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A Hybrid Flow Shop Scheduling: A Comparative Analysis of Minimizing Carbon Emission and Minimizing the Total Completion Time

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ABSTRACT

This article addresses the Hybrid Flow Shop Scheduling Problem with Sequence and Machine Dependent Setup Times (HFSSP-SMDST) in Industry 4.0. A flow-based positional mathematical formulation is proposed to provide tighter lower bounds to the problem. Two objective functions are used in this mathematical formulation to analyze the trade-off between economic benefits and environmental impacts. Model 1 minimizes the total completion time. Model 2 minimizes the total carbon emission. Computational experiments demonstrate that while optimizing total completion time, there is a loss in the total carbon emission, and vice-versa. Furthermore, the experiments show that minimizing carbon emission results in an easier model to solve than minimizing completion time. The proposed algorithms offer valuable solutions for scheduling optimization in Industry 4.0.

KEYWORDS. green scheduling, completion time, hybrid flow shop scheduling.

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1. Introdução

Scheduling plays a pivotal role in the manufacturing process as it involves making decisions to allocate jobs or tasks to machines, optimizing an objective function. In today's competitive business environment, efficient scheduling is considered one of the most critical factors for success, as highlighted by Afzalirad e Shafipour [2018]. The scheduling of jobs directly impacts a company's ability to fulfill demand and satisfy customers.

The advent of Industry 4.0 has brought about significant advancements in information and communication technologies, which have facilitated the implementation of scheduling production techniques [Mittal et al., 2019]. Smart manufacturers can now leverage innovative and data-driven approaches to scheduling decisions, enabling them to achieve various quantitative benefits, including cost savings and quality improvements [Kusiak, 2018].

Industry 4.0 represents a paradigm shift towards a more resource-efficient and environmentally conscious approach to manufacturing. The primary objective is to reduce energy consumption and achieve sustainable development without compromising economic benefits. Efficient scheduling of production systems contributes to the overall performance of a company, reducing raw material, labor, transportation costs, pollutants emission, and energy consumption. Consequently, the field of shop scheduling has garnered significant attention in research. In this context, this study focuses on addressing the Hybrid Flow Shop Scheduling Problem with Sequence and Machine Dependent Setup Times (HFSGSP-SMDST).

The hybrid flow shop represents a typical manufacturing environment. The Hybrid Flow Shop Scheduling Problem (HFSSP) entails assigning jobs to machines at each stage while sequencing the jobs assigned to the same machine such that one or a set of selected criteria are optimized. A traditional hybrid flow shop configuration comprises sequential stages, with at least one stage having two or more parallel machines. The inclusion of parallel machines enhances flexibility, increases capacity, and mitigates bottlenecks, particularly when certain operations are more time-consuming. Figure 1 illustrates a hybrid flow shop environment with n jobs, l stages and m_j machines in each stage S_j. For a comprehensive overview of HFSSP, readers may refer to Ribas et al. [2010], Ruiz e Vázquez-Rodríguez [2010], Fan et al. [2018], and Lee e Loong [2019].

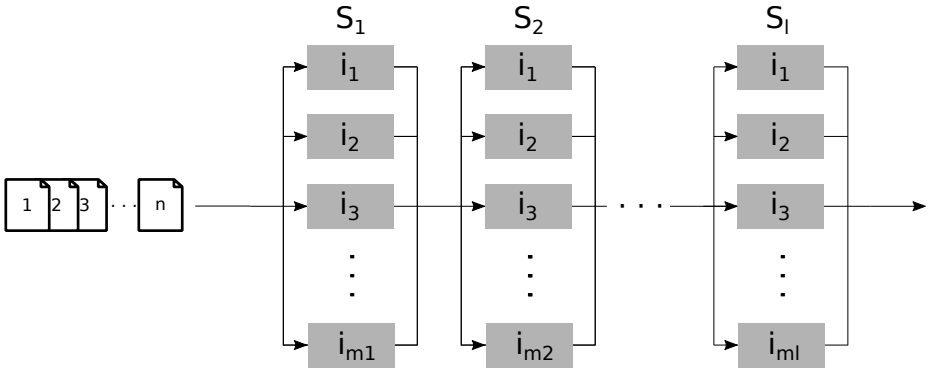


Figura 1: A Hybrid Flow Shop Environment.

