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Special Issue
Smart Manufacturing & Automation Control Systems for Industry 4.0/5.0

Edited by
Dr. Sergey Y. Yurish

MDPI

https://doi.org/10.3390/pr11082353

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The Industrial Digital Energy Twin as a Tool for the Comprehensive Optimization of Industrial Processes

Alejandro Rubio-Rico [1,*], Fernando Mengod-Bautista [1], Andrés Lluna-Arriaga [1,*], Belén Arroyo-Torres [1] and Vicente Fuster-Roig [2,*]

[1] Instituto Tecnológico de la Energía (ITE), Avda. Juan de la Cierva, 24, 46980 Valencia, Spain; fernando.mengod@ite.es (F.M.-B.); belen.arroyo@ite.es (B.A.-T.)
[2] Instituto de Tecnología Eléctrica, Universitat Politècnica de Valencia, Camino de Vera s/n Edificio 6C, 46022 Valencia, Spain
* Correspondence: alejandro.rubio@ite.es (A.R.-R.); andres.lluna@ite.es (A.L.-A.); vicente.fuster@ite.es (V.F.-R.); Tel.: +34-961366670 (A.R.-R.)

Abstract: Industrial manufacturing processes have evolved and improved since the disruption of the Industry 4.0 paradigm, while energy has progressively become a strategic resource required to maintain industrial competitiveness while maximizing quality and minimizing environmental impacts. In this context of global changes leading to social and economic impact in the short term and an unprecedented climate crisis, Digital Twins for Energy Efficiency in manufacturing processes provide companies with a tool to address this complex situation. Nevertheless, already existing Digital Twins applied for energy efficiency in a manufacturing process lack a flexible structure that easily replicates the real behavior of consuming machines while integrating it in complex upper-level environments. This paper presents a combined multi-paradigm approach to industrial process modeling developed and applied during the GENERTWIN project. The tool allows users to predict energy consumption and costs and, at the same time, evaluates the behavior of the process under certain productive changes to maximize consumption optimization, production efficiency and process flexibility.

Keywords: digital twin; smart manufacturing; energy; energy efficiency; productive flexibility

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Citation: Rubio-Rico, A.; Mengod-Bautista, F.; Lluna-Arriaga, A.; Arroyo-Torres, B.; Fuster-Roig, V. The Industrial Digital Energy Twin as a Tool for the Comprehensive Optimization of Industrial Processes. *Processes* **2023**, *11*, 2353. https://doi.org/10.3390/pr11082353

Academic Editor: Sergey Y. Yurish

Received: 5 June 2023
Revised: 31 July 2023
Accepted: 1 August 2023
Published: 4 August 2023

1. Introduction

In the context of evolution from “climate change” to “climate crisis”, the industrial sector must face a series of changes and evolve to new, more efficient manufacturing models in the context of the revolution of the Industry 4.0 paradigm and digitalization. Different tools are sufficiently developed and tested to be applied with success and help maximize productivity and minimize energy consumption and costs, both concepts highly related. The energy efficiency of manufacturing systems arises again as a key domain on which there is still a high degree of improvement to be achieved. Nevertheless, manufacturing companies present different levels of development and application of energy efficiency measures, and this situation gets even worse in cases where a minimum degree of digitization is required. In fact, a dynamic and continuous evaluation of the energy consumption of the process and its relationship with the internal and external environment seems to be necessary to effectively face previously cited challenges in a globally connected and competitive world.

Digital Twins (DT) are one of the main tools developed in this context. Appearing in the early 2000s [1], the concept represents the idea of developing a digital copy of a physical object. This copy, technically known as a twin, allows for the implementation of process improvements and optimization of its operation in a fully controlled and risk-free environment. However, different approaches can be examined when Digital Twins are developed and deployed— some of them more linked to the Internet of Things (IoT) concept than others, but in any case, are focused on replicating the actual performance of the manufacturing process. In this context, Digital Twins prove to be a valuable tool to predict and improve energy consumption as a specific use case. This document will examine the current context of DT developed and implemented in project GENERTWIN for improving the energy efficiency of manufacturing processes, their potential as energy efficiency improvement tools, and their consequent characteristics and particularities. The paper focuses on highlighting the advantages of multi-method integration of energy-production models in complex environments with the main objective of replicating energy consumption, energy cost and productive performance.

2. Digital Twins for Energy Efficiency Improvement of the Industrial Process

2.1. The Challenge of Improving Energy Efficiency in the Manufacturing Industry

The way to reach a good level of energy efficiency in manufacturing processes has traditionally been based on two trends; (1) the introduction of new process technologies to improve efficiency and (2) the introduction of specific improvements in plant operations [2]. However, this second approach has never been sufficient to understand the causality inherent in the operation of manufacturing processes in sufficient detail to propose improvements that dynamically adapt to the process context and changes. Some energy efficiency analysis techniques, such as performance measurement and verification protocols, come close to the level of detail needed to achieve such intuition. These kinds of tools, complemented by internationally recognized implementation support protocols such as ISO 50001 [3] referred to Energy Management Systems or energy audits (in Spain, according to Royal Decree 56/2016 following Energy Efficiency Directives), provide a general development framework that is explicitly adapted to the particularities of each application case [4]. As a consequence, the state of the art of energy efficiency analysis of industrial processes is usually quite far from the implementation of more advanced techniques than those described, seeking, in any case, high-impact technological changes but not so much an optimization methodology based on dynamically updated measures. Figure 1 summarizes the state of the art of tools for analyzing energy efficiency on manufacturing processes.

