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Optimizing Sustainable Production: A Mathematical Model for Energy Cost and Completion Time Minimization in Multi-State Manufacturing Systems

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Abstract: - The paper presents a mathematical optimization model designed to enhance sustainable production planning by minimizing both energy costs and total completion time in manufacturing processes. The model specifically addresses the complexities of multi-state single-machine systems with time-dependent electricity costs, integrating considerations such as sequence-dependent setup times and varying machine states. By optimizing job sequencing and scheduling, the model effectively aligns energy-intensive operations with periods of lower energy costs, reducing overall energy consumption and environmental impact. Validated in a real industrial environment within an Italian SME, the model demonstrated significant improvements in company operations, including a reduction in energy costs and completion time. The research contributes to the growing body of work on energy-efficient manufacturing, offering a robust framework for practical application in production systems. Future research directions include the development of advanced algorithms for larger-scale problems and the incorporation of additional factors such as renewable energy availability and the optimization of multiple machines.

Keywords: CO2 emissions reduction, Cost reduction, Energy-efficient scheduling, Mathematical optimization models, Sustainable production planning.

I. INTRODUCTION

In the last few years, due to the continual increase in raw material scarcity, environmental regulation, and raw material cost, production optimization supporting the reduction of environmental impacts have gained interest in production control systems [1]. Manufacturing firms have started to integrate sustainability in production planning and control logic to reduce costs and environmental impacts [2]. It is possible to state that the sustainability production concept has been a growing priority for businesses worldwide [3]. Consequently, energy efficiency has garnered significant attention from academics and industry due to the environmental and economic costs connected with energy consumption and the new global policies and goals, such as Europe's 2030 strategy [4]. The industrial sector is a significant energy consumer and is responsible for 24.2% of global GHG emissions. Addressing energy consumption minimization, cost reduction, and greenhouse gas emission reduction is therefore essential for the industrial sector [5].

The implementation of specific production management and planning techniques considering plants' energy demand and production, has the potential to reduce energy expenses and environmental impacts associated, without requiring costly capital investments [6]. These techniques involve processing energy-intensive orders during periods of low energy prices or greatest availability of renewable energy.

Researchers worldwide have broadly investigated methods for increasing a production system's energy consumption efficiency [7]. However, integrating energy efficiency and environmental impacts into applied production planning and scheduling remains a challenging task, due to the complexity of the models, the still scarce availability of updated data of the production system and the lack of flexibility in production parameters [8]. The evolution into a sustainable production system in line with today's needs also requires the consideration of environmental (product, process and system) issues and performance. Considering at least one of the three sustainability pillars (environmental, economic, and social) in traditional production planning extends its scope toward sustainable production planning [9] .

The study's first objective is therefore to understand how energy efficiency and sustainability can be integrated into the optimization logics of production management. The study's second objective, and core part of the research, is to develop a mathematical optimization model that incorporates the concurrent minimization of energy consumption, total completion time and energy cost into planning, to achieve a more sustainable production. This

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aims to impact the CO_2 emissions caused by energy use, which is a crucial aspect to support decisions related to production planning and scheduling.

II. State Of The Art Analysis

A. Challenges in Sustainable Production Planning

In recent years, several authors have explored approaches and developed various strategies for achieving the objectives of sustainable production planning. Central to these efforts are topics such as minimizing energy usage, reducing greenhouse gas emissions, and improving employee health and safety [10]. A prominent strategy in this domain is the low-carbon process design, which aims to achieve sustainable production planning goals [11]. Wichmann et al. [12] for example, investigated lot-sizing and scheduling processes to reduce machining time and energy usage, highlighting the importance of operational efficiency in sustainability. Additionally, sustainable production planning requires corporations to make integrated decisions that encompass multiple areas of the planning process, such as pricing, store selection, and labor time, all while considering environmental impacts [13]. However, balancing management and planning requirements with sustainability considerations can be challenging. Giret et al. [14] conducted a comprehensive review of sustainable production planning systems, examining both economic and environmental dimensions. They addressed sustainable manufacturing from a scheduling perspective and classified different scheduling operations based on their approach orientation.

On the economic front, Biel and Glock [15] focused on energy-oriented production planning, noting an increase in research dedicated to this area. They found that most studies emphasized job allocation and sequencing over other planning problems. Furthermore, Zarte et al. [16] explored various decision-making methods and sustainable indicators used in manufacturing, examining these from product and production life cycle perspectives. This broad analysis underscores the multifaceted nature of sustainable production planning, and the diverse strategies employed to meet its objectives.

