Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 107 (2022) 724–728

www.elsevier.com/locate/procedia

55th CIRP Conference on Manufacturing Systems

Using the Process Digital Twin as a tool for companies to evaluate the Return on Investment of manufacturing automation

Chiara Caccamo[a,*], Paolo Pedrazzoli[b], Ragnhild Eleftheriadis[a], Maria Chiara Magnanini[c]

[a]*SINTEF Manufacturing AS, Digital Production, Norway*
[b]*Department of Innovative Technologies, SUPSI, CH–6962, Lugano, Switzerland*
[c]*Department of Mechanical Engineering, Politecnico di Milano, Italy*

*Corresponding author. Tel.: +47-95040704; *E-mail address:* chiara.caccamo@sintef.no

Abstract

The fourth industrial revolution is gaining momentum, but still lacks full realization. Several studies suggest that many companies around the world have begun the digital transformation undertaking, but most are still far from full adoption and yet fail to see the full economic potential, being stuck in what has been called "pilot purgatory". Digitalization is largely recognized as an accelerator and enabler for full automation in manufacturing, but companies are still struggling to assess the return on investment and the impact on operational performance indicators. Therefore, companies, especially SMEs characterized by dynamic, high-value, high-mix, and low-volume contexts, are reluctant to invest further. By incorporating simulation, data analytics and behavioral models, digital twins may also be used to support automation solutions ramp-up, demonstrate their impact evaluation, usage scenarios, eliminating the need for physical prototypes, reducing development time, and improving quality. Few forward-thinking companies are pursuing the digital transformation path, while the majority are clipping the wings of a transformation that is essential for a sustainable manufacturing. This paper describes a theoretical approach to exploit the digital twin technology to gather insights towards a realistic economical assessment of full automation solutions, to back and encourage investments to realize the potential of the digital manufacturing transformation. The approach is being tested under the European Union's Horizon 2020 research and innovation program under grant agreement No. 958363, which provides an opportunity to assess how the various components of the method are constructed, how complex they are, and what level of effort is required, using a practical example.

Keywords: Digital Twin; Automation; Return on Investment

1. Introduction

In addition to the technological challenges that slow down the integration of Industry 4.0 technologies [1] characterizing today's industrial automation landscape, the problem of justifying the required investments in such efforts is just another face of the same coin. It can be even more challenging when dealing with a high mix/low volume context, or generally in a niche sector that produces high precision and highly customized products. In literature [2] [3] [4] [5] [6] there is agreement on the fact that companies can achieve a positive return on investment using manufacturing automation. However, the same literature also highlights both the importance and the difficulties of having the adequate investments flowing in this direction. In fact, it is not easy to quantify the process that leads to this value creation and to make a reliable assessment of the benefits (e.g., reduced labor hours and lead times, improved quality, or increased sales) that should be set against the associated costs (e.g., development, implementation, and maintenance of the automation solutions). Therefore, the aim of this paper is to propose an alternative theoretical approach based on Digital Twin to provide an operational method to evaluate the added value enabled by manufacturing automation. The return on investment is just one of the possible cash discount techniques used to measure the ratio of cost to benefit. The question, however, is not what type

10.1016/j.procir.2022.05.052

of technique is used, which is quite well covered in the literature [3] but rather the reliability of the inputs to these calculations. Alternative approaches have been proposed on the use of historical data from similar industries, up to and including the creation of process system models to extract the relevant parameters. Following the framework pattern established in previous research [7] [8] on linking the analysis around automation investment (in this case focusing on process performances that will be changed by the proposed automation) to the broader Key Performance Indicators (KPIs) of the company, this paper aims to provide a perspective on the process digital twin as an effective tool to reliably evaluate the improvement of manufacturing performance in dynamic, high-value, high-mix, and low-volume contexts, through the introduction of an automation solution based on Cyber-Physical Production System (CPPS). The CPPS can represent different solutios, e.g. a feedback control loop that replaces manual adjustments to reduce production warm-up time and ensure stable process performances, a feed-forward mechanism to avoid defect propagation in an assembly line, or a new tool for dispatching optimized work plans in production. In fact, with a virtual version of the real process, manufacturers can run simulations, perform what-if analysis, get real-time information about the behavior of the process, and then draw insights from the data to further improve the process design and eventually the product design too. In this way, before deciding (like investing in automation and IoT infrastructure), it is possible seeing what the outcome looks like in a virtual world, and then decide in the real world. In addition, when talking about the business and economic tradeoff and making decisions about automation solutions, manufacturers do not have to create digital twins for the entire product/process. It is possible to limit the effort and introduce only a cascading digital twin: a digital twin just for the specific part or critical process affected by the proposed changes.

