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Proposal and test of a configurable production system Digital Model to support Energy-based Asset Management

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Abstract: Amongst various industries, manufacturing is one of the most energy intensive. Given the increasing attention towards sustainability, huge effort has been put for increasing the energy efficiency of companies. The energy efficiency gain could be reached through different management practices, and Asset Management, which aims at governing the asset system throughout its lifecycle, has great potentialities in being a game changer for this matter. However, the complexity of energy issues requires both technical and managerial perspectives to be tackled, especially when analyzing the entire system rather than the single machine only, while looking for global optimization. Therefore, in this work, the energy modeling topic is primarily analyzed to develop a Digital Model that aims to be the virtual counterpart of physical production plants. The model has three functional blocks, which relate to monitoring, optimization, and prediction. The model is tested through a case study in the cosmetic sector. The Digital Model lays the foundation to develop a system-oriented Digital Twin to support Asset Management and move forward a sustainable and green production. Due to its configurability and design choices, the Digital Model also embeds the stochastic behavior related to maintenance issues; therefore, future works will allow rising the attention of the energy and maintenance aspects, jointly undertaken within the overarching control built on Asset Management principles.

Keywords: energy, manufacturing, digital model, asset management, simulation, optimization

1. INTRODUCTION

The manufacturing sector accounts for about 65% of the total energy used by industries in economically advanced countries ("Total Energy Monthly Data - U.S. Energy Information Administration (EIA)," 2021) and this amplifies the impacts of low efficiency of production activities. Findings in the scientific literature show that different hierarchical levels of companies (machine, multi machine, factory, multi factory, and supply chain levels) and the life stages of the assets (the machines) increase the complexity of energy issues. In fact, measures to exploit energy saving opportunities varies at the different levels and stages, and this toughens the current efficiency gap that has definitely extended to both technical and managerial fields (Trianni et al., 2019).

In this work, both these two perspectives are deployed. The technical perspective investigates modeling and data analysis techniques used in manufacturing in relation to the energy topic. The managerial one considers Asset Management (AM) as the body of knowledge due to its holistic capabilities and the strict connections with Energy Management (EM). In fact, the system orientation, which is a fundamental principle of Asset Management (Roda and Macchi, 2018), leads to investigate the local impacts of machines' failures and other performance decays at the system level from a maintenance point of view. At the same time, this reasoning about machines' impacts can be useful also in order to improve the overall plant efficiency, by creating synergies between AM and EM. Additionally, the projection of costs along the assets' lifecycle, by following the AM principle of life cycle orientation, makes tools such as the Total Cost of Ownership (TCO) eligible in evaluating energy costs. These overlaps between AM principles and EM allow fostering a joint action of the two managerial disciplines in an Energy-based Asset Management (EAM).

In the described framework, this work presents a production system Digital Model (DM) that aims to constitute the virtual counterpart of a physical production system and the first step toward the development of its Digital Twin.

The DM development is framed on the following three main *research questions*:

1. *What is the state of the art about energy modeling in manufacturing?*
1.1 What are the most analyzed hierarchical levels in the extant scientific literature?
2. *How to develop a system-oriented model to foster Energy-based Asset Management?*

Research questions 1 and *1.1* are both discussed in Section 2, through a systematic literature review. *Research question 2* refers to the developed production system Digital Model, presented in Sections 3. The Digital Model application in a case study is then reported in Section 4, while Section 5 resumes conclusions and future developments of the current work.

2. REVIEW OF ENERGY MODELING

The research about *energy modeling* is based on a systematic literature review (SLR). It consists in defining Research Protocol, Eligibility criteria, and screening steps, as shown in

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Table 1 and Figure 1. The main scope of the research is to investigate the state of the art of energy modeling in manufacturing, as declared in *research question* 1.

