Digital Twin Application to Energy Consumption Management in Production: A Literature Review

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Abstract. Economic and environmental issues that translate into energy costs and contaminations in production are growingly attracting attention from several parts and actors. Therefore, Energy Consumption Management (ECM) is gaining ever higher importance within production environments. Industry 4.0 provides several opportunities to address these challenges. One of the technologies presenting the best potentialities is the Digital Twin (DT), which has been found able to promote ECM improvements related to production assets and processes in different ways. Nonetheless, in the academic literature has not been found an extensive review of DT application to ECM in manufacturing. Therefore, this paper proposes a systematic literature review to investigate the current state of the art of the applications, features and characteristics, and implementation strategies of DT applied to ECM in production contexts. Attention has been also paid to the human role inside the application of the DT technology to ECM and the interaction modalities between humans and the DT itself.

Keywords: Digital twin · Energy consumption management · Production · Industry 4.0 · Supervision and reconfiguration of complex industrial systems

1 Introduction

Industry 4.0 (I4.0) is revolutionising the manufacturing sector [1]. The result is an unprecedent interconnection between physical and digital environments [2] and great potentials in many different contexts. In manufacturing, environmental sustainability is one of the paradigm I4.0 can improve [3]. Energy Consumption (EC) and the related atmospheric emissions reduction is among the main I4.0 areas of application [4–6].

Within I4.0, Digital Twin (DT) is described as a key paradigm [7, 8]. DT provides an extremely high-fidelity virtual modelling, enabling process control and precise decision making [9]. Some authors investigate from a high level perspective the potentials of DT shop-floor in the context of Energy Consumption Management (ECM), discussing the related applications [10]. Others perform extensive reviews on DT application in manufacturing, mentioning ECM as one of the main areas of intervention, but a detailed investigation is missing [11, 12]. Even though the applicability of DT in ECM is considered a

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relevant topic, an extensive review of current applications, features and implementation modalities is missing. Thus, the main aim of this paper is to explore the state of the art of DT applied to ECM in production contexts.

The rest of the paper is structured as follows. In Sect. 2 the adopted Literature Review (LR) methodology is explained. In Sect. 3 the results of the LR are shown and discussed. In Sect. 4 the conclusions and possible future works are presented.

2 Methodology

In order to properly conduct a systematic LR and to identify the correct research topics, the CIMO (Context, Intervention, Mechanism, Outcome) framework was implemented [13]. For Context, the manufacturing sector was considered as reference, focusing exclusively on the production phase. For Intervention, DT application has been considered in this work. Since Mechanisms explains the relationship between interventions and outcomes and their circumstances of activity, the ECM has been considered. Finally, as an Outcome, in this case the effects of intervention are related to EC reduction. Aiming at covering all the relevant aspects inside the research framework, three main topics still not clear in literature were identified: (i) the identification of DT applications that support ECM in production; (ii) the identification of specific features typical of DTs implemented in ECM context in production; (iii) the identification of methodologies supporting DT implementation in the ECM in production. The recognition of these aspects allowed to define three Research Questions (RQs):

RQ1. What are the possible applications of DT to ECM in production?
RQ2. Are there specific features and architectures to adapt DT to the ECM context?
RQ3. Are there methodologies to support the DT implementation in ECM context?

The literature search was conducted on Scopus and Web of Science, as reported in Fig. 1. In the screening phase filters such as duplicates, language and unkown authors were applied, resulting in 244 papers. In the eligibility phase the 78 documents focused on ECM and production were identified. Lastly, the entire papers were analysed to identify the 37 of them relevant to answer the RQs.

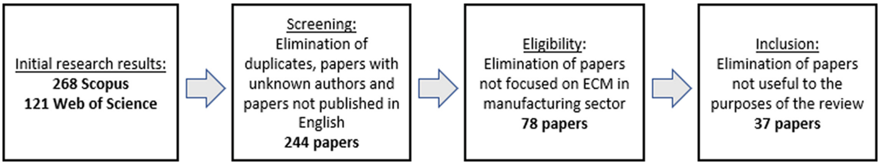

Fig. 1. Literature review methodology

The final papers were classified according to relevant criteria derived from the RQs:

- For RQ1, the interested area of ECM have been detected, i.e., the tasks that were described as performing by the DT to improve ECM.

- For RQ2, the description of the ECM DT features and the proposal of ECM DT architecture have been analysed.
- For RQ3, the description of implementation process, or structured implementation methodology have been considered.

All the analysed papers are presented and classified in Table 1 below. For each paper, in each column, has been inserted only the most underlined aspect in the document. Nonetheless, this does not mean, for each column, that the presented aspect was the only one discussed by the paper referring to that specific column.

