IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 28 June 2024, accepted 9 July 2024, date of publication 17 July 2024, date of current version 6 August 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3430218

APPLIED RESEARCH

Energy Estimation and Production Scheduling in Job Shop Using Machine Learning

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This work was supported in part by São Paulo Research Foundation (FAPESP) under Grant 2017/25987-3, and in part by the Centro Universitário FEI.

ABSTRACT Energy efficiency has become a significant challenge for manufacturing companies. Although it is possible to improve efficiency by applying new and more efficient machines, decision makers tend to look for less expensive alternatives. Furthermore, the current reality of manufacturing companies, brought about by Industry 4.0, requires more flexibility of production systems and increase the complexity off machine rescheduling without compromising sustainable requirements. This study contributes to the subject by applying machine learning techniques in a job shop to reduce the makespan and estimate the total energy consumption. First, an artificial neural network (ANN) was trained to estimate the total electrical energy consumption in the system. A new input variable for the network was defined to assist in energy estimation. This variable is called the Priority Factor (PF) and helps capture the different patterns in the job shop. Second, as the ANN was trained, a Genetic Algorithm (GA) was used to reduce the makespan. Therefore, it is possible to reduce the makespan and know in advance the total electricity consumption in production. This solution supports a more sustainable manufacturing process, and is completely developed in a digital manufacturing environment.

INDEX TERMS Artificial neural network, digital manufacturing, energy estimation, genetic algorithm, industry 4.0, job shop.

I. INTRODUCTION

Manufacturing companies that rely on classic production systems have business models oriented toward manufacturing high-quality, low-cost products. However, there is a change in market behavior, where strategies focusing only on the low cost of the product have been losing market, leaving to be as effective as in the past [1]. This has led to the emergence of new business strategies over the past few decades, which seek to enable companies to maintain and even increase their levels of competitiveness by migrating from a cost-based perspective to strategies aimed at providing services and increasing the efficiency of their processes. In this context, discussions have been conducted on the topics Product-Service System [2] and Industry 4.0 [3], [4].

Industry 4.0 aims to use new hardware technologies and information and communication systems to improve not only the individual economic competitiveness of manufacturers, but also the sustainability of the industrial sector in general [4]. The industrial sector is estimated to account for 36% of the total energy consumed worldwide [5]. Therefore, several studies have focused on developing techniques and models that increase the energy efficiency of manufacturing systems. Three main factors explain the growing interest in the topic: the increase in the cost of energy tariffs, the increase in the number of environmental regulations, which are more restrictive, and the behavioral change of consumers, who are looking for products and ecologically correct services [6].

It is expected that with the adoption of Cyber-Physical Systems (CPS), proposed by advanced manufacturing, data on production cycles will be available in real time, thus allowing the expansion of the use of machine learning techniques for better decision making in manufacturing. Such actions may be aimed at improving the sustainability aspects of the system's entry, such as the consumption of electricity and raw materials, reduction of the output aspects, such as the

The associate editor coordinating the review of this manuscript and approving it for publication was Yongming Li.

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emission of pollutants and waste, and even a mixed approach that contemplates both aspects [7].

Enhancing environmental sustainability and cutting energy expenses have emerged as key considerations in manufacturing decision-making. Manufacturers are increasingly seeking innovative solutions to enhance their energy efficiency and promote sustainability [4], [8]. This work identified the main themes that aim to maximize their potential in reducing energy consumption, natural resources, and the pollutant emissions. In addition, the authors pointed out that the study of new techniques to facilitate decision making in manufacturing, whether online or offline with the production system, urgently needs the development of new research. In today's manufacturing landscape, prioritizing productivity at the cost of excessive energy consumption is no longer tenable. However, with the advent of efficient scheduling technologies, we can maintain peak productivity levels while simultaneously curbing energy expenditure [9], [10]. Furthermore, it is imperative to pay greater attention to energy management within a factory, particularly in job shops [10].

Based on the context presented, this work contributes to the subject by applying machine learning techniques (ANN and GA) to minimize the makespan and estimate electrical energy consumption. A new variable, the priority factor (PF), was created, contributing to the literature on job shop systems. The machine learning tools used are embedded in a digital manufacturing solution, which is one of the pillars of Industry 4.0. An initial investigation of this work was presented in [11].

The remainder of this paper is organized as follows. Section II presents a literature review. In Section III, we present the problem description and formulation of energy estimation and scheduling. Section IV presents computational results and an analysis of the proposed approach. Finally, in Section V, conclusions and future work are presented.

II. LITERATURE REVIEW

The following is a literature review related to the research problem presented and the existing knowledge on the subject. The review was divided by subject for a better understanding.

A. SUSTAINABILITY IN MANUFACTURING

Sustainability has become an increasingly important requirement in manufacturing systems. This is evident when observing a greater focus on issues such as the reduction of non-renewable resources, the emergence of new and more restrictive environmental legislation, and an increase in electricity tariffs, among others. Several efforts have been made to search for more sustainable manufacturing systems [7], [12], [13].

Industrial activity, more specifically manufacturing systems, is among the main factors responsible for the actions that generate impacts on the environment. As pointed out by [14], these impacts range from the consumption of renewable and non-renewable material resources, such as water, metals, and fossil fuels, as well as the consumption of large amounts of electricity. The resource consumption mentioned was classified by [7] as an input aspect of manufacturing. However, the authors also highlighted the output aspects of the manufacturing system, such as carbon emissions and waste.

B. ENERGY EFFICIENCY IN PRODUCTION LINES

Creating a sustainable manufacturing system, particularly the design of a new production line, requires a prior assessment of the estimated energy consumption of the processes [15]. For this, it is necessary to use techniques and tools to estimate energy consumption. In this context, the use of simulation tools stands out, which enable the investigation of cause-and-effect relationships, in addition to allowing a deeper understanding of the dynamics of the system [16]. However, the current literature focuses on estimating the consumption of manufacturing systems already in production, whose goal is to improve energy efficiency and assist in planning the existing system. To assist the line design stage, [17] presented the Methods Energy-Measurement (MEM) methodology, which assists planners and decision makers in terms of energy consumption. This method makes it possible to estimate the potential energy consumption of production lines and manufacturing cells with greater complexity. This method allows for the analysis of energy costs and also of CO_2 emission levels.