The remaining of the paper is organized as follows: Section 2 introduces the proposed methodology, referring for example to a feedback closed-loop control, with respect to the assumptions and the building blocks, Section 3 describes the experimental industrial settings for the method validation and implementation, and finally Section 4 draws the conclusion and future research.

2. Methodology

The objective of the proposed methodology is to provide the required steps to evaluate the Return of Investments (ROI) of an automation solution by means of a Digital Twin integrated in a full closed-loop control.

The outline of the method should follow three steps, which are going to be detailed in the following sections:

Step 1: Multi-function characterization of the as-is situation at process- and economic- level. In this step, the different company functions should characterize by means of building blocks the technical and economic variables of the reference system. In particular, the process level should be characterized by a process Digital Twin, while the economic level should be characterized by an economic function with respect to the process output.

Step 2: Definition of the to-be situation by integration of functional control blocks (Cyber-Physical System). In this step, the Digital Twin is enriched with control strategies based on the planned new automation solutions.

Step 3: Synthesis and evaluation of the solution. In this step, the ROI is evaluated as a function of the process output, the economic function, and the to-be situation.

In this context, the challenges faced by companies include the integration of information and data coming from different sources at all company level. Hence, some assumptions for the application of this methodology in a real environment should be considered. In the following approach it is assumed that

1. it must exist a functional link between the process performances affected by the new system to be introduced in the current manufacturing process and the business performances;

2. the term Digital Twin [9] will cover the following classification categories: a) a Digital Shadow (automated one-way data flow from the physical system to its digital counterpart), b) Digital Twin (fully integrated bidirectional communication between the two).

We will also explore in the final paragraphs the potential as regards to the concept of Hybrid Data-Driven and Physics-Based Modelling and adapting Digital Twin [10], in case of very complex processes.

2.1. Conceptual model

Step 1

Nomenclature

P	Manufacturing process
$X(x_i)$	Vector X of the input parameters x_i to P (sensors measurements)
$Y(y_i)$	Vector Y of the output parameters y_i from P (sensors measurements)
$C(c_i)$	Vector C of the control parameters c_i of P
$Kpi(kpi_i)$	Vector Kpi of the key performance indicators kpi_i for Process P
$S(s_i)$	Vector S of input specification parameters s_i (Y shall be equal to S)
$E(e_i)$	Vector E of deviation errors between process outputs y_i and input specifications s_i
DT	Digital Twin of process P,
$mY(my_i)$	Vector mY of modelled output my_i of DT
Em (em_i)	Vector Em of deviation errors em_i between the modelled output my_i and the process output y_i
$F(kpi_i)$	the function that links the process performances kpi_i and the business performances KPI(i)
KPI(i)	Vector KPI of business performances

a. (Creation and) Validation of the Digital Twin DT of process P: the model will be fed with the same input (input parameters x_i) and control parameters (c_i) as in the real process; all such operations can happen in real-time or off-line, transferring all synchronized data from the real process to the DT, according to the specific data gathering architecture; this step will allow the testing and validation of the Digital Twin;

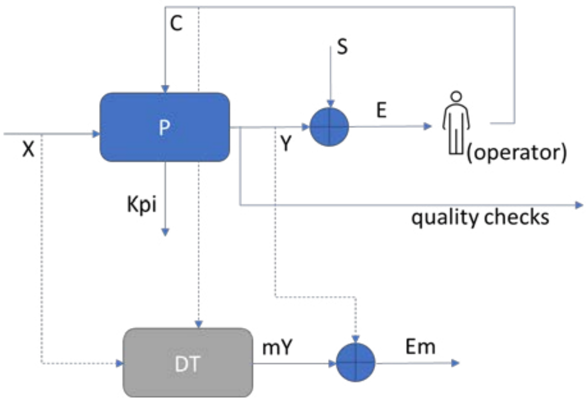

Fig. 1. Process Digital Twin validation framework.

b. Model the company Vector of business performances KPI as a function F of the process performances Kpi , so to have a clear link between process performances and the business results.