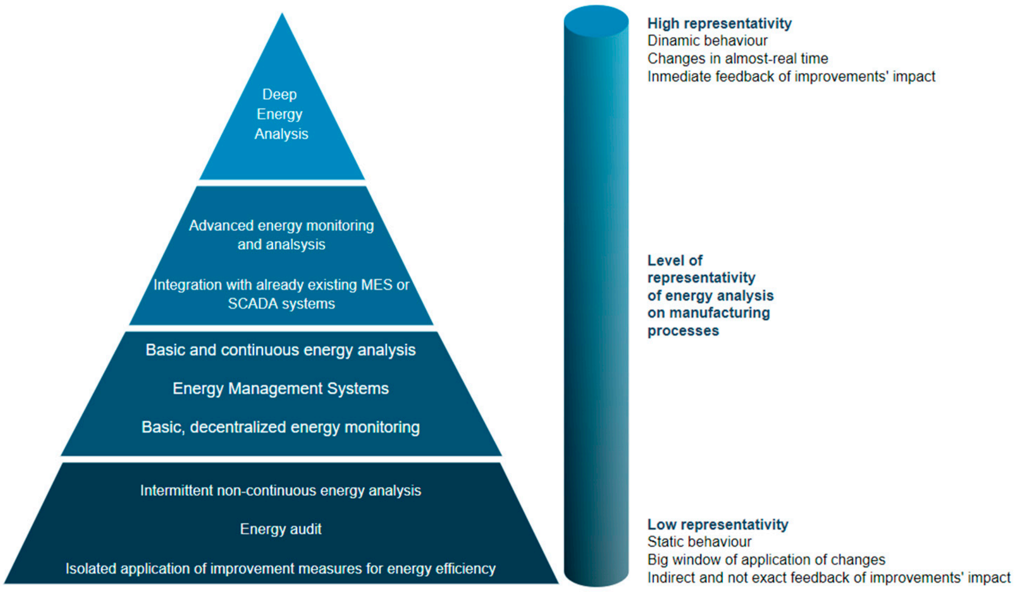


Figure 1. Different levels of representativity and commonly used tools for analyzing and optimizing the energy efficiency of the process. Source: ITE.

Even though it is not simple to accurately evaluate the current situation of the different manufacturing sectors in terms of energy efficiency techniques' degree of adoption (And, specifically, digitalization degree as a key dimension for energy efficiency optimization in time), systematic evaluations of some sub-sectors reveal a large potential for energy efficiency improvements in energy-intensive sectors [5]. This conclusion can be extended to other manufacturing sectors and can be affected by the economic environment and other complex factors, resulting in high discrepancies in energy efficiency among sub-sectors [6]. Another important consideration in scenarios of a medium-high degree of adoption of energy efficiency measures is the digital barrier of the traditionally conceived architecture of processes, which grow according to economic or legal requirements or needs, rather than evolving and growing in a more organic way and based on a structure that supports the integration of the basic mechanisms for calculating and evaluating energy efficiency. A representative example is the ceramics sector in Spain, which has achieved significant reductions in CO_2 emissions over the past two decades but still faces a great challenge of emissions reduction, most of which are directly related to the improvement of energy efficiency of the manufacturing process [7].

2.2. Digital Twins Usage for Energy Efficiency Optimization in Manufacturing Environments

The present and future context of manufacturing companies requires rethinking the strategy for maximizing process energy efficiency while meeting the required production and quality standards. Consequently, it is necessary to have tools that allow flexible adaptation to every change in productive and non-productive environments. In this context, multiple authors describe the DT as a key enabler in accomplishing this challenge, despite not being sufficiently implemented in Smart Manufacturing Systems (SMS) [8]. It is important to note that the design of DT has not been developed at the same pace as their interest has grown [9]. In fact, the concept proves to be sufficiently flexible to be applied to a heterogeneous set of industries, such as healthcare [10], farming [11] or construction [12]. This last example of application leads to highlight the importance of energy optimization in almost all use cases involving the usage of building and/or equipment. In the particular case of the manufacturing industry, this leads to considering energy consumption optimization as a key and valuable application of DT to industrial applications closely linked to operational efficiency [12].

Different approaches of DT focused on improving the energy efficiency of the manufacturing process arise when examining the state-of-the-art, most of them related to the concept of making existing and future manufacturing systems more sustainable. Energy consumption depends on different factors (it gets even more complex depending on the sector and manufacturing activities), but in any case, the manufacturing system operation, including equipment, human and material resources management, turns out to be the dimension most directly linked to the dynamic energy consumption of the industrial plant [13]. The concept of dynamic energy consumption is meant to reflect the importance of considering energy consumption as something variable in time, which leads to the formulation of how to integrate the energy consumption dimension of the plant with the inherent and future production and operational flexibility in an organic and coherent way. Manufacturing system reconfiguration and optimization is one of the references DT architectures allowing increasing productivity while reducing energy consumption, to the point of including energy consumption and energy cost as two of the most important Key Performance Indicators (KPI) when reconfiguring the optimized productive scenario. However, this reference architecture may cover different phases of the plant's use from the design and engineering phase, construction phase and, in the context of the construction sector, even the demolition phase, in addition to the already referenced maintenance and operation phase, making it possible to apply it to the concept of lifecycle of the project [14]. Even though energy consumption optimization has high importance in each and every one of the phases described above, the approach of DT presented in this paper is mainly focused on the operation phase of the industrial site.

In this application scenario, DT can potentially provide the company with the ability to predict the behavior of its process in different scenarios. These scenarios can be oriented to analyze different dimensions of the process, such as predictive maintenance, performance monitoring and control, better resource planning, or even facilitating renewable energy integration, to mention a few examples [15]. The DT can, in fact, be designed bearing one or more of these functionalities in mind, and it may even evolve to include new ones at a later stage. Nevertheless, the existence of Digital Twin manufacturing systems reflects how high levels of fidelity and complexity can be reached when proposing a bottom-up approach from the design phase of the SMS [16]. This approach seems highly interesting and even essential to the development of new manufacturing systems aligned with the Industry 4.0 paradigm, along with dynamic and advanced mechanisms to evaluate and promote energy efficiency in the complex context of manufacturing processes. As a consequence, it seems important to consider a flexible and adaptable architecture of DT highly focused on energy consumption prediction and evaluation considering process parameters, the productive environment and external factors following the requirements to provide energy efficiency improvements.

Digital Twins, as a tool for effectively integrating energy consumption with operational performance in industrial plants, is currently not sufficiently developed, at least considering the need to calculate a dynamic energy consumption value susceptible to being affected by every important productive parameter and integrated into their environmental context. When descending to the machine level, some models consider mathematical approaches to reproduce power consumption along with carbon footprint from the basis of the job scheduling of the simplified application case [17]. This approach proposes a correct focus on the problem of predicting energy consumption but also poses the problem of the replication of the model to other types of machines or scopes. In addition, the approach has the disadvantage of not considering a broader application and contextual environment in the model, as previously mentioned. This model should be integrated into a Digital Twin and would also cover part of the specifications needed to consider a Digital Twin for energy efficiency. Another alternative method also involves nonlinear planning models, to mention an example [18]. In any case, the results provided by the mathematical methods are not as important as the fact they depend on the quantity, quality and representativity of data and to which extent it can be extrapolated to other machines or processes.

