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# An Optimization Model for Smart and Sustainable Distributed Permutation Flow Shop Scheduling

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**Abstract**

Smart production scheduling has gained significant attention due to advancements in industrial informatics and technologies that enable the monitoring, control, and adaptation of task scheduling in response to disruptive events. These events can include machine breakdowns, variations in task processing times, and the arrival of new or unexpected tasks. Concurrently, sustainable production scheduling aims to optimize task scheduling by considering economic, environmental, and social factors. This paper introduces a novel optimization model for the development of smart and sustainable production scheduling in a distributed permutation flow shop. The proposed model aims to minimize the makespan while simultaneously limiting the number of lost working days and energy consumption. It also strives to increase job opportunities within acceptable limits. To evaluate the proposed model, we conduct numerical simulations using various examples and a real-case study focusing on auto workpiece production. The results demonstrate the superior performance of the proposed model. Sensitivity analyses are performed to assess the model's ability to deal with disruptions and uncertainties while satisfying economic, environmental, and social considerations.



*Keywords:* Smart Production; Sustainbale Production; Distributed Permutation Flow Shop; Optimization;

## 1. Introduction and literature review

In the current highly competitive manufacturing environment, organizations are increasingly focusing on creating sustainable production systems encompassing social, environmental and economic factors [1]. These companies

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recognize the importance of incorporating these aspects of sustainability, coupled with the ability to effectively manage uncertainties and disruptions in production scheduling. [2]. As a result, including task assignments on machines during the production scheduling process has become a key objective for manufacturing companies, especially to deal with uncertainty [3]. By doing so, they can improve their sustainability practices and ensure the efficient resources allocation in their operations.

With advances in technology in the context of Industry 4.0, various modes of machine operation are available, ranging from manual to highly automated processes. Therefore, production managers must carefully choose the appropriate mode for each machine, taking into account economic, environmental, and social factors [4]. These modes involve varying levels of human interaction, such as manual operation with significant human involvement or automated modes with little human intervention [5]. Based on these considerations, we develop a new optimization model for a smart and sustainable distributed permutation flow shop. This model addresses the challenges of task processing in the presence of disruptions, considering multiple machines within each factory. The primary objective is to minimize the makespan, which is the maximum completion time among all factories.

The distributed permutation flow shop problem has garnered attention in recent years. Early studies by Naderi and Ruiz [6] in 2010 focused on the minimization of makespan, introducing decision rules and variable neighborhood procedures for task assignment. Subsequent approaches included genetic algorithms [7], modified iterated greedy search [8], scatter search heuristics [9], and metaheuristic algorithms inspired by chemical reactions [10]. Fernandez-Viagas et al. [11] explored the minimization of total flow time, while Pan et al. [12] and Ruiz et al. [13] employed local search and simplified iterated greedy heuristics, respectively. Meng et al. [14] extended the problem to include multiple customers and developed an evolutionary swarm-based optimization algorithm. Environmental sustainability was later considered, with Wang and Wang [15] focusing on energy-efficient scheduling, Fu et al. [16] utilizing a brainstorm algorithm, while Wang et al. [17] employed a multi-objective whale optimization algorithm. Along the same lines, Lu et al. [18] integrated processing time penalties as a negative social factor in their energy-efficient distributed permutation flow shop approach, whereas Fathollahi-Fard et al. [5] formulated a multi-objective sustainable scheduling problem that considered lost working days, energy consumption, makespan, and number of job opportunities as objectives. For aerospace components, Jiang et al. [19] addressed the energy-efficient distributed permutation flow shop scheduling problem by introducing a lot-splitting model. They studied an enhanced crossover-based artificial bee colony algorithm. Finally, Yue et al. [20] proposed an energy-efficient scheduling model for the printed circuit board manufacturing industry utilizing a hybrid Pareto spider monkey optimization algorithm.

Within the scope of the reviewed literature, and to the best of our knowledge, only Lu et al. [18] and Fathollahi-Fard et al. [5] have ventured into integrating social, environmental, and economic factors simultaneously. However, their analyses fell short of encompassing the explicit treatment of uncertainty factors, such as lost working days, energy consumption, and job opportunities, within their constraints. Notably, none of the existing studies have effectively addressed the intricate challenges posed by the distributed permutation flow shop scheduling problem, characterized by uncertainties such as unforeseen tasks, machine breakdowns, and variances in task processing times.

In light of these gaps, this research seeks to address the following research question: How can a holistic optimization model be developed to address the complexities of the distributed permutation flow shop scheduling problem, integrating environmental, social, and economic considerations, while effectively managing uncertainties related to disruptive events? Our proposed model considers the presence of disruptive events like machine breakdowns, fluctuations in task processing times, and the abrupt emergence of unforeseen tasks within each factory setting. Additionally, we extend our makespan optimization framework to incorporate essential environmental and social constraints, thereby contributing to the overall scheduling system sustainability. By addressing these unaddressed intricacies, we aim to make a meaningful stride toward a more robust and comprehensive understanding of the distributed permutation flow shop scheduling challenge.