Despite the interesting approaches proposed, the analysed papers reveal several limitations in practical applicability for supporting decision-making within companies. Furthermore, they often focus on the optimization of a single parameter relevant to production control.

B. Sustainability driven Production Planning Mathematical Optimization models

Energy-efficient production planning has become a critical focus in manufacturing, driven by the need to reduce energy consumption and associated costs. Researchers have developed various decision support models and strategies to optimize production processes while minimizing energy usage. Biel and Glock [17] conducted an extensive literature review on decision support models for energy-efficient production planning. They observed a growing interest in energy-oriented production planning approaches, with most articles focusing on job allocation and sequencing over other planning problems. Their research emphasized short-term lot-sizing planning, directly relevant to the proposed study.

Lot-sizing approaches often involve the use of buffers to transition machines into idle states after processing batches. For instance, Zanoni et al. (2014) [18] explored buffer introduction for machine idling, while Fernandez et al. (2013) [19] examined buffer implementation in flow lines to reduce energy costs during peak periods.

Scheduling approaches have addressed various scenarios to enhance energy efficiency. Shrouf et al. [18] focused on single machine scheduling with fixed job numbers, considering machine switch-off potential. Similarly, Moon et al. [19]tackled parallel machine scheduling problems.

In job shop environments, Tang and Dai [20] delved into scheduling problems assuming predetermined job-to-machine assignments and processing orders. They aimed to minimize total energy consumption by adjusting the production rates of the machines. Flexible manufacturing systems with predetermined production targets were examined by May et al. [21], who aimed to minimize energy consumption by maximizing machine standby time. Masmoudi et al. [22] proposed a scheduling model for job shops, using heuristic methods to address NP-hard problems by optimizing machine start times and speeds.

Mixed Integer Linear Programming (MILP) models have been extensively utilized to optimize scheduling. Che et al. [23] developed a MILP model for job sequencing on a single machine, targeting minimal energy consumption and maximum tardiness. Similarly, Meng et al. [24] presented MILP models for flexible job shops, focusing on energy consumption minimization. In addition, Renna [25] introduced switch-off policies in flow-shop systems, while Giglio et al. [26] proposed a real-time energy flexibility control method for serial manufacturing lines with buffers. This approach aimed to align energy requirements with machine switch-off operations.

Finally, Abikarram and McConky [27] developed a method for controlling computer numerical control (CNC) machines to reduce peak energy loads. Their method used power load levels as constraints, allowing job execution only when the load remained within specified limits. By integrating these diverse strategies, researchers aim to enhance the practical applicability of decision support models for sustainable production planning, ultimately contributing to more energy-efficient manufacturing processes.

C. Research question

Our literature review showed that only few publications address the energy efficiency of a multi-state single-machine system, with a time-dependent electricity cost. Moreover, no one considers the possibility of defining different production sequences of jobs considering setup times between jobs. In our analysis, only one article [28] has been found that investigates the total energy costs minimization, combining it with the state-dependent and state-dependent energy consumption.

However, an important simplification was made, reducing machine states to just three. Additionally, no previous work has considered machine state-dependent energy consumption, job sequencing, and completion time together. This study focuses on minimizing the energy cost and completion time of a single machine system, considering different machine states, sequence-dependent time, and total completion time.

The primary aim of this research is to develop a comprehensive mathematical model that optimizes scheduling decision variables in a production system, with the goal of minimizing both energy costs and total completion time. The model will determine the state of CNC machines within defined time slots, accounting for all possible states. The sequence of jobs in the production system will not be fixed or predetermined; instead, the model will accommodate both equal priority for all jobs and varying deadlines. Furthermore, the model will incorporate sequence-dependent job characteristics, where setup times between jobs will vary based on the preceding and subsequent job characteristics.

Lastly, the research will focus on creating a model capable of budgeting optimal energy requirements, ensuring the achievement of the outlined objectives in the production system. The model will generate a series of possible production scenarios, reducing energy use and, consequently, the related environmental impact and costs, both in terms of reduced use and more profitable pricing.

III. MATERIAL AND METHODS

A. Model context and description

This chapter deals with the development of an optimisation algorithm for sequencing and scheduling. The model will allow sustainable production scheduling referred to low-level, short-term manufacturing operations or real-time decisions made in a manufacturing system, being at the basis of a decision support system for production job sequence reconfiguration.