Table 1. Synthesis of the analyzed papers

Paper	ECM applications	DT relevant features	Architecture proposal	Implementation
[14]	EM	DA&AI	N	N
[6]	EM	DA&AI	Y	N
[15]	EM	DA&AI	Y	PHI
[16]	EM	DA&AI	N	N
[17]	UO	VM&S	N	DI
[18]	EM	VM&S	N	DI
[19]	UO	_	Y	N
[20]	UO	HI	N	N
[21]	PEC	VM&S	N	PHI
[22]	AEW	DA&AI	N	SM
[23]	P&MO	DA&AI	Y	N
[24]	PEC	VM&S	Y	N
[25]	EPO	VM&S	N	N
[26]	EPO	VM&S	Y	N
[27]	Unspecified	_	N	PHI
[28]	P&MO	VM&S	Y	SM
[8]	P&MO	DAcq	N	DI
[29]	UO	_	Y	DI
[30]	AEW	DA&AI	Y	N
[31]	EPO	DA&AI	N	PHI
[32]	UO	_	N	PHI
[33]	UO	Dacq	Y	DI
[34]	EM	HI	N	DI

(*continued*)

Table 1. (*continued*)

Paper	ECM applications	DT relevant features	Architecture proposal	Implementation
[35]	P&MO	DA&AI	Y	DI
[36]	P&MO	_	Y	N
[37]	Unspecified	_	N	N
[38]	P&MO	VM&S	Y	DI
[39]	EPO	DA&AI	Y	DI
[40]	EM	Dacq	N	PHI
[41]	EM	DA&AI	Y	PHI
[42]	P&MO	DA&AI	Y	PHI
[43]	EM	HI	N	DI
[10]	EPO	DAcq	Y	PHI
[44]	EM	VM&S	Y	SM
[45]	EPO	DA&AI	N	DI
[46]	AEW	VM&S	N	N
[47]	EPO	VM&S	Y	SM

Energy Monitoring = EM; Unspecified Optimization = UO; Prediction of future Energy Consumption = PEC; Energy Parameters Optimization = EPO; Avoid Energy Waste = AEW; Process and Maintenance Optimization = P&MO
Data Analytics and Artificial Intelligence = DA&AI; Virtual Model and Simulation = VM&S; Human Interface = HI; Data Acquisition = DAcq
Yes = Y, No = N
Provides Hints for Implementation = PHI; Describes the Implementation = DI; Provides a Structured Methodology = SM

3 Results and Discussion

In this section the main results of the LR are described and discussed.

3.1 Applications of DT to ECM in Production

The main identified ECM applications are (i) Energy Monitoring (EM); (ii) Prediction of future Energy Consumption (PEC); (iii) Avoid Energy Waste (AEW); (iv) Process and Maintenance Optimization (P&MO) (v); Energy Parameters Optimization (EPO); (vi) Unspecified Optimization (UO).

PEC is related to the prediction of EC of assets, processes, or work cycles in future stages of the lifecycle or to compare alternative configurations. The main tool for PEC is simulation (e.g., [8, 21, 24, 28, 38, 42]). Simulation is also a key tool in the EC optimization through the production scheduling [28, 38, 42], which fell inside the P&MO cluster. Another interesting P&MO application is the optimization of machine states timing [8] to reduce EC. Maintenance process can also be a target of ECM optimization [23]. The analysis of the production process through a DT can lead also to AEW, by avoiding to use energy on not quality-compliant work in progress [22, 36], or by identifying energy consuming non value-added activities [28, 30]. A different approach concerns the possibility to perform the EPO, by directly controlling, through the DT, certain EC-related parameters [10, 25, 26, 35, 38, 39, 45, 47]. Finally, several cases did not specify how they wanted to optimize EC and fell under UO [17, 19, 20, 29, 32, 33]. As a final consideration, it is interesting to notice that all the analyzed applications do not substitute human-performed tasks: ECM DT enables the performing of new tasks, rather than allowing to perform better operations already human-performed. This is crucial, as it means that ECM DT would have a role of support and assistance to humans rather than substitution.

3.2 Features of DT for ECM

The main DT features identidied in the literature review are (i) Data Analytics and Artificial Intelligence (DA&AI); (ii) Virtual Model and Simulation (VM&S); (iii) Human Interface (HI); (iv) Data Acquisition (DAcq).

ECM-DT Features. *(i) DA&AI*. Heterogenous approaches can be observed according to situation, targets, and applications. Among the most notable cases, there are statistical approaches based on gaussian distribution [22, 39], mixed integer linear programming [24], and a hybrid model based on a self-adaptive population genetic algorithm and autoregressive moving average [31]. Such an heterogeneity is tackled by [16], underlining the absence of an overall accepted data exchange format. *(ii) VM&S.* It appears that many EC-related models are written in Matlab, for a Discrete Event Simulation (DES) approach [25, 40, 45–47]. There are exceptions, like [24] using Modelica for an Object Oriented Simulation, and [38] describing an integrated approach with elements of discrete event, dynamic system and agent based approaches. An important feature related to VM&S appears the integration between digital and physical entities. In [21] is used the sequential analysis technique "Page-Hinkley test" to let the virtual model cope with changes in the physical system. [25] describes an interactive mechanism where physical and digital spaces behave respectively as the client and the server. One last important feature about VM&S, can be the usage of an ontology to provide knowledge to the simulation [44]. *(iii) HI*. It is an aspect whose importance is enhanced by the crucial role it has in determining the humans-DT cooperation. Human intervention is crucial for many DT supported decision-making activities [48]. In [39] is used a Javascript Application Programming Interface (API) for rendering 2D and 3D interactive graphics. In [8] a Graphic User Interface (GUI) is built using Matlab. In [43] a GUI is programmed with Kivy, an open-source Python framework. In [34] is developed a mobile app for real-time visualization, which could have interesting consequences in the way humans relate to DT. No explicit mentioning was found about the usage of Augmented Reality with ECM DT, even though it can be a key element in the human-DT interaction. *(iv) DAcq*. A common feature is the usage of I4.0 technologies for the data sensing and transmission infrastructure [23, 29, 32, 34, 41, 42]. Another crucial point is the integration between DT and the field IT systems: [8] proposes a method for MES-integration and [33] for SCADA-integration.

