Integrating the Digital Twin of a Shop Floor Conveyor in the Manufacturing Control System

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Abstract. The paper describes the architecture design and implementing solution for the digital twin of a shop floor transportation system embedded in the global manufacturing scheduling and control system. The products are assembled on pallets travelling on the conveyor between workstations, where assigned resources perform scheduled operations. The main functionalities of the digital twin are: mirroring the current stage of the physical pallet transportation process and the state of the physical conveyor components, predicting the values of the pallet's transportation times along the conveyor's segments between any two workstations, applying these values for enhanced reality-awareness of optimized product scheduling and resource allocation, and detecting anomalies in the behaviour of the conveyor equipment. Starting from a shortlist of generic scenarios, AI techniques are applied in the cloud layer of the virtual twin to optimally schedule products and early detect conveyor anomalies in the context of predictive maintenance.

Keywords: Shop floor conveyor · PLC control · Embedded digital twin · Predicting travelling time · Optimized system scheduler · Anomaly detection

1 Introduction

The main characteristics of the 4th industrial revolution [1] are the digitalization [2] of manufacturing processes (IoT and embedded devices) and the interconnection of systems and services along the value chain. These two processes are called vertical respectively horizontal integration, both relying upon the concept of Cyber Physical Systems (CPS) for implementation [2]. Besides the data collection and communication in the CPS, usually with a centralized cloud system, other important processes such as: data storage, information aggregation from multiple sources, data analysis, predictive maintenance, remote monitoring, optimization/planning, and simulation of physical process arise when designing and implementing the control part of a manufacturing cell. These processes can be realized to obtain a global view done in an aggregate manner using the concept of Digital Twin (DT).

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The DT is a digital representation of a physical asset or process that merges with technologies like the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML) and Operations Research techniques in order to promote efficiency in the real world while testing and tracking states, behaviours and activities or projecting in control systems in the digital world [4, 5].

Even if the idea of creating a virtual model with real-time data from physical devices dates since log time, the term Digital Twin was originally coined at the Product Lifecycle Management (PLM) courses at the University of Michigan more recently - in early 2002 [6]. The DT concept contains three main components [6]: (i) a physical object in real world, (ii) a virtual object in the informational space and (iii) a set of connections between the real world and the informational system. At present, the DT concept evolved to a highly advanced modelling and simulation used in various fields (design [7, 8], simulation [9, 10], control [3, 11], monitoring [12], maintenance [13]) and industry domains such as: manufacturing [14, 15], automotive [11], healthcare [16] and even learning [17]), integrating additional features like process optimization, ability to run test scenarios without needing the physical object perform them, usage of AI to do preventive maintenance, a.o.

From the point of view of modelling reality there are also two types of DT: (i) DT with a physical counterpart or data-driven DT which relies on IoT to collect data; this model is used to synchronize the virtual twin with the physical counterpart and (ii) DT without a physical counterpart or model-driven DT which is a digital simulation used for modelling, design, (analysis and forecasting). In the second case there is no IoT and no setup. Its usage case comprises different processes and views outcomes prior to developing infrastructure (resources & technology). Commonly used for PLM, the term ‘product’ was extended to the terms ‘resource’ and ‘system’ used in manufacturing processes, and there exist now aggregated DT for Smart Manufacturing [18].

In this context the current article describes the architecture of an embedded Digital twin for a shop-floor material and product transport system (closed-loop, multi-branch twin-track belt conveyor), part of its monitoring and control system and integrated in an existing manufacturing planning, scheduling and control architecture. Products on pallets travel on the conveyor belt being piloted by a dedicated PLC. The DT monitors and forecasts the conveyor’s operating parameters: travelling times of pallets, response times of stoppers, diverting and transfer devices.

The article is structured as follows: Sect. 2 introduces the networked twins architecture used to collect, process, update, and analyse the data acquired from the physical transport system in order make decisions for the informational world. Section 3 describes the physical twin and the scenarios that will benefit from the conveyor’s virtual model: reality-awareness of product scheduling and resource allocation, and predictive maintenance. Section 4 describes the data transmission protocol and variables that are passed via the PLC – the physical twin’s controller –in order to interconnect the components of the DT: sensory and actuating devices on the physical conveyor with its virtual twin for high level model-based processing and analysis in real time. Section 5 describes the model that replicates the real transport process. Section 6 presents how the gathered data is processed and timing details in the perspective of predicting operating parameter values. The article ends with Sect. 7 by presenting experimental results and formulating a set of conclusions.

