Energy analysis and management in flowshop into Industry 4.0 context

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Abstract: With global warming, external pressure to apply sustainable practices and rising energy prices are increasingly important factors in today's society. Moreover, the cost of energy has become increasingly significant, and must to be considered in business competitiveness. This work investigates energy efficiency within the context of manufacturing systems. The methodology includes the development of a simulation model using digital manufacturing software, one of the pillars of Industry 4.0. The scenarios evaluated involve an automotive engine flowshop, where different simulation strategies were implemented that aim to reduce the overall electricity consumption. The results show that control actions using digital manufacturing systems enable the more efficient use of available resources by identifying opportunities to increase energy efficiency indicators, even in well-designed production systems. This work is aligned with the concept of Industry 4.0, where the sustainability of the process is mandatory.

Keywords: energy efficient manufacturing; simulation; Industry 4.0; energy management; digital manufacturing; sustainability.

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1 Introduction

Global climate change, pressure to apply sustainable practices, energy generation costs, and the transmission and distribution of electrical energy from the perspective of growth are factors that are increasingly discussed (Bunse et al., 2011).

Since electrical energy is a primary component of the production of goods for society, the costs involved and environmental impacts associated with its consumption are also becoming progressively more influential in manufacturing operations (Abele et al., 2015a).

In view of these challenging, competitive and regulated conditions, several studies have confirmed the significant potential for improving energy efficiency indicators in the manufacturing industry, with the possibility of a 30% increase solely through applying current technologies (Herrmann et al., 2011). However, correlation of the use of technology with the operations carried out within manufacturing systems represents a challenge, due to the complexity of the production systems and the huge number of data sources (Vijayaraghavan and Dornfeld, 2010). In this case, statistical calculations, artificial neural networks, fuzzy logic, and system simulations are four alternative approaches that may be applied to analyse the consumption of industrial installations, and simulation has proved to be an important approach for this type of application (Herrmann et al., 2011).

The use of computational simulation systems has proved to be a potential tool for analysing and supporting decision making in terms of the global energy efficiency of industrial installations. This is because such decisions have an impact on the energy consumption of a production system, and are part of the overall operation of an industrial facility.

In this context, the proposed study involves the generation of various simulation scenarios for a production line of automotive engine blocks, including variables associated with energy efficiency within the context of the analysis of manufacturing systems. The proposed analysis recommends reducing the global energy consumption of the line, based on the current relationship between this variable and the productivity, manufacturing processes, and production programming of the industrial plant. Even though the modelling and simulation of manufacturing systems have been used for a long time, they became one of the pillars of Industry 4.0. Moreover, the digital manufacturing tool which the simulation software is inserted in allows melting the real and virtual systems in a cyber-physical system (CPS). It is well known that the concept of industry 4.0 came from the discussion of the benefits of using CPS in production.

This work contributes to the fields of energy analysis and management in manufacturing systems through the use of digital manufacturing tools to perform simulations. These digital manufacturing tools consist of a software package that allows the construction of the 'digital twin of a given process. In this package, energy analysis tools are already integrated with traditional simulation resources, thus making the analysis more complete.

This study is structured as follows: Section 2 presents a theoretical review; in Section 3, the methodology used is discussed; Section 4 describes the manufacturing system; Section 5 presents the simulation results; and finally, Section 6 presents the conclusions.

2 Theoretical review

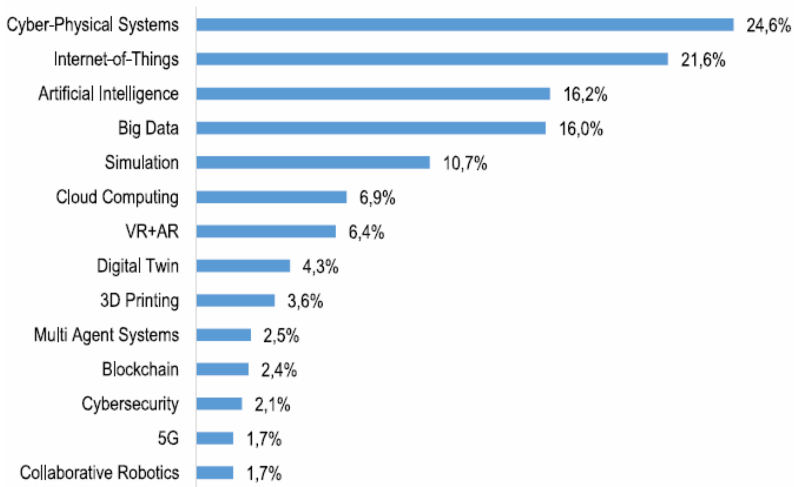
2.1 Industry 4.0 and energy management in manufacturing

First used at the Hanover Fair in 2011, the term 'Industry 4.0' refers to the fourth industrial revolution, and is often understood to be the application of the generic concept of cyber-physical systems (CPSs) to industrial production systems (cyber-physical production systems) (Drath and Horch, 2014). The use of CPSs can provide, for example, a combined approach between the process and the product in automated production systems, as proposed in Vogel-Heuser et al. (2017). Among the concepts arising from this new production model is the search for more sustainable manufacturing. As stated by Acatech (the National Academy of Science and Engineering, Germany) in Kagermann et al. (2013): "Today, energy efficiency is already an important requirement for machinery, and a key enabler for meeting this requirement is the ability to systematically power down inactive parts of a line during breaks in production".

Leitão et al. (2020) presented an extensive literature review, from 2013 to 2020, to discuss the actual status of Industry 4.0 as well as its trends. From the proposed methodology, 13.636 articles were analysed. Figure 1 presents the enabling technologies of Industry 4.0 focusing on its appearances in the literature. It is worth to mention that simulation is the fifth technologies in occurrence.

