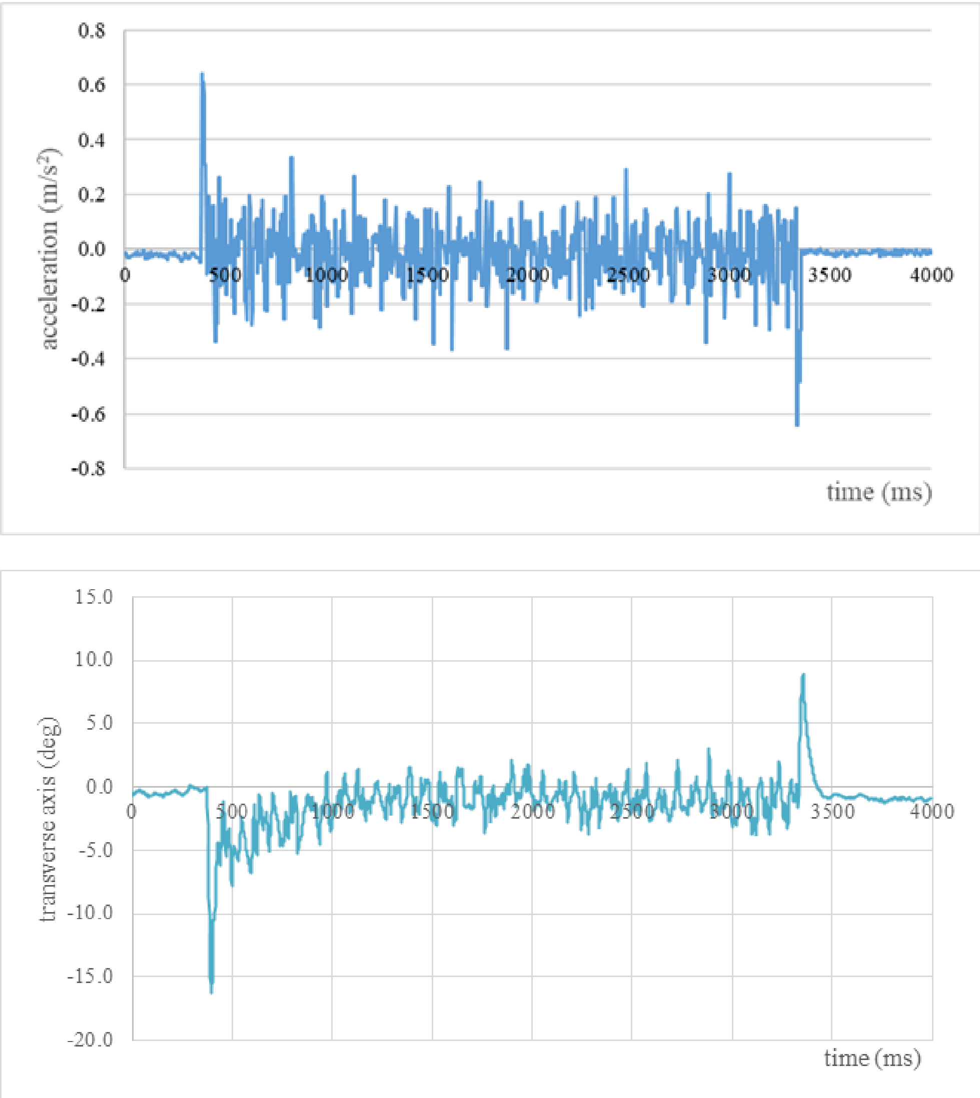

Figure 5. Sensor data from the IIoT device

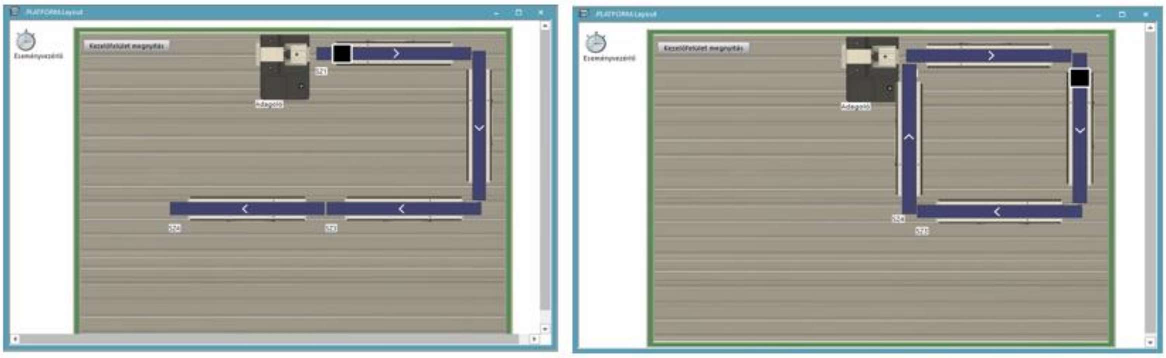

Figure 6. *An illustration of several layouts that can be constructed utilizing the platform.*