The remaining sections of this paper are structured as follows: In Section 2, a model is established to define the optimization problem leading to a smart and sustainable distributed permutation flow shop scheduling. Section 3 presents the proposed approach to solve various test instances as well as a real-case study. Additionally, sensitivity analyses on key parameters of the optimization model are provided. Finally, Section 4 summarizes the main findings, discusses the limitations, and suggests avenues for future research.

## 2. Proposed problem

The primary objective of the proposed problem is to obtain the best possible order to process *N* tasks on *M* machines having *P* different modes of operation and being dispersed among *F* factories. These tasks entail several operations. We will first explore the factors associated with environmental (Section 2.1) and social criteria of sustainability (Section 2.2), followed by parameters and formulations related to uncertainty (Section 2.3). Ultimately, we will present the optimization problem that has been established (Section 2.4).

### *2.1. Environmental considerations*

Given the significance of energy consumption and its potential environmental impact, particularly about electrical energy use and its association with greenhouse gas emissions from sources like fossil fuels, effective energy management is of paramount importance [5]. To address this crucial aspect, our study meticulously categorizes machine energy consumption into three distinct levels, each corresponding to different operational states: ultra-low idle, idle, and processing. These operational levels are denoted as $EC_{mpf}$, $IEC_{mf}$, and $UEC_{mpf}$, respectively. Ensuring adherence to a predefined upper bound ($UBEC$), the cumulative energy consumption across these levels is meticulously regulated to minimize potential environmental impacts.

Moreover, the machines can be operated in either manual or automatic mode, each mode corresponding to a distinct rejection rate ($RW_{mpf}$). These rejections rates specifically refer to the number of faulty components produced by machines. Furthermore, there exists a predefined threshold for the overall acceptable waste during the production planning, denoted as $MW$. The inclination towards automatic mode, as opposed to manual operation, is grounded in its ability to curtail wasteful outcomes. This efficacy is primarily attributed to the precision and consistency inherent in automated processes, which play a pivotal role in mitigating the occurrence of flawed components.

### *2.2. Social considerations*

While addressing the multifaceted dimensions of social sustainability requires consideration of various factors, such as reducing child labour, ensuring equal pay, prioritizing work safety, and providing social security, this paper strives to encompass the realm of societal well-being by integrating the social aspects within production planning. This approach takes into account not only the creation of job opportunities and the reduction of lost working days to enhance workers' welfare and environmental conditions [5], but also other key elements relevant to sustainable development.

The allocation of workers needed for task processing ($JO_{mpf}$) inherently varies based on the operational mode of the machine. Manual operation typically demands a larger workforce compared to automated operation. In line with promoting a greater number of job opportunities, a lower bound is established for the anticipated job opportunities ($LBJ$). Furthermore, the operational mode significantly influences operators' training duration, leading to the loss of productive working days ($LD_{mpf}$). The minimization of this factor aligns with both economic and social considerations. An upper bound ($UBL$) is specified to regulate the acceptable number of lost working days.

### *2.3. Uncertainty considerations*

Incorporating uncertainties and disruptive events into the proposed model, this paper presents a simulation-based optimization approach that captures the dynamics of an uncertain production environment. This approach involves the estimation of task processing times and the anticipation of potential disruptions, encompassing scenarios such as the sudden introduction of new tasks and unexpected machine breakdowns. By considering pessimistic, realistic, and optimistic scenarios, the processing time ($PT_{nmpf}$) of task n by machine *m* operated in mode *p* at factory *f* can be estimated. Inspired by the fuzzy method developed by Jiménez et al. [21], the expected processing time ($EPT_{nmpf}$) is determined using the pessimistic ($PT^{pes}_{nmpf}$), realistic ($PT^{rea}_{nmpf}$), and optimistic ($PT^{opt}_{nmpf}$) estimates.

$$EPT_{nmpf} = \frac{PT_{nmpf}^{pes}, +2PT_{nmpf}^{rea} + PT_{nmpf}^{opt}}{4} \tag{1}$$

To enhance our estimation, we incorporate machine failure and repair rates into the processing time calculation. In the proposed distributed permutation flow-shop system, machines are classified into two states: able to process tasks or in need of repairs. Random machine breakdowns follow an exponential distribution, as described by He and Sun [22]. Each machine in a specific production mode has fixed failure and repair rates noted respectively $\gamma_{mp}$ and $\delta_{mp}$,. The processing time ($PC_{nmpf}$) for an operation is determined by adding to the expected processing time ($EPT_{nmpf}$), the production delay caused by machine breakdowns and the time needed for repairs, as outlined in the probabilistic theory introduced by Ghaleb et al. [23]:

$$PC_{nmpf} = EPT_{nmpf} + \left\{\left(TF_{nmpf} + \frac{1}{\delta_{mp}}\right) \times \left(\frac{e^{-\gamma_{mp}EPT_{nmpf}}}{1 - e^{-\gamma_{mp}EPT_{nmpf}}}\right)\right\} \tag{2}$$

where the occurrence of a failure within the expected processing time ($EPT_{nmpf}$) is represented by $TF_{nmpf}$ and is estimated as follows:

$$TF_{nmpf} = \frac{\frac{1}{\gamma_{mp}}\left(1 - e^{-\gamma_{mp}EPT_{nmpf}}\right) - EPT_{nmpf}e^{-\gamma_{mp}EPT_{nmpf}}}{1 - e^{-\gamma_{mp}EPT_{nmpf}}} \tag{3}$$