Fig. 2. Functional link between process and business performances

Step 2

Nomenclature	
mCPPS	Model of the CPPS to be introduced
mC(mc_i)	Vector mC of the modeled control parameters mc_i, as output from mCPPS
mKpi($mkpi_i$)	Vector mKpi of the key performance indicators $mkpi_i$ for DT
mE(me_i)	Vector of deviation errors between model outputs myi and input specifications si
mKPI	Vector of the modelled business performance (due to the modifications introduced by mCPPS)

a. Create the model for the system to be introduced (mCPPS) and estimate the variation induced in the process performances (mKpi) and business performances (KPI) through DT, assuming the same functional link F applies.

b. Validate the mCPPS: the output of the mCPPS (which are the modeled control parameters mc_i for the process under analysis P) can provide guidance to the operator who manually set the control parameters c_i. The operator can also ignore the results of the mCPPS where recognizes that the suggested interventions mc_i do not zero the error e_i between the output (sensors measurements of the output parameters y_i) and the input specifications s_i.

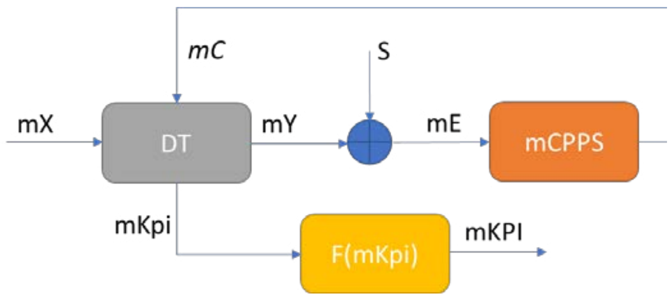

Fig. 3. Framework for estimation of the impacts of the CPPS on the process

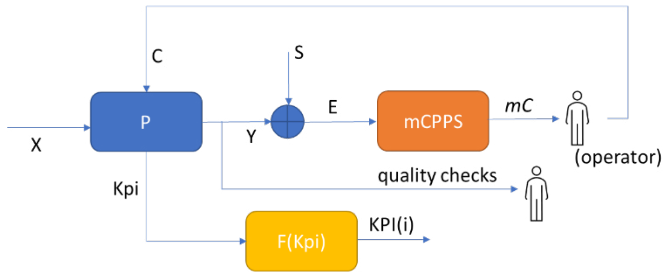

Fig. 4. Framework for validation of the mCPPS

c. testing of the modeled CPPS can be realized through a prototype system implementation via low cost HW tools (like Raspberry computers) and where possible through small-scale factory facilities typically used for educational and Research and Development activities [11] [12] [13].

Step 3

Based on the results from experiments in step 2, reliable estimates on benefits from a full introduction of the CPPS can be made, including the benefits of the flexibility added to the process (e.g. capacity increase, reduction of systematic, manual quality controls) what if scenarios can be run based on the cost to industrialize the CPPS solution and create the proper data infrastructure vs the benefits derived from the improved business performances KPI, using traditional discounted cash flow techniques, to assess the risks and provide ground for the decision on investment.

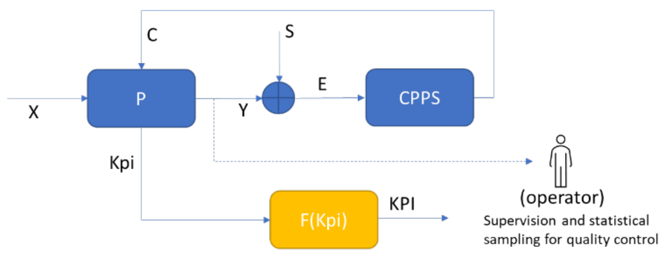

Fig. 5. Framework for analysis of the solution CPPS

Depending on the digital maturity of the company, the effort can be very limited like an internal project entirely run using internal/existing equipment, SW and human resources, or may need the intervention of external resources for the creation of the Digital Twin, identification and supply of sensors/instrumentations for testing and validation, support during experiments and for the final assessment phase.

2.2. Integration of the methodology in a decision-support tool

The proposed methodology is used to solve investment problems for companies where automation solutions are still considered expensive and for which the ROI is not clear a priori. Once the proposed framework is implemented in the company, it can be used for decision support.