The model considers multi-states single machine scheduling problem when the sequence of the jobs not pre-emptive, and the time-of-use (TOU) electricity tariffs are considered for each period. So, the energy costs are varying among the periods and the energy consumption of the machine’s states are different. Therefore, in this problem the scheduling problem search an optimal schedule to allocate the states with low consumption in the peak time periods, and the states with high consumption in the off-peak time periods. Moreover, the model minimizes the total completion time considering sequence-dependent setup time between job and the penalty delay.

The model considers a finite set of I jobs $I = j\acute{\imath}$ which require being processed within a given planning horizon T and before a define deadline for each job d_i. No pre-emption is allowed on jobs, and the production system has enough capacity to complete all jobs defined in the time horizon T. The equipment runs on electricity, and therefore, is subject to TOU electricity tariffs. The horizon T is divided into t periods with the same length which can be characterized by their unit of energy price, or they job process time.

The proposed model is built under the context of a sequence-dependent of the job to be processed and the scheduling decisions are assumed to be affected by time-of-use electricity prices and maximum completion time possible for the jobs. Thus, the objective is to develop an optimal sequencing schedule of jobs such that electricity and completion time are minimized.

The assumptions and the constraints of this problem are considered as follows. There is one machine and multiple jobs to be worked on this machine over a given time horizon T.

All the jobs j = 1, ..., n are available during the whole time horizon (from period t = 0 to t = T). It means that, if the machine goes in state s, it must be in the same state during the period. So, for the processing jobs, if the machine was started to perform job *j*, it must continue to perform this job during the allocated periods. This assumption is necessary in order to reduce the complexity of calculation. Also, every job requires a setup time, i.e., a time to setup the machine to start processing that job. However, the setup time depends on the last completed job, meaning that the setup time for a given job can be longer or shorter depending on which job was processed immediately before. Finally, some jobs may also have a deadline, i.e., a time strictly before the end of the time horizon by which the job must be completed. The set of jobs j to be processed, constitute the project to which is assigned a deadline (pd), i.e. the period t in which all jobs must be completed. The variable pd can be denoted in the interval T and is not restricted by the model. In fact, based on the value of the delay penalty variable (dp), the model looks for the best solution between penalty and energy cost.

The considered machine has five possible states (Shutdown, Starting up, Setting up, Processing and Idle). The transition states between different machine state are defined. The initial and final states of the machine are assumed as OFF states.

B. Mathematical model

The declarations of sets, parameters, variables, objectives, and constraints are necessary to describe models. The set index is the feature that permits a concise model to describe a large mathematical program. Almost all of the parameters, variables, and constraints in a typical model are indexed over sets, and many expressions contain operations (usually summations) over sets.

1) Set of indices

I = Total number of jobs to be processed by the machine
T= Total number of period of time t
S =Total number of machine state k

- Shot down
- Starting up
- Setting up
- Processing
- Idle

2) Parameters

st_k = State transitions, i.e., list of states that the machine can go from state k.
k_0 = State if the machine at the beginning of the time horizon. Initial state of the machine at time 0
(st_{k0} = State transitions, i.e., list of states that the machine can go from state k_0.)
c_t = Cost of energy (Euro per unit of energy) in Period t.
d_i = Deadline to complete job i (the last time period of the horizon by default)
r = Ram up time (number of time periods), i.e the time it takes to start up the machine from the shutdown state.
s_{ij} = Setup time (number of time periods) to start processing Job j when the last completed job was Job i.
p_i = Process time (number of time periods) of job i.
e_k = Amount of energy (unit of energy per period of time) that machine consumes during state k.
pd = Project deadline, i.e., the period by which all jobs are expected to be completed.
dp = Delay penalty (Euro per period), i.e., amount changed for each period that exceeds the project deadline.

3) Decision Variables

Index convention: i,h,j for jobs; t for time periods; k for machine states
x_{it} = Equal 1 if the machine starts processing Job i in period t, 0 otherwise.
y_{ijt} = Equal 1 if the machine setup from job i to job j in period t. 0 otherwise.
z_{kt} = Equal 1 if the machine is in State k in Period t, 0 otherwise.
v = Last period of the horizon that the machine is operational.