The following method is proposed for estimating the progress speed of the workpiece from the IMU signals (Figure 7). The procedure starts with detecting a change of state, and then the interval *t* over which the acceleration is likely to occur is determined based on the relative pitch angle values of the sampling points. At this interval, the acceleration data concerning the elapsed time units are integrated to calculate the workpiece speed.

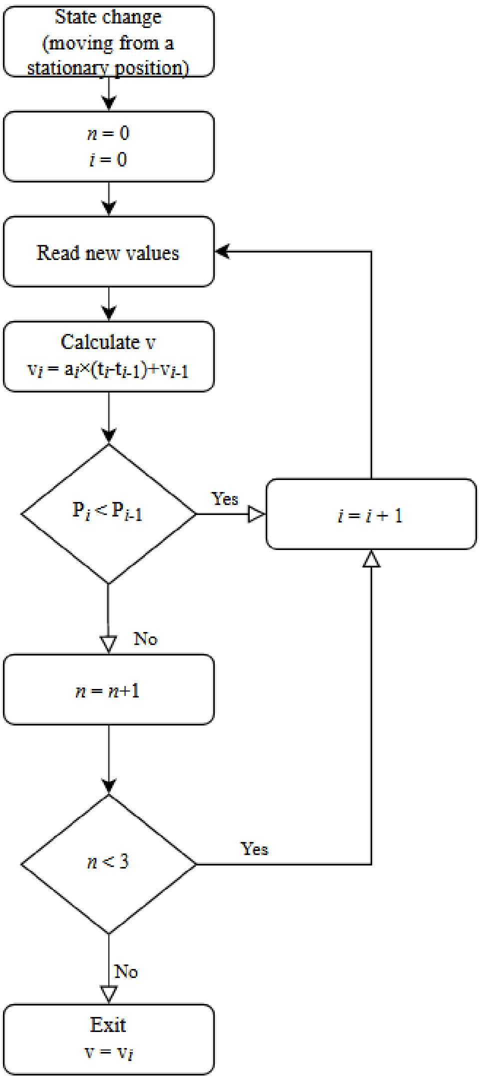

Figure 7. Proposed speed estimation flow chart

The platform on which the experiments are based, as mentioned above, can change the speed of the belts. In order to measure the effectiveness of the proposed algorithm, it has been tested in four different settings. During each experiment, in addition to recording IMU data, a video recording was made. The video recordings were analyzed and evaluated using the Tracker open-source video analysis software. The speed calculated by the software was taken as the reference for each comparison. The comparisons revealed that the IMU data could not be evaluated for extremely slow setting (setting_1), almost seemingly sectional motion. In all other cases, the average result was 90%. A large range of deviations was obtained in each of the individual measurements, probably due to inaccuracies and errors in the sensor. However, these can be eliminated by several measurements. Figure 8 illustrates the averages of 100 measurements in one setting. The figure shows that after about 50 measurements, the average calculated speed is close to the reference value with an accuracy of over 99%.