Other uncertainties are related to the machine state ($MS_{mpft}$) which is taken into consideration. When a machine is actively participating in an operation, its state is set to 1. Conversely, if the machine is not occupied with any operation, it may be subject to maintenance or repair, resulting in to a state of 0. The time allocated to machine repairs is denoted $RP_{mpft}$, while $AV_{mpft}$ represents the time needed for the machine to complete a task ($MS_{mpft} = 1$). Moreover, the feasibility of executing a task on a specific machine ($H_{nimpft}$) depends on its processing capacity.

### *2.4. Proposed optimization model*

The proposed optimization model aims to minimize the expected total makespan ($CMAX_t$) for all factories at time *t*. The model incorporates two main decision variables: the mode of operation selected for each machine ($Y_{mpf}$) and the assignment of tasks to the machines ($X_{nimpft}$) determining the sequence. Additionally, there are four auxiliary decision variables: the expected task start time on a machine ($S_{impft}$) related to the task sequence ($X_{nimpft}$), the number of tasks assigned to each factory ($A_{ft}$) determined by the task assignment ($X_{nimpft}$), the task completion time ($C_{impft}$) dependent on task assignment ($X_{nimpft}$) and the task start time ($S_{impft}$), and the expected completion time of the tasks within a factory ($CT_{ft}$) calculated using task completion times ($C_{impft}$). Using these notations, a new mixed integer linear programming model that addresses both sustainability dimensions and uncertainties is presented:

$$Z = \min(CMAX_t = \max(CT_{ft})) \tag{4}$$

*s.t.*

$$\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{f=1}^{F}(Y_{mpf} \times JO_{mpf} \times CJ_{mpf}) + \sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{f=1}^{F}(Y_{mpf} \times CO_{mpf}) \leq B \tag{5}$$

$$\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{f=1}^{F}(Y_{mpf} \times RW_{mpf}) \leq MW \tag{6}$$

$$\sum_{i=1}^{N}\sum_{f=1}^{F}X_{nimpft} = 1, \qquad \forall n \in \mathcal{N}, m \in \mathcal{M}, p \in \mathcal{P}, time\ t \tag{7}$$

$$\sum_{n=1}^{N}\sum_{f=1}^{F} X_{nimpft} = 1, \qquad \forall i \in \mathcal{N}, m \in \mathcal{M}, p \in \mathcal{P}, time\ t \tag{8}$$

$$\sum_{n=1}^{N}\sum_{i=1}^{N}\sum_{m=1}^{M}\sum_{p=1}^{P}(X_{nimpft}) = A_{ft}, \qquad \forall f \in \mathcal{F}, time\ t \tag{9}$$

$$\sum_{n=1}^{N}\sum_{i=1}^{N} X_{nimpft} < N \times Y_{mpf}, \qquad \forall m \in \mathcal{M}, p \in \mathcal{P}, f \in \mathcal{F}, time\ t \tag{10}$$

$$\sum_{p=1}^{P} Y_{mpf} = 1, \qquad \forall m \in \mathcal{M}, f \in \mathcal{F} \tag{11}$$

$$X_{nimpft} \le H_{nimpft} \qquad \forall i, n \in \mathcal{N}, m \in \mathcal{M}, p \in \mathcal{P}, f \in \mathcal{F}, time\ t \tag{12}$$

$$ST_{i,m,pft} \ge \sum_{n=1}^{N}(X_{nimpft} \times \{MS_{mpft}AV_{mpft} + (1 - MS_{mpft})RP_{mpft}\}), \quad \forall i \in \mathcal{N}, m \in \mathcal{M}, p \in \mathcal{P}, f \in \mathcal{F}, time\ t \tag{13}$$

$$C_{impft} \ge ST_{i,m-1,pft} + \sum_{n=1}^{N}(X_{nimpft} \times PC_{nmpf}), \qquad \forall i \in \mathcal{N}, m > 1, p \in \mathcal{P}, f \in \mathcal{F}, time\ t \tag{14}$$

$$C_{impft} \ge ST_{i-1,mpft} + \sum_{n=1}^{N}(X_{nimpft} \times PC_{nmpf}), \qquad \forall i > 1, m \in \mathcal{M}, p \in \mathcal{P}, f \in \mathcal{F}, time\ t \tag{15}$$

$$CT_{ft} \ge \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{p=1}^{P} C_{impft}, \qquad \forall f \in \mathcal{F}, time\ t \tag{16}$$

$$\sum_{m\in M}\sum_{p\in P}\sum_{f\in F}(Y_{mpf} \times EC_{mpf}) + \sum_{m\in M}\sum_{p\in P}\sum_{f\in F}\sum_{n\in N} UEC_{mpf} \times Y_{mpf} \times PC_{nmpf} + \sum_{m\in M}\sum_{f\in F} IEC_{mf} \times (\sum_{p\in P} Y_{mpf}) \le UBEC \tag{17}$$

