Reducing Carbon Emission by two Dispatching Rules for Multi-Objective Flexible Job Shops

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Abstract

Manufacturing direct or indirect is accountable for almost one-third of carbon emission. Carbon eventually has trapped in the atmosphere in the shape of Co2; the dangerous gas that causes climate change and threatens human life. On the other hand, albeit the significant share of flexible job shops in manufacturing systems; few studies have been executed to overcome the carbon emission issue. Thus two fast algorithms called MCT and MCE have been introduced to reduce carbon emission along C-max and total machine workload. Then the results have been examined alongside some well-known meta-heuristic algorithms. Investigating results have shown a reasonable standard deviation; which proves a proper balance in production lines. Furthermore, for most instances, a minimum workload has been reported. Moreover, the completion times were acceptable, as well. Then reported data guaranteed the quality of the offered algorithm regarding time and accuracy. Furthermore, implementing a random operator or hybridizing these methods with meta-heuristics might enhance the performance.

Keywords: Environment, Carbon emission, Flexible job shop, Dispatching rules, Multi-objective, Makespan

1 Introduction

Eventually, human has apprehended that protecting the environment guarantees a better life for the next generation. From1980 to 2010, carbon emission (CE) rate increased by 72% notwithstanding a 3% decline in the emission intensity; this outlines a serious greenhouse impact matter called the global climate change. Anthropogenic events such as coal-fired electricity have increased the carbon dioxide (CO_2) concentration in the atmosphere; a dangerous gas that traps heat and threatens the environment [1]. Some have anticipated that the emitted CO_2 resultant from energy consumption in 2035 possibly increases by 43% higher than the 2007 reported data [2]. Some others believe that keep pumping emitted carbon to the atmosphere at the current rate may increase the global temperature by 1.9 C in the year 2100; that means a 3.8m higher level of water in the sea [3]. Thus, as a universal matter, any activity leads to it needs to be monitored consciously [4]. On the other hand, circulated reports have emphasized the manufacturing is accountable for 29% of the total emitted CO2 directly. The aforementioned incites the manufacturers to consider diminishing strategies regarding carbon emission [5–7].

Researches indicated on manufacturing regarding sustainable manufacturing have existed; however, the lack of efficient strategies adopted by literature remained obvious. Some had clustered carbon emissions declining approaches in three fields: 1- strategic; as pre-production decisions consist of supply chain planning and structural layout decisions. 2- Tactical during manufacturing and distribution phases; like changing the cutting tools, the turn on/off policy, and speed-level of machines. 3-operational; that decision makers concentrate on scheduling and planning more than anything else. Nonetheless, previous studies significantly have been directed on the first two perspectives and production focus strategies like scheduling have been neglected [1,2,8]. That was the reason Piroozfard et al. have described carbon footprint problems as an inventory control problem [6]. For instance, a turn on/off policy on scheduling model has been initiated by Mouzon et al. Albeit their objective was to lessen the energy costs, diminishing emitted carbon will be guaranteed [9]. Fang et al. offered another tactical strategy regarding the speed-level of machining. They have reported the higher speed level implies a lower machining time, but the higher energy utilization [10]. Lin et al. have used mentioned strategies along with a delay policy. To apply this, all operations but the last of each job have delayed as much as possible to reduce the machine pauses [8].

The aforementioned besides turn on/off policy eliminate most of the wasted energy during the machine pauses. Speed and feed rate of machining was the other considered policy that they had studied. Jiang et al. also employ a speed scaling strategy to minimize total completion time (C-max) and carbon emission (CE) on a distributed permutation flow-shop [11]. Furthermore, Chen et al. and

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Lu and Jiang assumed a multi-speed strategy to control energy consumption [12,13]. Wu and Sun relatively have practiced a multi-speed model with a turn on/off switcher; which an excessive number of switching could damage the machines [14]. Despite the importance of these contributed approaches, some believed strategic and tactical methods which concern machine tools, were barely applicable and may harm the machine and job; especially for small and medium enterprises (SMEs) with no multi-speed machines and the exceeding cost of updates [12–16].