Table 1. Fixed and variable keywords

Fixed keywords	**Variable keywords**
Energy **and** *Manufacturing* **and**	**About modeling techniques:** *Digital Twin* *Simulation* *Programming* *Markov* *Queueing* *Finite Element Method*
	About data Analysis techniques: *Statistical Process Control* *Machine Learning* *Artificial Intelligence*

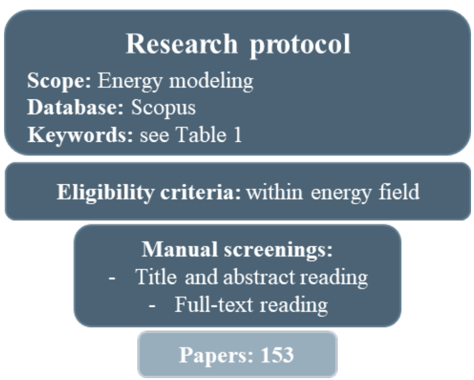

Figure 1. Literature review process

With reference to this question, the application of the systematic literature review has led to find two main energy modeling approaches:

- *Asset states*: this first approach analyzes energy consumption associated with the state of the machines under analysis;
- *Processes or tasks*: this second approach analyzes energy consumption based on manufacturing processes performed by machines to fulfill production requirements.

The review has also highlighted as, in the framework of Industry 4.0, the concept of *Digital Twin* (DT) refers to a promising model type that aims to represent the virtual counterpart of physical production systems, in which data from the real plant are received, analyzed, and sent back to solve issues as energy-related ones. In a DT, multiple modeling and data analysis techniques are deployed to solve issues of manufacturing plants.

The SLR provides an answer also to *research question 1.1*. In a bottom-up order, it is possible to consider the machine, multi machine and factory levels as the first levels of company's structure. The review points out that analysis about single machines is the most common case, while the research is going toward higher hierarchical levels of the company to include multiple machines or the entire factory especially when the *asset states* approach is adopted (Figure 2).

Therefore, the concept of DT together with the different energy modeling approaches and analyses towards high hierarchical levels open the way to future research and developments. It is the case of the DM presented in the next section, which aims to intercept this trend and lay the foundation for the development of a DT.

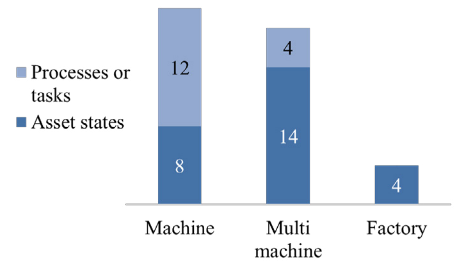

Figure 2. Papers for each main modeling approaches in literature

Overall, the following literature gaps have been considered to develop the model presented in this work:

- the first gap follows *research question 1.1* and is related to the need of creating a model able to represent entire production systems, up to the building of a factory, and energy fluxes passing through it;
- the second gap is related to the partial lack of integration between modules in companies through a holistic way of doing, such as between production schedule and assets control system (Feng et al., 2020);
- the third gap concerns the poor number of papers found in the literature that analyzes energy issues by pursuing the system orientation principle; it is aligned with the first gap and confirms the interest for the second research question.

From the SLR results and gaps, the production system Digital Model is framed. Used methods and achieved results from its development are discussed in the next section.

3. PRODUCTION SYSTEM DIGITAL MODEL

In this work, a production system Digital Model is proposed. It is related to the concept of Digital Twin, which has a scalable structure composed of two sublevels. They correspond to the intermediate stage of its development and, in top-down order, are (Cimino et al., 2019):

i) *Digital Shadow*: in this model the interaction is only from the physical system to the virtual counterpart;
ii) *Digital Model*: in this model there are no actual interactions from/to the real system.

The developed DM is based on the energy modeling approach of *asset states*. This choice is due to the theoretical background built with the SLR, which indicates this modeling approach as promising to model high hierarchical levels, in compliance with the need of pursuing the system orientation principle. In the model, *Energy asset states* (EAS) are defined by associating to each *asset state* its *consumption level* (see also Subsection 3.1). In this way, based on the machine activity a state is accessed and the model accounts for energy consumption during it.