The manufacturing industry plays an indispensable role in the global economy, and is responsible not only for transforming materials and information on goods to meet the needs of human beings and other industries around the world, but also provides a significant source of employment and represents great economic power. Likewise Salonitis and Ball (2013), the manufacturing sector also represents 37% of the world's total primary energy consumption (IEA, 2009), meaning that the costs and environmental impacts involved are increasingly influential factors in the operation of these organisations.

Figure 1 Percentage of occurrences of enabling technologies (see online version for colours)



Source: Leitão et al. (2020)

Since manufacturing companies need energy as a primary resource in order to produce goods for society, limiting production is not a viable option. In this context, and faced with conditions that are increasingly challenging, competitive and regulated, Herrmann et al. (2011) argue that improvements to energy efficiency have become an extremely promising option for manufacturing companies. In addition, according to Zhou et al. (2016), improving energy efficiency in manufacturing activities is an inevitable trend for energy conservation, reduction of emissions and adherence to sustainability practices.

In view of the above discussion, the field of energy efficiency has faced increases in terms of its scope that go beyond traditional energy-intensive industries such as steel, cement, chemical and pulp and paper. In Palm and Thollander (2010), as noted in Duflou et al. (2012), it was found that the attention of academic and industrial researchers into energy efficiency was drawn to those sectors focusing on discrete manufacturing during the 2000s, driven by tangible improvements in economic and environmental terms

Despite the great efforts already undertaken, such as the isolated replacement of electrical drives and integral improvements in production processes, significant potential still lies in the implementation of energy efficiency measures that are economically feasible for the manufacturing industry (Abele et al., 2015b). As presented in Abele et al. (2015a), new approaches must be developed that enable the implementation of energy efficiency solutions in dynamic manufacturing systems, which involve demanding conditions and changing requirements.

In this regard, the modelling of energy consumption can provide a better understanding of where and how power is being used, thus allowing the identification of potential areas of improvement (Thiede et al., 2013). However, a thorough analysis of a production system should consider the dynamics of all the variables involved, adding to this technical assessment and economic aspects such as the output of products, availability and costs involved.

Based on the increasing importance of energy in manufacturing systems, the work in Muller et al. (2014) presents the integration of energy consumption within the value-stream mapping of a process. This is an efficient way to understand how much of the energy used in a process actually adds value.

In Liu (2016), the authors studied new variants of the discrete lot-sizing and scheduling problem. Their strategy considers new solutions to the scheduling problem as well as the combined use of renewable energy to reduce CO_2 emissions.

An assessment of energy efficiency in manufacturing was carried out in Aguirre et al. (2011). The authors proposed the creation of energy-production signatures (EPSs) that are used to compare the energy efficiency for similar manufacturing industries. The authors mention that developing the ideal EPS is a difficult task, due among other factors to a lack of knowledge of the most advanced technologies. Since digital manufacturing is an emerging technology that allows for energy efficiency management, our work makes an important contribution towards filling this gap.

In Shui et al. (2015), a study of manufacturing productivity and energy efficiency is performed in which the authors evaluate several energy sources in addition to electricity, using stochastic models. They emphasise that because of the lack of systematic data collection and limited use of analytics in the manufacturing industry, comprehensive studies of energy efficiency have rarely been reported in the literature. Again, simulations using digital manufacturing tools that focus on energy analysis can provide another approach to energy efficiency in manufacturing, and can contribute to filling the literature gap in this subject.

The works of Wang et al. (2017), Ab. Rashid and Hadi Osman (2020) and Zhang et al. (2019) deal with production scheduling in flowshops considering energy consumption. Scheduling is important in flowshop systems where several different parts are produced.

A literature review considering the application of machine learning tools for energy efficiency in industry is conducted by Narciso and Martins (2020). The authors demonstrate that the number of published works in this field is rapidly growing. The majority of contributions address challenges in petrochemical industries, and namely in ethylene production. There is still a very limited number of published papers addressing the application of machine learning tools on energy related objectives in other types of industries.

2.2 Simulation applied to energy efficiency

Discrete event simulations are often used in the design phase to evaluate concepts and improve system solutions before investment decisions are made. The common goal is to identify problem areas and to quantify and improve the performance of the production systems, such as performance under average and peak loads, use of resources, workers and machines, personal needs, work shifts, bottlenecks and storage requirements of materials (Heilala et al., 2008).

In this context, the study in Thiede et al. (2013) shows that the use of simulations of manufacturing systems offers a promising way to address new issues related to the environment such as energy consumption, when considered alongside other traditional dimensions of analysis such as cost, time and quality. The authors also state that the use of theoretical models to establish an energy baseline is useful in identifying opportunities for power optimisation.

Initial studies using these tools for energy efficiency analysis in industrial plants were conducted in Solding and Thollander (2006) and Solding and Petku (2006); these presented simulation models for the analysis and reduction of energy consumption, with a focus on smelters and their specific characteristics.

In addition to these initiatives, Ghani et al. (2012) propose a simulation model that aims to reduce the energy consumption of a machine in the automotive industry during the design phases. A simulation proposed by the authors allowed the identification of components with high power consumption while the machine is in an idle state, enabling a change to be made to the design of the machine automation system which resulted in a reduction in total energy consumption of 3.2%.

The study conducted in Kohl et al. (2014) presents a simulation model for a production line that matches the flow of materials and energy variables, resulting in the prediction of both individual energy consumption per product variant produced and their costs.

In addition, in terms of reducing energy consumption, recent academic studies have also focused on the use of simulation tools to explore reductions in the demand for electricity in manufacturing systems at peak times.

In Fernandez et al. (2013), Sun et al. (2014) and Bego et al. (2014), buffer application models are presented that aim to reduce the demand for electricity during peak hours in multi-machine systems, from the insertion of intermediate stocks between machines and changes in production planning for off-peak periods.