The work presented in [18] proposed a systematic approach to programming operations during the machining process in two stages. First, the aim was to determine the best machining center configuration parameters for each item produced. The quality of the finish is considered as a constraint in modeling, whose function of multiple objectives is to reduce the energy consumption and increase the productivity of the system. The variables considered for the first stage were the rotation speed, cutting speed, depth of cut, and width of cut. Owing to the non-linearity between the controlled variables and objectives of the problem, ANN were used to calculate the indicators related to the selected input parameters. Heuristics were then applied to find the best input parameters, and finally, the best manufacturing settings for each part were recorded on each machine. The second stage uses the best results obtained in the first stage to identify the combination that maximizes the objective output function. Again, the objective function is normalized by considering the parameters of energy consumption and total manufacturing time. From this, heuristics are applied to select the machine in which each part will be manufactured, thereby reducing the manufacturing time and improving the system's energy efficiency.

Another work of great importance related to the reduction in energy consumption during the planning of operations in manufacturing systems was presented in [19]. The authors proposed a mathematical modeling for programming the operations of a single-machine system, aiming to reduce electricity costs, considering the continuous variation of the energy price throughout the day. Although the initial objective of this study was to reduce production costs, it was observed that the model allows for a reduction in consumption during peak periods, thus contributing to the reduction of negative impacts due to the high demand of the distribution system.

Reference [20] presented a method for managing energy performance based on the distribution of responsibilities and at clear definition of a baseline, which allows a quick view of the system status and decision-making at the tactical level. This work indicates that research linked to the creation of metrics for assessing energy performance usually focuses on strategic or operational levels, with the tactical level rarely mentioned. However, the tactical level is responsible for linking the other two. According to the authors, the number of indicators applied at the tactical level, should be greater than the number of strategic level indicators and less than operational-level indicators, forming a pyramidal structure. However, the investigation indicated that the current literature scenario follows a double-pyramid structure. This interaction between the different levels is also highlighted in [21], where the authors point out the existence of non-trivial aspects between the levels, suggesting that the best results can be achieved when analyzing the levels together.

C. PRODUCTION SCHEDULING

In general, it is observed that scientific studies related to energy efficiency can be grouped into two main fronts [22], [23]. First, there are studies on reducing energy consumption through technological improvements in equipment or production processes. The second seeks to improve the energy efficiency through adjustments in the management parameters, which directly or indirectly influence the efficiency of the system. The first may require high investments to obtain efficiency, therefore, decision makers tend to move to the second option, seeking to improve the use of existing equipment based on the best planning and programming of the operations performed, which also has the potential to reduce consumption [22].

In this context production planning and programming are the stages. The works presented in [7] and [24] review the main models described in the literature linked to production planning and scheduling, which seek to improve the sustainability aspect of manufacturing systems. In particular, [24] proposed linking these models to classic activities performed during production planning.

In the work of [24], the authors observed that approximately 57% of the identified studies were focused on allocation and sequencing. However, it was also possible to observe the lack of studies related to the increase of energy efficiency in systems characterized as job shop type, since, according to the authors, it is the type of manufacturing system that best represents the reality of the industry. The perception that job shop systems have not been well investigated with the aim of reducing energy consumption was also shared by [25]. The following section presents this type of system and discusses the main studies that address energy efficiency identified in the literature.

The application of machine learning and optimization algorithms in production scheduling continues to advance, providing more sophisticated solutions to complex scheduling problems. Recent studies have demonstrated significant progress in this domain. The work of [26] introduced a novel Q-learning based variable neighborhood iterative search algorithm for solving disassembly line scheduling problems, showcasing the potential of reinforcement learning techniques in optimizing production processes. Similarly, [27] proposed an ensemble artificial bee colony algorithm combined with Q-learning for bi-objective disassembly line scheduling, emphasizing the efficacy of hybrid optimization methods in handling multi-objective scheduling challenges. Furthermore, [28] presented an improved artificial bee colony algorithm with Q-learning to address permutation flow-shop scheduling problems, highlighting enhancements in algorithmic performance for complex scheduling scenarios. These studies provide valuable insights and methodologies that complement and extend the findings of the present research, which utilizes ANN and genetic algorithms GA to estimate energy consumption and optimize makespan in job shop environments. The integration of advanced machine learning techniques and hybrid algorithms, as evidenced in these recent works, underscores the importance of continually evolving approaches to achieve higher efficiency and sustainability in production systems [26], [27], [28].

D. ENERGY EFFICIENCY IN JOB SHOP

A classic job shop manufacturing system was proposed in the 1960s [29]. It is a problem with a high degree of difficulty in solving it and, is classified as NP-hard [30], [31]. However, because it represents the reality of most companies, especially small and medium-sized companies [25], the job shop has become a widely adopted model in the manufacturing industry. This type of problem has also become very popular in the scientific community, where several investigations using heuristics and optimization methods have been applied [29].

According to [32], the programming of operations in job shop systems, over the last few decades has been widely studied from the perspective of the system's productivity. However, as pointed out by [24] and [25], little attention has been paid to system analysis from the perspective of energy efficiency.

The authors [33] compared different energy policies for using machines in a job shop manufacturing system. From the definition of the energy states and the link between the operating states of the machines, four strategies were defined and compared in this study.

In [34], an investigation into the impacts of the energy policy adopted by the Chinese government was conducted. In this work, the authors carried out a study on the effects of power supply interruptions on the planning of job shop systems, where the total energy cost was considered in addition to the total energy consumption and delays in delivery times. The energy cost variable was added to the study as companies tend to adopt their own diesel generators to maintain their plans and delivery times.

In a study by [35], the authors presented a model whose main objective was to identify opportunities for shutting down machines during long periods of idleness. The model called Genetic Algorithm Electricity Saving in job Shop (GAEJP) was based on the NSGA-II model [36], in which two complementary steps were added to reduce energy consumption. In the first stage, the model seeks to increase the idle windows of machines without compromising the total production delay time. During idle windows, the feasibility of completely shutting down the equipment is evaluated, reconnecting it only when there is a new demand, without compromising the production schedule previously defined by the NSGA-II algorithm. In the second stage, the solutions obtained during the first stage are selected following the criteria of non-dominance and elitism, generating families of solutions that allow observing the Pareto frontier for the problem.