The inclusion of Sequence and Machine Dependent Setup Times (SMDST) implies that these are influenced by the job, its predecessor, and the machine where both are processed. Extensive literature on scheduling models incorporating setup time/costs can be found in Allahverdi et al. [2008] and further expanded upon in Allahverdi [2015].

About the objection function, to explore some trade-offs between economic benefits and

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environmental impacts, we solve two versions of the HFSSP-SMDST. While the first minimizes the total completion time, the second minimizes the total carbon emission.

Considering the various characteristics that scheduling problems can possess, the HFSSP-SMDST proposed in this study makes the following assumptions: (i) each machine can process only one job at a time, (ii) all machines are capable of processing all jobs, (iii) preemption is not allowed, meaning once a job begins processing, it runs until completion, (iv) each job can be processed by at most one machine simultaneously, (v) all jobs follow the same technological route, progressing through the stages in a predefined order, (vi) unlimited buffers exist between the stages, (vii) each stage comprises at least two unrelated parallel machines, (viii) setup times are dependent on the job sequence and the machines, and (ix) machines only emit pollutants while in operation.

Various formulations have been proposed to tackle scheduling problems, typically involving flow variables, positional variables and time-indexed variables. However, these formulations require a trade-off between the quality of the lower bounds obtained and the computational time required to find optimal or good solutions. On one hand, formulations utilizing flow and positional variables along with big-M constants in disjunctive constraints tend to yield weaker lower bounds but converge more quickly. On the other hand, time-indexed formulations produce stronger lower bounds but can pose challenges in guaranteeing optimality. Formulating an efficient algorithm involves overcoming these shortcomings while achieving fast convergence and strong lower bounds.

Gomes [2017] presented a mathematical formulation that replaces the big-M constant with dummy jobs and proposed a Column Generation algorithm to solve the Unrelated Parallel Machine Scheduling Problem. This article extends Gomes [2017]' work, which focuses on scheduling problems with only one stage, whereas the present study formulates solutions for multistage problems. This new variant makes the problem more challenging due to the interconnectivity between stages.

Therefore, this study contributes in two ways. First, introduces a new formulation based on positional variables and dummy jobs. This formulation eliminates the need for big-M constants in disjunctive constraints, leading to increased efficiency in problem-solving. Second, analyze two objective functions while solving scheduling problems: minimizing completion time and minimizing carbon emission. The objective is to investigate how the minimization of the total completion time influences the total carbon emission and vice versa.

The remainder of this paper is organized as follows: Section 2 describes the problem and introduces the mathematical formulation. Section 3 details the generation of instances and outlines the computational experiments conducted. Finally, Section 4 concludes the paper and suggests potential avenues for future research.

2. Notation and Mathematical Formulation

In this section, we introduce the notation and mathematical formulations used in this work. We consider positional variables, x_{ijp}, which are equal to 1 if job j is allocated to machine i in position p, and 0 otherwise. The number of positions in a machine is equal to the number of jobs, but not all positions are necessarily occupied by jobs. To handle this, Wagner [1959] uses a big-M constant in disjunctive constraints. However, this choice leads to poor linear relaxations. To overcome this weakness, the formulation presented in this work utilizes dummy jobs instead of disjunctive constraints with big-M constants. These dummy jobs fill the empty positions.

Let $J^0 = \{0, .., n\}$ be the set of jobs. Job 0 represents the dummy job, n is the number of jobs to be processed, and $J = J^0 \backslash \{0\}$. Let E be the set of stages and $I^e = \{1, .., m^e\}$ be the set of machines in stage $e \in E$, in which m^e is the total number of machines in each stage. Each job $j \in J$ consumes a processing time π^e_{ij} on machine $i \in I^e$ in stage $e \in E$ and is available to be processed at time zero. There is a setup time, σ^e_{ijl}, which corresponds to the time required between

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the end of job $j \in J$ and the beginning of job $l \in J$ on machine $i \in I^e$ in stage $e \in E$. The setup can be performed during idle time. The carbon emission μ^e_{ij} and λ^e_{ijl} occurs during the process of job $j \in J$ on machine $i \in I^e$ in stage $e \in E$ and during the setup between job $j \in J$ and job $l \in J$ on machine $i \in I^e$ in stage $e \in E$, respectively.

The processing times, setup times, and carbon emissions are deterministic and non-negative integer parameters. A job sequence refers to the order in which jobs are processed on a specific machine in a stage. Each job is processed only once per stage, and once a job starts processing, it continues until completion. The objective is to find the job sequences that minimize the total completion time or the total carbon emissions.