In terms of its expected use, the DM structure is constituted by three main functional blocks reported in Figure 3.

Figure 3. Digital Model functional blocks

The first functional block regards the monitoring capability of the DM and its support to define a strategy for improvements. To this end, given the current configuration of the production system (As-Is), the DM simulates production activities. This is possible thanks to its configurability enabled by its capability of synchronizing data about:

- Machine features (see the case study in section 4);
- Production activities:
  - production times;
  - setup times;
  - preventive maintenance times;
  - corrective maintenance times.

The energy use is then monitored and calculated based on accessed EAS that specify consumption levels. In this way, the DM calculates technical performances (see also Section 4), both of a single asset and the entire production system and plots strategic matrices. The matrices aim to support the prioritization of the strategic improvement for enhancing the plant efficiency. Indeed, the first strategic matrix considers on the horizontal axis the total sum of *Energy Saving Windows* (ESWs) of each machine. It is plotted against the electric power consumed by them. Figure 4 reports this matrix on the top and allows to understand how high priorities can be assigned to machines with a high total length of ESWs (that means a potentially high amount of energy saved) and power consumption at the same time. The second strategic matrix has on the horizontal axis the total number of ESWs, which indicates their fragmentation. Therefore, from this second matrix, shown at the bottom of Figure 4, the user can assign high priority for improvement to those machines with a low fragmentation (that means easier exploitability of ESWs) and high power consumption at the same time.

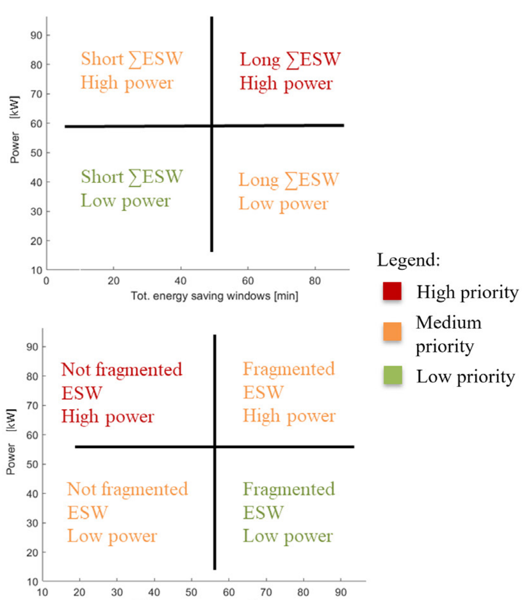

Figure 4. Strategic matrices

The second functional block is about cost analysis and optimization, performed by using Mixed-Integer Linear Programming (MILP) as a technique. The MILP (see details in subsection 3.2) allows evaluating the economic convenience of each identified ESWs for reducing consumption during these periods of time. In fact, the economic value of energy is added into the model and this also allows to compute economic performances (see also Section 4), based on technical ones already available from the previous block.

These last can be computed both from the perspective of single assets and the entire production system, given the comprehensive nature of the model which points to analyze high hierarchical levels.

In the third functional block, the DM offers the opportunity to simulate the future behavior of machines characterized by higher efficiency, that is the configuration of the system To-Be. This is possible thanks to the generation of a policy to switch off machines during ESWs based on optimization's results. In this way, new performances are computed, strategic matrices can be re-plotted to check the change of priorities in them. In addition, the differential version of the Total Cost of Ownership (Roda et al., 2020) can be calculated. As already said, it is an AM tool considered eligible in creating synergies with EM. This is because the TCO can highlight improvements along the entire lifecycle of assets enhancing the awareness about costs generated by consumptions. Furthermore, the differential form consists in making the difference between the To-Be (third functional block) and the As-Is systems (first functional block), therefore, it is effective to guide decisions related to improvements.