Alternative approaches integrate both energy and production data through cyber-physical systems, focused on sustainable production [19] but basically framed within the traditional concept of an energy monitoring system. In fact, most approaches employ discrete modeling of the process or production chain to introduce discretized energy consumption concepts [20]. These approaches present the same problem of a purely mathematical approach as the previously described, that is, the lack of a dynamic design of calculation criteria intrinsic to the operation of machinery in which possible internal and external changes are considered. Those models are focused on the site supply chain logistics and optimization of material resources in most cases in which energy consumption shows a characteristic dynamic behavior that this kind of model cannot process. On the other hand, this kind of model can be adapted to different machines and environments in an easier way. These models aligned with the concept of DT for energy efficiency of the process are supposed to be designed to allow for the study of the final and disaggregated impact of the variation of specific operational control parameters while improving technical service and maintenance—all of which should be performed in a digital environment that is controlled, connectable and with a much lower risk.

Further approaches involve working with sufficiently representative datasets, including energy consumption and the rest of the related productive and non-productive parameters, to apply purely mathematical algorithms or other advanced enablers, such as machine learning algorithms. In fact, Artificial Intelligence (AI) as a technology is a very valuable key enabler to boost and utilize the capabilities a DT can provide in the best possible way [14]. However, again, in this case, we start from a difficult point since this approach imposes the need for a high quantity of well-structured and significant registers of energy and related data to train the corresponding algorithms. Some examples show good results of a Neural Network (NN) trained to predict energy consumption in specific applications at a low abstraction level of a machine, and considering all the necessary data for training, the algorithm is available. Nevertheless, this approach also poses the problem of the difficulty of the task of developing energy consumption models based on the interrelated parameters that influence energy consumption [21].

As a conclusion of the previous approach, it can be deduced that the real challenge lies in developing Digital Twins with a specific focus on the detailed calculation of the energy consumption of the machinery, which, in turn, must consider operational characteristics of the models, but, at the same time, not excessively depending of data availability since, in most cases, and particularly related to energy digitalization, the data are not easily accessible and complete datasets including energy, productive and non-productive data are not available.

2.3. Project GENERTWIN

The objective of the GENERTWIN "Sistema Digital de Análisis de procesos industriales para GENERación de escenarios alternativos bajo consideraciones productivas y de eficiencia energética" project is the development and implementation of a DT applicable to different manufacturing sectors considering the optimization needs and energy dependence of these processes. The Digital Twin (DT) is developed following the identified needs after a deep situation analysis, including the identification of the use cases and the functionalities that this twin must provide to the company.

The DT is developed to a low level of detail and considers the internal dynamics of the machinery involved in the process, its operation, the relationship with the necessary resources and the impact of the different possible variations on the quality and type of products obtained. By considering it as a DT, the model consequently scales in complexity and capabilities, allowing not only to analyze the operation and interactions of the aforementioned elements that are part of the process but also to add value to the company's decision-making process. The DT presents an architecture specifically designed to maximize the representativeness of energy consumption and cost prediction and its relationship with productive and non-productive contexts.

2.4. Constraints and Challenges

The development and implementation of the proposed architecture of DT present a series of constraints and challenges. The first of them is the identification of the real expectations and needs of the companies on which the development of the tool is focused. On many occasions, a bad design of the DT can lead to an excess of work in the development that entails a higher final cost. On the other hand, insufficient development of the model can result in the DT losing the representativeness of its results. Therefore, an optimal balance between both points must be found to achieve a balanced, accessible system that meets the needs of the company.

In order to mitigate the potential design problem as much as possible, a previous design phase has been developed in which the company using the process, participates by receiving the appropriate feedback. In addition, a multisectoral analysis of requirements and possible interests of other follower companies is carried out in the project to maximize the representativeness and conduct the final solution to the most effective development possible. Another major challenge to solve when developing a model is data accessibility, as previously explained. It is common to find a lack of information, even among process specialists, about the details of its operation and internal mechanisms. In addition, the relatively low penetration rate of digital monitoring systems collecting energy and production data is also a handicap that hinders development, as cited above.

3. Digital Twin Development

3.1. Basic Architecture

The Digital Twin is structured in different layers, as shown in Figure 2. The lower layer refers to the Energy Productive Model (EPM), which represents the simulation core considering the dynamic models of the processes together with the simulation of discrete events to reproduce the manufacturing activity. The Digital Twin environment, which gathers the interaction and analysis functionalities in a digital environment, is developed using a specialized hybrid and multi-paradigm simulation software, including multi-agent modeling, which also allows integrating and testing models and interfaces. Finally, there is an upper layer of the system itself, which is designed to be integrated with other types of plant systems with specific interconnectivity capabilities and connect the simulation models as analytical advanced digital tools with the Internet of Thing layers and other automation architectures [22].

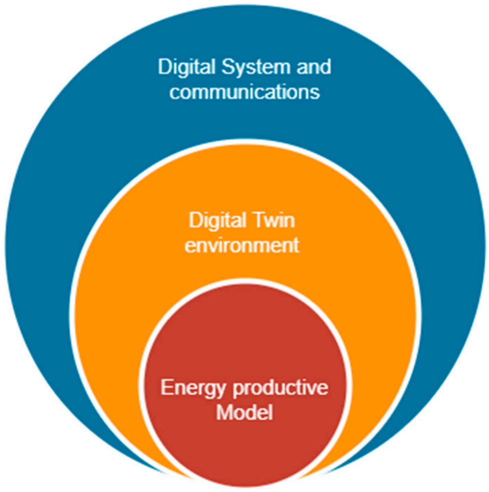


Figure 2. Structure of the DT architecture in basic high-level layers. Source: ITE.