As described in May et al. (2015), simulation tools can also be used within the broad yet largely unexplored field of study of the energy behaviour of productive resources for different scenarios, allowing energy consumption forecasts to be obtained and providing relevant information on process decision making, such as choosing the best supply contracts and changes to the operation of a plant. These scenarios may involve results achieved through the application of different instruments, such as the relationship between energy states and the states of manufacture of machinery, inventory management and buffers and production planning (May et al., 2015).

These authors also report that when properly supported by performance indicators, simulation environments allow not only the evaluation of different scenarios, but also monitoring of the effectiveness of improvements made over time.

The work of Singh et al. (2018) analyses four individual units in a flowshop system (two milling machines, a drilling machine and a machining machine). A bee colony-based algorithm minimises the individual energy of each machine, making the process more sustainable.

An energy optimisation of robotic cells is presented by Bukata et al. (2017). The study focused on the energy optimisation of industrial robotic cells, which is essential for sustainable production in the long term. The outcomes, based on simulations and measurements, indicate that, compared with the previous state, the energy consumption can be reduced by about 20 %.

Finally, the importance of considering the energy aspects in the simulation of modern manufacturing systems is presented in Wenzel et al. (2018).

3 Methodology

This work involves the simulation of production systems in order to obtain an accurate match to the system behaviour and to enable analysis of the results. The following activities were carried out:

1 acquisition of data related to the energy performance of equipment and subsystems

2 development and validation of models to obtain indicators

3 representation and analysis of results.

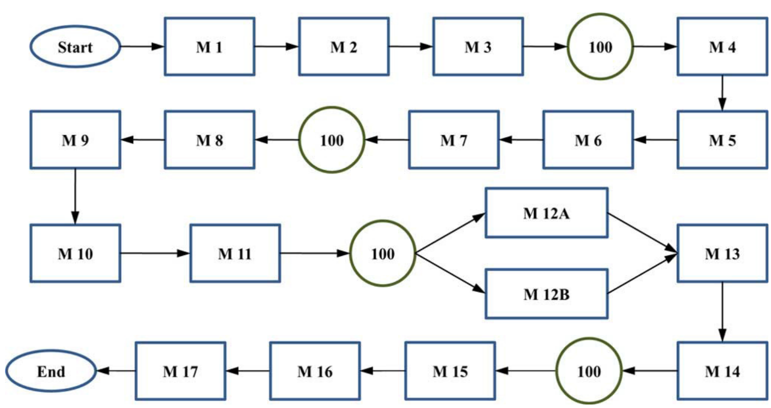
'Siemens Plant Simulation®' software was used as a tool to analyse production systems and their energy indicators in this work. Simulations offer several advantages, such as relatively low time requirements for building the model and ease of use, supported by menus and user-friendly graphics.

The choice of this digital manufacturing tool is due to the focus in this research on energy efficiency and which considers the relationship of this variable with productivity, manufacturing processes, production scheduling and interaction between the environments present in an industrial plant.

4 System description

Through the application of a simulation technique, this work presents a method for the integration of the manufacturing states and the power management of multi-machine production lines.

Figure 2 Engine production line (see online version for colours)



Source: Chang et al. (2013)

A production line responsible for the manufacture of engine blocks in an automobile industry was selected as the basis for this study (Chang et al., 2013). This line consists of eighteen automated workstations and four buffers, each with a storage capacity of 100 pieces. A simplified representation of this line and the respective flows are shown in Figure 2.

The production parameters for this engine line were extracted from the study presented in Chang et al. (2013) and are shown in Table 1, where MTTR is the mean time to repair.

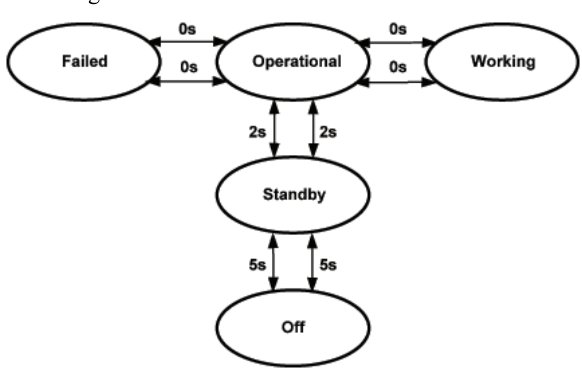
Table 1 Production parameters

Station	*Cycle time (s)*	*Availability (%)*	*MTTR (min)*
M1	29.35	94.49	21.82
M2	24.43	96.24	34.07
M3	29.27	96.15	68.37
M4	28.94	95.53	46.65
M5	28.11	96.26	34.25
M6	28.99	95.93	41.8
M7	28.61	96.15	39.62
M8	28.4	95.81	34.48
M9	29.98	95.05	34.35
M10	28.37	97.90	58.12
M11	26.78	96.07	16.28
M12A	57.8	94.73	18.28
M12B	58.5	94.05	15.85
M13	30	95.88	27.42
M14	27.25	95.95	20.12
M15	30.81	94.81	12.62
M16	27.85	96.88	95.13
M17	28.98	96.61	59.17
M18	28	97.60	17.2

Source: Adapted from Chang et al. (2013)

The choice of a production line with approximately synchronised operation is justified by the importance of seeking opportunities to improve energy efficiency, even in production systems that were well designed from the outset.

Figure 3 Energy state diagram



In order to correctly establish the relationship between the manufacturing states and the line power management, the possible energy states of the equipment were identified.

Figure 3 shows a diagram of the power states of the machines associated with the respective transitions.

Each power state has an associated nominal power, which is used to obtain projections of consumption and demand for electric power in the proposed simulation scenarios. A description of the energy states used for the production line analysis is presented in Table 2.