The literature on sustainable manufacturing significantly has been focused on managing energy. Albeit, reducing energy utilization leads to higher beneficial aspects, and may satisfy manufacturers economically; involving energy expenses, planning, inventory, maintenance, machines life cycle, and other associated prices. Still, another crucial environmental issue, carbon emission, has been neglected entirely [5,8]. Adversely the classics in modern systems, the new high-performance machines are multi-task; this leads manufacturers to flexibility besides more complications regarding energy utilization and carbon emission control. For instance, a flexible job shop represents the job shop with the advantage of multitasking machines [17].

Recently flexible job shop scheduling problem (FJSP) has studied by many researchers due to broadly applicable fields. FJSP being NP-hard problem seems obvious since traditional job shop scheduling problem (JSP) had classified as one. Augmenting flexibility by using more than one capable machine modifies the job shop scheduling problem (JSP) to a flexible one [6,17–19]. Although the foremost scheduled FJSP has practiced by Bruker and Schlie at 1990; still, researchers keep seeking novel approaches to optimize complex FJSPs [20,21].

The FJSP mainly presents two difficulties. To assign every operation to a machine out of a set of fit machines and to determine the sequence of indicated operations, respectively. The aforementioned has created two flexibilities regarding the machine selection and process plan [20,22–24]. In reality, multiple objectives may cause trade-offs. Hence the Single-objective FJSP further investigated in the literature; due to some papers [25]. The contributed approaches to deal with the multi-objective flexible job shop scheduling (MO-FJSP) roughly have been categorized to the weighting approach and the Pareto-based ones. Turn the problem to a single objective using coefficients is what the weighting approach does. On the other hand, the Pareto face considers all objectives simultaneity and generates a set of optimums [2,26].

Due to the complexity of FJSP, the exact approaches and JSP solvers have been emphasized inapplicable or time-consuming. Thus heuristic methods have been applied to find the best possible solution close enough to the global optimum. Thus heuristic methods have been applied to find the best possible solution close enough to the global optimum. Thus heuristic methods have been applied to find the best possible solution close enough to the global optimum. Other than these heuristics, the new generation of iterative algorithms, called meta-heuristics, have been offered to tackle FJSP cases; includes Genetic algorithm (GA), Ant colony optimization (ACO), Artificial bee colony (ABC), Tabu search (TS), Annealing simulation (SA), particle swarm optimization (PSO), and etc. [17–23,27].

As mentioned above, meta-heuristics have been applied to FJSP to save time while other objectives almost neglected. In other words, environment-oriented papers mostly have reviewed flow shops, JSP, and other manufacturing. Moreover, despite some studies on energy consumption, carbon emission rarely has been targeted in FJSP [6,14,21,26,28,29]. Zheng and Wang studied project scheduling with limited resources using an estimation distribution algorithm (EDA) aimed to minimize C-max and carbon emission [1]. Moreover, some considered carbon emission dealing multi-objective flow-shops scheduling problems [10,11,30]. Another research has been done by Lin et al. to reduce the carbon footprint in flow-shops [8]. They employed three methods named: 1-postponing; by reducing the gap between completion of operation $o_{i,j}$ and commence of$o_{i,j+1}$ in i^{th}job, 2-setup concerned; by turn on/off the machines on their idle time, beside 3-parameter concerned; adjusting tools at proper processing parameters. Regarding job shops, Yi et al. simultaneously targeted minimizing carbon footprint and C-max [15]. Lei and Gao, likewise, executed their novel method on a dual-resource constraint job shop [5]. Furthermore, Seng et al. tried to reduce carbon footprint and total completion time on a job shop equipped by multi-speed machines using an NSGA-II [31].