The lower layer of the DT contains all simulation methods and behaviors at the machine and resource levels. This layer combines the necessary technologies and calculation mechanisms to solve every energy prediction problem in the most standardized and replicable way. Every part of this layer is developed to maximize the ratio of the representativity of the predictions against the complexity of the programmed behavioral functions. A representative example developed in the project is the implemented mechanism for calculating the energy consumption of an industrial furnace. Every piece of this simulation element has been developed, combining the expert knowledge of this kind of thermal-transfer process with some simplifications with the goal to be potentially adapted to similar industrial furnaces of similar characteristics. It has also been developed, guaranteeing the exact correlation between energy consumption and production parameters, such as the dimensions of the product, type of material and other characteristics (ambient conditions, quantity of products per productive line, initial humidity of the sub-product entering the furnace, etc.). Including this kind of parameter also justifies the importance of the proposed architecture of DT connected to the production schedule. It is important to note that every problem has been divided into sub-problems to be solved by different means, including machine state characterization and implementing a variety of calculation algorithms with the common framework of replicating the energy behavior of the machine, its power consumption curve and all the necessary calculations of energy consumed in every case.

The use of System Dynamics (SD) calculation methods is highlighted as a powerful approach to replicating individual behaviors of different agents, especially for transient states. In fact, the representativeness of the process is guaranteed in this layer as a solution for the referred challenge in Section 2.4 since the proposed architecture allows for separate testings of every element and module, while the general requirements, such as comparing the integration of the power curves of different consuming elements with general consumption (which is the most commonly available energy data in the manufacturing industry), can be met.

The intermediate layer of the DT includes all the environments in which machines develop their behavior and interact with human and material resources and the typical constraints of manufacturing scenarios, such as work schedules, scheduled stops, or failures of machinery. This layer is an important environment in which previously referred machines develop their behaviors and where the impact of external changes (not depending on the machine configuration itself or operational parameters) is calculated. This layer also integrates the impact of different machines to provide aggregated KPIs affecting production lines or even a whole factory, depending on the scope of the DT and the need for output information required. This layer has been developed following the needs and restrictions of companies participating in the project.

Finally, the higher layer of the DT is mainly focused on connecting and exchanging information with other systems and allowing interactions with users through User Interfaces (UI). The development of this layer is determined by the already existing data and the type and amount of data to be exchanged. It also includes the use of internal or external DataBases (DB) according to the characteristics imposed by such data. The project has considered non-relational databases. In particular, a time series database because of the structure of the registers. However, it also can connect to relational DB, such as those developed in SQL.

The proposed architecture aims to deal with some of the problems identified in Section 2.4. The communication layer is intended to solve the challenge of data availability along with the simulation layer; when the data are available (in fact, when data are available with enough quality and can be effectively imported from already deployed energy meters), this layer implements all the necessary mechanism to integrate dataflow in the DT while, at the same time, simulation layer will include numerical or mathematical models to represent each DT element behavior, following a black-box approach. Alternatively, when the data are only partially available or not available at all, the burden of effectively replicating the behavior of the elements of which the DT is composed falls upon the Simulation layer, implementing energy models depending on a first-principles approach in a higher degree, rather than excessively depending on data. The following Figure 3 represents these layers' structure and the related element, tools and dimensions with which each layer is related.

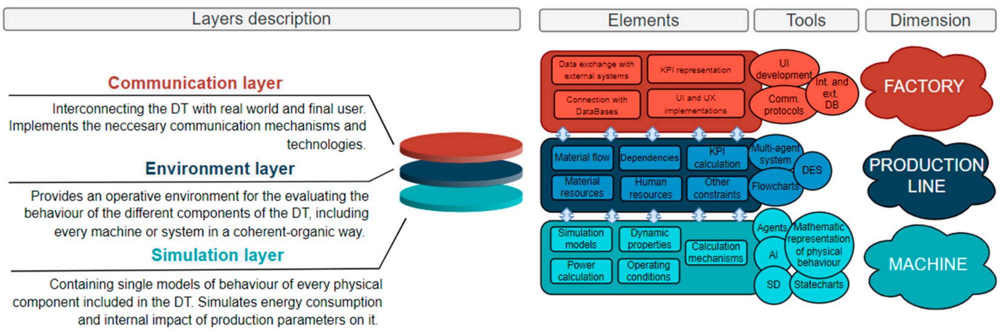


Figure 3. Description and elements of each layer of the DT. Source: ITE.

3.2. The DT Implementation Process

The process of implementing a DT is complex and, sometimes, not straightforward, particularly during model design and development. In fact, it is difficult to find research documents about DT implementation methodologies with formal applications to the manufacturing industry. Similar approaches, in this case concerning the development and application of a DT to a ship, show how the manufacturing process of the object is followed by corresponding steps of development of the DT, from design/development of the "digital mockup", to operation/application of the DT to production phase [23]. Other references current implementation procedures based on defining individual DT to be integrated into an aggregated DT as a hierarchical composition of the rest [24]. This kind of methodology is designed to consider the deployment of multi-purpose DT using a standardized architecture whose data model is, in this case, based on AutomationML. Nevertheless, the scope of this kind of DT is much greater than the proposed in this paper, focused on the energy efficiency of the process. The DT for Energy Efficiency developed and applied in GENERTWIN could potentially serve to be integrated into higher-level DT like those described in the preferred source. At a low level, referred methodology splits DT into different components such as storage, method, access control, communication interface, etc. [24]. This approach is not compatible with the architecture presented in the project since the interdependence of each of the three layers containing all the mentioned elements prevents the development of each of the elements independently if this development path is intended to be followed.

Therefore, it is determined that the implemented methodology should include a design phase focused on identifying key functionalities. Also, due to the importance of developed models and their performance and degree of accuracy during operation, the development phase is divided into different steps to iteratively develop the model. Finally, the operation phase is not considered since the proposed methodology just aims to be applied to the deployment procedure, not to the operation procedure. In consequence, a standardized methodology was developed and followed to guide the implementation process based on stages, in which clear objectives are defined with end users. It is important to agree on the functionalities the system must achieve before launching the development and to continue working on these functionalities during the development of the model. Figure 4 represents all the referred steps and the methodology structure.