Table 2 Energy states

Energy state	*Description*
Off	Equipment is off: no energy consumption
Standby	Equipment presents the most components off and is not ready to process parts. Only a few active components are maintained on and consume energy in order to reduce the time of reactivation of equipment.
Failed	Equipment is in maintenance, with some actions that require energy.
Operational	Equipment is not processing parts, but remains energised all the necessary components to resume production immediately upon request.
Working	Equipment is processing parts.

Source: Adapted from May et al. (2015)

Through these data and the information on the machine power reported by Fernandez et al. (2013), Sun et al. (2014) and Bego et al. (2014), attributions of the values for each power state of the equipment in the line were made, as shown in Table 3.

Table 3 Energy parameters for the equipment of the line

Station	*Working (kWh)*	*Operational (kWh)*	*Failed (kWh)*	*Standby (kWh)*
M1	14.0	8.4	3.5	1.4
M2	24.0	14.4	6.0	2.4
M3	14.0	8.4	3.5	1.4
M4	15.0	9.0	3.75	1.5
M5	25.0	15.0	6.25	2.5
M6	25.0	15.0	6.25	2.5
M7	13.0	7.8	3.25	1.3
M8	15.0	9.0	3.75	1.5
M9	12.0	7.2	3.0	1.2
M10	14.0	8.4	3.5	1.4
M11	21.0	12.6	5.25	2.1
M12A	24.0	14.4	6.0	2.4
M12B	24.0	14.4	6.0	2.4
M13	14.0	8.4	3.5	1.4
M14	20.0	12.0	5.0	2.0
M15	12.0	7.2	3.0	1.2
M16	14.0	8.4	3.5	1.4
M17	14.0	8.4	3.5	1.4
M18	15.0	9.0	3.75	1.5

For all equipment, the rated power for the 'off' state was taken as 0 kW. The production of a single engine block model was used for the simulation. The energy states of the machines were parameterised using the settings of the software and their respective power ratings. Additionally, the following assumptions were adopted in the preparation of the model:

1 Each station has a nominally constant speed, as determined by the respective cycle time. However, a station can operate outside of its nominal cycle if there are no parts to process or the next station is lock.

2 There is a mechanism which controls the continuous release of parts. Each piece is passed to the first machine for processing only if it is available.

3 After the completion of processing, the part is removed from the line and forwarded directly to another section of the plant.

4 There is no rework and no rejected parts. All parts that complete the processing are considered to be good.

5 Each piece of equipment can take the following power states: off, standby, failed, operational and working. The transition between two states is triggered by the occurrence of a control event, such as the arrival of a part or the absence of feedstock.

6 The production baseline for the system is 5,591 pieces, as calculated in equation (1) for a period of 48 hours.

$$\begin{aligned} Number\ of\ parts &= \frac{Total\ time - Heating\ time}{Biggest\ cycle\ time} \\ &= \frac{2{,}880 \text{ min} - 8.553 \text{ min}}{0.5135 \text{ min}} = 5{,}591 \end{aligned} \tag{1}$$

5 Modelling and simulation results

The operation of the manufacturing plant was set as three shifts of eight hours, seven days per week. In this study, the analysis and comparison of energy requirements were carried out over a period of 48 hours. This period included 8.553 minutes corresponding to line heating, as defined by the time required to fill the total system after initialisation of the empty line.

Set-up operations and their associated energy states are not considered in this study.

For a comparative analysis of the context of the different strategies proposed in this study, the following scenarios were proposed:

1 *Scenario 1* – A production line involving unplanned random stops and equipment that can take only the power states of 'operational' and 'processing'. This scenario aims to analyse the electrical energy indicators in a normal production situation in which the synchronism is affected due to the occurrence of unpredicted individual stoppage events of the machines. The use of only two energy states is due to the usual industry practice, proposed in Chang et al. (2013).

2 *Scenario 2* – Addition of a 'standby' state to scenario 1. This scenario aims to assess the potential for an increase in energy efficiency from the application of multiple operating states with automatic transition to a situation with random disturbances in operation. The automatic transition between energy states is implemented through strategic decisions according to the state of the previous machine and the occupation of the buffers. Therefore, the equipment is set to standby mode if the immediately preceding machine is not processing a part or is in a failure state, as shown in Figure 4.

3 *Scenario 3* – A line layout change involving the inclusion of individual buffers, each with the capacity to store only one part. This scenario proposes the inclusion of these buffers for each machine, focusing on the activation control of energy states based on monitoring of the occurrence of equipment failure. The desired efficiency in this scenario arises from allocating the respective parts of a machine to unitary buffers after processing it if the next machine is in failure, making it possible to put this equipment into standby mode, thus consuming less electricity. Figure 5 illustrates this line layout change, where BM1 and BM2 are the buffers for machines M1 and M2 respectively.

Additionally, this scenario also uses routines to balance the contents of the buffers implemented to reduce power consumption, as shown in Figure 5. The strategy is as follows: if a buffer is close to its maximum occupation (X parts), then the upstream machines are blocked and placed in standby mode until the buffer occupation reaches a minimum number of parts (Y), at which point the upstream machines are progressively released to process new parts.