Let P be the set of positions for each machine in each stage. The number of positions in each machine is equal to the total number of jobs, including the dummy job. At each stage, jobs $j \in J$ should be allocated in only one position. Dummy jobs fill the positions not occupied by jobs $j \in J$. For all $i \in I^e, e \in E$, and $j \in J$, let π^e_{i0}, μ^e_{i0} , σ^e_{i00}, σ^e_{i0j}, λ^e_{i00} and λ^e_{i0j} be equal zero and σ^e_{ij0} and λ^e_{ij0} be equal a large value. These parameters minimize symmetry problems because they ensure that dummy jobs will be allocated before "real jobs". This allocation does not affect the objective function since the values of carbon emission, processing and setup times of the dummy jobs are zero. Furthermore, the allocation of dummy jobs after "real jobs" implies worse objective function values, as it incurs in setup time which is a considerable value. For example, assume a problem of four "real jobs" and then, $|P| = 5$. Figure 2 represents the available positions for a feasible solution with four jobs and two stages with two machines. Note that sequence [3,4] is represented as [0,0,0,3,4].

		p = 1	p = 2	p = 3	p = 4	p = 5
Stage 1	Machine 1	0	0	0	3	4
	Machine 2	0	0	0	2	1
Stage 2	Machine 1	0	0	3	4	1
	Machine 2	0	0	0	0	2

Figura 2: An example of positions filled with real and dummies jobs.

With the notation mentioned above and definitions, the flow-based positional formulation is presented. We introduce the variables $C^e_{ijp} \geq 0$, which represent the completion time of job $j \in J^0$ on machine $i \in I^e$ in position $p \in P$ in stage $e \in E$. Let $x^e_{ijp} \in \{0, 1\}$ be equal to 1, if job $j \in J^0$ is processed in position $p \in P$ of machine $i \in I^e$, in stage $e \in E$, 0 otherwise; let $z^e_{ijlp} \in \{0, 1\}$ be equal to 1, if jobs $j, l \in J^0$ are processed in positions $(p-1)$ and p, respectively, of machine $i \in I^e$ in stage $e \in E$, 0 otherwise. The flow-based positional model can be formulated as follows:

$$\min \sum_{i \in I^e} \sum_{j \in J^0} \sum_{p \in P} C^{e=|E|}_{ijp} \parallel \tag{1}$$

$$\min \sum_{i \in I^e} \sum_{j \in J^0} \sum_{p \in P} \sum_{e \in E} \left(\pi^e_{ij} \mu^e_{ij} x^e_{ijp} + \sum_{l \in J^0} \sigma^e_{ijl} \lambda^e_{ijl} z^e_{ijl(p+1)} \right) \tag{2}$$

$$\sum_{i \in I^e} \sum_{p \in P} x^e_{ijp} = 1, \qquad \forall j \in J, e \in E \tag{3}$$

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$$\sum_{j \in J^0} x^e_{ijp} = 1, \qquad \forall e \in E, i \in I^e, p \in P \tag{4}$$

$$\sum_{l \in J^0} z^e_{ijl(p+1)} = x^e_{ijp}, \quad \forall e \in E, i \in I^e, j \in J^0, p \in P, p \leq |P| - 1 \tag{5}$$

$$\sum_{j \in J^0} z^e_{ijlp} = x^e_{ilp}, \qquad \forall e \in E, i \in I^e, l \in J^0, p \in P, p \geq 2 \tag{6}$$

$$C^1_{ij1} = \pi^1_{ij} x^1_{ij1}, \qquad \forall i \in I^1, j \in J^0 \tag{7}$$

$$\sum_{l \in J^0} C^e_{ilp} \geq \sum_{j \in J^0} C^e_{ijp-1} + \sum_{j \in J^0} \sum_{l \in J^0} \sigma^e_{ijl} z^e_{ijlp} + \sum_{l \in J^0} \pi^e_{il} x^e_{ilp}, \qquad \forall e \in E, i \in I^e, p \in P, p \geq 2 \tag{8}$$

$$\sum_{i \in I^e} \sum_{p \in P} C^e_{ijp} \geq \sum_{i \in I^e} \sum_{p \in P} C^{e-1}_{ijp} + \sum_{i \in I^e} \sum_{p \in P} \pi^e_{ij} x^e_{ijp}, \qquad \forall e \in E, e \geq 1, j \in J^0 \tag{9}$$

$$C^e_{ijp} \leq M x^e_{ijp}, \qquad \forall e \in E, i \in I^e, j, l \in J^0, p \in P \tag{10}$$

$$C^e_{ijp} \geq 0, \qquad \forall e \in E, i \in I^e, j \in J^0, p \in P \tag{11}$$

$$x^e_{ijp} \in \{0, 1\}, \qquad \forall e \in E, i \in I^e, j \in J^0, p \in P \tag{12}$$

$$z^e_{ijlp} \in \{0, 1\}, \qquad \forall e \in E, i \in I^e, j, l \in J^0, p \in P \tag{13}$$