Manufacturing companies have different sources of production interruptions, such as machine failures, order cancellations, and delivery delays. In some cases, the initial schedule of activities can absorb these interruptions when less significant, without affecting the total production time. However, there are cases in which planning actions are required to quickly re-establish the original schedule, minimizing the effects of interruptions. In this sense, [37] suggested a new technique to reschedule the activities of job shop systems after interruptions, which aims to minimize the energy consumption for the resumption of the original schedule from the variation of the machines' operating speeds. The variation in machine speed directly affects the energy consumption and inversely affects the operating time [21], [37], [38]. The authors proposed algorithms for identifying the time needed the time needed to resume the system, using this time as a restriction for generating a new schedule. The new programming of the affected operations was performed by combining the GA and Local Search (LS) heuristics. The objective function of the problem considered the parameters of Total Completion Time (TCT) and Total Energy Consumption (TEC), weighted by a sensitivity coefficient, which allows the evaluation of the behavior of the trade-off between production time and energy consumption.

E. ARTIFICIAL NEURAL NETWORKS APPLIED TO ENERGY ANALYSIS

Artificial Neural Networks have been widely used for energy analysis, particularly for analyses related to the industrial sector. The applications are diverse, ranging from the classification of energy patterns of the operating states of the machines [39] to the control of the amount of energy used for the chemical processing of materials [40], to reaching the demand management of the facilities [41], [42]. In this sense, 483 publications aimed at predicting energy consumption were reviewed by [43], where the authors observed that an artificial neural network is the main model used in this type of approach, representing approximately 40% of the analyzed publications. In [6], the authors broadened the research horizon and identified other applications in the literature.

The study of electricity demand plays an important role in planning distribution networks and energy generation systems as because it improves efficiency and avoid problems such as blackouts or sudden power outages [44].

The study in [45] applied an ANN to forecast the energy demand in the US industrial sector. This study also applied the model conduct future projections, considering the period between 2013 and 2030. The authors observed that the energy demand in the industrial sector was significantly affected by the price of energy. From the proposed model, it is possible to estimate a 16% increase in energy demand in the US industrial sector by 2030.

The work developed by [6] also identified applications of ANN to predict the consumption of industrial plants, transport and commercial buildings. According to the authors, these studies seek to compare the energy prediction with the actual consumption values of the installation to identify deviations of greater significance.

In [46], the authors used an ANN for short-term analysis, considering 15-minute intervals, when forecasting the load of a commercial complex of three office buildings. Initially, the authors evaluated the performance of different machine learning techniques and selected the artificial neural network to obtain the best results. An analysis of the most relevant available variables was then carried out and segregated into three groups: environmental, time indicators, and operational conditions.

III. PROBLEM DESCRIPTION AND FORMULATION

From the point of view of energy analysis, the model proposed in this work fits the level of the production line because it seeks to assist during the programming phase of the machines but does not consider issues related to the way of executing the processes, types of machines, and installation layouts.

For the modeling and simulation of the research problem, the Plant Simulation® software, developed by Siemens PLMSoftware Inc., was used to model and simulate the research problem. It is a discrete event simulation software aimed at creating digital models of logistics systems (e.g., production lines), allowing the exploration of the characteristics of the systems and improving their performance [47]. In addition, the software has tools for combinatorial improvement (e.g., genetic algorithms), ANN, energy analysis.

Job shop systems process N different jobs on M machines. Unlike flow shop systems, where all jobs follow the same route through machines, job shop systems allow different routes for each job processed [48]. In addition, [49] suggests classifying job shop systems as static or dynamic based on the type of decision rule adopted for the execution of each operation. In static systems, the priority of jobs is defined in advance and is the same for all machines (e.g., the first one to arrive is the first to be processed). However, dynamic systems have the flexibility to define different priorities for each machine.

The work can be divided into two main stages. First, a simulation model was created based on the identified research gap, allowing the collection of experimental data for training. It is worth mentioning that the data used in this first stage were generated randomly; that is, the simulated sequencing did not commit to minimizing or maximizing any variable in the system but was allowed to accelerate the information collection process. In the second stage, the trained ANN was used to estimate the consumption of different GA-generated machine schedules (recall). The algorithm was used to minimize the makespan such that the sequencing of the operations was the closest to a real scenario. Finally, the energy consumption estimated by the ANN was compared with the value simulated by the software. The job shop model and ANN and GA tools were integrated into the Plant Simulation® software, which is at digital manufacturing package from Siemens. This brings the advantage that the proposed solution is ready to produce a digital twin of the process [50]. Creating digital twins is one of the pillars of Industry 4.0.

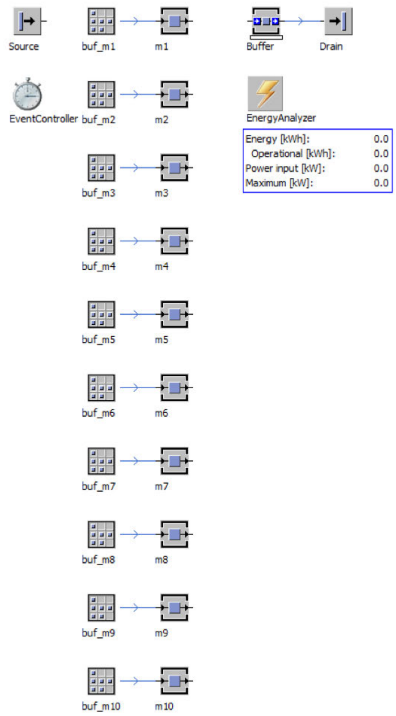

FIGURE 1. Simulation model of the job shop.

A. GENERAL DESCRIPTION OF THE MODEL

First, it is necessary to insert buffers before the entry of each machine to modeling a job shop system. This is because the priority of execution of each job must be analyzed before its processing, in addition to the possible accumulation of activities awaiting the availability of the machine for execution. The simulation model used in this study is illustrated in Fig. 1. At the beginning of the simulation, all the jobs were available for execution. Thus, at time t = 0, jobs are allocated to the respective input buffers for each machine during the execution of the first operation. When the operation is completed, the job is forwarded to another machine responsible for performing the next operation. When the last operation is performed, the job is completed and forwarded to the system exit (drain).

According to the classification of job shop systems pointed out in [49], the model used is classified as a dynamic type. This is because the jobs have different execution priorities for each machine in the system. Thus, even if different jobs are waiting to be processed in the input buffers, only the one with the highest priority defined for the given time will be processed. This priority is defined from the input vector, whose representation adopted in this work is the same as that proposed in [51], and is called Permutation with Repetition.

In the adopted representation, each job occurs the same number of times as the number of operations required for its execution. Thus, when evaluating the input vector from the first to the last position, the k-th occurrence of a job refers to its kth operation. In practice, this representation allows decoding in a Gantt chart, allocating each operation to its respective machine. Fig. 2 illustrates an example of decoding the input vector and resulting programming.