Figure 4 Electrical energy control strategy (see online version for colours)

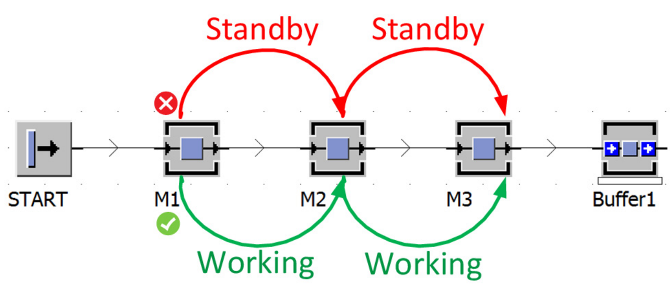


Figure 5 Buffers content balancing strategy (see online version for colours)

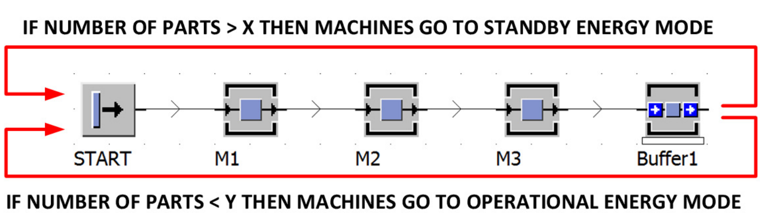
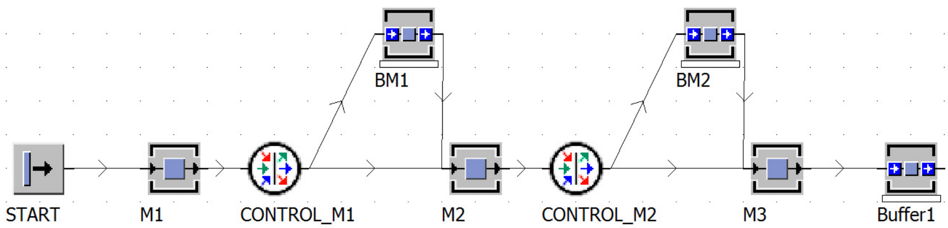
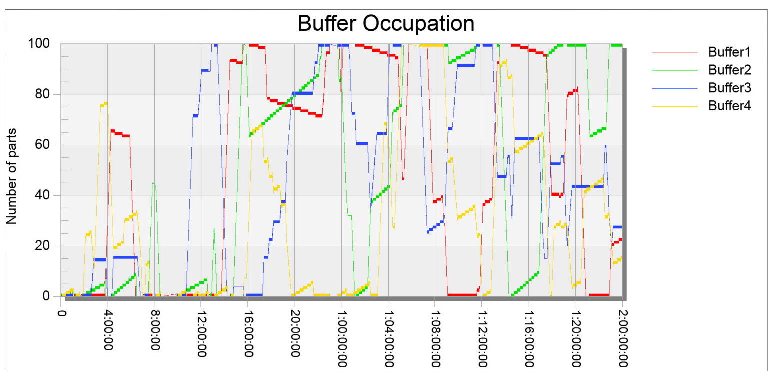


Figure 6 Proposed changed layout (see online version for colours)



Based on scenario 1, Figure 7 illustrates the occupation of the buffers over the simulation period. It can be observed that there is a huge variation in the contents of the buffers. This behaviour is related to both the temporary storage of parts and the release of these parts to the downstream machines in case of unplanned stops affecting the total stoppage of the line.

Figure 7 Buffers occupation (see online version for colours)



The results obtained from the study of an operating period of 48 hours encompass both manufacturing parameters and variables related to energy consumption. Table 4 summarises the main manufacturing data for the scenarios under consideration.

Over a period of 48 hours of production, scenarios 2 and 3 produced 4,147 finished pieces. This means that the implemented strategies resulted in the loss of six produced units in relation to scenario 1, representing a decrease of 0.144% in the total production. This loss is due primarily to the energy management strategies implemented, which place the equipment into standby mode in certain situations. This also impacts the amount produced by the equipment, as represented by the slight variations in individual production observed when compared to scenario 1.

In a second approach, the simulation also provides data for the energy behaviour of the line during the period considered. Tables 5 and 6 show the absolute values for individual consumption in the different states for each piece of equipment, the overall line consumption and a comparison of the scenarios. For better visualisation of the data in Tables 5 and 6, Figures 8, 9 and 10 present energy graphs for scenarios 1, 2 and 3. This represents a powerful analysis tool for the digital manufacturing environment.

Table 4 Production data

Station	*Quantity produced (un.)*			*Processing time (%)*		
	Scenario 3	*Scenario 2*	*Scenario 1*	*Scenario 3*	*Scenario 2*	*Scenario 1*
M1	4,318	4,316	4,336	73.35	73.32	73.65
M2	4,317	4,315	4,335	61.04	61.01	61.29
M3	4,316	4,314	4,334	73.12	73.08	73.42
M4	4,293	4,290	4,310	71.90	71.85	72.19
M5	4,292	4,289	4,309	69.83	69.78	70.10
M6	4,291	4,288	4,308	72.00	71.95	72.28
M7	4,290	4,287	4,307	71.04	70.99	71.32
M8	4,194	4,191	4,206	68.94	68.89	69.13
M9	4,193	4,190	4,205	72.75	72.70	72.96
M10	4,192	4,189	4,204	68.83	68.78	69.03
M11	4,191	4,188	4,203	64.96	64.91	65.15
M12A	2,118	2,116	2,117	70.86	70.80	70.83
M12B	2,050	2,053	2,057	69.43	69.50	69.64
M13	4,167	4,168	4,173	72.36	72.36	72.45
M14	4,167	4,167	4,172	65.71	65.71	65.79
M15	4,150	4,150	4,155	74.01	74.01	74.10
M16	4,149	4,149	4,154	66.88	66.88	66.97
M17	4,148	4,148	4,154	69.58	69.58	69.67
M18	4,147	4,147	4,153	67.21	67.21	67.29