To the best of the author's knowledge, few papers have been concerned emitted carbon as the central objective. The most related works in this area were a low-carbon pattern that has been studied by Zhang et al. to diminish C-max, the total workload and the emitted carbon [2]. and a different multi-objective Genetic Algorithm (MOGA) suggested by Piroozfard et al. to decrease total work and carbon footprint concurrently [6]. They claimed there was no low-carbon FJSP regarding job routing and sequencing. Following that Yin et al. had investigated the emitted carbon from different points of view includes productivity, energy consumption, and noise [28]. At the same time, a fruit fly optimization algorithm (FOA) has been offered by Liu et al. to decrease the makespan and carbon footprint considering 1-plant inputs, 2-material inputs, 3-process energy inputs and 4-transportation [21].

Kacem et al. believe the efficiency of an approach depends on how intelligently it seeks the solution area; to spend the precious time on valuable paths and nothing else [17]. On the other hand, meta-heuristics methods generally take a lot of time and energy, especially for big problems [30,32]. Therefore, in this study, an innovative approach with the original minimum completion time (MCT) by Maheswaran et al. has been investigated. MCT is one of the dispatching rules algorithms that discover the nearest completion time among the sets of capable machines [32]. Nevertheless, the second provided method is not time concerned and has revised the MCT method to a carbon emission based attempting to hit the minimum possible emitted carbon in each iteration. Furthermore, to the best of the author's knowledge, this is the first study that has been used the carbon emission criteria to select operations per iteration; All other methods focused on time while carbon emission assumed as the second objective. Section 2 describes the methodology and offered methods. Results have given in section 3 following by discussion and conclusion in section 4 and 5. Moreover, some potential future works have been declared succeeding.

2 Proposed methods

This paper investigates a multi-objective flexible job shop scheduling. The availability of more than one nominee machine to process each operation modifies a flexible job shop as a more complicated Np-Hard scheduling problem. Thus two main sub-problems have been described to be tackled regarding time, cost, and resource barriers. The operations sequence of each job and the design of allocated machines to the operations define those two difficulties.

Technically, the FJSP represents by n jobs meant to process on m machines. Every job includes j sequenced operations; independent from other job's. These jobs have released at time zero; besides, in particular cases, cancelation or the arrival of new orders at an expected or random time have affected the scheduling. On the other hand, if all machines were able to perform any operations, flexibility is total; otherwise, partial. Assuming the following limitations may ease simulating carbon emission FJSP. 1- Jobs and machines are available from time zero. 2- The sequencing between the operations of each job shall consider. 3- Machines are independent, and always are available with full capacity and power. 4- Each machine can only process one operation per time. 5- Operations are not authorized to run on more than a device simultaneously. 6- Pre-emption is not allowed; interruption or pause is impossible after an operation initiated on a machine. 7- There is no buffer limit. 8- Transportation time and setup time have neglected; assumed as part of defined process time. 9-Machines are simple; mono-speed with no turn on/off switcher at the idle time. 10- The emitted carbon per kilowatt power utilization is constant [17,18,22,27].

2.1 Minimum completion time (MCT) algorithm

One of the simplest methods among scheduling heuristics is Dispatching rules (DR). Their mechanism is like when a machine is free, the DR ranks jobs based on their characteristics or system circumstances, to determine which job should run succeeding. Fast reacting to dynamics is DR's strength; which led them to obtain high-quality answers in a much better execution time comparing metaheuristic methods. Nonetheless, the proposed DRs rarely have studied different scheduling cases [33,34].

In this paper a minimum completion time (MCT) heuristic has performed; a fast greedy method introduced by Maheswaran et al. MCT is an immediate mode heuristics which works indicating every job to a machine aim to achieve the closest completion time. In "immediate" models, jobs rapidly allot to machines at the arrival. Job selection per iteration is conditional and temporary; it means the second priority in this iteration may not preceding at the next round [32].