The first objective function (1) aims to minimize the total completion time while the second objective function (2) minimizes the total carbon emission. Constraints (3) ensure that each job is processed by exactly one machine in each stage. Constraints (4) ensure that all machine positions of all stages are occupied, *i.e.*, those positions will be occupied by real or dummy jobs. Constraints (5) and (6) describe the precedence relationships between jobs. Constraints (7) calculate the completion time at the first position of each job in each machine in the first stage. Constraints (8) and (9) calculate the completion time at all positions except the first one of each machine in each stage. Constraints (10) allow the completion time to be different from zero if and only if a job j is allocated in the position p in machine i of the stage e. Finally, constraints (11) to (13) define the domain of the variables.

Flow-based positional formulation offers innovative approaches to addressing the Hybrid Flow Shop Scheduling Problem with Sequence and Machine Dependent Setup Times (HFSSP-SMDST). This formulation provides stronger representations for the problem by avoiding the use of the big M constant, which can lead to poor linear relaxations. Also, the flow-based positional formulation stands out for its polynomial-size number of variables and constraints. This characteristic enables the explicit enumeration of all variables, making the formulation easily implementable. Moreover, commercial solvers can efficiently handle this formulation without requiring additional approaches or implementations.

3. Computational Experiments

In this section, we first describe the set of instances used in our experiments. Then, we report the results of the computational experiments. Finally, we explore some trade-offs between economic benefits and environmental impacts.

3.1. Generation of test data and experimental design

To compare the proposed formulation, a set of instances was generated, considering number of jobs n = {4, 6, 12, 16, 20}, number of machines m = {2, 3, 5} and number of stages e = {2}, and the same number of machines in each stage. For each job j and stage e, a standard processing time $\bar{\pi}^e_j$ is randomly generated by a uniform distribution of one of the four ranges available in Table 1, for example, group 1, U[5, 30]. Processing time π^e_{ij} is obtained dividing the standard processing time $\bar{\pi}^e_j$ by the relative speed of the machine (v^e_{ij}), which is randomly generated in the range of U[0.7, 1.3]. Additionally, for each pair of jobs j and l, stage e, and machine i, sequence

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and machine-dependent setup time σ^e_{ijl} is randomly generated by one of the four uniform distributions available; for example, group 1, U[5, 10]. Finally, carbon emission during the processing time (μ^e_{ij}) are generated in the range U[2,4], while the carbon emission during setup times (λ^e_{ijl}) are generated in the range U[1,3]. For each combination of jobs and machines, three instances were generated. This work does not allow instances in which the number of jobs is less than the number of machines, because in this case the problem consists only of assigning jobs to machines, not requiring scheduling decisions. Thus, this procedure generates a total of 56 instances. Jungwattanakit et al. [2008] used a similar procedure.

Tabela 1: Ranges of processing times of jobs, machine speed and setup times

Group	1	2	3	4
$\bar{\pi}^e_j$	U[5, 30]	U[10, 100]	U[100, 1000]	U[5, 1000]
v^e_{ij}			U[0.7, 1.3]	
σ^e_{ijl}	U[5, 10]	U[10, 30]	U[100, 300]	U[5, 300]
μ^e_{ij}			U[2, 4]	
λ^e_{ijl}			U[1, 3]	

All computational tests have been carried out on a computer equipped with an Intel Core i7- 4790K 4.00GHz processor with 16 GB of memory and Ubuntu 18.04 LTS. The formulation has been implemented using the Python API of CPLEX and solved by IBM ILOG CPLEX 12.10. We set a maximum time limit of 3600s of CPU time.

3.2. Experimental Results

Table 2 shows the results for both objective functions: Model 1 ((1) - (13)) and Model 2 ((2) - (13)) . Columns 1 to 3 identify the instance. Columns 4, 5, and 6 show the objective function, formulation lower bound, and time spent while minimizing completion time, respectively. Columns 7, 8, and 9 present the objective function, formulation lower bound, and time spent while minimizing the carbon emission, respectively.