Table 5 Energy data 1

Station	*Total consumption (kWh)*			*Consumption – working (kWh)*		
	Scenario 3	*Scenario 2*	*Scenario 1*	*Scenario 3*	*Scenario 2*	*Scenario 1*
M1	539.58	553.62	584.93	492.89	492.68	494.91
M2	824.30	878.33	967.79	703.17	702.87	706.03
M3	523.77	523.56	568.60	491.35	491.13	493.35
M4	554.46	560.32	630.74	517.71	517.35	519.77
M5	901.53	903.91	1,039.20	837.90	837.31	841.24
M6	918.10	915.86	1,065.41	863.95	863.34	867.38
M7	474.22	471.73	548.90	443.26	442.95	445.02
M8	559.27	559.53	622.01	496.33	495.98	497.76
M9	442.70	448.48	505.00	419.06	418.76	420.26
M10	503.14	510.07	588.75	462.54	462.20	463.87
M11	742.20	741.87	855.51	654.77	654.31	656.67
M12A	925.82	936.56	992.15	816.33	815.57	815.98
M12B	898.23	918.39	983.54	799.89	800.67	802.26
M13	514.97	527.62	581.36	486.26	486.27	486.87
M14	710.25	705.17	811.71	630.84	630.84	631.62
M15	450.91	472.26	505.99	426.27	426.28	426.81
M16	508.99	519.72	565.70	449.44	449.44	450.01
M17	505.75	512.44	590.46	467.58	467.57	468.15
M18	536.46	536.63	620.40	483.92	483.92	484.52
Total	*12,034.65*	*12,196.07*	*13,628.15*	*10,943.46*	*10,939.44*	*10,972.48*
Total (%)		*100.0*		*90.93*	*89.69*	*80.51*

Table 6 Energy data 2

Station	*Consumption – operational (kWh)*			*Consumption – standby (kWh)*		
	Scenario 3	*Scenario 2*	*Scenario 1*	*Scenario 3*	*Scenario 2*	*Scenario 1*
M1	26.18	43.26	78.42	8.91	6.08	0.00
M2	88.53	153.67	257.61	28.45	17.64	0.00
M3	0.83	0.79	52.44	8.78	8.83	0.00
M4	15.16	22.53	104.42	15.04	13.89	0.00
M5	24.11	27.49	185.60	27.16	26.75	0.00
M6	24.01	21.83	196.93	29.04	29.59	0.00
M7	13.74	11.00	101.37	14.71	15.27	0.00
M8	44.13	44.70	117.75	12.31	12.35	0.00
M9	5.18	12.33	78.53	12.25	11.18	0.00
M10	23.73	32.27	124.88	16.87	15.60	0.00
M11	56.62	56.48	190.30	22.27	22.54	0.00
M12A	78.34	91.74	158.01	12.99	11.09	0.00
M12B	61.39	84.41	160.87	16.54	12.90	0.00
M13	3.84	18.81	82.65	13.03	10.70	0.00
M14	47.40	40.99	167.99	19.91	21.24	0.00
M15	6.49	31.90	71.80	10.77	6.70	0.00
M16	36.01	48.63	103.19	11.04	9.15	0.00
M17	21.55	29.31	122.31	16.62	15.56	0.00
M18	32.67	32.56	132.44	16.43	16.71	0.00
Total	*609.91*	*804.70*	*2,487.51*	*313.12*	*283.77*	*0.00*
Total (%)	*5.07*	*6.60*	*18.25*	*2.60*	*2.33*	*0.00*

Figure 8 Energy in scenario 1 (see online version for colours)

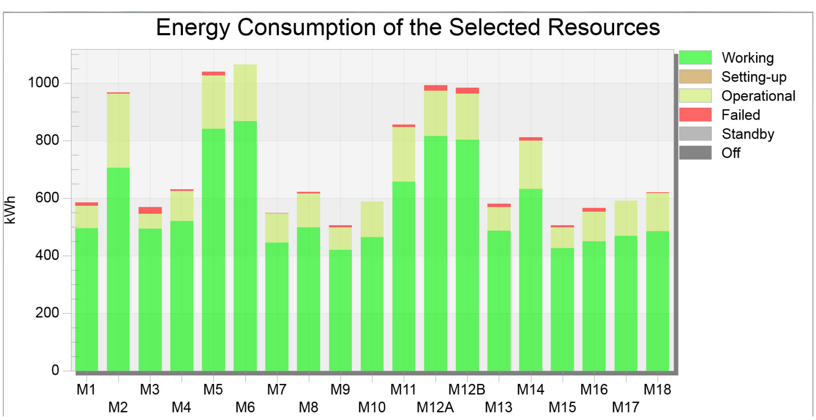


Figure 9 Energy in scenario 2 (see online version for colours)

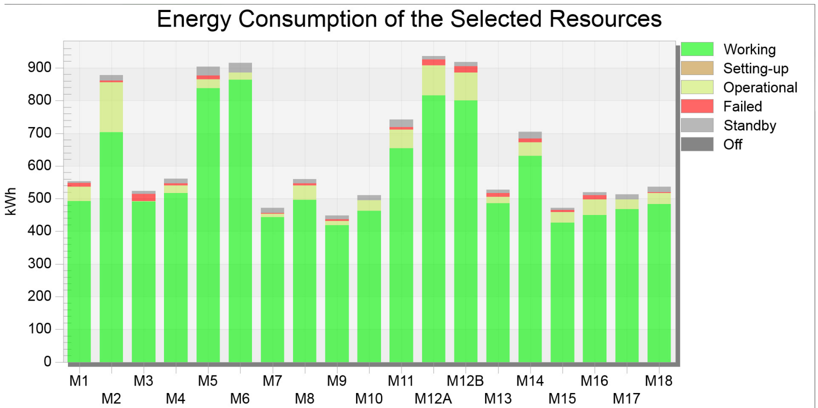
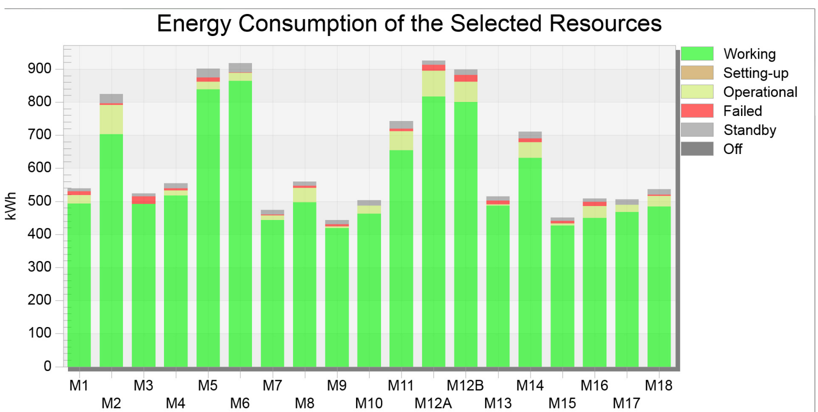