2 Digital Twin Control Architecture

The DT of the transport system is embedded in the product scheduling (batch planning, product scheduling and resource allocation) and execution control of a manufacturing system, and was designed in the following context:

1. Gather information from the physical space
2. Create a digital model based on which decisions will be taken in the digital twin, and
3. Use the decisions to act upon the physical space.

These high-level functionalities are assigned to four layers through which the data flows in both directions as depicted in Fig. 1: from the physical layer to the informational layer where decisions are taken and backwards. The first layer, *Data collection and edge processing*, is an extension of the existing programs responsible with the automation of the physical process. It is here that raw information about the process is created and then forwarded to the second layer responsible with communication – *Data transmission*. The first layer is also responsible with the implementation of orders received from the upper layers. The following two layers reside on the cloud and they are responsible with data aggregation model update (*Data update and aggregation*) and with decision making (*Analysis and decision making*).

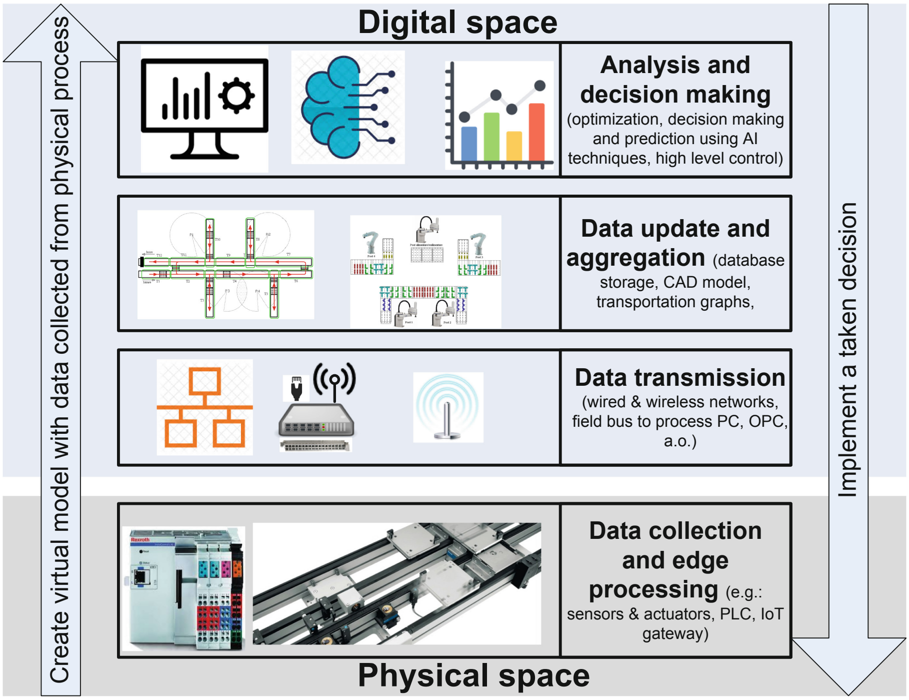

Fig. 1. The informational flow used in gathering data for digital twin utilization

3 Description of the Physical System and Scenario Set

The proposed DT system will be implemented for an existing flexible manufacturing cell consisting of a set of four independent workstations interconnected by a closed-loop conveyor controlled by a PLC (Fig. 2). Products are assembled on pallets that use RFID technology to identify and locate them on the conveyor. Based on this information, products are routed to assigned workstations to receive scheduled operations.