$$\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{f=1}^{F}(Y_{mpf} \times JO_{mpf}) \ge LBJ \tag{18}$$

$$\sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{f=1}^{F}(Y_{mpf} \times LD_{mpf}) \le UBL \tag{19}$$

$$A_{ft}, ST_{impft}, C_{impft}, CT_{ft}, CMAX_t \ge 0 \tag{20}$$

$$Y_{mpf}, X_{nimpft} \in \{1,0\} \tag{21}$$

The main objective (Eq. 4) is to minimize the makespan, which is the maximum duration required to complete all tasks in all the factories. Constraint (5) considers the economic concerns by keeping the total expenses linked to the selection of different operation modes and worker salaries under a predefined budget. Additionally, Constraint (6) plays a role in managing quality by imposing an upper limit on the ratio of rejected products. Constraints (7) and (8) contribute to establishing a coherent and well-structured task schedule. Constraint set (9) quantifies the number of tasks assigned to each factory. Significantly, Constraints (10) and (11) enforce the stipulation that once a machine's operational mode is determined, it remains fixed throughout the entire planning period. Constraint set (12) addresses the practicality that not all tasks are suitable for execution on every machine. Instead, each specific type of operation corresponds to a defined set of tasks. Navigating the intricate relationship between task timing, Constraints (13) to (15) oversee the scheduling process based on task starting and completion times. In a complementary fashion, Constraint set (16) establishes completion times for each factory, ensuring synchronization and orderliness. Turning attention to sustainability, Constraints (17) to (19) set upper limits on energy consumption, job opportunities, and lost working days, instilling these critical considerations into the optimization process. Lastly, rounding out the comprehensive framework, non-binary and binary variables are formally introduced in Eqs. (20) and (21).

## 3. Computational experiments

To assess the effectiveness of our optimization model, we undertook a comprehensive evaluation covering a range of testing scenarios, encompassing diverse scales of test instances and a real-world case study. Furthermore, we conducted an array of sensitivity analyses, delving deeper into the underlying behaviour of the model. For all analyses, the computational framework hinged on the CPLEX solver within the GAMS software, with computations executed on a laptop powered by an Intel(R) Core(TM) i7-10850H CPU @ 2.70GHz 2.71 GHz.

This evaluative journey takes place in the following sections. In Section 3.1, we embark on the resolution of the proposed problem by immersing ourselves in the exploration of random instances. In Section 3.2 a real case study is defined, where the practical applicability of our model takes centre stage. The sensitivity analyses, outlined in the subsequent sections, scrutinize pivotal parameters and sustainability constraints, illuminating their influence and implications. This holistic and multifaceted evaluation framework strives to foster a comprehensive understanding of the model's performance, pragmatic utility, and adaptability across different scenarios.

### *3.1. Random instances*

We generated random test instances by referencing benchmarks from the literature [5, 23], which informed the definition of parameter ranges outlined in Table 1. This process yielded four distinct test instances, each meticulously solved. Their respective details are provided in Table 2. Notably, our T1 to T3 test instances exclusively considered two operating modes: automatic and manual. In contrast, the T4 test instance explored a broader spectrum with three operating modes: one manual and two automatic modes, involving programmable logic controllers (PLC) and advanced process controllers (APC).

Our comprehensive analysis of these test instances revolves around two key aspects: the resolution time and the quality of the derived solutions. In particular, we scrutinize the impact of varying the number of tasks on the model's behaviour. This influence is evident through both the quality of the solutions, as gauged by the makespan, and the time required for resolution. Our findings underscore the model's sensitivity to changes in the number of tasks, shedding light on its dynamic responsiveness to different operational scenarios.

### *3.2. Case study*

A case study was conducted using data provided by Wuhan Huazhong Numerical Control Co. to validate the effectiveness of the presented model. The case study focused on the production of flanges such as that shown in Fig. 1, which are essential components in automotive manufacturing. This production process involves several CNC machines operating in different modes: a manual mode (MAN), and two automatic modes using either a PLC or an APC. The production of a flange includes ten tasks performed on five CNC machines located in the same factory. The processing times of these tasks according to the different operation modes are estimated on the basis of Table 1. Additionally, parameters such as energy consumption levels and economic and social factors are specified in Table 3. The case study resulted in an optimal makespan of 488.19 minutes, which was achieved in a computational time of 8.45 seconds.