Finally, the mathematical model regarding the objectives produces the answers. Since minimizing carbon emission and C-max along with total workload has targeted in this study, equations 1-3 presents how these objectives have fulfilled.

$$min\, Z_{CE} = \alpha * \{\sum_{j=1}^{k} Pow_{w_j} * load_j + \sum_{j=1}^{k} Pow\_idle_j * M_{idle\,j}\} \quad (1)$$

$$min\, Z_{C-max} = Max(load_j) \quad (2)$$

$$min\, Z_{work\,load} = \sum_{j=1}^{k} load_j \quad (3)$$

2.2 The procedure of MCT algorithm

The original MCT algorithm comprises these steps. First, process-times have imported from “EXCEL”; using the “XLSREAD” function. Then, four different instances including: “4X4”, “8X8”, “10X10”, and “15X10” have been extracted from literature [35]. The first number in the mentioned instances (nXk) represents the number of jobs (n), while the second one refers to the number of machines (k). Along the process times, power consumption data had extracted too the process times, power consumption data is extracted too [6]. In step2 some indexes, parameters, and variables of a general FJSP were introduced; which have listed below:

- **Indexes**

i:	operation index (1, 2, . . ., mn)
l:	Job index (1, 2, . . ., n)
j:	Machine index (1, 2, . . ., k)

- **Parameters**

m:	Maximum no. of operation of all jobs
n:	Total number of jobs
mn:	Total number of operation
k:	Total number of machines
d (i,l,j):	Process time for op. i of job l on machine j
Pow_w (j):	Power consumption of machine j at working time
Pow_idl (j):	Power consumption of the j^{th}machin at idle time
α :	Quantity of emitted carbon per kilowatt hour
BigM :	Assumed as a big number

- **Variables**

st (l,j):	Start time of job l on the j^{th}machin
ct (l,j):	Finish time of job l the j^{th}machin
M_avlbl (j):	Availability of the j^{th}machin
M_idle (j):	Duration of the idle state for the j^{th}machin
load (j):	Total workload on the j^{th}machine
Cmax:	Total makespan (C-max)
Carbon_E:	Total emitted carbon footprint of the solution
kdd(i):	Priority index (0,1)
t(l):	Completion time of job l

- **Variables of Results**

X (i,1):	Chromosome place
X (i,2):	Operation number
X (i,3):	Process time
X (i,4):	Machine number

X (i,5):	Power consumption
X (i,6):	Start time of operation
X (i,7):	Completion time of operation

The only priority here was the sequencing among operations of every single job. Then, through each iteration n candidates (kdd) processes. In the first iteration, for example, the first operation of any job will be picked. Equation 4 declares how a simple m-steps counter in the range of [1 mn] can handle difficulty.

$$kdd(1{:}\,m{:}\,mn) = 1; \qquad (4)$$

Following step3 that has explained, in step4 a "SORT" function was applied regarding the objective criterion. Since only prior operations of each job have "kdd" with value 1 and others were 0, and then sorting function sorts these n candidates. Here the iterations start using an index i in the range[1 mn]. At each run or iteration, the result variables will produce and save. The result variables will produce and save. Next, in step5, the algorithm updates the variable, and after mn iterations the counter stops. Figure 1 illustrates the update phase of the presented algorithm.

At first, the algorithm checks if the operation was real or dummy. In the case of being dummy (branch1), there will be some updates following with another conditional statement that asks if this operation was the last of its job. If there were some unallocated operation in this job yet (branch4), the priority shifts to the next one; oppositely (branch3), priority doesn't change, except its process time alters to a $BigM$ later to prevent reselection. And left of updates applies at the end.

On the other hand, if the operation was not dummy (branch2), the same question regarding the possibility of being the last operation will be examined. Updates and adjusting$BigM$, as the processing time, follows the yes scenario (branch5). Oppositely, changing candidates, and updating the variables before moving to the next possible iteration happens.

Steps3 to 5 repeats for mn iteration and finally when$i = mn$, step6 commences. At this step, the results to the objective will count.

2.3 Minimum carbon emission (MCE) algorithm

The MCE algorithm, on the other hand, almost follows the same steps. First importing data, then indexes and variables have addressed in the second step; similar to section 2-2. Later in step3 and step4, the candidate operations have been selected. The only contrast here was the criteria; the original method was time oriented while in this algorithm, carbon emission was the criterion. Per iteration, a compare between candidates declares the best operation to assign with the lowest amount of power consumption (or carbon emission). Devices at a production line are busy, or in the idle mode; with adverse power utilization [6][8]. Utilizing a machine alters others to idle mode. Hence two equations of power consumption have been calculated; operating using of machine j (equation 5) along with the idle consumption of others (equation 6).