In particular, the following problem can be finally addressed, since all variables and parameters have been defined:

$$max_{\omega \in \Omega}\, ROI = f(KPI)$$

s.to

kp i≥ kpi* (1)

kpi = g(ω) (2)

where

$\omega \in \Omega$ represents the set of available automation solutions which can be integrated in the considered process

kpi* represents the target process performance which should be guaranteed by the new automation solution.

3. Experimental industrial settings

The presented methodology will be experimented in the industrial demonstrators of the ongoing project DAT4.Zero, from which a more complex scenario can be represented. In the following schema, P1 represents a generic material processing (machining, moulding, extrusion, casting, …) and P2 a generic assembly process of finished goods. M1 will be for example a Hybrid Data-Driven and Physics-Based Modelling and M2 a product-variation modelling along the assembly chain, aimed at discovering and isolate part variation modes [14] and mechanisms and identify relevant propagation paths; in this case F represent the functional link between the performances of processes P1 and P2 (matrix Kpi[N,2] of N-rows and 2 columns represented by the N-components vectors (Kpi) of each process P1 and P2), to obtain the company performance indicators (vector KPI). All the process steps previously described will be replicated; in a case of a continuous flow from P1 to P2, an additional validation step for the whole chain, as described in Fig.6, is required.

The proposed experimental settings are then going to be used for the evaluation of automation opportunities within the project. The advantages of this methodology include the easy scalability of modelling to support investment decisions in complex environments.

3.1. Extension and expected benefits of the proposed methodology

The Digital Twin is empowered by data captured across the life-cycle of the real asset. Through data, the Digital Twin collects information about the asset operations, reports about status and simulates future state, to support decisions. Yet, the manufacturing system evolves over its life-cycle through several modifications (due to changes of its components or in its processes).

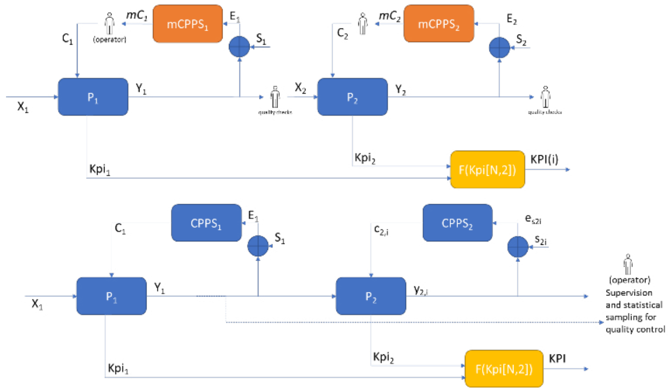

Fig. 6. Extension of the framework to two processes

Thus, in order to mirror the real manufacturing system, the models, underlying the DT capability to mimic the assets, must be adapted to the changes in the asset, across its life-cycle [15]. A mis-aligned DT, whose model does not replicate the actual system, can't be used to evaluate the return of investment, even when fed with actual data from the real system. The implementation of Adaptive Digital Twins, defined as digital twins where a context change triggers an automatic modification of data sources and underlying models (clearly, within a given range of flexibility) towards an optimal reflection of the physical asset [10], is clearly a step forward in implementing the evaluation of the Return on Investment of manufacturing automation as earlier described, because it lowers needed skill sets and implementation costs of an updated DT, making the proposed methodology further applicable. However, this technique is still very new and should be mentioned here as it is a natural next step of the proposed methodology after it has been validated in a real industrial environment.

4. Discussion and conclusions

This paper presents a Digital Twin approach that can be used to reliably estimate the economic impact and return on investment of automation solutions deployed in manufacturing, for companies where automation solutions are still considered expensive and for which the ROI is not clear a priori. The potential of such a methodology is also assessed in terms of the concept of Adaptive Digital twins which could facilitate the adoption of this solution by reducing the need to update the DT itself. Further results and considerations are expected from the application of such a methodology in the industrial settings covered by the DAT4.Zero project.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation program DATA4.Zero under grant agreement No 958363. This paper reflects only the author's views, and the Commission is not

responsible for any use that may be made of the information contained therein.