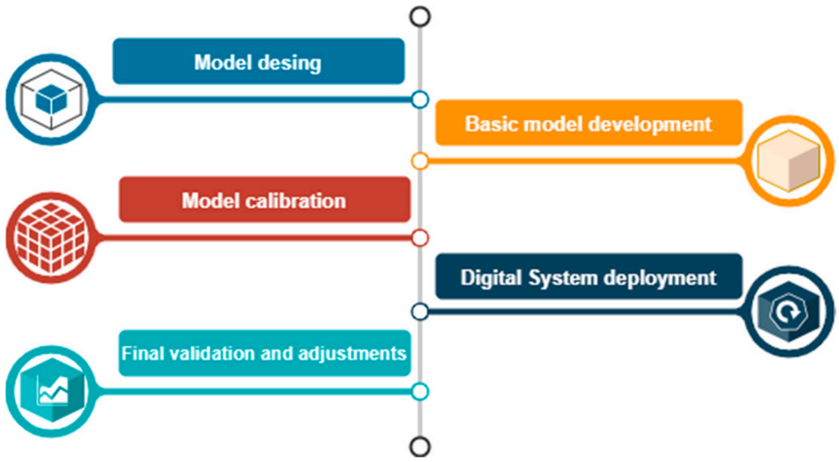


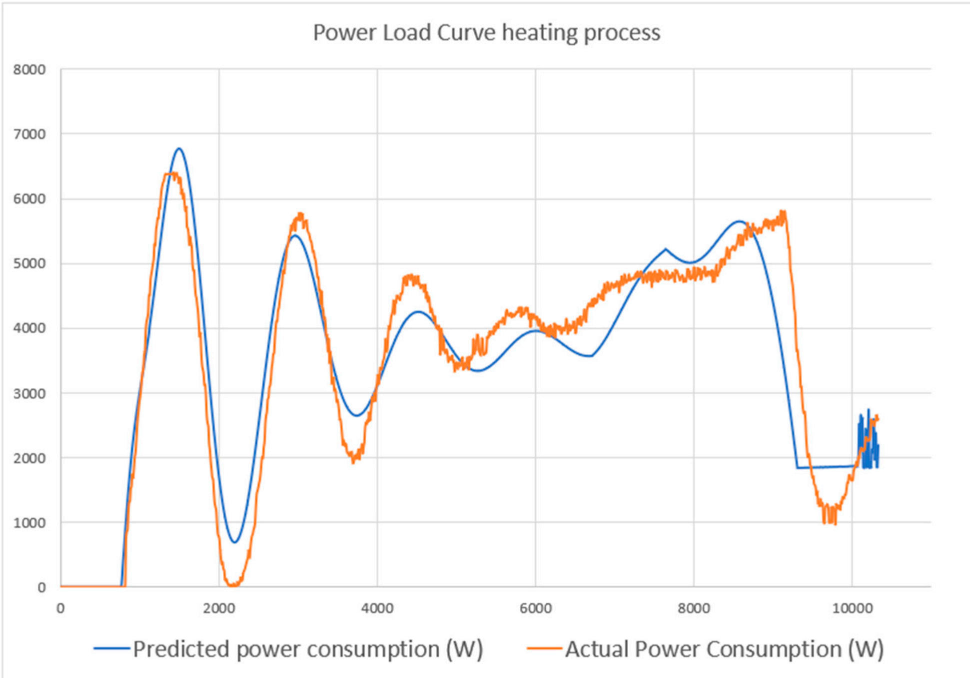
Figure 4. Necessary steps to accomplish in the project. Source: ITE.

It should be noted that the developed methodology in the project aims to structure a highly iterative process, such as a development that includes a Digital Twin. For this reason, the model must be constantly reexamined and reevaluated to ensure that it meets the required representativeness, allowing it to be sufficiently flexible to add necessary new elements or functionalities. However, the project seeks a balance between sufficient representativeness in terms of energy performance and the feasibility of a time-bound development. This approach seems the most adequate to deal with managing client expectations of the size and complexity of the implemented DT, a major challenge previously identified in Section 2.4.

3.3. Functionalities and Examples of Implementation

As mentioned above, DT for energy efficiency analysis and optimization offers a wide range of possibilities for simulations and improvements to the manufacturing process. The main functionalities provided by the developed DT cover energy consumption and cost prediction of the replicated environment as a core. Some practical application cases are described in the following point, but it is important to note how this approach replicates a detailed level of energy consumption and productive behavior of every machine implemented and how its impact is scaled, along with the impact of other machines, resources, and other agents in a complex environment, as represented in the architecture's description. This application is aligned with the potential of DT identified in previous research, which can provide valuable information in production phases evaluating an operating system under different conditions [24]. It is also noted that DT can help small and medium-sized enterprises to improve operational performance and data acquisition systems. In fact, the GENERTWIN project considers data will not always be easily available and integrable in the DT. This lack of data is compensated with the use of physical and mathematical models that are not excessively dependent on data availability.

An example of energy prediction is shown below in Figure 5. The following graphs show a reconstruction of a power load curve of a process under specific operating conditions of a thermal heating element during a transitory heating phase.



Total estimated consumption	9.59 kWh
Total real consumption	10.04 kWh
Error	1.3%

Figure 5. Power load prediction and actual prediction of heating element, in kW. Source: ITE.

The model, in this case, shows a good accuracy, calculated through the Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n} \times \sum_{i=1}^{n} \left| \frac{y_{actual} - y_{predicted}}{y_{actual}} \right|$$

Energy consumption and the economic cost of energy are also calculated. This model has been implemented by adapting and combining convection, radiation, and heat storage equations in a single model. An example of a convection heat transfer equation is possible, the simplest one of them:

$$\dot{Q}_{conv} = hA_s(T_s - T_\infty)$$

For this specific example, this combination of equations is used because the heating process is made without admitting biomass or other kind of materials. In the event of a material input entering the region heated by the element, its characteristics are integrated into the model to adapt simulations to it. This example shows the level of detail of simulations implemented since this element is integrated into bigger and more complex elements and modules, as explained before. This continuous nature of the energy variable must, however, be integrated into the discrete logic of the operation of the industrial machinery. The following Figure 6 represents a State Machine Diagram (SMD), or statechart, which implements the behavior of different elements integrated into a single logic agent, either machine or resource:

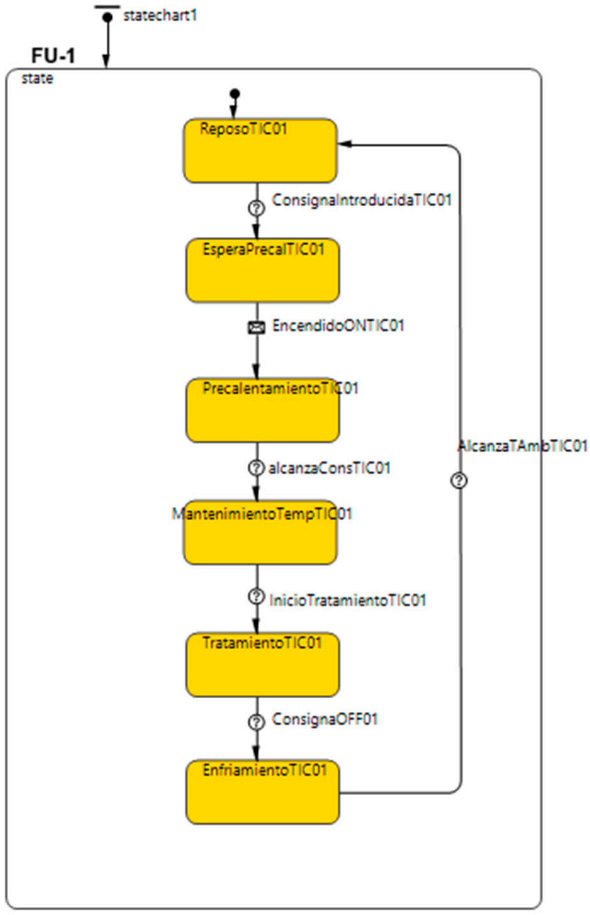


Figure 6. Example of statechart implementing machine's behaviors. Source: ITE.

This chart is implemented by splitting the real behavior of a component into different phases, which significantly helps to model this behavior in different parts while maintaining its continuous nature. Although being a powerful combination of both continuous and discrete behaviors, individual models of energy consumption and statecharts are not the single tools implemented in the proposed architecture of DT for energy efficiency of the process. In fact, some complex structures are created to integrate data and scale up KPI calculation. The following Figure 7 shows an example of the implementation of a mass flow balance.

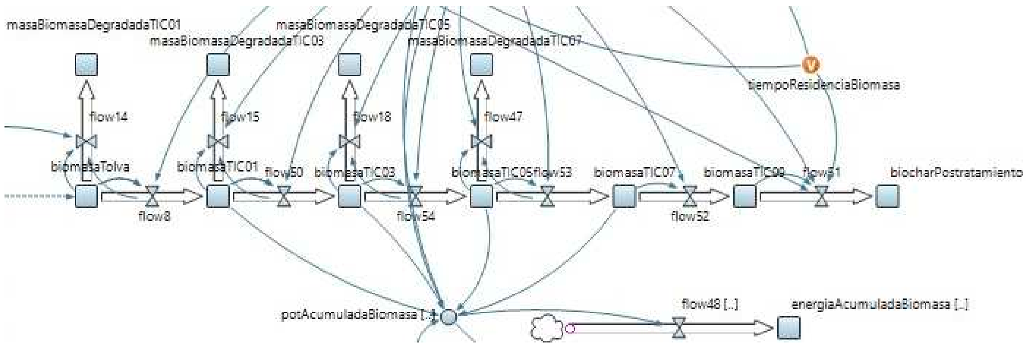


Figure 7. Example of mass flow balance for a horizontal element. Source: ITE.

The development of this mass flow includes the use of differential equations to dynamically evaluate changes, in this case, related to a biomass' flow through each horizontal section, considering degraded and not-degraded fraction change:

$$\frac{dm_t}{dt} = \frac{dm_{nd}}{dt} + \frac{dm_d}{dt}$$

To conclude, the following final example shows in Figure 8 a more complex system of burners of a machine, including process parameters, energy consumption and data interactions of the DT, with the final objective of calculating the energy consumption of different integrated elements of a single machine. This structure of variables, equations and data connections considers the behavior of each burner of a furnace along with interactions with the characteristics of the burning zone, the air, the gas, and the rest of the burners and their influence on the heart of the furnace.

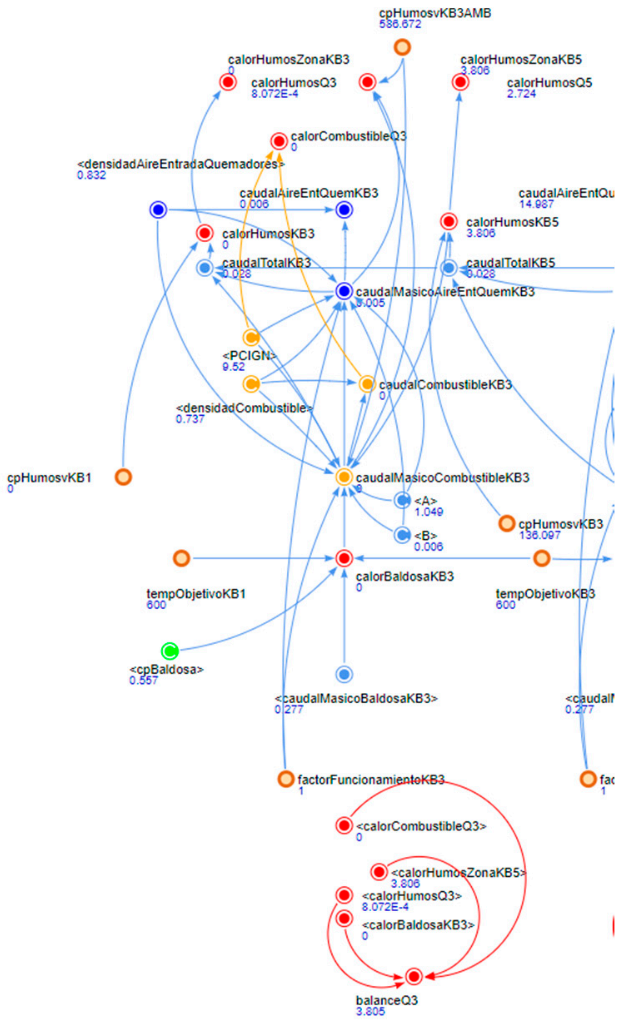


Figure 8. Implementation of correlation between parameters and energy consumption calculation of a complex environment of a DT of the thermal process. Source: ITE.