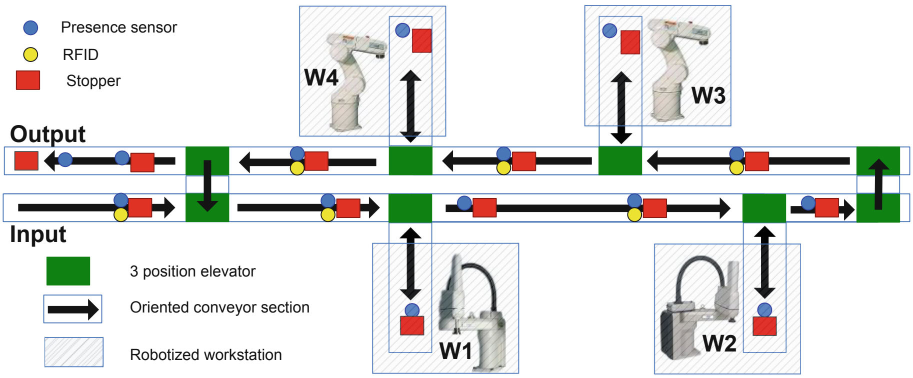

Fig. 2. The manufacturing system with closed-loop, multi-branch conveyor

In this context the first stage in implementing the DT is to define a set of scenarios that will benefit from having a digital model updated with information in real-time. Based on the authors' previous work on resource allocation and implementation of the results of the optimization process [19], we concluded that a model indicating permanently the quality of the services performed by resources [20] from accurate information updated in real time would improve the resource utilization. Thus, we propose to collect the transportation times on each segment of the conveyor, analyse the data, predict future values and add transport times calculated between workstations to product operations while assigning resources with optimized batch execution time. Also, pallets travelling on each conveyor section are monitored to detect abnormal transport delays. A 'conveyor section' means the segment between two consecutive stoppers (Fig. 2), and is modelled as an edge in an oriented graph.

By analyzing this information, the following scenarios are realized: improved usage of the transport system with reality-aware scheduling optimization, and advanced diagnosis of the transportation system by detecting sections that operate faulty (Fig. 3).

As a partial conclusion, the following scenarios will benefit from the introduction of a Digital Twin solution:

i. The creation of a more *exact and realistic model* (fed with real-time data) used as input to the scheduling process at full batch horizon to improve resource usage and production makespan. Traditionally, the data used in resource scheduling is

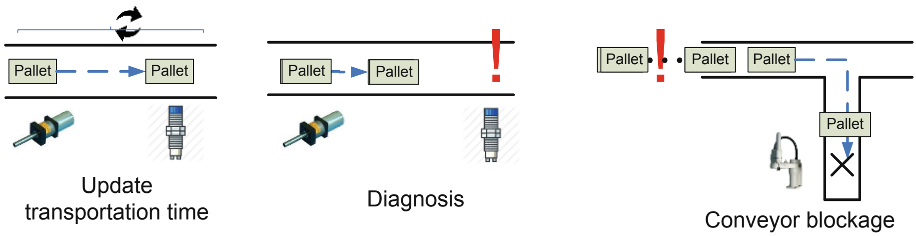

Fig. 3. Scenarios that will benefit from the introduction of a Digital Twin solution

static (or an average of a set of data). The idea is to capture its evolution, and instead of using static data to use forecasted data.

ii. *Advanced diagnosis* for PLC conveyor control programs aiming at detecting the successful realization of given commands. The problem is that movement commands might not work correctly due to faulty conveyor parts (diverting an transfer devices) or external blockage (e.g., due to mechanical belt driving imperfections there are situations where a conveyor section does not transport the pallet to its destination). A proposed solution for this problem would consist in evaluating the effects of the actuators through a set of inputs (e.g.: the movement of a pallet is initiated through the release of a stopper and the realization of the transport process is detected by a sensor located at the end of the considered conveyor).

iii. Avoid situations where pallets interlock each other on the conveyor belt causing pallets accumulation on the transportation system (e.g.: pallets blockage on the main conveyor loop). Since differences appear between the planned and the executed products the DT will automatically do WHAT-IF simulation to see if recirculating the blocking pallets on the main conveyor loop minimizes waiting time.

The project aims at developing a DT stored in the cloud and replicating a cyber-physical production system (Fig. 2) consisting of five cyber-physical shop-floor units: four robot stations and a transportation system. Every unit updates the DT with personal information in order to create a centralized model of the complete system.