Tabela 2: Comparison between Model 1 and Model 2 while solving the proposed instances grouped by jobs and machines.

Instance			Model 1			Model 2		
# of Jobs	# of Machines	Time Range	OF	RL	Time	OF	RL	Time
4	2	0005-0030	163.00	161.00	0	439	397	0.04
4	2	0005-1000	3968.00	3732.50	0	9702	9035	0.04
4	2	0010-0100	560.00	530.00	0	1135	1015	0.05
4	2	0100-1000	6436.00	6113.50	0	16364	15280	0.05
4	3	0005-0030	142.00	135.50	0	357	340	0.06
4	3	0005-1000	4091.00	4091.00	0	10887	10541	0.05
4	3	0010-0100	578.00	533.50	0	1585	1504	0.04
4	3	0100-1000	4955.00	4725.00	0	13377	12635	0.07
6	2	0005-0030	295.00	244.50	4	551	476	0.08
6	2	0005-1000	10833.00	9415.67	13	19025	18122	0.07
6	2	0010-0100	782.00	652.33	6	1446	1236	0.14
6	2	0100-1000	10523.00	9595.83	1	19983	18026	0.13
6	3	0005-0030	229.00	209.00	1	484	432	0.17
6	3	0005-1000	6631.00	6382.00	1	13111	12092	0.13
6	3	0010-0100	823.00	798.50	0	1962	1840	0.13
6	3	0100-1000	7798.00	7341.50	1	18988	17603	0.16
6	5	0005-0030	207.00	199.00	1	520	489	0.14
6	5	0005-1000	5349.00	5325.50	0	14451	13927	0.15
6	5	0010-0100	695.00	662.00	2	1788	1641	0.19
6	5	0100-1000	7039.00	6895.00	0	17127	15992	0.20

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Table 2 continued from previous page

Instance			Model 1			Model 2		
# of Jobs	# of Machines	Time Range	OF	RL	Time	OF	RL	Time
12	2	0005-0030	1063.00	837.85	3600	1281	1134	0.84
12	2	0005-1000	29940.00	21655.21	3600	39635	37725	0.96
12	2	0010-0100	3302.00	2392.81	3600	3820	3442	1.16
12	2	0100-1000	30950.00	27751.83	656	38778	33737	1.54
12	3	0005-0030	651.00	525.67	3600	960	819	1.58
12	3	0005-1000	20040.00	18320.92	3600	30271	28642	1.76
12	3	0010-0100	2018.00	1642.33	3601	3084	2756	1.24
12	3	0100-1000	22044.00	19584.87	3600	32203	27965	1.84
12	5	0005-0030	469.00	425.50	276	856	741	2.86
12	5	0005-1000	11371.00	10580.85	3600	23814	22535	2.68
12	5	0010-0100	1689.00	1586.00	162	3161	2877	2.52
12	5	0100-1000	13426.00	12488.50	1925	26892	23769	2.62
16	2	0005-0030	1606.00	1121.43	3600	1424	1212	2.32
16	2	0005-1000	41654.00	31709.48	3600	41784	39910	3.57
16	2	0010-0100	4995.00	3091.92	3600	4678	4132	3.78
16	2	0100-1000	48039.00	39945.41	3600	51795	46484	6.22
16	3	0005-0030	1155.00	926.78	3600	1389	1187	6.17
16	3	0005-1000	19433.00	16903.65	3600	27719	25888	13.02
16	3	0010-0100	3071.00	2374.42	3601	4380	3884	3.68
16	3	0100-1000	36173.00	30201.89	3600	44020	39023	4.91
16	5	0005-0030	896.00	774.17	3601	1507	1324	10.90
16	5	0005-1000	19557.00	18594.46	3600	31966	29977	11.36
16	5	0010-0100	2370.00	2140.08	3600	4319	3849	11.98
16	5	0100-1000	27212.00	24181.06	3600	43949	39241	11.01
20	2	0005-0030	2959.00	1841.29	3600	2109	1849	35.28
20	2	0005-1000	62202.00	51413.91	3600	50602	48255	31.25
20	2	0010-0100	7548.00	4941.06	3600	5974	5333	11.12
20	2	0100-1000	83178.00	50314.21	3600	60492	54054	29.87
20	3	0005-0030	1769.00	1318.38	3600	1956	1709	69.75
20	3	0005-1000	43895.00	38734.83	3600	48536	46477	15.31
20	3	0010-0100	5862.00	4509.28	3600	6034	5404	18.63
20	3	0100-1000	60695.00	47024.02	3600	65642	59055	21.09
20	5	0005-0030	1227.00	951.44	3600	1658	1419	48.38
20	5	0005-1000	27303.00	24918.15	3600	38639	36422	27.47
20	5	0010-0100	2952.00	2428.57	3600	4369	3785	45.57
20	5	0100-1000	34992.00	28393.97	3600	51144	45650	35.70