4) Object function

The goal is to minimize total energy cost while completing all jobs as early as possible:

$$\min \sum_{k,t} (e_k \times c_t \times z_{kt}) + (v \times dp)$$

5) Constrains

1. $z_{kt} \leq \sum_{k' \epsilon\, st_k} z_{k'(t+1)}\,,\ \forall k, t$
2. $\sum_{k' \epsilon\, st_{k0}} z_{k' t_0} = 1$
3. $z_{1(t-1)} + z_{2t} - 1 \leq z_{2t'},\ \forall t > 1, t + 1 \leq t' \geq t + r - 1$
4. $\sum_{t''} y_{ijt''} + x_{jt} - 1 \leq z_{3t'},\ \forall i, j, t, t - s_{ij} \leq t' \geq t - 1$
5. $x_{it} \leq z_{4t'},\ \forall i, t, t \ \leq t' \geq \ t + p_i - 1.$

$$x_{it} \leq 1 - x_{jt'}, \qquad \forall i \ \neq j, t, t \leq t' \geq \ t + p_i - 1.$$

6. $\sum_k z_{kt} = 1\,,\ \forall t$
7. $\sum_{t \leq \min\,(d_i - p_i\,,\, t_{end} - p_i)} x_{it} = 1\,,\ \forall i$
8. $\sum_i x_{it} \leq 1,\ \forall t$
9. $\sum_i \sum_t y_{ijt} \leq 1,\ \forall j$
10. $\sum_j \sum_t y_{ijt} \leq 1,\ \forall i$
11. $x_{ht} \leq \sum_i \sum_{t' \leq\, t - s_{ih}} y_{iht'},\ \forall h, t,$
12. $x_{ht} \leq \sum_j \sum_{t' \geq\, t + p_h} y_{hjt'},\ \forall h, t,$
13. $t \times z_{4t} \leq pd + v,\ \forall t$
14. $\sum_{t'' \leq t'} y_{ijt''} + x_{jt} - 1 \leq z_{2t'} + z_{4t'} + z_{5t'},\ \forall i, j, t, t' = t - s_{ij} - 1$
15. $x_{it} \leq z_{1t'} + z_{3t'} + z_{5t'},\ \forall i, t, t' = t + p_i$

The optimization model includes several constraints that ensure proper scheduling and state transitions for the machine. Equation (1) defines the possible state transitions for the machine from state kk. Equation (2) specifies the initial state of the machine. Equation (3) accounts for the sequential ramp-up time, ensuring that enough time is allocated for the machine to start up. Equation (4) governs the setup time between jobs, stipulating that if the machine transitions from job i to job j and starts processing j at time t, the machine must first be in the setup stage for job j. This ensures that the necessary setup time is included before processing can begin. Similarly, Equation (5) ensures that each job is processed for the full duration of its required time slot. Equation (6) enforces that at every period, the machine must be in one of its defined states, preventing any undefined behavior. Equation (7) requires that each job is completed before its deadline. Equation (8) ensures that only one job can initiate at any given time period, preventing overlap in job start times.

Equations (9) and (10) limit job transitions.

Equations (11) and (12) define the time allocation for setup both before starting and after finishing a job, ensuring that proper time slots are reserved for changeovers.

Equation (13) tracks the last period during which a job was processed, enabling the model to calculate delay penalties for the objective function. Finally, Equations (14) and (15) ensure that the machine transitions correctly before starting the setup phase and after finishing the processing phase, maintaining consistent state transitions throughout the scheduling process.

IV. Model Testing: Industrial Use Case

Validating the proposed mathematical optimization model is essential to ensure its effectiveness in minimizing energy costs and total completion time in a sustainable production environment. To achieve this, a comprehensive approach involving both theoretical and practical evaluation was undertaken.

The model was validated within a real industrial environment of a dynamic Italian SME located in northern Italy. This company specializes in processing metal and plastic materials, producing mechanical components for machinery. Each component is custom-made, typically in single sets, positioning the company as a specialized

player in customized production for highly demanding industrial clients. This tailored production involves machinery ranging from CNC machining and turning centres to waterjet and laser cutting machines.
Production planning and scheduling are managed daily. Orders are organized by due date and subdivided by processing type and material. For validation, the focus was on three CNC machines, each handling different types of machining and materials, thus modelled as individual entities. An order is processed by one CNC machine and then assembled manually by operators. Deadlines vary significantly, with some orders requiring completion within hours and others by the end of the day. Each order is presented as a CAD drawing, and the production planning operator defines a production order each morning, generating a G-code file for each selected order. Setup time between orders varies depending on the thickness of the metal sheet, necessitating machine calibration and tool changing. If the thickness remains unchanged, setup time only involves loading the sheet.
Analysis of the current situation revealed that the company's typical work shift is eight hours. However, as the machine operates without an operator during machining, extra hours are often utilized for planning to ensure parts are ready by the next morning. Job scheduling data, covering one working day, was retrieved directly from the company. Energy costs and machine consumption in various states were gathered directly from the company. Table 1 lists the variables utilized in the model.