B. GENERAL CONFIGURATION OF THE SYSTEM

This work adopts the classic FT10 problem proposed by [52] as a basis for developing a simulation and energy consumption estimation model. The FT10 problem architecture was selected because it is commonly used in the study of job shop systems, in addition to considering a high number of machines in the system (10 machines), when compared to real systems.

Machine sequencing of the operations required for each job and their respective processing times were randomly generated. The sequencing and processing times for each operation are summarized in Table 1. Here, the values presented in parentheses represent the processing time for each $O_{i,j}$ operation, and the values outside parentheses indicate the machine on which the operation will be performed.

After defining the sequencing aspects and processing times for operations, the next step is to define the electrical power consumed by each machine. Therefore, it is necessary to define the energy policy applied to the production system, which indicates the possible energy states of the machines. Considering that this work adopts energy policy number two, presented by [32], the behavior of the machines is given by

1) At the initial instant ($t = 0$), all machines are off;
2) Then, the machines are turned on individually when the first operation requires the use of the machine;
3) At the end of the operation, the machine is placed on standby, consuming less energy. If the operation

TABLE 1. Sequencing and times of operations for each job.

Jobs	Machine (Processing Times)									
	$O_{i,1}$	$O_{i,2}$	$O_{i,3}$	$O_{i,4}$	$O_{i,5}$	$O_{i,6}$	$O_{i,7}$	$O_{i,8}$	$O_{i,9}$	$O_{i,10}$
J_1	4(95)	1(69)	5(13)	3(92)	2(85)	6(50)	7(31)	9(90)	8(65)	10(4)
J_2	5(82)	1(9)	4(93)	2(27)	3(25)	7(69)	10(45)	9(91)	(95)	6(7)
J_3	4(4)	2(88)	5(67)	1(1)	3(93)	8(2)	6(13)	7(99)	10(92)	9(42)
J_4	5(77)	4(90)	1(13)	2(10)	3(42)	7(9)	6(75)	8(16)	10(15)	9(47)
J_5	3(77)	1(46)	2(24)	4(34)	5(36)	9(30)	8(41)	10(91)	7(73)	6(28)
J_6	2(51)	3(97)	5(56)	4(31)	1(63)	6(97)	9(23)	7(25)	10(70)	8(56)
J_7	2(89)	3(84)	4(82)	5(36)	1(79)	8(4)	9(89)	7(20)	10(71)	6(25)
J_8	1(99)	5(92)	4(95)	2(85)	3(90)	9(39)	10(92)	8(69)	6(24)	7(48)
J_9	1(20)	3(79)	2(14)	5(10)	4(46)	8(10)	6(72)	7(62)	9(6)	10(96)
J_{10}	3(81)	5(54)	4(3)	1(96)	2(63)	6(53)	8(39)	9(90)	7(36)	10(9)

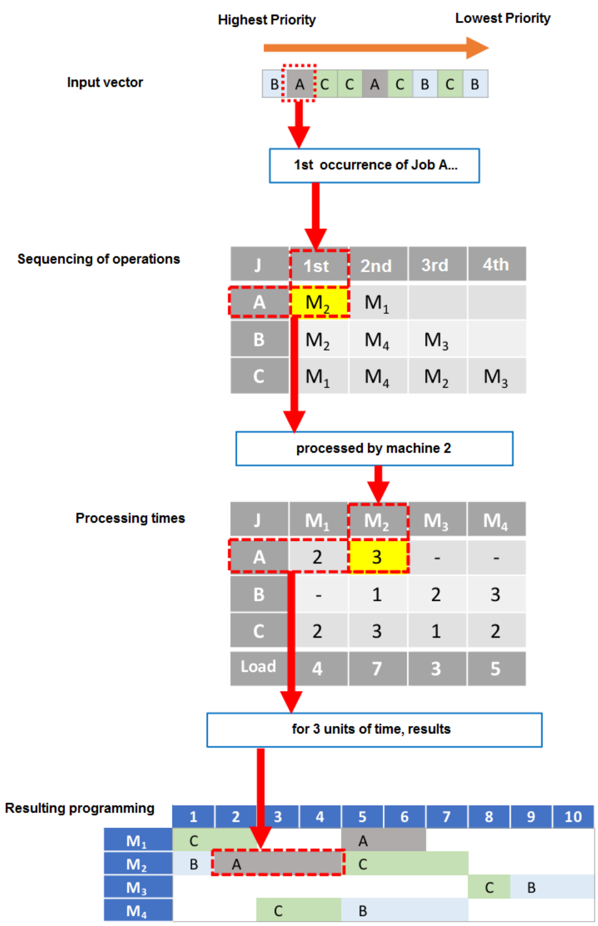

FIGURE 2. Example of decoding input vector.

performed was the machine's last plan, it was switched off.

Based on the described energy policy, machines can have three energy states: off, operating and on standby. In the off state, there is no electricity consumption. The operating state has the highest energy consumption when the machine performs an operation. Finally, the standby state refers to the low-power state, where the machine is not processing any jobs but is energized and ready to start a new operation.

A method similar to that used in defining the processing times was used to determine the power consumed by each machine during the operating state. Random values were generated evenly in the range [15,50] kW.

As discussed in [53], the total energy of a machine can be broken down using Eq. 1. In this equation, the E_{proc} value represents the fraction of energy required to perform physical processing of the job, that is, during the operating state. On the other hand, the E_{periph} energy fraction, represents all other peripheral devices on the machine, which remain on even when the machine is in the standby state (e.g., cooling pumps, ventilation systems, and lighting). The authors pointed out that even during periods of idle equipment, machines can consume more than 50% of their maximum power. However, as this value is not a rule and may vary depending on the type of equipment and/or manufacturer, the values adopted in this study were randomly defined between 40% and 60% of the total power for each machine. This results in the values listed in Table 2.

$$E_{total} = E_{proc} + E_{periph} \tag{1}$$

TABLE 2. Power consumed by the machines.

Machine	Power consumption in each state		
	Off [kW]	Standby [kW]	Operating [kW]
M_1	0.00	15.49	28.06
M_2	0.00	20.39	40.68
M_3	0.00	21.03	43.08
M_4	0.00	14.86	30.23
M_5	0.00	12.69	25.04
M_6	0.00	7.16	16.34
M_7	0.00	17.32	34.41
M_8	0.00	10.60	18.17
M_9	0.00	17.82	42.89
M_{10}	0.00	18.26	41.94

C. TRAINING SET FOR ESTIMATING THE ENERGY CONSUMPTION

The main function of the ANN in this study was to estimate the total energy consumption of a job shop system based on an input vector for sequencing activities. As illustrated in Fig. 2

the length of the input vector directly depends on the number of jobs selected and the number of operations required by each job. Thus, it is necessary to define a criterion that allows the number of ANN input variables to be fixed for different job combinations. It is necessary to seek generalization of the model, without having to model a new network for each new input vector.