In the following Figure 9, a standard example of a dashboard for energy consumption is presented, designed to dynamically show a representation of energy consumption and cost divided by period, machines and other criteria aligned with final user requirements.

Contents, UI design, and navigation are adapted to meet final client requirements, in this case, to predict energy consumption per hour, day, week and month, energy consumption per machine, and the power load curve of the whole process and every machine. It is important to emphasize the complexity underlying showing all this information, in this case, including a complete cost-calculation mechanism applied to energy consumption forecasting to give much more representative results of the economic impact of every simulated scenario.

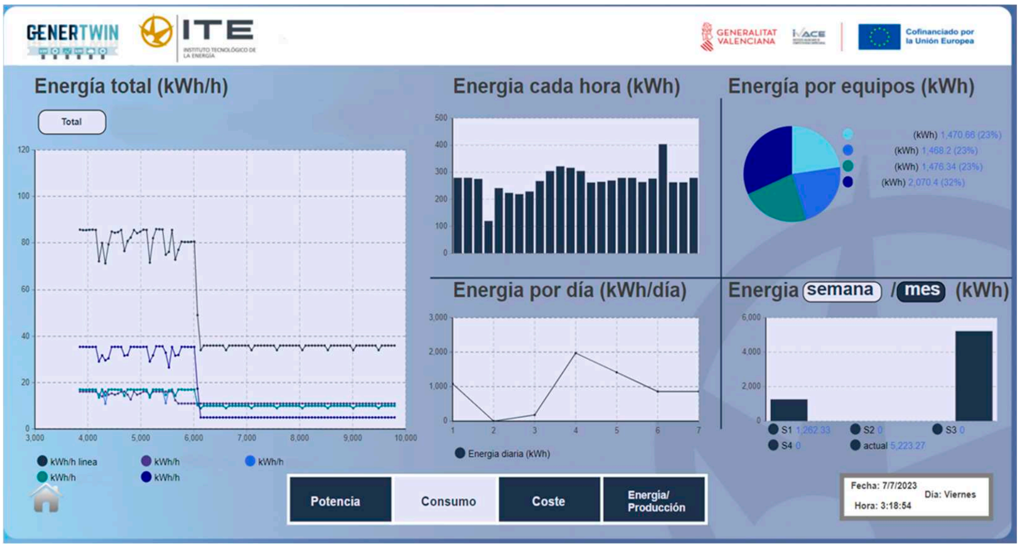


Figure 9. Example of User Interface implemented for visualizing energy consumption and cost of each DT scenario generated. Source: ITE.

3.4. Application and Impact

The DT is designed with the clear functionality of predicting process behavior in the face of substantial production changes, especially focused on the impact on energy consumption of both productive and non-productive variables. In this sense, it simulates different states of the system, displaying predictions and integrating them into the data environment in which the process is developed. This allows optimization adjustments to be made and even optimal production sequencing algorithms to be executed according to the energy cost. At this point, a definition of Energy Efficiency must be provided as a core concept of the proposed definition of DT. The International Performance Measurement and Verification Protocol (IPMVP) [25] proposes defining a baseline situation and calculating differences before and after applying measures for improving energy consumption, as represented in Figure 10. This protocol includes different options for evaluating the impacts of changes affecting energy consumption (such as temperature for HVAC systems, for example) as adjustments. A final form of adjustment is, in fact, using Simulation Models to assess the exact impact of Energy Efficiency measures in a reliable way when measuring is not possible.

Consequently, it can be stated that the proposed DT simulation environment is completely aligned with this approach if all the representative parameters affecting the energy consumption of simulated systems are included. The energy efficiency of a system will be considered as energy savings depending on the defined context as follows:

$$EE(\%) = \frac{EC_{baseline} - EC_{change}}{EC_{baseline}} \times 100$$

This formula includes a calculation of energy consumption (EC) in both the baseline simulation scenario (Business As Usual) and the analyzed scenario, in which changes to models have been made to evaluate the response of the DT. EC will be calculated in energy consumption units (kWh, for example) or in another conveniently chosen KPI, which assures to assess the pursued representation of impacts. Some examples of KPI could be kWh/produced units. Nevertheless, the selection of a specific KPI will depend entirely on the defined simulation. For example, for a scenario of a fixed quantity of produced units, the assessment of consumption in kWh may be sufficient. With this in mind, the following Table 1 shows the potential for improving the economic cost of energy by shifting the batches according to two scenarios of different industrial flexibility.

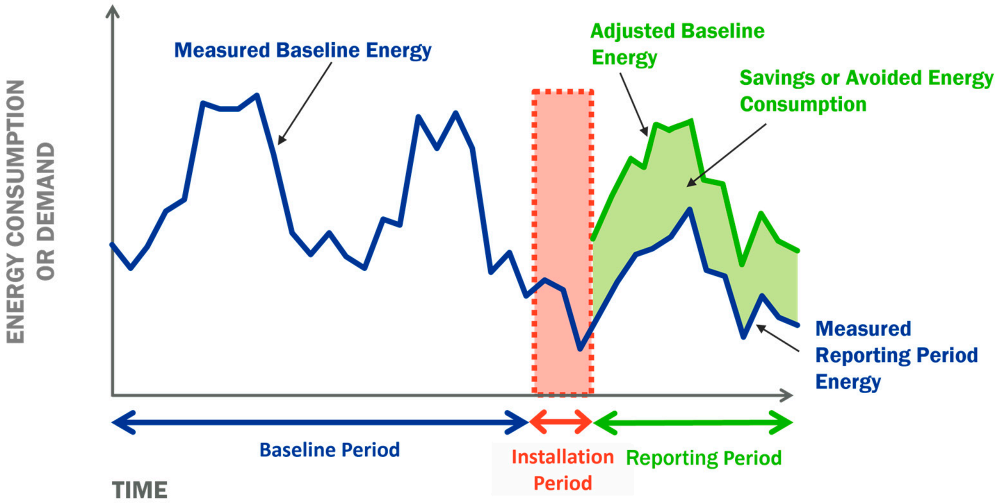


Figure 10. Energy savings adjustments defined by IPMVP. Source: EVO.