4 Data Transmission for Twins Interconnection

As presented previously the DT concept has three main components [6]: an *object in the physical space*, *its representation in the informational space* and the *connection* between these two in order to update the informational model with data. The connection between the two twins is partially realised by the data transmission layer (Fig. 1) which has three components (i) the communication infrastructure, (ii) the communication protocols and (iii) the interaction protocols used between the data collection layer and model creation and storage layer.

In the research presented we have made the following choices concerning the three components of data transmission. The communication infrastructure will run over the existing network (ETHERNET and WiFi). The communication protocol used will be

OPC since it is an industrial high-level protocol able to convert generic R/W requests into device specific requests, more specifically at model layer we can access directly the variables from the physical layer. Concerning the sequential exchange of messages between the layers of the global DT architecture and the associated processes we propose the interaction protocol represented in Fig. 4.

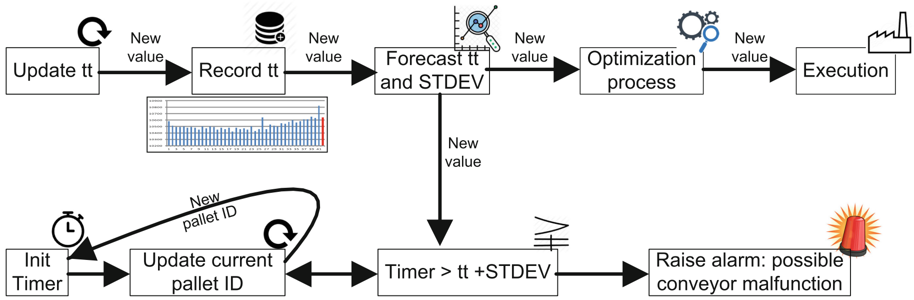

Fig. 4. Real-time conveyor monitoring and using prediction techniques for travel time forecast and anomaly detection at conveyor section level

The following data will be collected for each conveyor section: transportation times (*tt*), current pallet (*pallet ID*), batch identification number (*batch_ID*) and the timestamp for the registered data (Timestamp). In order to collect the proposed data OPC variables will be defined on the PLC and an agent will read them in real-time, process them in order to obtain other derived information (e.g.: for what pallet was recorded a given transportation time and with what timestamp) and update the DT data.

Two processes are of interest in our case: the actualization of the transportation times and the monitoring of the current pallet, each of them being computed for each conveyor section. These two processes are depicted in Fig. 4. The bottom process is performed for diagnosis and for detection of abnormal situations like resource malfunction or blockages, in which case an alarm will be risen (bottom of Fig. 4). The scope of the top process (top of Fig. 4) is to obtain a more accurate model of the physical system, a model which will be used in the optimization of its operation (in this case the minimization of the makespan, respectively, the maximization of resource usage).

The result of the optimization process is the sequence or product execution orders, each order containing a sequence of operations and their associated resources representing the computed resource allocation. This is implemented using an array of structures containing the following information for each the product execution step: the workstation that will perform the operation, the operation that needs to be performed and a code which describes the operation execution status.

5 Informational Model of the Physical Transport System

The control of the transportation system is realized by a PLC executing in parallel a set of programs, each one responsible with a single belt or device (stopper, transfer) actuator. The central part of the conveyor has one single motor continuously driving the two central belts (sections 1–4 respectively 6–8), while its branches have dedicated belt driving motors. In this particular case actuators are represented by stoppers that halt temporarily pallets at the end of the central conveyor sections, and diverting devices transfer pallets between the central conveyor sections and its brabces.

Analyzing this transport structure, we have considered that a sufficiently detailed description of the transport process between the four workstations W1–W4 can be obtained by modelling the virtual twin of the transport at system as an oriented graph that interconnects the workstations where available resources are located (Fig. 5).