To overcome this problem, the criterion adopted was to link the number of ANN entries to the number of machines in the system. This strategy allows the approach of the proposed model to the typical configurations of manufacturing companies, where the number of machines is usually fixed in the system, varying the configuration of the production order. Five groups of variables were selected, as discussed in the following subsections.

1) PRIORITY FACTOR

The first set of variables is related to the priority of the machine to enter operation. As previously discussed and illustrated in Fig. 2, the input vector can be interpreted as a list of execution priorities, where the operations to the left of the vector have a higher priority than those located on the right.

Thus, if a machine is allocated to perform the first operation of all jobs (e.g., raw material inspection), it will have a higher priority factor than a machine used only in the final step of the process (e.g., packer). Thus, the priority factor for each machine (PFm) can be defined as the sum of the inverse values of priority index i of the operations performed by machine m.

$$PF_m = \sum \lambda \times \frac{1}{i} \tag{2}$$

where i is the priority index, which corresponds to the position of the operation within the input vector, λ is the choice factor and receives a value equal to 1 when the operation of position i is performed by machine m and 0, when not.

Fig. 3 exemplifies the calculation of the priority factor for machine 2. Thus, a priority factor FPm must be calculated for each machine present in the system.

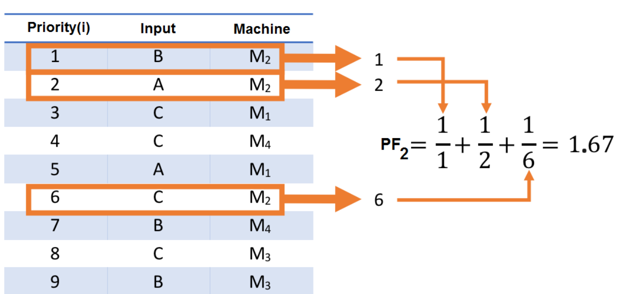

FIGURE 3. Example of calculating the priority factor.

The algorithm 1 presents the calculation of PF.

2) STARTING TIME

The second set of variables refers to the instant at which the first operation of each machine begins (STm). The starting time can be determined using the semi-active programming algorithm illustrated in [51]. Semi-active schedules are those in which no operations can be anticipated without changing the sequencing of a machine [48].

In Algorithm 2, the vector containing the starting time of each machine, STm, is initialized to an infinite value. At each iteration, it was checked whether the machine started the current operation at an instant less than the one registered. If this is true, the position of the vector for the machine used in the current operation is updated.

Algorithm 1 Algorithm for Calculating the Priority Factor

Input: Input Vector C
Input: Machine Scheduling Matrix S
Output: Set of Priority Factors PF

```
/* Initiating the Priority Factor */
FP ← 0;
/* Initiating the operation pointer */
op ← 0;
/* Search the input vector C */
foreach i ← 1 until C.length do
    /* Identifies the job of position i */
    job ← C[i];
    /* Identifies the machine associated to position i */
    machine ← S[job, op];
    /* Increase the value of Priority Factor */
    FP[machine] ← FP[machine] + 1/i;
    /* Updates current job operation */
    op[job] ← op[job] + 1;
```

3) ENDING TIME

Analogously to the set of variables in the starting time, the instant of termination of operations, ET_m, is also calculated by the algorithm. However, the vector initialization is done with a null value for all positions. After that, the operation's instant completion is verified at each iteration. The value is updated if the observed value is higher than that recorded in ET_m.

4) MACHINE LOAD

The fourth set of variables refers to the total processing time, ML_m, predicted for each machine. This value can be extracted from the table of processing times, as illustrated in Fig. 2, by following the steps described below.

1) Identify the jobs present in the production order;
2) From the table of processing times, the lines related to jobs not identified in the previous step are removed;
3) Finally, we add the values by columns and assign the total to the respective variable ML_m. If there were unused machines, at null value was assigned.

5) NUMBER OF JOBS

Finally, the fifth nuance used in the model refers to the restricted count of job J present in the input vector ($NumJobs$).

Algorithm 2 Algorithm for Calculating STm and ET_m

```
Input: Input Vector C
Input: Machine Scheduling Matrix S
Input: Processing Time Matrix T
Output: Set of starting times ST
Output: Set of ending times ET
ST ← ∞;
ET ← 0;
foreach i ← 1 until C.length do
    /* Identifies the current operation */
    job ← C[i];
    op ← nextoperation[job];
    machine ← S[job, op];
    t ← T[job, machine];
    if (Machineuse[machine] > jobuse[job]) then
        /* Identifies the beginning of current operation */
        operations[job, op] ← Machineuse[machine];
        /* Icrease the use of machine */
        Machineuse[machine] ← Machineuse[machine] + t;
        jobuse[job] ← Machineuse[machine];
    else
        /* Identifies the beginning of current operation */
        operations[job, op] ← jobuse[job];
        /* Increase the makespan of a job */
        jobuse[job] ← jobuse[job] + t;
        Machineuse[machine] ← jobuse[job];
    /* Updates the value of ST(m) */
    if ((Machineuse[machine] − t) < ST[machine]) then
        ST[machine] ← Machineuse[machine] − t;
    /* Updates the value of de ET(m) */
    if ((Machineuse[machine]) > ST[machine]) then
        ST[machine] ← Machineuse[machine];
    /* Increase the job operation */
    op ← op + 1;
    nextoperation[job] ← op;
```

That is, the number of different jobs is processed in the current production order.

D. COLLECTING DATA FOR TRAINING THE MODEL

To generate the training set for this work, three new methods were implemented in the *SimTalk 2* programming language, native to the Plant Simulation software, and aimed at expanding the tool's resources [54]. The new methods were performed at each acquisition round, and the training examples were recorded in an auxiliary table.

The first method is responsible for the random generation of production orders. In this method, the number of jobs or products in the production order to be processed was first determined. The jobs from each position defined by the first draw are then drawn. The drawing of the types of jobs performed out recursively, where a job could not be selected more than once within the same production order. The composition of the training bench with jobs of different sizes and configurations, sought to generalize the model to the configuration of the adopted system, thereby providing flexibility for the production of different combinations. In the second method, the algorithms described in the previous section were implemented to extract nuances from the configuration of the randomly selected production order. Finally, the third method was used to read the energy analysis module. The total electrical energy consumed by the simulated system was obtained and recorded, making up the training set.