3.1 Energy assets states in the Digital Model

In the DM, the concept of asset state is related to AM and maintenance particular, as described in the standard CEN EN 13306. Inside of it, a state represents a period of time during which the machine is analyzed in terms of service delivered. Therefore, during each state, the machine functionality leads to the use of different types of energy, whose amount is indicated by the consumption level. Table 2 reports examples of EAS defined in the DM.

Table 2. Energy asset states

Energy Asset states (EAS)	
Asset state	Consumption level
Operation	On
Standby	On
Standby	Off
Idle	On
Idle	Off
Setup	
Preventive maintenance	
Corrective maintenance	

As one can notice by looking at Table 2, EAS such as *standby* and *idle* are present twice to associate them with both consumption levels *On* and *Off*. This allows achieving higher accuracy when approximating machines' consumptions. Therefore, just by considering their definition, it is possible to notice that EAS such as *standby-on* and *idle-on* constitutes unjustified costs because even if the asset is not producing it

consumes energy. The correspondent periods of time to these specific states are the already cited ESWs. For periods of time characterized by setups or maintenance interventions, specific EAS are defined and called *setup* or *corrective/preventive maintenance* respectively.
Overall, by using the modeling approach of asset state represented machines are split into two main parts:

i) *asset structure*: products pass through it during simulations;
ii) *asset identity*: where EAS are accessed based on the machine's operation and consumptions are monitored.

3.2 Mixed-Integer Linear Programming

The second functional block of the DM allows optimizing machines with high priorities signaled in strategic matrices. Specifically, the DM evaluates the economic convenience of each ESW, when reducing consumption of assets during activities is technically feasible. To this end, the MILP can assess whether the final balance of this maneuver is in favor of savings or not because it possibly generates additional setups or scraps. The evaluation is performed through a minimization of the *objective function* (total cost function), which in the case of energy, setup, and quality costs appears as follows:

$$Total\ cost = \sum_{i=1}^{n} Energy\ cost_i + \sum_{i=1}^{n} Setup\ cost_i + \sum_{i=1}^{n} Quality\ cost_i \qquad (1)$$

Costs in (1) require to be modeled in compliance with EAS and the objective function. To this end, in the model *optimization vectors* are defined as follows:

$$M_i = [s_1 \dots s_j \dots s_m]' \qquad (2)$$

$$with\ j = 1, \dots, m\ where\ m\ is\ the\ number\ of\ ESWs$$

In the equation, the apostrophe indicates the transpose of the vector, while each *decision variable* s_j is constrained to be Boolean variable, i.e. 0 and 1, that are the two EAS *standby off* and *standby on* respectively. In this way, at the end of the optimization, each M_i vector contains the most convenient EAS to maintain during each ESWs of optimized machines.
Costs are defined analogously. For example, the energy cost dependent on time t is defined as follows:

$$Energy\ cost\ (t) = ESW_i' \times [\, I * (cost\ over\ time_{\ off}) + M_i * (\Delta cost\ over\ time_{on-off})\,] \qquad (3)$$

I is an identity vector, while ESW_i contains all the lengths l_j of ESWs during production activities as follows:

$$ESW_i = [\, l_1 \dots l_j \dots\ l_m]' \qquad (4)$$

Due to space limits, other *constraints* are not reported here. After the optimization, vectors M_i constitute the link with the third functional block about the predictive capability of the model, given they indicate the most convenient EAS for each ESW. So, in the third block, this information is embedded into a policy sent to optimized machines. In this way, it lets these assets pass from *standby-on/idle-on* to *standby-off/idle-off* during ESWs by saving energy, by simulating the behavior of the To-Be system.