Table 1: Range of parameters

| Parameter | Range |
|---|---|
| $MW$ | **if** *sum*($RW_{mpf}$)>1 *randi*([*round*(*sum*($RW_{mpf}$)/2), *round*(*sum*($RW_{mpf}$))]) **else** *rand*()+(*sum*($RW_{mpf}$)/2)**end** |
| $\delta_{mp}$ | $\frac{1}{\frac{3}{2} * sum(H_{nimpft} * EPT_{nmpf})}$ |
| $\gamma_{mp}$ | $\frac{1}{7 * sum(H_{nimpft} * EPT_{nmpf})}$ |
| $RP_{mpft}$, $AV_{mpft}$ | **if** $MS_{mpt} == 0$ $RP_{mpft} = normrnd\ (sum(H_{nimpft} * PC_{nmpf}), 2 * sum(H_{nimpft} * PC_{nmpf}))$**else** $AV_{mpft} = exp\left(3 * sum\left(H_{nimpft} * PC_{nmpf}\right)\right)$ **end** |
| $H_{nimpft}$ | *round(rand*(N, I, M, P, F)*0.9) |
| $MS_{mpft}$ | *round(rand*(M, P)*0.8) |
| $B$ | *randi*([*round*(*sum*($JO_{mtf}.* CJ_{mtf} + CO_{mtf}$)/2), *round*(*sum*($JO_{mtf}.* CJ_{mtf} + CO_{mtf}$))]) |
| $UBEC$ | *round* (*sum*($(IEC_{mpf} + UEC_{mpf} + EC_{mpf}) * (\frac{2}{3})$)) |
| $EC_{mpf}$ | (*randi*([20, 40],M, P, F)+*rand*())*$10^5$ |
| $UEC_{mpf}$ | (*randi*([2, 7],M, P, F)+*rand*())*$10^5$ |
| $IEC_{mf}$ | (*randi*([8, 12],M, P, F)+*rand*())*$10^5$ |
| $RW_{mpf}$ | *rand*(M, P, F)*0.1 |
| $UBL$ | *round* (*sum*($LD_{mpf} * (\frac{2}{3})$)) |
| $LBJ$ | *round* (*sum*($JO_{mpf}/3$)) |
| $LD_{mpf}$ | *randi*([8, 30],M, P, F) |
| $CJ_{mpf}$ | *randi*([8, 20],M, P, F) |
| $JO_{mpf}$ | *randi*([2, 9],M, P, F) |
| $CO_{mpf}$ | *randi*([8, 20],M, P, F)*$10^4$ |
| $PT_{nmpf}^{opt}$ | *randi*([2, 4],N, M, P, F) |
| $PT_{nmpf}^{rea}$ | *randi*([4, 6],N, M, P, F) |
| $PT_{nmpf}^{pes}$ | *randi*([6, 8],N, M, P, F) |

* These functions are sourced from the definitions provided in MATLAB software from Mathworks.

Table 2: Results of test instances.

| Test instances | Sizes | | | | Results | |
|---|---|---|---|---|---|---|
| | Number of factories (F) | Number of machines (M) | Number of production modes (P) | Number of tasks (N) | Optimal makespan (*h*) | CPU time (*s*) |
| T1 | 2 | 2 | 2 | 4 | 58.55 | 10.98 |
| T2 | 2 | 2 | 2 | 8 | 121.62 | 14.75 |
| T3 | 2 | 4 | 2 | 20 | 638.43 | 34.72 |
| T4 | 3 | 4 | 3 | 30 | 1009.6 | 65.74 |

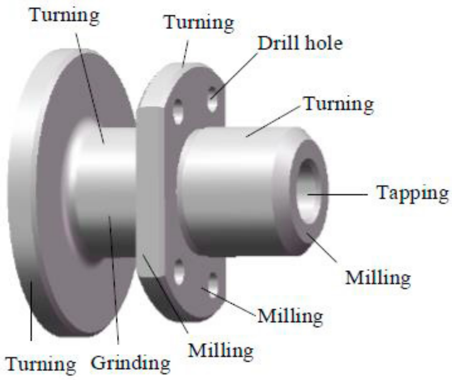



Fig. 1: Our case study

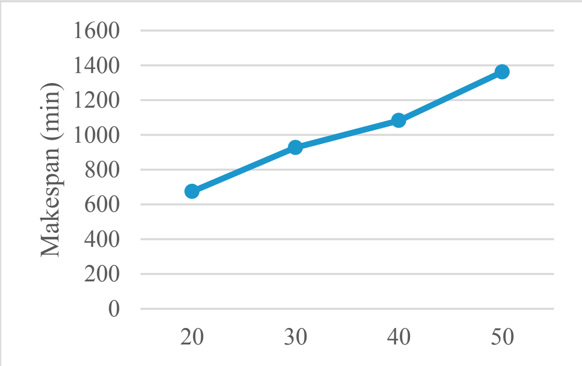
A sensitivity analysis is conducted to examine the impact of key parameters, such as the number of tasks (*N*), number of factories (*F*), the allocated budget (*B*), the limit imposed on the energy consumption (*UBEC*), the maximum number of workdays lost (*UBL*), and the minimum number of job opportunities created (*LBJ*), on the results obtained. Thus, the nominal value of each parameter is increased uniformly to generate four additional cases. For example, the nominal value of 10 tasks is increased to 20, 30, 40, and 50 tasks. The makespan is then evaluated for each case. The variation of the makespan (in minutes) resulting from the variation of the parameters is shown in Fig. 2. This analysis highlights the sensitivity of the results to changes in these key parameters.