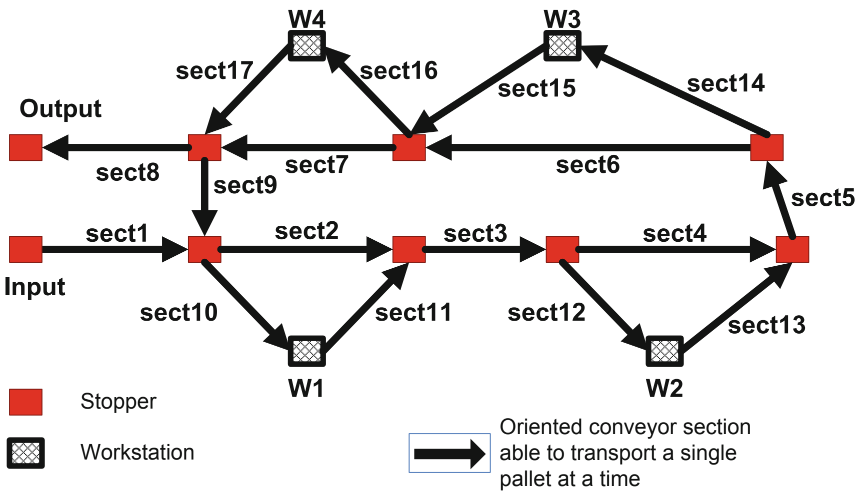

Fig. 5. The oriented graph virtualizing the physical twin (conveyor segments and routes)

The proposed model is an oriented graph where edges represent oriented conveyor sections on which, due to technical constraints, only a single pallet can be transported. The vertices are the informational representations of stoppers. Routing decisions are taken in these vertices based on the information written on the RFID tags associated to the pallets on which products are progressively assembled by robots while the pallets are stopped at the workstations reachable from the conveyor's branches. In the solution adopted, the virtual twin will monitor which pallet is transported and how much time is necessary to move it along each section of the conveyor.

Using real-time monitoring of the transportation time (Fig. 4 upper line) for each conveyor section, the graph model in Fig. 5 is updated. This model serves as input for the optimization engine and as reference for the module which detects errors in the operation of resources; warnings are generated if pallets do not move on the conveyor due to mechanical faults or logical blockages). For the optimization engine an important parameter of the input model is the transportation time between (any) two workstations (W1–W2, …, W1–W4; … W4–W1, …, W4–W3, see Fig. 5), as it adds to the total processing time of a selected operation. In this situation the proposed graph model together with the path followed by the pallet are used to compute the transportation time (e.g., from workstation W4 to workstation W1 the pallet must cross sections 17, 9 and 10, and thus the transportation time will be the sum of these three transportation times).

The informational model this is implemented software as a set of tables into a database that stores the history of the transportation times, the current location of pallets on the transportation system and data related to the communication between the physical world and in virtual twin. The data is collected by means of OPC shared variables by an application running on a cloud system and updates in the production database are realized each time an event takes places. The monitored events are 'entrance of a new pallet on a conveyor section' and 'transportation time on a conveyor section exceeds a forecasted value'. These activities are shown in Fig. 6.

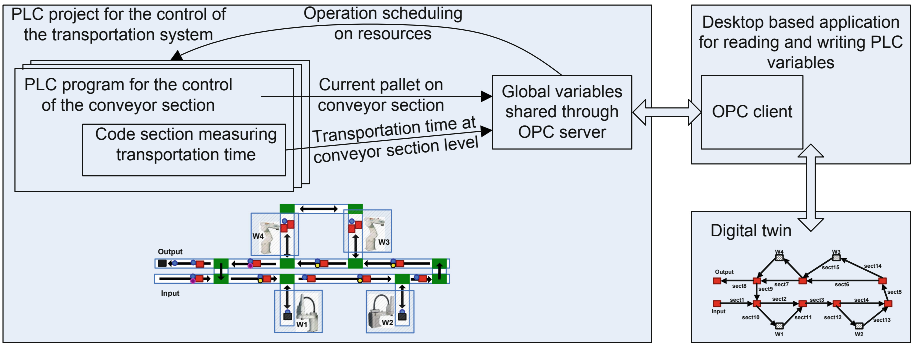

Fig. 6. Communication infrastructure for production data transfer from the monitored conveyor

6 Advanced Data Analysis and Experimental Results

The proposed architecture was tested with data gathered from the industrial pilot platform in the Robotics & CIM Laboratory (http://www.cimr.pub.ro) of the University Politehnica of Bucharest. The collected data consisting of transportation times on the subsection 9 (Fig. 5) of the conveyor was forwarded for storage and analysis to a private cloud platform IBM CloudBurst where the DT resides. The specified section has been chosen because it consists of several mechanical elements (two main conveyor lines moving continuously and an intermediary line operated at request whose objective is to transfer a pallet between the two main conveyor lines) which lead to variable transport times. These times are influenced by the pallet detection, the actuation of the intermediary line and by the friction between the pallet ant the mechanical structure.