4. MODEL TESTING

The model testing is conducted both through numerical tests and a case study. About the former, the DM has been tested numerically to simulate configurations of a job shop and production system with technical building services. These experiments are not shown here for the sake of brevity, however, they have confirmed the opportunity of configuring the model for various applications and open the way for future investigations. Regarding the latter, a case study is reported hereafter and it is about a company belonging to the cosmetic sector. The DM for the case study has been developed in *MATLAB* and *Simulink*. In particular, EAS are modeled in the Simulink's package *Stateflow* with conditions that determine transitions from one state to another based on production activities. The DM aims to represent 35 machines involved during the cosmetic bulk's production. Machine types and the routing throughout the plant are shown in Figure 5. The entire group of machines constitutes the *shop floor* of the company. This level of analysis can be considered an intermediate one between the multi machine and factory levels, according to the objective declared of modeling high hierarchical levels.
The DM testing aims to show how it supports the company to foster EAM through the application of its three functional blocks. Specifically, a company's interest is to verify whether fusing machines, involved in bulk production, can constitute a strategic improvement if their efficiency is enhanced.

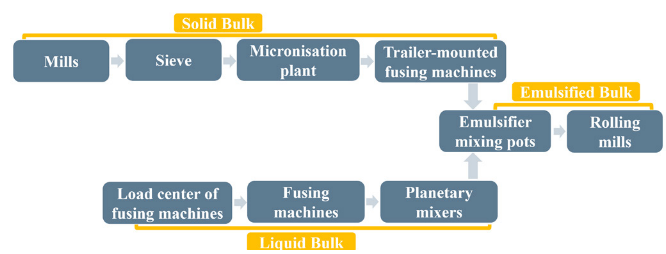

Figure 5. Bulk production routing in the production system

The types of data about machines features imported in the model are the following:

- Flow rate [l/h]: bulk liters produced each hour by the machine;
- Power [kW]: electric power consumed by the machine;
- Average yearly working hours [h]: average operating time of the machine;
- Years of purchase and decommissioning: respectively, the years when the machine was bought and it will be uninstalled from the plant.

The model is configured to use the following production data from the schedule to simulate activities:

- Production time [min]: time needed by each machine type to process the bulk;
- Setup time [min]: the setup is considered needed only by fusing machines, which require a preheating of their chamber;
- Preventive maintenance: preventive interventions are considered at the end of each shift to clean machines, also given the cosmetic use of the final product that requires high hygiene;

- Corrective maintenance: the DM embeds the failure register of mills. Given the failure probability $f(t)$ and the simulation length (t_1-t_2), the model computes the number of failures (N_f) as follows:

$$N_f = \int_{t_1}^{t_2} f(t) * dt * N_{f\,tot} \tag{5}$$

The DM stochastically chooses production processes during which failures occur and lets affected machines pass to the EAS *corrective maintenance*.

The testing and results obtained from the DM in the case study are described below, following its three functional blocks.

The first functional block allows plotting strategic matrices. The first matrix confirms the interest of the company in fusing machines (M6) and their high priority for improvements (Figure 6). Additionally, this matrix suggests to the company that milling machines (M1) and emulsifier mixing pots (M8) hide huge energy savings and, consequently, high priorities too. The second strategy matrix is not reported in this paper, anyway, it indicates that the level of fragmentation of ESWs is low for all the machines (at most equal to five ESWs). So, efforts for achieving savings are not burdensome, therefore, high priorities for efficiency improvements of machines group M1, M6, and M8 are confirmed.