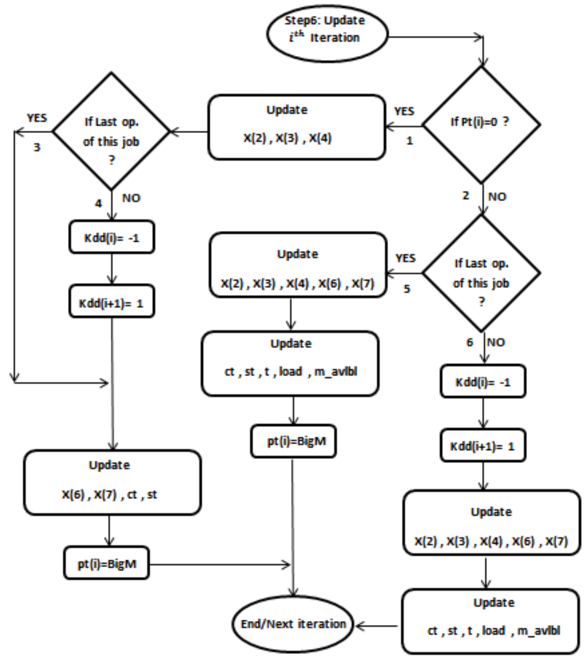

Figure 1: MCT algorithm – updating per iteration

$$CE_{w(j)} = Pow_{w(j)} * \left(ct(l,j) - st(l,j)\right); \qquad (5)$$

$$CE_{idl(j)} = CE_{idl(j)} + \left[Pow_{idl(r)} * \ \left(ct(l,j) - \ M_{avlbl(r)}\right)\right]; \qquad (6)$$

3 Results

Four instances have extracted from literature and results for the proposed algorithms have been revealed; three total flexible job shop (4X5, 10X10, and 15X10 respectively) and a partial (8X8). Later these results have been compared with reported results of some quality methods offered by [17,35]. In "Total 4X5" to ease the simulation, one dummy operation has been allocated to jobs 1 and 2, while two dummies completed job 4.

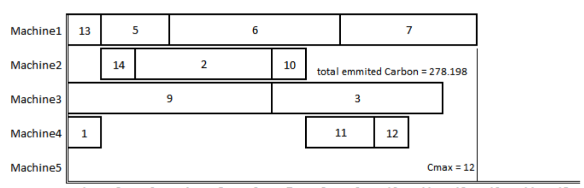

Figure 2: Gant chart of result for MCT algorithm (Total emitted carbon=278.198, C-max=12)

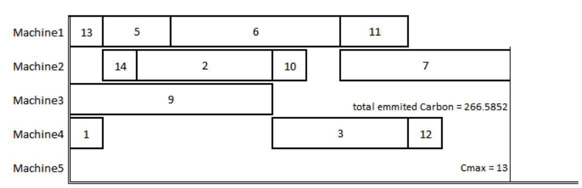

Figure 3: Gant chart of result for MCE algorithm (Total emitted carbon=266.585, C-max=13)

In this “Partial 8X8” dummy operation has been applied on every job except the second, fifth, and eighth. On the other hand, instead of infinite, a constant (BigM=1000) has been employed to present the incapability of machines regarding the allocation.

Table 1: Processing times of instance “Total 4X5”

Jobs	4X5	M1	M2	M3	M4	M5
1	o1	2	5	4	1	2
	o2	5	4	5	7	5
	o3	4	5	5	4	5
	o4	0	0	0	0	0
2	o5	2	5	4	7	8
	o6	5	6	9	8	5
	o7	4	5	4	54	5
	o8	0	0	0	0	0
3	o9	9	8	6	7	9
	o10	6	1	2	5	4
	o11	2	5	4	2	4
	o12	4	5	2	1	5
4	o13	1	5	2	1	12
	o14	5	1	2	1	2
	o15	0	0	0	0	0
	o16	0	0	0	0	0