The pilot implementation is aiming to demonstrate two aspects of the proposed DT architecture: (i) correct and timely collection, transmission and storage of data from the physical system, and (ii) how data analysis is used in order to forecast transportation times and to detect anomalies in the system's operation. Concerning the first aspect, the manufacturing system has been used for the execution of a batch of products and a sample of transportation times had been recorded for the considered conveyor section. As seen in Fig. 7 the recorded data is grouped around a single value (average is 10500 ms) with a small standard deviation (120 ms) for a set of 180 recorded points.

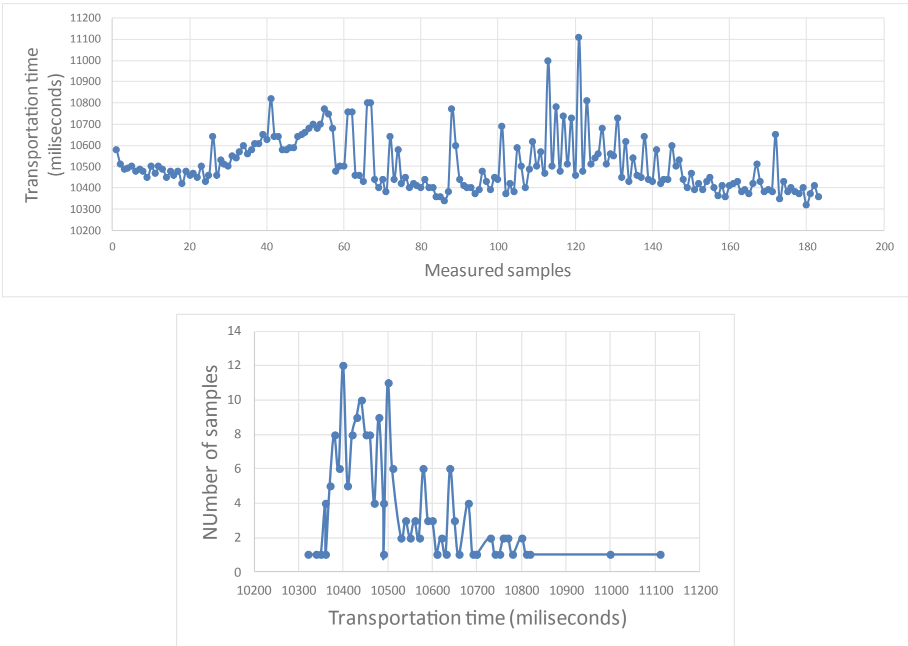

Fig. 7. Measured transportation times (up) and data distribution (down)

Taken into account this observation and the fact that the transportation time is influenced by the friction between the pallet and the conveyor (which after a significant utilisation period is expected to decrease extremely slow) we decided to model the forecasted time value using a *level* (average observed value) and a *trend* (the rate of growth or decline in transportation time for the next period) [21] evaluation. In this case the most appropriate mathematical solutions are the computation of the average value and linear regression.

Using these techniques, a data set was forecasted and then tested against the online recorded data. Results are presented in Fig. 8 for both methods used (average calculus and regression). By analysing the error of both prediction methods, it can be observed that both methods have similar accuracy, with the method using regression being a little more accurate (the maximum and the average error being lesser than in the average value computing).