Table 1. Impact of scheduling optimization based on previous results. Source: ITE.

Application Case	Energy Cost Improvement (%)	Considerations
Ceramic industry process	4	Low flexibility
Glass industry process	37	High flexibility

This scenario of optimization applies the concept of DT developed to estimate energy cost and re-organize the sequence based on a minimum energy cost criterion, considering energy estimation and consequent cost estimation following the energy cost structure of each company. The first application case considers the impact on the energy cost of modifying the production schedule in an industrial furnace (ceramic case). In this case, the flexibility admitted due to productive constraints is low because of the demand-oriented production model of the company, and in consequence, some restrictions have been imposed on the calculation algorithm. In the second case (glass production process), each production batch is quite independent of the rest, and the machinery has a high degree of availability. These results are obtained by comparing two scenarios of minimum energy cost and maximum energy cost, respectively, implementing an optimization tool based on a solver using an approach of mixed integer linear programming (MILP).

In a second application case summarized below in Table 2, two kinds of simulations were launched along with a calculation of a specific KPI of energy consumption per produced unit (In this case, in an application case of the automotive industry) following variation of different process parameters. As a result, in both a constant period and constant production set of simulations, a similar impact of increasing the medium time during which an operator manually manipulates machinery is detected. On the other hand, other what-if scenarios were analyzed, such as an increase in losses (break of products in some production steps), concluding a relatively low impact on energy consumption compared to baseline simulation.

Finally, another possible use of the DT involves modifying the design or the use of the resources of the process. This approach may seem to be similar to previous works as described in Section 2.2, but GENERTWIN includes all of these approaches in a single multi-paradigm development that combines discrete and continuous dynamics as the main strength, which constitutes the project's primary strength. In this way, the model can be easily adapted to include new functionalities once the base knowledge of the process is strongly replicated.

Table 2. Impact of different simulation cases on energy consumption. Source: ITE.

Simulation Nº	Type of Simulation	Description	KPI (kWh/Unit)	Impact *
S1	Constant period—3 working days	Baseline	0.526	0%
S2	Constant period—3 working days	Increasing procedure time + 40 s	0.542	3.1%
S3	Constant period—3 working days	Increasing losses by 4.5%	0.527	0.2%
S4	Constant period—3 working days	Variation in operator speed	0.53	0.8%
S5	Constant production—10,000 units	Baseline	0.527	0%
S6	Constant production—10,000 units	Increasing procedure time + 40 s	0.542	3.0%
S7	Constant production—10,000 units	Increasing losses by 4.5%	0.528	0.3%
S8	Constant production—10,000 units	Variation in operator speed	0.529	0.6%

* Impact related to baseline case in each type of simulation.

4. Discussion

Finally, we would like to highlight that the functionalities and impacts shown can be obtained in the productive environment with the implementation of the energy analysis models developed in the form of Digital Twins that integrate energy data with production data. These models specialize in analyzing the optimization of energy and its cost with reference to production, and in this case, are adjusted to two concrete industrial processes, such as the ceramic tiles furnace process and break friction materials manufacturing. Although it is considered that the methodology and approach presented can be extrapolated to other production process lines, this will be the future line of work to be developed by ITE in the following research and development projects. One of the most important objectives to be achieved is to obtain, characterize and determine industrial scenarios in which energy cost improvements can be achieved by considering situations of energy production flexibility in their production planning. In this sense, this approach of the proposed DT is sufficiently developed to acquire its own entity as the Digital Energy Twin (DET) of a manufacturing process.

So, the tool allows users to predict energy consumption and costs and, at the same time, evaluate the behavior of the process under certain productive changes in order to maximize consumption optimization, production efficiency and process flexibility. And in this respect, with the intention of obtaining the best results and total interoperability, another of the main challenge on which future development must work is the effective connection of the DT to the reality of the plant by means of key automation industry systems like Manufacturing Execution System (MES) or Supervisory Control and Data Acquisition (SCADA) systems, as appropriate. The connectivity of the application with direct Machine to Machine (M2M) field elements should also be addressed by analyzing the options of developing customized communication drivers such as Modbus TCP or making use of OPC UA as a reference protocol with a high level of application in the industry.

5. Conclusions

The proposed development and application framework of DT for energy efficiency implemented in project GENERTWIN aims to simulate the energy consumption behavior of the process under different productive and contextual changes. For this purpose, a multi-paradigmatic model is developed that encompasses the complexity of the production environment and the impact of the energy consumption of the process to offer advanced analysis possibilities such as scenario generation, energy cost optimization or energy impact assessment of production actions. The proposed Digital System model of energy—production advanced analysis is implemented in two demonstration experimental pilots: (a) ceramic tiles furnace process and (b) break friction materials manufacturing process in the automotive industry.

Author Contributions: Conceptualization, V.F.-R. and A.L.-A.; methodology, V.F.-R., A.L.-A. and A.R.-R.; software, F.M.-B. and B.A.-T.; validation, A.R.-R., F.M.-B. and B.A.-T.; formal analysis, A.R.-R. and A.L.-A.; investigation, A.R.-R., F.M.-B. and B.A.-T.; resources, A.R.-R.; data curation, F.M.-B. and B.A.-T.; writing—original draft preparation, V.F.-R., A.L.-A. and A.R.-R.; writing—review and editing, A.L.-A. and A.R.-R.; visualization, F.M.-B.; supervision, V.F.-R.; project administration, A.R.-R. All authors have read and agreed to the published version of the manuscript.

Funding: GENERTWIN "Sistema Digital de Análisis de procesos industriales para GENERación de escenarios alternativos bajo consideraciones productivas y de eficiencia energética", IMDEEA/2022/16, has been co-financed by IVACE (Instituto Valenciano de Competitividad Empresarial) and ERDF funds (European Regional Development Fund).

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to confidentiality and trade secret of participating companies.

Conflicts of Interest: The authors declare no conflict of interest.

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