Table 3: Characteristics of the machines used in the case study

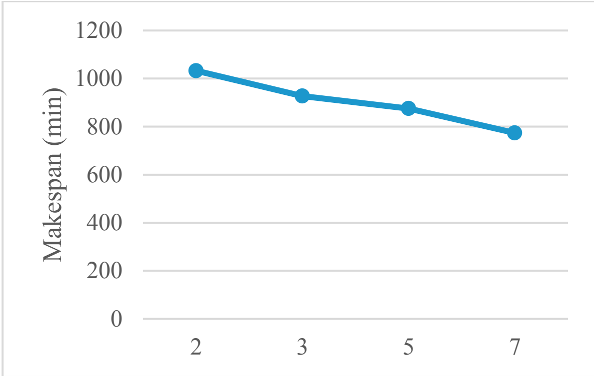
| Machine | Production mode | $IEC_{mpf}$ $(kWh)$ | $UEC_{mpf}$ $(kWh)$ | $EC_{mpf}$ $(kWh)$ | $CO_{mpf}$ ($) | $CJ_{mpf}$ ($) | $JO_{mpf}$ (Person) | $LD_{mpf}$ (Days) | $RW_{mpf}$ |
|---|---|---|---|---|---|---|---|---|---|
| CNC 1-turning | PLC | 0.5 | 4.1 | 2.9 | $32.4\times10^3$ | 2 | 3 | 7 | 0.04 |
| | APC | 0.45 | 4.15 | 3 | $34.2\times10^3$ | 2 | 3 | 7 | 0.03 |
| | MAN | 0.52 | 4.3 | 3.2 | $20.4\times10^3$ | 1 | 8 | 2 | 0.14 |
| CNC 2-milling | PLC | 0.3 | 3.8 | 3.1 | $41.5\times10^3$ | 3 | 2 | 7 | 0.02 |
| | APC | 0.35 | 3.75 | 3.15 | $42.1\times10^3$ | 3 | 2 | 7 | 0.02 |
| | MAN | 0.57 | 4.5 | 5.2 | $28.5\times10^3$ | 1 | 6 | 2 | 0.12 |
| CNC 3-drilling | PLC | 0.2 | 2.6 | 1.8 | $31.2\times10^3$ | 3 | 4 | 7 | 0.02 |
| | APC | 0.3 | 2.75 | 1.9 | $32.4\times10^3$ | 3 | 4 | 7 | 0.01 |
| | MAN | 0.4 | 3.5 | 2.4 | $16.3\times10^3$ | 2 | 8 | 2 | 0.17 |
| CNC 4-tapping | PLC | 0.5 | 3.1 | 1.9 | $23.3\times10^3$ | 4 | 5 | 7 | 0.01 |
| | APC | 0.45 | 3.2 | 2 | $22.5\times10^3$ | 4 | 5 | 7 | 0.03 |
| | MAN | 0.75 | 4.5 | 3.2 | $11.7\times10^3$ | 2 | 6 | 2 | 0.15 |
| CNC 5-grinding | PLC | 0.3 | 2.6 | 1.3 | $32.1\times10^3$ | 4 | 4 | 10 | 0.02 |
| | APC | 0.35 | 2.65 | 1.4 | $31.7\times10^3$ | 4 | 4 | 10 | 0.03 |
| | MAN | 0.8 | 3.76 | 2.3 | $18.5\times10^3$ | 1 | 8 | 3 | 0.15 |

Remarkably, our findings in Fig. 2(a) reveal an intriguing twist: contrary to conventional assumptions, an upsurge in the number of tasks surprisingly extends the makespan. Fig. 2(b) illustrates that an increase in the number of factories leads to a decrease in the makespan due to the reduction in task assignments per factory then generated.

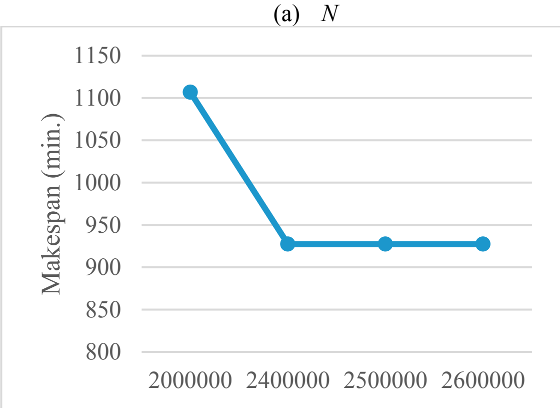
Unveiling further nuances, Fig. 2(c) uncovers an intriguing limitation. While the maximum allocated budget does exert an influence, its impact on the makespan remains intriguingly confined. In a captivating demonstration, Fig. 2(d) showcases a rather unanticipated scenario. Elevating the maximum total energy consumption appears to hold untapped potential for curbing the makespan, albeit with a captivating twist of modest enhancement. A parallel narrative unfolds in Fig. 2(e), where the influence of the maximum number of working days lost on the optimal makespan mirrors that of the maximum allowed energy consumption. Lastly, Fig. 2(f) shows that, surprisingly, elevating the minimum count of job opportunities crafted does not yield the anticipated reduction in makespan.