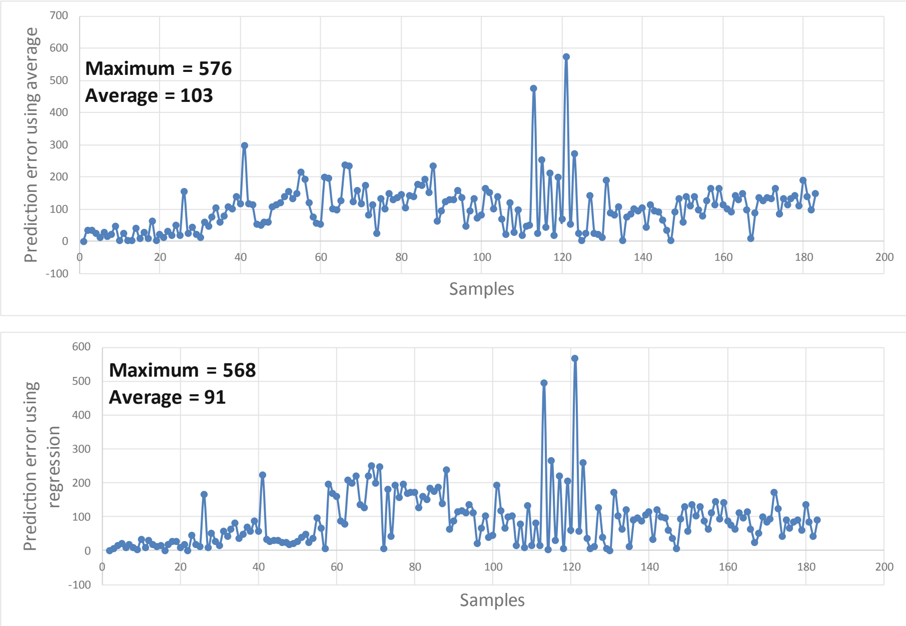

Fig. 8. Prediction error with average (above) and regression (below)

Using the measured data, the Digital twin forecasts future values which are then applied as input for the optimization module in the resource scheduling process (Fig. 4 upper process) and for the anomaly detection module (Fig. 4 lower process). An example of the transportation matrix between the endpoints used as processing resources (see Fig. 5) in the optimization engine is given in Table 1. The transportation time values were predicted from experimental measurements and stored history.

Table 1. Transportation times (in seconds) between the robotized workstations

	W1	W2	W3	W4	Output
Input	10.62	20.32	35.3	41.24	**N/A**
W1	**N/A**	20.14	35.42	39.77	45.11
W2	44.49	**N/A**	24.3	30.15	35.1
W3	29.52	39.46	**N/A**	15.58	20.61
W4	24.17	33.63	49.15	**N/A**	15.12

7 Conclusions

The paper proposes a layered architecture for collecting data from a physical transport process and equipment, and creating its digital twin. Collected data passes through a series of intermediary layers which are responsible with data communication, model creation, prediction and decision making. The approach presented in this paper has the following important characteristics: scalability in terms of data collection and model representation, and modularity at data analysis and decisional layers. The data collection and model representation scalability is based on the fact that the architecture uses network based automation devices to acquire data which is forwarded to a cloud system where storage and processing resources are adjusted according to the demand. Regarding the modularity at the data analysis and decisional making layer, the same informational model can be used as input for different algorithms. In the present research, this model was used for optimization and data analysis; given the particular patterns of the data collected from the physical process, artificial intelligence (AI) techniques can be used to detect specific operating modes and act accordingly.

Future work will be oriented towards increasing the level of detail in creating the DT and using AI techniques in order to detect patterns in the operation of the physical system. These patterns will be used for detecting operation faults and as production rules for resource scheduling.