By constructing a simulation model and creating the aforementioned methods, each simulation round resulted in only one example for training the network. In this manner, the training set was generated by repeatedly running the simulation model.

IV. EXPERIMENTAL RESULTS

A. ANN ARCHITECTURE

The experimental data collection began with the generation of the ANN training set. Several simulations were performed by considering different production orders. The production orders were randomly defined, and the number of jobs was drawn to compose the order and then the types of jobs, as shown in Table 1. Fig. 4 illustrates the process of generating the training set, where each cycle represents a simulation round that results in a lesson for the training bench.

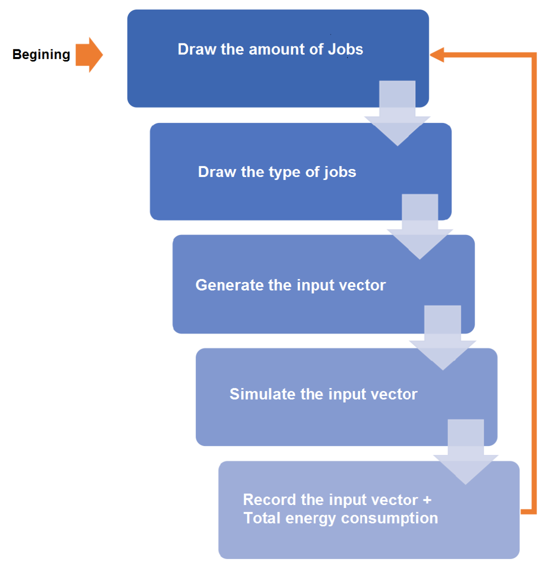

FIGURE 4. Training data set generation cycle.

Because the proposed model uses simulated data, the user can determine the number of samples for training. In this study, the number of samples was determined empirically, and the analysis started with a training bank containing 1000 lessons, with the hypothesis that it would be oversized.

From the generation of the initial training bank, a Multi-Layer-Perceptron (MLP) ANN was used in this study. The training set was divided into two partitions, the first consisting of 70% of the lessons for training and the second consisting of the remaining 30%, used in the validation of the ANN. The default values of the simulation software were maintained

TABLE 3. Summary of results for each ANN configuration.

Experiment	Number of neurons Hidden layer 1	Hidden layer 2	RE	Time (Min:Sec)
1	2	0	0.548%	01:48.61
2	4	0	0.439%	03:04.00
3	6	0	0.433%	04:31.20
4	8	0	0.413%	04:22.13
5	2	2	0.312%	02:02.14
6	2	4	0.250%	02:08.35
7	2	6	0.303%	02:20.89
8	2	8	0.261%	02:30.59

TABLE 4. ANN performance for different moment coefficients.

Experiment	$\alpha = 0$	$\alpha = 0.2$	$\alpha = 0.4$	$\alpha = 0.6$	$\alpha = 0.8$	$\alpha = 1$	$\alpha = 1.2$	$\alpha = 1.4$	$\alpha = 1.6$	$\alpha = 1.8$	$\alpha = 2$
1	0.250%	0.240%	0.235%	0.230%	0.241%	0.249%	0.620%	0.257%	0.626%	0.317%	0.402%
2	0.250%	0.240%	0.235%	0.230%	0.348%	0.249%	0.873%	0.259%	0.626%	0.317%	0.402%
3	0.250%	0.240%	0.235%	0.452%	0.253%	0.239%	0.334%	0.239%	0.609%	0.251%	0.402%
4	0.250%	0.240%	0.235%	0.276%	0.264%	0.249%	0.873%	0.259%	0.626%	0.251%	0.402%
5	0.250%	0.240%	0.258%	0.425%	0.348%	0.249%	0.620%	0.239%	0.223%	0.206%	0.271%
6	0.250%	0.240%	0.258%	0.230%	0.253%	0.249%	0.873%	0.259%	0.609%	0.206%	0.402%
Average	0.250%	0.240%	0.243%	0.307%	0.285%	0.247%	0.699%	0.252%	0.553%	0.258%	0.380%
Maximum	0.250%	0.240%	0.258%	0.452%	0.348%	0.249%	0.873%	0.259%	0.626%	0.317%	0.402%
Minimum	0.250%	0.240%	0.235%	0.230%	0.241%	0.239%	0.334%	0.239%	0.223%	0.206%	0.271%

for the activation function, activation magnitude, restart, and learning rate parameters. Finally, the moment coefficient is adjusted to zero. In summary, the ANN configuration parameters were:

1) Activation function: Hyperbolic Tangent
2) Activation magnitude: 0.9
3) Restarting: 1%
4) Learning rate: $0.2 \sim 2$
5) Momentum (α): 0

Considering the scenario presented in the previous paragraph, the first experiments performed to identify the number of neurons for configuring the ANN. Eight experiments were performed by alternating the number of neurons and layers of the ANN. The training evolution graph was used to evaluate the response of each configuration, and the average validation error value was calculated using Eq. 3.

$$\mathrm{RE} = \frac{1}{n} \cdot \sum_{i=1}^{n} \frac{(y_i - o_i)}{y_i} \cdot 100\% \tag{3}$$

where y_i represents the actual output value of the training set, o_i the output value estimated by ANN and n the total number of lessons in the training set.

Table 3 summarizes the experimental results. The last column shows the total processing time required to train the network for 500 iterations. This number of iterations was adopted to allow the comparison between the different configurations where, after carrying out preliminary experiments, it was observed that this quantity would be sufficient for the convergence of the results of the different configurations experienced. It was observed that the total processing time was strongly influenced by the number of neurons employed in the first hidden layer of the ANN. The increase from 2 to 8 neurons in experiments 1 and 4 resulted in an increase in the total processing time of more than 2 minutes, while the same increase in the second layer for experiments 5 and 8 resulted in an increase of approximately 30 seconds.

Based on the results presented in Table 3, the ANN configuration used in experiment 6 was chosen because it had the lowest average error and training time, which were very close to the lowest time found among the other configurations. This resulted in an ANN with the following configuration:

1) Input layer: 41 neurons
2) Hidden layer 1: 2 neurons
3) Hidden layer 2: 4 neurons
4) Output layer: 1 neuron

After defining the configuration of the ANN, a study on the influence of the momentum coefficient (α) was conducted. Starting from the adopted configuration, the parameter value was changed between 0 and 2, with a step equal to 0.2. Six experiments were performed for each value of α and the minimum, average, and maximum values of the average training error were identified. Table 4 presents the results.