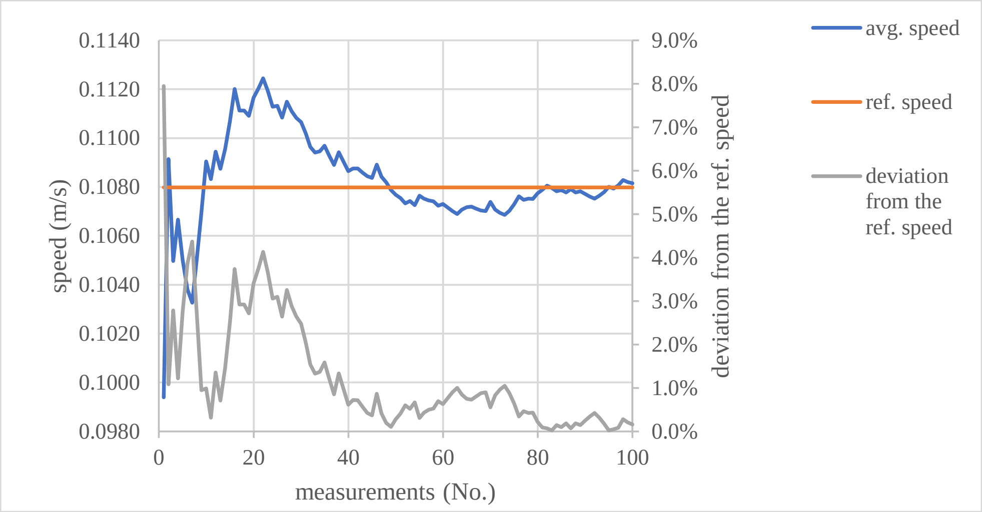

Figure 8. *An illustration of several layouts that can be constructed utilizing the platform*

The results of 50-50 measurements at different settings are shown in Table 3.

Table 3. Results of the speed estimation algorithm

	reference speed [m/s] (data on 50 measurements)			speed based on IMU data [m/s] (data on 50 measurements)			
	min.	max.	avg.	min.	max.	avg.	accuracy (%)
setting_1	0.03349	0.03702	0.03561	no data	no data	no data	–
setting_2	0.07350	0.07360	0.07352	0.05915	0.76090	0.07346	99.918
setting_3	0.10797	0.10799	0.10798	0.08568	0.13322	0.10768	99.722
setting_4	0.14415	0.14472	0.14470	0.12661	0.15887	0.14433	99.744

The results obtained using the IMU data can be integrated into the extended digital twin framework so that the material flow processes of the real production line can be modeled and mapped in more detail in the digital space. The synchronization between the digital twin and the physical system is improved, and anomalies between the two layers can be quickly detected. Furthermore, the time required to obtain the input data needed to build traditional DES simulations is reduced.

5. Conclusion

In this paper, a digital twin model of a newly developed research and demonstration platform has been created in a DES environment. In addition to existing PLC information, the system uses data collected by a smart workpiece with an embedded IMU sensor to achieve a more accurate correspondence between the physical and digital layers. From the IMU data, the motion state of the workpiece could be determined in near real-time. Without any user interaction, the digital twin created in the proposed framework can compare the data from the PLC and the smart device to detect various anomalies, such as a jammed workpiece or a reduced conveyor speed.

The present study began by addressing numerous industry partners, namely machine producers. The target machine producers surveyed understand the possibility for adding value to their goods by applying DES and DT techniques. However, given the price sensitivity created by the severe price rivalry, the recent poll verified the necessity for a solution that involves relatively small extra labor, skills in programming, and time. Based on these criteria, the authors developed the following framework criteria: no disturbance with the PLC program (supplementary use), no need to modify the current automation program, minimal complexity of the system, simplified usability even without experience with programming, and user interface appropriate for visualization of data, process monitoring, and troubleshooting. The next step is to establish a very fast deployable DES-based DT framework and then evaluate the usefulness of extra data accessible through an IIoT device that may be utilized independently but also incorporated into the framework. Data collected specifically rather than in isolation will be more reliable and easier to obtain utilizing the suggested approach. The goal was to provide a framework and principles that could be implemented modularly by small and medium-sized businesses while still applying to large corporations.

The experiments demonstrated that anomalies and faulty situations can occur under normal operating conditions using only PLC data, but they are exponentially worse when the real and digital layers are faulty. To improve system robustness and synchronization, data from the smart device's IMU sensor is coupled into the framework. The microcontroller's 500-1000 Hz data acquisition limit initially made it difficult to extract IMU sensor data, leading to gaps of orders of magnitude larger than 1-2 ms. To address this, processor cores are dedicated to measurements and data transfer, with permanent, frequent sampling allowed for data use.

The fusion of smart product and PLC data with machine learning support provides high-accuracy workpiece state determination for universal usability. The method predicts motion characteristics with 98.7% accuracy on the training data set, while test datasets had 98.45% accuracy. Another efficiency-boosting feature is extracting length-oriented objects like conveyors from sensor data and conveyor sensor distances.

Compact and low-power MEMS IMU sensors are ideal for measuring material flow in production lines, but noise from these sensors can affect results. Researchers propose estimating workpiece progress speed from IMU signals to improve results. This involves detecting a state change and calculating uniform motion acceleration time and speed. The proposed algorithm was tested in four settings, with an average result of 90%.