Figure 10 Energy in scenario 3 (see online version for colours)



By analysing the data obtained, it can be seen that the strategies used in scenarios 2 and 3 were able to reduce both the overall energy consumption of the line and individual consumption relating to operational and working conditions, when compared to scenario 1. The reduction in these rates is linked to the decrease in the number of processed parts, and particularly to the application of energy control strategies for the equipment in scenarios 2 and 3, thus enabling the use of the standby state in situations where machines remain operational with an increased consumption of electricity.

From the data available, it is also possible to analyse the energy efficiency of the different scenarios, as represented by indicators such as the amount of energy consumed per unit produced [equation (2)], as shown in Figure 11.

$$Energy\ consumption\ per\ part = \frac{Total\ consumption\ [kWh]}{Total\ produced\ parts} \tag{2}$$

In addition, the lean energy indicator [equation (3)] proposed in May et al. (2015) shows the ratio between the energy consumed in the production of saleable products and the overall power consumption of the equipment, i.e., how the overall consumption of energy is converted to activities that generate value. Figure 12 shows a comparison of this indicator for the three scenarios proposed here.

$$\begin{aligned}&Lean\ energy\ indicator\\&=\frac{Consumption\ that\ generates\ value\ (processing)}{Total\ consumption}\end{aligned} \tag{3}$$

Figure 11 Comparison of energy consumption per unit produced

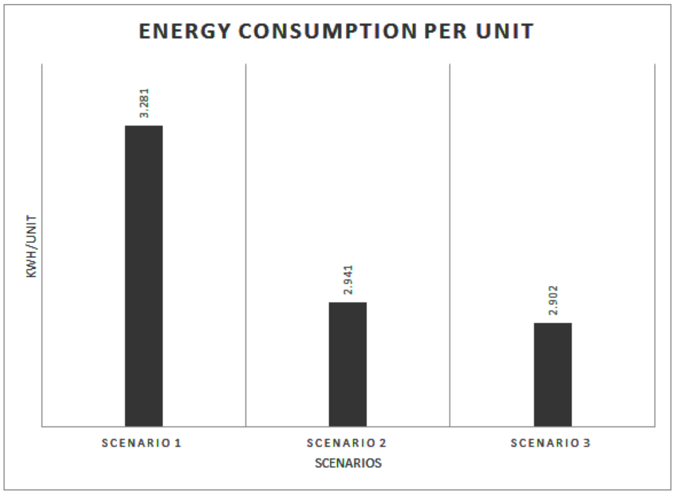
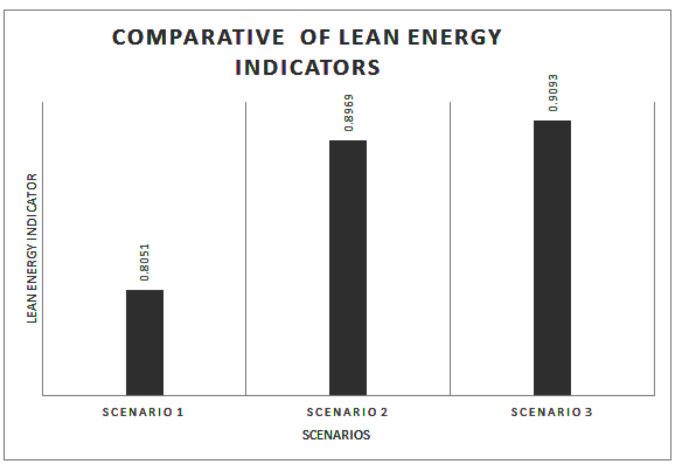