References

1. Hermann, M., Pentek, T., Otto, B.: Design principles for Industrie 4.0 scenarios. In: 2016 at 49th Hawaii International Conference on System Sciences (HICSS). IEEE Xplore (2016). https://doi.org/10.1109/hicss.2016.488. e-ISBN: 978-0-7695-5670-3
2. http://www.businessdictionary.com/definition/digitalization.html. Consulted in April 2019
3. Graessler, I., Poehler, A.: Intelligent control of an assembly station by integration of a digital twin for employees into the decentralized control system. Procedia Manuf. **24**, 185–189 (2018). https://doi.org/10.1016/j.promfg.2018.06.041
4. Data-Driven Work Spaces. IoT and AI Expand the Promise of Smart Buildings, 27, September 2018. https://hbr.org/resources/pdfs/comm/microsoft/DATA.DRIVEN.Work.Spaces.pdf. Consulted in April 2019
5. Parrott, A., Warshaw, L.: Industry 4.0 and the Digital Twin. Manufacturing Meets its Match. A Deloitte Series on Industry 4.0, Digital Manufacturing Enterprises, and Digital Supply Networks. Deloitte University Press (2017)
6. Grieves, M.: Digital twin: manufacturing excellence through virtual factory replication. White paper (2014). http://www.apriso.com
7. Caputo, F., Greco, A., Fera, M., Macchiaroli, R.: Digital twins to enhance the integration of ergonomics in the workplace design. Int. J. Ind. Ergon. **71**, 20–31 (2019). https://doi.org/10.1016/j.ergon.2019.02.001
8. Schleich, B., Anwer, N., Mathieu, L., Wartzack, S.: Shaping the digital twin for design and production engineering. CIRP Ann. **66**(1), 141–144 (2017). https://doi.org/10.1016/j.cirp.2017.04.040
9. Negri, E., Fumagalli, L., Cimino, C., Macchi, M.: FMU-supported simulation for CPS digital twin. Procedia Manuf. **28**, 201–206 (2019). https://doi.org/10.1016/j.promfg.2018.12.033

10. Yang, W., Tan, Y., Yoshida, K., Takakuwa, S.: Digital-twin simulation for a cyber-physical system in Industry 4.0. In: DAAAM International Scientific Book, Chap. 18, pp. 227–234 (2017)
11. Uhlemann, T., Lehmann, C., Steinhilper, R.: The digital twin: realizing the cyber-physical production system for Industry 4.0. Procedia CIRP **61**, 335–340 (2017). https://doi.org/10.1016/j.procir.2016.11.152
12. The promise of a digital twin strategy. Best practices for designers and manufacturers of products and industrial equipment. https://info.microsoft.com/rs/157-GQE-382/images/Microsoft%27s%20Digital%20Twin%20%27How-To%27%20Whitepaper.pdf. Consulted in April 2019
13. Vathoopan, M., Johny, M., Zoitl, A., Knoll, A.: Modular fault ascription and corrective maintenance using a digital twin. IFAC-PapersOnLine **51**(11), 1041–1046 (2018). https://doi.org/10.1016/j.ifacol.2018.08.470
14. Rosen, R., Wichert, G., Lo, G., Bettenhausen, K.D.: About the importance of autonomy and digital twins for the future of manufacturing. IFAC-PapersOnLine **48**(3), 567–572 (2015). https://doi.org/10.1016/j.ifacol.2015.06.141
15. Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W.: Digital twin in manufacturing: a categorical literature review and classification. IFAC-PapersOnLine **51**(11), 1016–1022 (2018)
16. Healthcare innovation could lead to your digital twin. https://www.digitalnewsasia.com/digital-economy/healthcare-innovation-could-lead-your-digital-twin. Consulted in April 2019
17. Brenner, B., Hummel, V.: Digital twin as enabler for an innovative digital shop-floor management system in the ESB Logistics Learning Factory at Reutlingen – University. Procedia Manuf. **9**, 198–205 (2017)
18. Qia, Q., Taoa, F., Zuoa, Y., Zhaob, D.: Digital twin service towards smart manufacturing. Procedia CIRP **72**, 237–242 (2018). https://doi.org/10.1016/j.procir.2018.03.103
19. Borangiu, T., Gilbert, P., Ivanescu, N.A., Rosu, A.: An implementing framework for holonic manufacturing control with multiple robot-vision stations. Eng. Appl. Artif. Intell. **22**(4–5), 505–521 (2009)
20. Borangiu, T., Răileanu, S., Berger, T., Trentesaux, D.: Switching mode control strategy in manufacturing execution systems. Int. J. Prod. Res. **53**(7), 1950–1963 (2015). https://doi.org/10.1080/00207543.2014.935825
21. Chopra, S., Meindl, P.: Supply Chain Management: Strategy, Planning, and Operation. Prentice Hall, Upper Saddle River (2007)