The extended digital twin framework can use IMU data to improve synchronization between the digital twin and the physical system, detect anomalies between the two layers, and reduce the time needed to obtain input data for traditional DES simulations.

Acknowledgement: The research was technically supported by the project no. TKP2021-NKTA-48. It has been implemented with the support provided by the Ministry of Technology and Industry of Hungary from the National Research, Development and Innovation Fund, financed under the TKP2021-NKTA funding scheme.

References

Agalianos, K., Ponis, S. T., Aretoulaki, E., Plakas, G., & Efthymiou, O. (2020). Discrete Event Simulation and Digital Twins: Review and Challenges for Logistics. *Procedia Manufacturing*, *51*, 1636–1641. https://doi.org/10.1016/j.promfg.2020.10.228.

Barlas, P., & Heavey, C. (2016). Automation of input data to discrete event simulation for manufacturing: A review. *International Journal of Modeling, Simulation, and Scientific Computing*, *07*(01), Article 01. https://doi.org/10.1142/S1793962316300016.

Boyes, H., & Watson, T. (2022). Digital twins: An analysis framework and open issues. *Computers in Industry*, *143*, 103763. https://doi.org/10.1016/j.compind.2022.103763.

Dafflon, B., Moalla, N., & Ouzrout, Y. (2021). The challenges, approaches, and used techniques of CPS for manufacturing in Industry 4.0: A literature review. *The International Journal of Advanced Manufacturing Technology*, *113*(7–8), 2395–2412. https://doi.org/10.1007/s00170-020-06572-4.

Delgado Sobrino, D. R., Rychtarik, V., & Cagáňová, D. (2022). Digital Twin design at the material flow level. *Journal of Physics: Conference Series*, *2212*(1), 012012. https://doi.org/10.1088/1742-6596/2212/1/012012.

Ding, K., Chan, F. T. S., Zhang, X., Zhou, G., & Zhang, F. (2019). Defining a Digital Twin-based Cyber-Physical Production System for autonomous manufacturing in smart shop floors. *International Journal of Production Research*, *57*(20), 6315–6334. https://doi.org/10.1080/00207543.2019.1566661.

Feng, H., Gomes, C., & Larsen, P. G. (2023). *Model-Based Monitoring and State Estimation for Digital Twins: The Kalman Filter* (arXiv:2305.00252). arXiv. http://arxiv.org/abs/2305.00252.

Garrido, J., & Sáez, J. (2019). Integration of automatic generated simulation models, machine control projects and management tools to support whole life cycle of industrial digital twins. *IFAC-PapersOnLine*, *52*(13), 1814–1819. https://doi.org/10.1016/j.ifacol.2019.11.465.

Haraszkó, C., & Németh, I. (2015). DES Configurators for Rapid Virtual Prototyping and Optimisation of Manufacturing Systems. *Periodica Polytechnica Mechanical Engineering*, *59*(3), 143–152. https://doi.org/10.3311/PPme.7888.

Hughes, K., Fernando, H., Szkilnyk, G., Surgenor, B., & Greenspan, M. (2014). Video event detection for fault monitoring in assembly automation. *International Journal of Intelligent Systems Technologies and Applications*, *13*(1/2), 103. https://doi.org/10.1504/IJISTA.2014.059302.

Kassen, S., Tammen, H., Zarte, M., & Pechmann, A. (2021). Concept and Case Study for a Generic Simulation as a Digital Shadow to Be Used for Production Optimisation. *Processes*, *9*(8), 1362. https://doi.org/10.3390/pr9081362.

Kepper, J. H., Claus, B. C., & Kinsey, J. C. (2019). A Navigation Solution Using a MEMS IMU, Model-Based Dead-Reckoning, and One-Way-Travel-Time Acoustic Range Measurements for Autonomous Underwater Vehicles. *IEEE Journal of Oceanic Engineering*, *44*(3), 664–682. https://doi.org/10.1109/JOE.2018.2832878.

Kocsis Szürke, S., Kovács, G., Sysyn, M., Liu, J., & Fischer, S. (2023). Numerical Optimization of Battery Heat Management of Electric Vehicles. *Journal of Applied and Computational Mechanics*, *9*(4), 1076–1092. doi: https://doi.org/10.22055/jacm.2023.43703.4119.

Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, *51*(11), 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474.

Ladj, A., Wang, Z., Meski, O., Belkadi, F., Ritou, M., & Da Cunha, C. (2021). A knowledge-based Digital Shadow for machining industry in a Digital Twin perspective. *Journal of Manufacturing Systems*, *58*, 168–179. https://doi.org/10.1016/j.jmsy.2020.07.018.