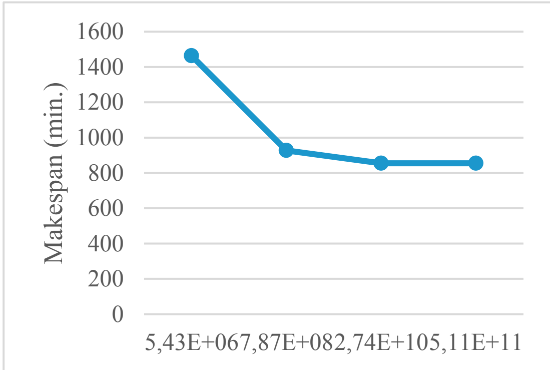

(a) *N*



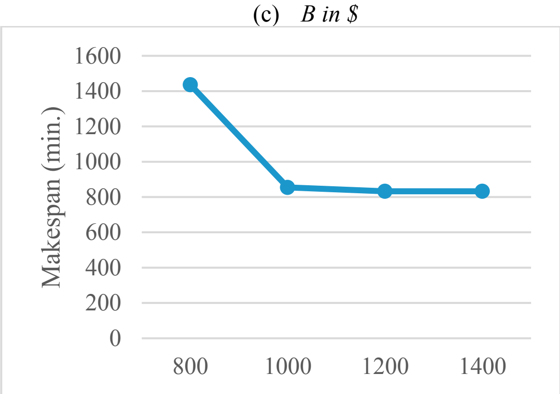

(b) *F*



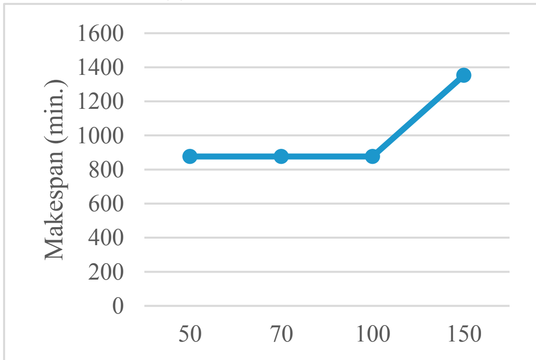

(c) *B in $*




(d) *UBEC in kWh*




(e) *UBL in days*




(f) *LBJ*

Fig. 2: Sensitivity analyses

## 4. Conclusions and future works

In this study, we introduced a comprehensive optimization model that integrates sustainability and uncertainty aspects into the distributed permutation flow-shop scheduling problem. Our primary objective is to minimize makespan while effectively addressing practical constraints about working days lost, energy consumption, and job opportunities created. The incorporation of these specific constraints, which have received limited attention in prior research, underscores the distinctiveness and significance of this study within the field. By considering aspects such as working days lost, energy consumption, and job opportunities, managers can optimize production processes while contributing to social and environmental goals.

The model's effectiveness is demonstrated through its successful application to various benchmark instances, affirming both the quality of solutions generated and the efficiency of resolution. A real-world case study focusing on flange production further attests to the practical applicability of our approach. Furthermore, a sensitivity analysis elucidates the influential role of key parameters in shaping the makespan. Using our analyses, managers can leverage this insight to focus efforts on optimizing these parameters, thereby influencing the makespan and overall system performance.

While our research contributes significantly to intelligent and sustainable scheduling, we recognize its limitations, which highlight avenues for further exploration in future studies. To address these limitations, we recommend incorporating real-time events using scenario-based methods to enhance the model's robustness. Additionally, we propose expanding the model's scope beyond makespan to encompass supplementary criteria such as task assignment stability and tardiness, thereby transitioning towards a multi-objective optimization framework.

In anticipation of future work, we envisage the incorporation of setup times and lot sizes as integral components of our optimization framework [24]. The application of local search metaheuristics, including variable neighborhood search, tabu search, and simulated annealing algorithms, holds the potential for generating efficient solutions [25]. Lastly, the exploration of adaptive large neighborhood search within the context of production scheduling models [26], including the one presented here, opens intriguing avenues for future investigation.