Table 2 shows that minimizing the total carbon emission is easier than minimizing the total completion time. When the objective was to minimize the total completion time, the solver had trouble finding optimal solutions in 32 instances. The same did not happen while minimizing the total carbon emission.

Observing the linear relaxation provided by the formulations, we notice that when the carbon emission is minimized, the formulation generates better gaps than when the completion time is minimized. The gap of linear relaxation was, on average, 14.22% and 9.27%, for Model 1 and Model 2, respectively.

To analyze the trade-offs between economic benefits and environmental impacts, we calculate the total carbon emission and the total completion time when Model 1 ((1) - (13)) and Model 2 ((2) - (13)) are solved, respectively, for instances with 4, 6, and 12 jobs. Table 3 shows the results obtained. Columns 1 to 3 identify the instance. Columns 4 presents how far Model 1 is from the optimal total carbon emission and columns 5 presents how far Model 2 is from the optimal total completion time.

As seen in Table 3, on the one hand, when the objective is to minimize the total completion time, the carbon emission is, on average, 19.59% worse than the optimal carbon emission value. On the other hand, when the objective is to minimize the total carbon emission, the time to complete all jobs is, on average, 68.92% worse than the optimal value. These preliminary results show the

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Tabela 3

Instance			Model 1	Model 2
# of jobs	# of machines	Time Range		
4	2	0005-0030	8%	129%
4	2	0005-1000	31%	80%
4	2	0010-0100	41%	85%
4	2	0100-1000	12%	45%
4	3	0005-0030	10%	20%
4	3	0005-1000	0%	34%
4	3	0010-0100	16%	21%
4	3	0100-1000	17%	38%
6	2	0005-0030	17%	62%
6	2	0005-1000	11%	39%
6	2	0010-0100	16%	144%
6	2	0100-1000	22%	54%
6	3	0005-0030	25%	47%
6	3	0005-1000	42%	52%
6	3	0010-0100	9%	58%
6	3	0100-1000	13%	66%
6	5	0005-0030	7%	26%
6	5	0005-1000	27%	73%
6	5	0010-0100	13%	29%
6	5	0100-1000	30%	45%
12	2	0005-0030	23%	143%
12	2	0005-1000	16%	79%
12	2	0010-0100	14%	42%
12	2	0100-1000	16%	97%
12	3	0005-0030	28%	116%
12	3	0005-1000	23%	123%
12	3	0010-0100	19%	90%
12	3	0100-1000	17%	63%
12	5	0005-0030	41%	75%
12	5	0005-1000	17%	73%
12	5	0010-0100	21%	108%
12	5	0100-1000	25%	51%

negative impact on carbon emission when the total completion time is minimized and the negative impact on total completion time when the total carbon emission is minimized. Therefore, it is essential to integrate the minimization of environmental impacts and the maximization of economic benefits.

4. Conclusion

In this paper, the Hybrid Flow Shop Scheduling Problem with Sequence and Machine Dependent Setup Times (HFSSP-SMDST) was investigated. Two mathematical formulations were proposed: one minimizes the total completion time and the other one minimizes the total carbon emission.

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Instead of using a big-M constant in disjunctive constraints, the formulations employed dummy jobs to occupy empty positions, aiming to provide tighter lower bounds. Computational experiments demonstrated that minimizing total carbon emission is easier than minimizing total completion time. It is worth noting that the experiments focused on two-stage problems, and further tests are required to assess the performance of both models when considering more stages.

Overall, this research provides valuable insights and approaches to tackle the Hybrid Flow Shop Scheduling Problem, offering potential solutions to minimize carbon emission and optimize scheduling in the context of Industry 4.0. An evolution of the research consists of integrating classical objective functions for scheduling problems with carbon emission minimization.

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