Lee, C. G., & Park, S. C. (2014). Survey on the virtual commissioning of manufacturing systems. *Journal of Computational Design and Engineering*, *1*(3), 213–222. https://doi.org/10.7315/JCDE.2014.021.

Monek, G. D., & Fischer, S. (2023). IIoT-Supported Manufacturing-Material-Flow Tracking in a DES-Based Digital-Twin Environment. *Infrastructures*, *8*(4), 75. https://doi.org/10.3390/infrastructures8040075.

Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., Sauer, O., Schuh, G., Sihn, W., & Ueda, K. (2016). Cyber-physical systems in manufacturing. *CIRP Annals*, *65*(2), 621–641. https://doi.org/10.1016/j.cirp.2016.06.005.

Németh, A., Fischer, S. (2021). Investigation of the Glued Insulated Rail Joints Applied to CWR Tracks. *Facta Universitatis. Series: Mechanical Engineering*, *19*(4), 681–704. https://doi.org/10.22190/FUME210331040N.

Park, H.-T., Kwak, J.-G., Wang, G.-N., & Park, S. C. (2010). Plant model generation for PLC simulation. *International Journal of Production Research*, *48*(5), 1517–1529. https://doi.org/10.1080/00207540802577961.

Pfeiffer, A., Kádár, B., Popovics, G., Kardos, C., Vén, Z., Kemény, L., & Monostori, L. (2012). Applying model-reconstruction by exploring MES and PLC data for simulation support of production systems. In *Proceedings of the 2012 Winter Simulation Conference (WSC)*, Berlin, Germany, 1–13, https://doi.org/10.1109/WSC.2012.6465069.

Popovics, G., & Monostori, L. (2013). ISA Standard Simulation Model Generation Supported by Data Stored in Low Level Controllers. *Procedia CIRP*, *12*, 432–437. https://doi.org/10.1016/j.procir.2013.09.074.

Prat, S., Cavron, J., Kesraoui, D., Rauffet, P., Berruet, P., & Bignon, A. (2017). An Automated Generation Approach of Simulation Models for Checking Control/Monitoring System. *IFAC-PapersOnLine*, *50*(1), 6202–6207. https://doi.org/10.1016/j.ifacol.2017.08.1014.

Reinhardt, H., Weber, M., & Putz, M. (2019). A Survey on Automatic Model Generation for Material Flow Simulation in Discrete Manufacturing. *Procedia CIRP*, *81*, 121–126. https://doi.org/10.1016/j.procir.2019.03.022.

Ruppert, T., & Abonyi, J. (2018). Software Sensor for Activity-Time Monitoring and Fault Detection in Production Lines. *Sensors*, *18*(7), 2346. https://doi.org/10.3390/s18072346.

Szalai, S., Kocsis Szürke, S., Harangozó, D., Fischer, S. (2022). Investigation of deformations of a lithium polymer cell using the Digital Image Correlation Method (DICM). *Reports in Mechanical Engineering*, *3*(1), 116–134. https://doi.org/10.31181/rme20008022022s.

Szántó, N., Csapó, Á., & Horváth, I. (2023). Information Basis of Digital Twins: A Quantifiable Metric for Spatio-Temporal Expressivity. *Acta Polytechnica Hungarica*, *20*(6), 151–171. https://doi.org/10.12700/APH.20.6.2023.6.9.

Tao, F., & Zhang, M. (2017). Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing. *IEEE Access*, *5*, 20418–20427. https://doi.org/10.1109/ACCESS.2017.2756069.

Turner, C. J., & Garn, W. (2022). Next generation DES simulation: A research agenda for human centric manufacturing systems. *Journal of Industrial Information Integration*, *28,* 100354. https://doi.org/10.1016/j.jii.2022.100354.

Vieira, A. A. C., Dias, L. M. S., Santos, M. Y., Pereira, G. A. B., & Oliveira, J. A. (2018). Setting an Industry 4.0 Research and Development Agenda for Simulation – a Literature Review. *International Journal of Simulation Modelling*, *17*(3), 377–390. https://doi.org/10.2507/IJSIMM17(3)429.

Zdravković, M., & Korunović, N. (2023). Novel methodology for real-time structural analysis assistance in custom product design. *Facta Universitatis, Series: Mechanical Engineering*, *21*(2), 293-305. https://doi.org/10.22190/FUME200828008Z.