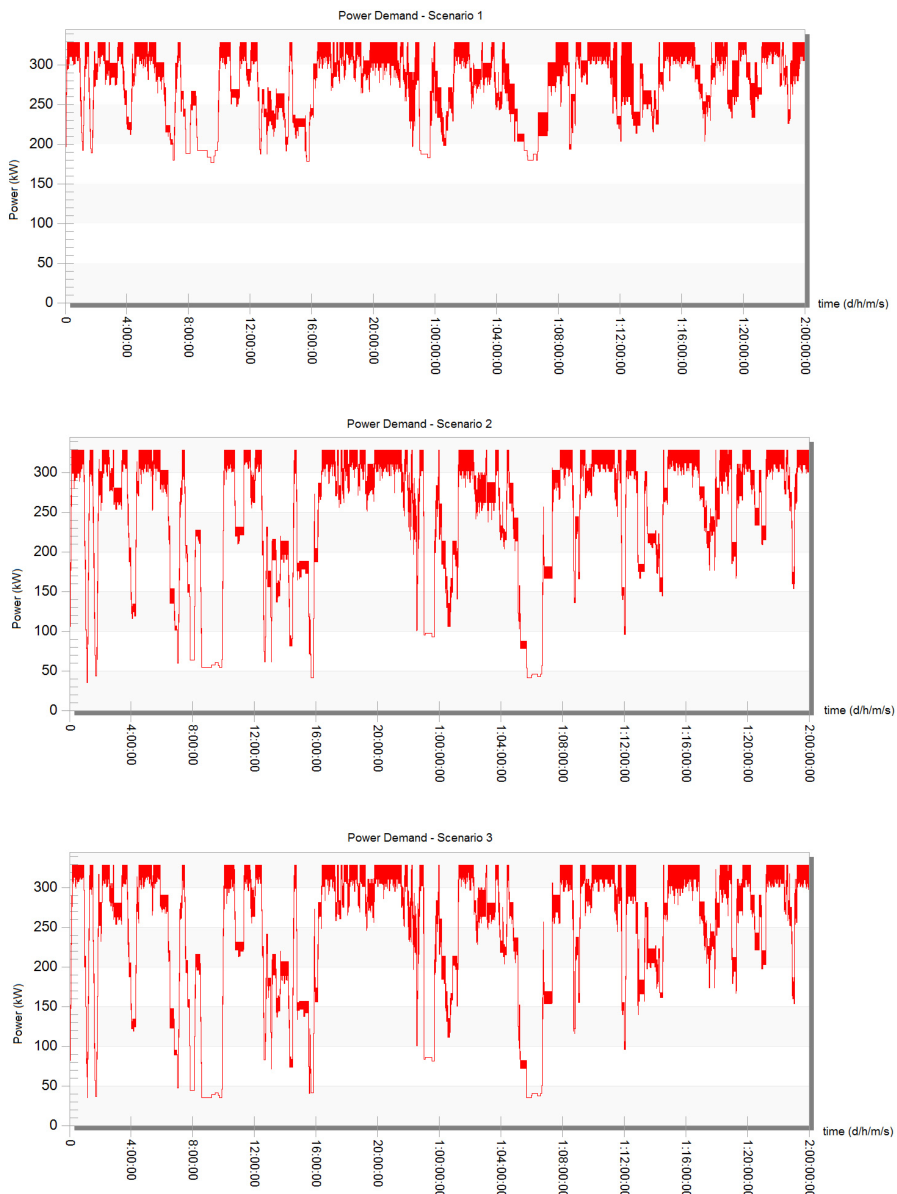
Figure 12 Comparison of lean energy indicators



The index calculated for the lean energy indicator in scenarios 2 and 3 is considerably higher than that obtained in scenario 1; this is justified by the implementation of control measures that enable the use of the standby state under certain failure conditions of the equipment and the occupancy of the buffers. However, it is also noted that the actions taken allow the increase of this indicator, even in conditions already considered favourable.

This is verified in scenario 3, which shows the best result for this indicator of the three scenarios evaluated, and is justified by the power control actions implemented during blockage of the line due to a failure, which greatly reduces the consumption at times when the equipment is not performing activities that generate processing value.

Figure 13 Electric power demand of comparing scenarios (see online version for colours)



Scenario 3 shows the lowest energy consumption based on the indicators evaluated for the proposed scenarios. However, it is also necessary to compare the gain from reducing consumption using the proposed power control strategies and production losses (six units in a 48-hour period) for scenarios 2 and 3. Thus, the analysis of the viability of implementation of this power control should analyse the profitability obtained per unit produced for scenarios 2 and 3 and also the investment required for the installation and maintenance of the buffers at the line in scenario 3. However, this profitability and cost evaluation is particular of each manufacturing industry and it is not in the scope of this work.

Regarding the demand for electric power, the maximum demand in all scenarios assessed is 329 kW, and this is achieved in the periods in which all machines are undertaking processing activities. The behaviour of the demand for electrical power for all three proposed scenarios is shown in Figure 13.

In scenarios 2 and 3, there is a larger change in power demand, showing values below 100 kW. The large variation observed and the presence of periods of lower demand in scenarios 2 and 3 result from the power control actions implemented, which change the equipment to standby mode when applicable and hence momentarily reduce the power demand for system operation.

In scenario 3, the power demand is similar to scenario 2 with the minimum values sometimes less than scenario 3. This arises from the allocation of equipment to the standby state in blocking situations.

According to the results and indicators obtained in the proposed scenarios, it is clear that the proposed strategies are fully applicable to cases in which a reduction in energy consumption is admissible for a small loss in production. In addition, the change in the line layout leads to an increase in the energy efficiency indicators of the system, thus confirming the existence of opportunities for intervention in existing systems, the goal of which is the best use of the available energy resources.

6 Conclusions

This study presents several simulation scenarios for the reduction of electricity consumption in an engine block production line. The introduction of a new variable to the traditional production planning allows the joint analysis of manufacturing data and the energy behaviour of the line through the proposed actions. In addition, simulation using a digital manufacturing environment has proved to be an effective tool for the analysis of the energy behaviour of the line supporting future investment decisions in this area. The results also show that the simulation of different control actions allows not only for a diagnosis of the current status of the facility but also enables the most efficient use of available resources by identifying opportunities for improvements in energy efficiency indicators, even in production systems that are already well designed. It is also found that the use of equipment with multiple power states allows consumption to be minimised during periods in which the devices are idle or when surplus production occurs, thereby enhancing the results achieved through the implementation of control measures focusing on power management. This work also supports the implementation of sustainable practices in organisations, seeking to motivate the analysis of energy efficiency indicators in order to propose new solutions for reducing energy consumption in industrial plants. Although these simulations were performed for a specific production line, the situations considered here are typical of most industrial processes, and the actions discussed here can be easily adapted to other processes in which machines can be allocated to the proposed energy states. The limitations on this work are related to the costs and feasibility of implementing the buffers proposed in the last scenario. For future works we suggest the integration of the digital manufacturing environment with the physical system for validating the proposed control actions in a closed loop.

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