ECM-DT Architectures. For what concerns architectures proposal, in the analyzed cases appears as quite recurrent the division in layers, usually three (in few cases four): one layer for DAcq, one for VM&S, and the last one for DA&AI (or applications) and HI. Sometimes, a further layer for data transmission is added between DAcq and VM&S [19, 23, 29, 30, 35, 42]. In [29] is also proposed to develop many separate DTs for the single physical elements, and then to link them all. Considering alternative typologies of DT architecture, in [10] the bottom layer presents synchronized physical and digital equipment, and above are placed ECM services. [39] presents an architecture focused on the transfer of data from PLCs to the web API. In [26] the data analytics module warns the operator, involved as a crucial component of the DT architecture, who triggers the simulation module. The architecture by [33] includes six modules (i.e., behaviour models repository, multi-physical models repository, parameters monitoring, process virtualization, forecast for process evolution prediction, planning management). [44] proposes a framework for a DT applied to an industrial robot split into physical and cyber space.

3.3 Strategies of Implementation of DT in ECM

Four of the analyzed works define a structured DT implementation and 11 describe the implementation. The descriptions usually focus on a specific implementation phase [29, 34, 43, 45]. [45] describes a process of design focused on the theoretical model and the results. In [29] the focus is set on the description of DT hardware implementation. [34, 43] center on the description of the DT software requirements and the hardware architecture of the solution. [44, 47] offer a complete description of the implementation strategy giving an idea of the path that companies could take to implement ECM DT. However, the DTs in both works are implemented on a cutting-edge industrial Robot which simplifies the process. To identify the high level implementation methodology of ECM DT, each document was analyzed and a common path of implementation was identified. Three main phases are counted (Fig. 2).

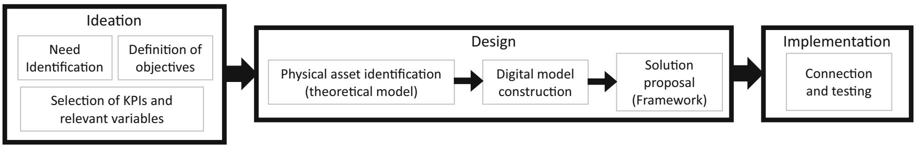

Fig. 2. Identified DT implementation methodology in ECM

The DT implementation requires a systematic approach to track the implementation process and the tasks to be executed in it [22]. In [28] is highlighted that one of the most relevant steps in the ECM DT implementation is the initial definition of KPIs and objectives to be achieved through the DT. Nevetheless, in most of the analysed implementation strategies, such definition varies depending on the interaction among such factors [8, 22, 28, 33, 35]. Specifically, in [8] the energy-Overall Equipment Effectiveness is defined to be the most relevant KPI to monitor. In [35] a dynamic sleep DT for ECM is proposed and modelled, and the KPIs and strategy to address are different from [8]. In some documents the way in which the definition of the objectives and KPIs for the DT were reached are not discussed [22, 29]. In summary, the way in which the implementation strategy varies in the different contexts of ECM is still fuzzy and can create confusion for companies interested in the DT implementation.

4 Conclusions and Future Work

This work proposed to investigate the state of the art of the of DT applied to ECM through a LR articulated into three RQs. The answer to RQ1 uncovered how the field of applications appears large, variegated, and full of potentiality. Furthermore, ECM DT clearly appears to be supporting humans rather than substituting them. RQ2 uncovered a great heterogeneity in the ways ECM DTs work and in the features that characterize their structuring. The only recurrent characteristic seems to be the modelling through Matlab and usage of DES, but without evidence of a correlation between this and the ECM objective of the DTs. Indeed, DT features seem to change according to specific targets, industries, and situations. Thus, a topic to be developed in future might be an analysis of the eventual correlation between DT features and ECM applications. There seems to be though a pattern towards the definition of a recurrent type of DT architecture, structured in layers, representing the sensing infrastructure, DA&AI and VM&S, and applications and HI. Finally, for RQ3, even though there are few implementation examples available and a common high-level implementation methodology has been identified, there is a lack of structured methodologies to support companies in the ECM DT implementation. This seems an issue related not just to ECM DT, but to generic DT implementation, and analysis and works about it should be performed. Finally, there are very few considerations about human role in ECM DT paradigm.

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