Table 1 Entry parameters for the current production scheduling scenario

Machine state	Energy cons. (kWh)
Shutdown	0
Starting up	5
Setting up	3
Processing	4
Idle	2

Job	Process Time (n° periods)	Deadline (period)	Deadline project (t)	Delay penalty
1	3	32	16	0
2	2	32		
3	4	32		
4	3	32		
5	3	32		

Job / Setup	1	2	3	4	5
1					
2	0				
3	0	0			
4	0	0	0		
5	0	0	0	0	

A clearer view of the as-is state is provided by Table 2. It illustrates the current production scheduling state (S0) for a single day, divided into 24 slots periods and applied to 1 CNC machine. Green cells indicate periods where jobs (J1 to J5) are being processed. The chart visually represents the changes in machine states throughout the day and their associated energy costs.

Table 2 Current production scheduling scenario S0

Production sequencing - S0																								
Period (t)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Cost (cent €/kWh)	15	15	18	18	20	20	22	22	25	25	25	25	22	22	22	20	20	18	18	18	15	15	15	15
Machine state																								
Shutdown																								
Starting up																								
Setting Up																								
Processing			J1				J2			J3								J4				J5		
Idle																								

Table 2 represents the current production scheduling scenario (S0) for a single day. The green cells indicate the processing of jobs (J1 to J5) across different periods. The visualization highlights both the machine's idle times and the actual working periods, revealing inefficiencies such as extended idle times and multiple setup transitions that increase the overall energy consumption and operating costs.
Following the application of the algorithm and considering the same entry parameters, Table 3 presents the new optimized production scenario.

Table 3 Optimized scheduling scenario S1

Production sequencing - S0																								
Period (t)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Cost (cent €/kWh)	15	15	18	18	20	20	22	22	25	25	25	25	22	22	22	20	20	18	18	18	15	15	15	15
Machine state																								
Shutdown																								
Starting up																								
Setting Up																								
Processing			J1			J4				J2			J5					J3						
Idle																								

The completion time is shortened by approximately 30 minutes (one period). In this scenario, the production sequence was modified, allowing for more effective management of setups. The more efficient job sequencing and

minimized idle times in this optimized scenario are key contributors to the energy cost savings and reduced completion time.
The analysis of the results clearly indicates an improvement in performance. The total cost decreased by 10%, while the completion time was shortened by 30 minutes (t = 1). However, it's important to note that the standard working shift is 8 hours, with up to 4 additional hours available for overtime. Typically, the last task begins before the previous one is fully completed. In the initial scenario (S0), the last task starts at time t = 22, resulting in 5 overtime slots, equivalent to approximately 2 hours and 30 minutes. In contrast, in the optimized scenario (S1), the overtime is reduced to just one slot, or 30 minutes.
If the company aims to complete the tasks within the standard 8-hour shift, management could assign an appropriate penalty value, and the model would then optimize the schedule accordingly to ensure all work is completed within the 8-hour timeframe.

V. Conclusion And Future Development

The research presented in this paper has presented a mathematical optimization model focused on minimizing energy costs and total completion time in a production environment. The model effectively integrates the consideration of varying machine states, time-dependent electricity tariffs, and sequence-dependent setup times, thereby providing a robust framework for sustainable production scheduling. Through the validation process, the model demonstrated significant improvements in reducing both energy costs and production times, affirming its potential for practical application in real-world industrial environments.
However, despite these promising results, there are areas where the model can be further enhanced to increase its effectiveness and applicability. One critical aspect for future development is the optimization of the solution phase. Given the NP-hard nature of the problem, the current method may not always yield optimal solutions within a reasonable timeframe, particularly for large-scale problems. Developing advanced solving algorithms, such as genetic or heuristic algorithms, is crucial for addressing this limitation.
Additionally, the model's adaptability to various real-world scenarios can be expanded by incorporating additional factors. These include considering renewable energy availability, which could optimize energy-intensive tasks based on renewable energy supply, thus further reducing costs and environmental impact. Another potential improvement is refining the model to account for different energy consumption rates per job, which would be especially relevant for modern machining centres that integrate diverse manufacturing processes. Moreover, the model could be extended to handle multiple machines and job release times, allowing for the simulation and optimization of more complex and realistic production environments, such as flow shops and job shops.
By addressing these areas, the model can be further refined to meet the evolving demands of sustainable production, offering greater flexibility and efficiency in diverse industrial contexts.

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