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## References

[1] Gahm C, Denz F, Dirr M, and Tuma A. Energy-efficient scheduling in manufacturing companies: A review and research framework. *European Journal of Operational Research*. 2016 Feb 1;248(3):744-57.
[2] Dolgui A, Ivanov D, Sethi SP, and Sokolov B. Scheduling in production, supply chain and Industry 4.0 systems by optimal control: fundamentals, state-of-the-art and applications. *International journal of production research*. 2019 Jan 17;57(2):411-32.
[3] Al-Behadili M, Ouelhadj D, and Jones D. Multi-objective biased randomised iterated greedy for robust permutation flow shop scheduling problem under disturbances. *Journal of the Operational Research Society*. 2020 Nov 1;71(11):1847-59.
[4] Varelmann T, Erwes N, Schäfer P, and Mitsos A. Simultaneously optimizing bidding strategy in pay-as-bid-markets and production scheduling. *Computers & Chemical Engineering*. 2022 Jan 1;157:107610.
[5] Fathollahi-Fard AM, Woodward L, and Akhrif O. Sustainable distributed permutation flow-shop scheduling model based on a triple bottom line concept. *Journal of Industrial Information Integration*. 2021 Dec 1;24:100233.
[6] Naderi B, and Ruiz R. The distributed permutation flowshop scheduling problem. *Computers & operations research*. 2010 Apr 1;37(4):754-68.
[7] Gao J, and Chen R. A hybrid genetic algorithm for the distributed permutation flowshop scheduling problem. *International Journal of Computational Intelligence Systems*. 2011 Jun 1;4(4):497-508.
[8] Lin SW, Ying KC, and Huang CY. Minimising makespan in distributed permutation flowshops using a modified iterated greedy algorithm. *International Journal of Production Research*. 2013 Aug 1;51(16):5029-38.
[9] Naderi B, and Ruiz R. A scatter search algorithm for the distributed permutation flowshop scheduling problem. *European Journal of Operational Research*. 2014 Dec 1;239(2):323-34.
[10] Bargaoui H, Driss OB, and Ghédira K. A novel chemical reaction optimization for the distributed permutation flowshop scheduling problem with makespan criterion. *Computers & Industrial Engineering*. 2017 Sep 1;111:239-50.
[11] Fernandez-Viagas V, Perez-Gonzalez P, and Framinan JM. The distributed permutation flow shop to minimise the total flowtime. *Computers & Industrial Engineering*. 2018 Apr 1;118:464-77.
[12] Pan QK, Gao L, Wang L, Liang J, and Li XY. Effective heuristics and metaheuristics to minimize total flowtime for the distributed permutation flowshop problem. *Expert systems with applications*. 2019 Jun 15;124:309-24.
[13] Ruiz R, Pan QK, and Naderi B. Iterated Greedy methods for the distributed permutation flowshop scheduling problem. *Omega*. 2019 Mar 1;83:213-22.
[14] Meng T, Pan QK, and Wang L. A distributed permutation flowshop scheduling problem with the customer order constraint. *Knowledge-Based Systems*. 2019 Nov 15;184:104894.
[15] Wang JJ, and Wang L. A knowledge-based cooperative algorithm for energy-efficient scheduling of distributed flow-shop. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*. 2018 Jan 18;50(5):1805-19.
[16] Fu Y, Tian G, Fathollahi-Fard AM, Ahmadi A, and Zhang C. Stochastic multi-objective modelling and optimization of an energy-conscious

distributed permutation flow shop scheduling problem with the total tardiness constraint. *Journal of Cleaner Production*. 2019 Jul 20;226:515-25.

[17] Wang G, Gao L, Li X, Li P, and Tasgetiren MF. Energy-efficient distributed permutation flow shop scheduling problem using a multi-objective whale swarm algorithm. *Swarm and Evolutionary Computation*. 2020 Sep 1;57:100716.

[18] Lu C, Gao L, Gong W, Hu C, Yan X, and Li X. Sustainable scheduling of distributed permutation flow-shop with non-identical factory using a knowledge-based multi-objective memetic optimization algorithm. *Swarm and Evolutionary Computation*. 2021 Feb 1;60:100803.

[19] Jiang X, Tian Z, Liu W, Suo Y, Chen K, Xu X, and Li Z. Energy-efficient scheduling of flexible job shops with complex processes: A case study for the aerospace industry complex components in China. *Journal of Industrial Information Integration*. 2022 May 1;27:100293.

[20] Yue L, Wang H, Mumtaz J, Rauf M, and Li Z. Energy-efficient scheduling of a two-stage flexible printed circuit board flow shop using a hybrid Pareto spider monkey optimisation algorithm. *Journal of Industrial Information Integration*. 2023 Feb 1;31:100412.

[21] Jiménez M, Arenas M, Bilbao A, and Rodrı MV. Linear programming with fuzzy parameters: an interactive method resolution. *European Journal of Operational Research*. 2007 Mar 16;177(3):1599-609.

[22] He W, and Sun DH. Scheduling flexible job shop problem subject to machine breakdown with route changing and right-shift strategies. *The International Journal of Advanced Manufacturing Technology*. 2013 Apr;66:501-14.

[23] Ghaleb M, Zolfagharinia H, and Taghipour S. Real-time production scheduling in the Industry-4.0 context: Addressing uncertainties in job arrivals and machine breakdowns. *Computers & Operations Research*. 2020 Nov 1;123:105031.

[24] Tian G, Fathollahi-Fard AM, Ren Y, Li Z, and Jiang X. Multi-objective scheduling of priority-based rescue vehicles to extinguish forest fires using a multi-objective discrete gravitational search algorithm. *Information Sciences*. 2022 Aug 1;608:578-96.

[25] Fathollahi-Fard AM, Dulebenets MA, Hajiaghaei-Keshteli M, Tavakkoli-Moghaddam R, Safaeian M, and Mirzahosseinian H. Two hybrid meta-heuristic algorithms for a dual-channel closed-loop supply chain network design problem in the tire industry under uncertainty. *Advanced engineering informatics*. 2021 Oct 1;50:101418.

[26] Mara ST, Norcahyo R, Jodiawan P, Lusiantoro L, and Rifai AP. A survey of adaptive large neighborhood search algorithms and applications. *Computers & Operations Research*. 2022 Oct 1;146:105903.