References

[1] Caccamo C., Eleftheriadis R., Magnanini M.C., Powell D., Odd Myklebust (2021) A Hybrid Architecture for the Deployment of a Data Quality Management (DQM) System for Zero-Defect Manufacturing in Industry 4.0. In: Dolgui A., Bernard A., Lemoine D., von Cieminski G., Romero D. (eds) Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems. APMS 2021. IFIP Advances in Information and Communication Technology, vol 632. Springer, Cham. https://doi.org/10.1007/978-3-030-85906-0_8

[2] Hoda ElMaraghy, Laszlo Monostori, Guenther Schuh, Waguih ElMaraghy, Evolution and future of manufacturing systems, CIRP Annals, Volume 70, Issue 2, 2021, Pages 635-658, ISSN 0007-8506, https://doi.org/10.1016/j.cirp.2021.05.008.

[3] Pedro Palominos, Luis Quezada, Javier Donoso, Miguel Gonzalez, A Model of Economic Evaluation for the Acquisition of Flexible Manufacturing Technologies, Procedia Manufacturing, Volume 39, 2019, Pages 565-573, ISSN 2351-9789, https://doi.org/10.1016/j.promfg.2020.01.420

[4] Saeed Albukhitan, Developing Digital Transformation Strategy for Manufacturing, Procedia Computer Science, Volume 170, 2020, Pages 664-671, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2020.03.173.

[5] Niels L. Martin, Antal Dér, Christoph Herrmann, Sebastian Thiede, Assessment of Smart Manufacturing Solutions Based on Extended Value Stream Mapping, Procedia CIRP, Volume 93, 2020, Pages 371-376, ISSN 2212-8271, https://doi.org/10.1016/j.procir.2020.04.019.

[6] J. Walker, S. Childe, Y. Wang, Analysing manufacturing enterprises to identify opportunities for automation and guide implementation - a review., IFAC-PapersOnLine, Volume 52, Issue 13, 2019, Pages 2273-2278, ISSN 2405-8963, https://doi.org/10.1016/j.ifacol.2019.11.544.

[7] Stanko Strmĉnik, Matjaz Miŝiĉ, Janko ĉernetiĉ, Simplified Assesment Of Benefits In Automation And Information Technology Projects, IFAC Proceedings Volumes, Volume 39, Issue 4, 2006, Pages 59-64, ISSN 1474-6670, ISBN 9783902661050, https://doi.org/10.3182/20060522-3-FR-2904.00010

[8] G. Azzone, U. Bertele (1989) Measuring the economic effectiveness of flexible automation: a new approach, International Journal of Production Research, 27:5, 735-746, http://dx.doi.org/10.1080/00207548908942583

[9] Alexandros Koulouris, Nikiforos Misailidis, Demetri Petrides, Applications of process and digital twin models for production simulation and scheduling in the manufacturing of food ingredients and products, Food and Bioproducts Processing, Volume 126, 2021, Pages 317-333, ISSN 0960-3085, https://doi.org/10.1016/j.fbp.2021.01.016.

[10] Karl Hribernik, Giacomo Cabri, Federica Mandreoli, Gregoris Mentzas, Autonomous, context-aware, adaptive Digital Twins—State of the art and roadmap, Computers in Industry, Volume 133, 2021, 103508, ISSN 0166-3615, https://doi.org/10.1016/j.compind.2021.103508

[11] Andrea Ferrario, Matteo Confalonieri, Andrea Barni, Gabriele Izzo, Giuseppe Landolfi, Paolo Pedrazzoli, A Multipurpose Small-Scale Smart Factory For Educational And Research Activities, Procedia Manufacturing, Volume 38, 2019, Pages 663-670, ISSN 2351-9789, https://doi.org/10.1016/j.promfg.2020.01.085.

[12] Matt, Dominik & Rauch, Erwin & Dallasega, Patrick. (2014). Mini-factory – A Learning Factory Concept for Students and Small and Medium Sized Enterprises. Procedia CIRP. 17. 178–183. 10.1016/j.procir.2014.01.057.

[13] Manufacturing Technology Norwegian Catapult Centre, https://www.sintef.no/en/projects/2018/manufacturing-technology-norwegian-catapult-centre/ , accessed on December 3rd at 20:20.

[14] Eger, F., Tempel, P., Magnanini, M. C., Reiff, C., Colledani, M., & Verl, A. (2019, February). Part variation modeling in multi-stage production systems for zero-defect manufacturing. In 2019 IEEE International Conference on Industrial Technology (ICIT) (pp. 1017-1022). IEEE.

[15] Magnanini, M. C., & Tolio, T. A. (2021). A model-based Digital Twin to support responsive manufacturing systems. CIRP Annals. https://doi.org/10.1016/j.cirp.2021.04.043