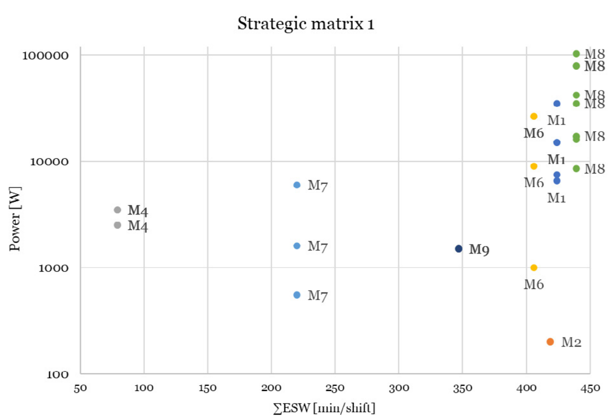

Figure 6. First strategic matrix system As-Is

In addition, the model computes technical performances thanks to the monitoring of energy consumption during production activities of the system As-Is. Given the capability of the model to represent the entire shop floor, in Table 3 performances of both single groups of machines (in particular fusing machines) and the entire system are reported.

In the second functional block, the economic value of consumption is added, and this allows to compute economic performances of fusing machines (Table 3).

In this block, the introduction of two parameterizations allows to overcome the lack of data due to the actual study of fusing machine (i.e. the thermal behavior of this group of machines is currently ongoing by the company):

1. ESWs exploited: three scenarios are considered, where are exploited respectively only the longest ESWs, longest and medium ESWs or all the ESWs;
2. Power during ESWs: it is assumed that during *standby-on* and *idle-on*, which are ESWs, a machine consumes 100%, 80%, 60%, 40%, or 20% of the power consumed during *operation-on*.

For example, by considering the first two cases of each parameterization, in the first scenario the longest ESW is exploited with a power of 100%. Therefore, each machine under optimization will pass into *standby-off* or *idle-off*, instead of *standby-on* or *idle-on*, during the longest ESW as prefigured by the first parameterization. In addition, by switching off the machine, the energy saved is equal to the entire machine's power, given that the second parameterization considers the 100% of power during operations.

The third functional block considers the fifteen scenarios which come from the combination of the two parameterizations, with as many generated policies for fusing machines. In this way, the predictive capability of the model is enabled given it can reproduce the behavior of the system To-Be. In terms of results, it allows computing new technical and economic performances (Table 3), which consequently leads to new priorities for improvements. As an example of new priorities, it is possible to notice in Figure 7 the different positions of fusing machines in the first strategic matrix according to scenarios of the second parameterization. The more ESWs are exploited the lower is the priority for improvements of these machines (points moves to the left), with consequent higher savings for the company.

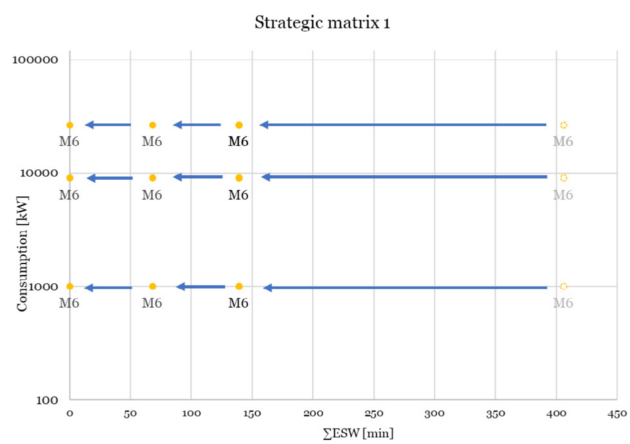

Figure 7. Parameterization effect on the first strategic matrix

The differential TCO is computed (Table 4) to quantify possible savings in relation to both the parameterization as follows:

$$\Delta TCO = TCO_{To-Be} - TCO_{As-Is} \tag{6}$$

Given that the first term is lower compared to the second, the ΔTCO represents possible savings. Before computing it, for each year between purchasing and dismissal years, differential energy savings $\Delta e_{j,k}$ are calculated as follows:

$$\Delta e_{j,k} = e_{j,k\,To-Be} - e_{j,k\,As-Is} \tag{7}$$

for all $j = 1, \dots, n$ *where n is the number of fusing machines*
for all $k = 1, \dots, N$ *where N is the number of years*

Therefore, the following formulation is used to compute the differential TCO of fusing machines and it accounts for the time value of money thanks to the actualization rate *i*:

$$\Delta TCO_{fusing\ machines} = \sum_{k=1}^{N} \frac{\sum_{j=1}^{n} \Delta e_{j,k}}{(1+i)^k} \tag{8}$$

Looking at savings in Table 4, it is possible to notice that they are relevant in particular when all the ESWs are exploited to save energy. This result is also confirmed by comparing performances of Table 3 especially those about the cost per litre produced of fusing machine in the As-Is and To-Be cases.