For the experiments carried out, it was observed that the minimum training error occurred when the value of $\alpha = 1, 8$ is applied. However, if the moment coefficient

TABLE 5. Estimation of energy consumption for production orders after heuristic algorithm.

Experiment	Drawn jobs	Makespan	Energy Simulated (kWh)	Estimated Energy (kWh)	Estimation error (%)
1	J_2 J_3 J_8	12:23:00	1387.31	1388.49	0.08%
2	J_9 J_{10} J_5	10:16:00	987.83	998.77	1.11%
3	J_4 J_1 J_2	10:57:00	1029.48	1036.43	0.67%
4	J_2 J_7 J_3	10:46:00	1188.15	1194.45	0.53%
5	J_7 J_1 J_5	10:30:00	1209.99	1210.40	0.03%
6	J_9 J_6 J_5 J_8	12:50:00	1537.88	1535.57	-0.15%
7	J_4 J_9 J_1 J_3	12:50:00	1537.88	1535.57	-0.15%
8	J_7 J_{10} J_6 J_5	12:44:00	1532.92	1527.83	-0.33%
9	J_3 J_2 J_5 J_1	11:35:00	1501.45	1508.17	0.45%
10	J_8 J_{10} J_9 J_6	13:14:00	1558.43	1557.58	-0.05%
11	J_6 J_2 J_9 J_5 J_3	12:43:00	1679.40	1687.66	0.49%
12	J_3 J_{10} J_2 J_5 J_6	11:52:00	1700.58	1707.75	0.42%
13	J_6 J_2 J_{10} J_8 J_3	13:53:00	1981.55	1986.99	0.27%
14	J_9 J_3 J_1 J_7 J_{10}	13:29:00	1717.57	1730.25	0.74%
15	J_{10} J_8 J_5 J_2 J_1	13:27:00	1878.47	1887.84	0.50%
16	J_7 J_1 J_3 J_2 J_{10} J_5	13:30:00	2104.45	2119.61	0.72%
17	J_{10} J_8 J_9 J_1 J_6 J_3	15:45:00	2236.63	2246.44	0.44%
18	J_3 J_5 J_6 J_1 J_2 J_9	13:08:00	2061.71	2075.45	0.67%
19	J_{10} J_6 J_5 J_9 J_8 J_1	14:29:00	2146.13	2154.96	0.41%
20	J_9 J_8 J_1 J_5 J_6 J_{10}	14:42:00	2097.98	2109.38	0.54%
21	J_2 J_{10} J_3 J_6 J_4 J_5 J_9	15:06:00	2083.76	2109.28	1.22%
22	J_2 J_8 J_4 J_6 J_1 J_{10} J_3	15:47:00	2559.81	2567.73	0.31%
23	J_4 J_{10} J_7 J_9 J_6 J_1 J_5	15:46:00	2362.53	2371.83	0.39%
24	J_4 J_2 J_3 J_1 J_9 J_6 J_8	15:52:00	2393.07	2409.56	0.69%
25	J_1 J_3 J_4 J_7 J_9 J_6 J_5	15:24:00	2350.66	2366.75	0.68%
26	J_4 J_6 J_3 J_9 J_1 J_8 J_2 J_5	16:48:00	2749.67	2758.15	0.31%
27	J_6 J_1 J_2 J_7 J_8 J_5 J_{10} J_9	17:12:00	2776.92	2780.66	0.13%
28	J_8 J_4 J_3 J_6 J_7 J_1 J_2 J_9	17:32:00	2777.85	2782.30	0.16%
29	J_1 J_{10} J_3 J_8 J_5 J_4 J_2 J_6	16:43:00	2806.67	2811.00	0.15%
30	J_9 J_4 J_{10} J_2 J_6 J_8 J_7 J_3	17:40:00	2738.47	2742.91	0.16%
31	J_9 J_6 J_5 J_{10} J_3 J_8 J_7 J_2 J_1	19:33:00	3169.64	3170.53	0.03%
32	J_1 J_{10} J_5 J_6 J_9 J_3 J_7 J_2 J_8	18:19:00	3133.70	3131.78	-0.06%
33	J_{10} J_3 J_1 J_6 J_8 J_5 J_7 J_2 J_4	18:09:00	3007.87	3012.94	0.17%
34	J_4 J_7 J_9 J_6 J_8 J_1 J_5 J_{10} J_2	17:45:00	3061.37	3061.13	-0.01%
35	J_{10} J_9 J_1 J_3 J_5 J_8 J_6 J_4 J_2	18:54:00	2975.12	2980.64	0.19%
36	J_7 J_{10} J_5 J_1 J_2 J_6 J_8 J_3 J_9 J_4	19:01:00	3289.43	3294.54	0.16%
37	J_4 J_8 J_5 J_7 J_3 J_2 J_9 J_1 J_6 J_{10}	19:32:00	3329.11	3330.81	0.05%
38	J_9 J_6 J_8 J_5 J_{10} J_3 J_4 J_2 J_1 J_7	19:43:00	3267.04	3271.74	0.14%
39	J_2 J_1 J_5 J_4 J_6 J_3 J_7 J_9 J_8 J_{10}	18:44:00	3448.97	3451.87	0.08%
40	J_4 J_8 J_2 J_6 J_{10} J_3 J_9 J_7 J_5 J_1	20:31:00	3293.91	3297.02	0.09%

evaluates the mean, than the lowest value obtained is $\alpha = 0,2$. However, for $\alpha = 0$, all the experiments performed in this configuration showed zero discrepancy for the collected values. Thus, because it had the lowest mean error value identified, the momentum coefficient adopted for the network was $\alpha = 0,2$.

B. ENERGY ESTIMATION FOR DIFFERENT SIZE PRODUCTION ORDERS

As presented earlier, the ANN training set was generated randomly. This means that the input vectors would hardly meet the criteria of lower energy consumption or makespan. Therefore, these combinations would certainly only be applied to the programming of a real production system after first going through an improvement step in sequencing the operations carried out by each machine.

Finally, the GA heuristic is applied to the model. Production orders containing different quantities and types of jobs were generated and submitted to the heuristic, to reduce the makespan. A total of 40 experiments were carried out, where the quantity per production order varied from 3 to 10 jobs. The types of jobs in each order were randomly drawn.

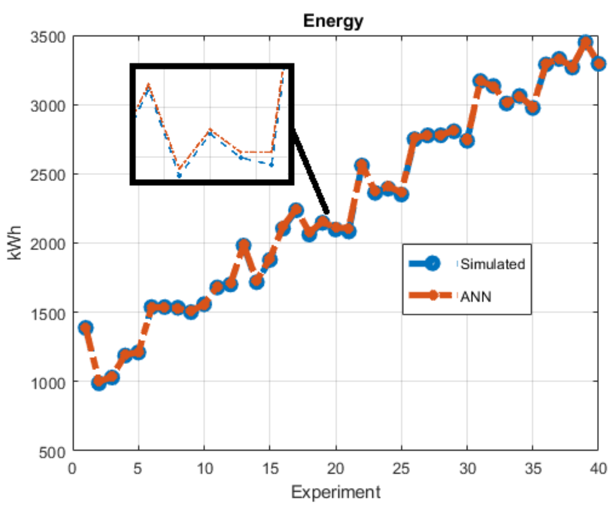

FIGURE 5. Comparison between target value and ANN output.

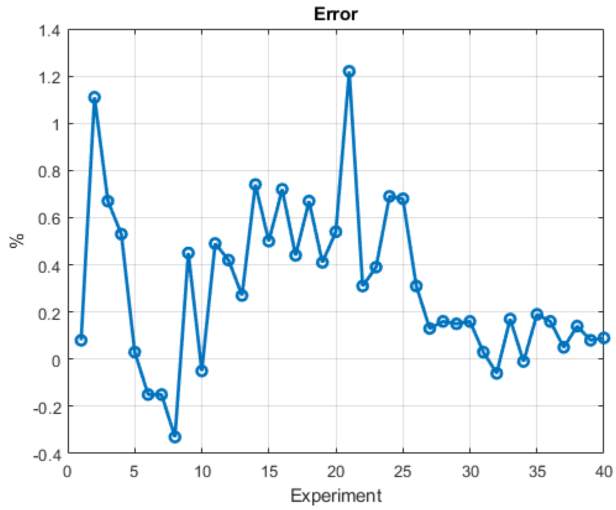

FIGURE 6. Estimation error.

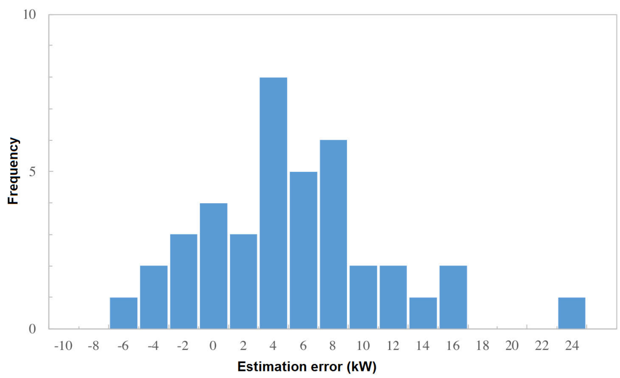

FIGURE 7. Histogram of ANN estimation error.

After executing the heuristic, an input vector with a reduced makespan sequencing was obtained. The simulation model was then adjusted to perform sequencing. The makespan and the total electrical energy consumed during the execution of each sequencing vector were recorded. Finally, the ANN estimates the total energy consumed based on the extraction of the nuances of the vectors. The values obtained for each experiment are presented in Table 5.

For each experiment, the column estimation error (%) shows the relative error between the total energy obtained through the simulation and that estimated by the ANN. It is observed that the errors are relatively low, where the maximum value obtained was 1.22%, which occurred in experiment 21. The graph in Fig. 5 shows a comparison between the values of the simulated energy (target value) and the estimated energy (ANN output) for each experiment. It is possible to observe the non-linear characteristics of the system and the low estimation errors, as shown in Fig. 6. Fig. 7 shows a histogram of the estimation error for the experiments carried out, where it is possible to observe that the distribution is very close to zero.

For all metrics, it was possible to observe the accuracy of the estimation model for the 40 experiments performed. In particular, the average relative error found during this validation step was close to the errors observed during the training phase of the ANN (Table 4), demonstrating the good generalization of the model.

V. CONCLUSION

This study presents an application of ANN as a support tool for the estimation of electric energy consumption in job shop production systems. Such an application makes it possible to contribute to reducing the gap in the literature regarding the study of these systems from an energy perspective, describing a methodology for creating a support tool for the decision-making process based on the decision-making aspect of sustainability.

In particular, this study uses ANN to estimate the total electricity consumption of a job shop system, considering different combinations of production orders. In this way, the proposed model can assist decision-makers in planning production orders from a sustainable perspective where, for example, aspects related to the required energy demand in a given period can be previously evaluated.

Another significant contribution is the possibility of replacing simulation tools to estimate energy consumption. Based on the accuracy of the model, energy consumption can be estimated from the ANN, which is easily used in free software or open-source programming languages available in the market, reducing costs with the acquisition and maintenance of these types of tools.

The modeling carried out starts from the chromosomal representation of permutation with repetition, where the operations of the jobs that make up the system are added to a priority vector, and decomposed by an algorithm for sequencing the operations. During the development of the presented model, it was observed that the length of this vector is a critical point for modeling. Real job shop systems have the flexibility to process different combinations of jobs, implying different production orders that can have varying lengths. Thus, the input vector can also have different dimensions, making it impossible to use the same network for different combinations of jobs. To overcome this issue, modeling is performed from the perspective of machines because, typically, the number of machines in a factory is the same. Thus, the number of independent variables was established based on the number of machines that comprise the system. This restriction allows the number of variables in the input vector to be fixed, and consequently, the number of neurons in the ANN input layer, in such a way that the same network can perform the estimation for different production orders.

The work also involves the addition of a new variable called Priority Factor, which introduces a nuance of processing order to the ANN training. This variable is novel in the literature and represents another important contribution of this work.

As a suggestion for future work, this study could be expanded based on the performance analysis of the proposed ANN in view of different energy policies employed in the system, such as the shutdown of idle machines or the introduction of transient energy stages during the energization and de-energization of equipment. Another possible study front is the use of different machine learning techniques, such as extreme machine learning networks, networks with radial base functions, and vector support machines.

Finally, this work directly contributes to the aspect of sustainability in the context of Industry 4.0, as it proposes the use of machine learning techniques in the manufacturing decision-making process. Once trained, the proposed ANN could act online and directly with the production planning and scheduling system in such a way that the choice between different schedules could be made based on energy efficiency.

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