Table 3. Technical and economic performances

Hp: 80% power during ESWs and all of them exploited	**Performance indicator**	**Unit of measure**	**Value**
Fusing machines (M6)	Consumption during ESWs (As-Is)	kWh	341.04
	Consumption during ESWs (To-Be)	kWh	57.12
	Power per liter produced (As-Is)	kWh/l	0.83
	Power per liter produced (To-Be)	kWh/l	0.24
	Cost per liters produced (As-Is)	c€/l	0.31
	Cost per liters produced (To-Be)	c€/l	0.18
Production system	Power per liter produced (As-Is)	kWh/l	3.68
	Consumption during ESWs (As-Is)	kWh	3177.41
	Cost per liter produced (As-Is)	c€/l	1.37

Table 4. Differential TCO of fusing machines

Energy saving in TCO of fusing machines (To-Be – As-Is) [€]					
	100% power	80% power	60% power	40% power	20% power
All ESW	8754.43	7003.54	5252.66	3501.77	1750.89
Longest and medium	7935.05	6348.04	4761	3174.02	1587.01
Longest only	2177.83	1742.26	1306.7	871.13	435.56

5. CONCLUSIONS

The topic of this scientific research has been energy modeling in manufacturing. The need for investigating comes from actual requirements of improving the sustainability of production systems.

The systematic literature review is reported with the two found modeling approaches for energy – *asset states* and *processes or tasks* –, thus providing an answer to *research question 1*. In addition, the evidence found in literature about the increasing interest for high hierarchical levels (multi machine and factory levels) provides an answer also to *research question 1.1*.

Then, the production system Digital Model is presented, by showing its development through the modeling approach of *asset states*. The model contributes to *research question 2* fulfilling gaps found in the literature.

The model application in a case study about the shop floor of a company in the cosmetic sector has been also presented, thus showcasing the capability to model high hierarchical levels of the company from an energy point of view. In fact, the Digital Model configurability has allowed its use to analyze the entire shop floor, as demonstrated by the case study. Additionally, the model offered the opportunity to compute performances of those machines of interest or about the entire system, with high flexibility in passing from one perspective to another, and helping the company define its strategy for improvements, thanks to strategic matrices.

Regarding the integration between modules such as production schedule and assets control systems, which is a practical issue to be solved when implementing the model in a given context, it is worth remarking that the Digital Model generates a policy that indicates the most convenient EAS during ESWs of the optimized machines. It constitutes an effective support in order to connect machines' scheduled activities to the capability of controlling them during production.

Overall, the paper pursues the system orientation principle when addressing energy issues. The nature of the model, set to represent high hierarchical levels, allows obtaining a wide perspective of the system under analysis, which is fundamental to evaluate the impacts of local decisions at a system level. The Digital Model also pursues the system orientation joined with the life cycle orientation principle, through a computation of the TCO, to effectively highlights possible systemic impacts of energy costs or savings, and their projection over the entire lifecycle of assets.

The Digital Model structure opens the way also for further developments. The first is the model's evolution in a Digital Shadow, by improving the synchronization with information systems of companies. The second evolution is in a Digital Twin, which can be achieved by also improving the model capability of actuating machines' control system. The third deals with the integration of maintenance aspects: the aim is to embed the stochastic effect of failures and the impacts of different maintenance policies, joined with energy issues, on the overall performance of the production systems and costs along the lifecycle.

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