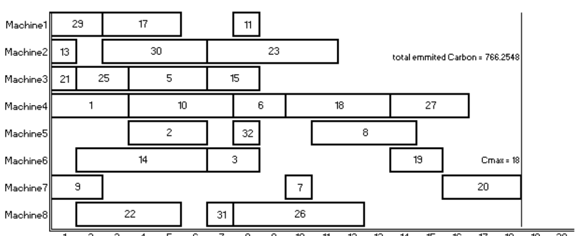

Figure 4: Gant chart of result for MCT algorithm (Total emitted carbon=766.2548, C-max=18)

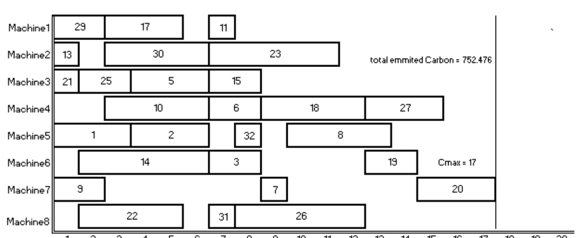

Figure 5: Gant chart of result for MCE algorithm (Total emitted carbon=752.476, C-max=17)

Table 2: Processing times of instance “Partial 8X8”

Jobs	8X8	M1	M2	M3	M4	M5	M6	M7	M8
1	o1	5	3	5	3	3	1000	10	9
	o2	10	1000	5	8	3	9	9	6
	o3	1000	10	1000	5	6	2	4	5
	o4	0	0	0	0	0	0	0	0
2	o5	5	7	3	9	8	1000	9	1000
	o6	1000	8	5	2	6	7	10	9
	o7	1000	10	1000	5	6	4	1	7
	o8	10	8	9	6	4	7	1000	1000
3	o9	10	1000	1000	7	6	5	2	4
	o10	1000	10	6	4	8	9	10	1000
	o11	1	4	5	6	1000	10	1000	7
	o12	0	0	0	0	0	0	0	0
4	o13	3	1	6	5	9	7	8	4
	o14	12	11	7	8	10	5	6	9
	o15	4	6	2	10	3	9	5	7
	o16	0	0	0	0	0	0	0	0
5	o17	3	6	7	8	9	1000	10	1000
	o18	10	1000	7	4	9	8	6	1000
	o19	1000	9	8	7	4	2	7	1000
	o20	11	9	1000	6	7	5	3	6
6	o21	6	7	1	4	6	9	1000	10
	o22	11	1000	9	9	9	7	6	4
	o23	10	5	9	10	11	1000	10	1000
	o24	0	0	0	0	0	0	0	0
7	o25	5	4	2	6	7	1000	10	1000
	o26	1000	9	1000	9	11	9	10	5
	o27	1000	8	9	3	8	6	1000	10
	o28	0	0	0	0	0	0	0	0
8	o29	2	8	5	9	1000	4	1000	10
	o30	7	4	7	8	9	1000	10	1000
	o31	9	9	1000	8	5	6	7	1
	o32	9	1000	3	7	1	5	8	1000

In this “Total 10X10”, there was no dummy, nor a “BigM”. Moreover, all machines were capable of being assigned to every operation.

In the "Total 15X10", sixth and seventh jobs were the exceptions; which two dummies have been attached to preserve the unity of operation numbers.

Table 3: Processing times of instance "Total 10X10"

Jobs	10X10	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
1	o1	1	4	6	9	3	5	2	8	9	5
	o2	4	1	1	3	4	8	10	4	11	4
	o3	3	2	5	1	5	6	9	5	10	3
2	o4	2	10	4	5	9	8	4	15	8	4
	o5	4	8	7	1	9	6	1	10	7	1
	o6	6	11	2	7	5	3	5	14	9	2
3	o7	8	5	8	9	4	3	5	3	8	1
	o8	9	3	6	1	2	6	4	1	7	2
	o9	7	1	8	5	4	9	1	2	3	4
4	o10	5	10	6	4	9	5	1	7	1	6
	o11	4	2	3	8	7	4	6	9	8	4
	o12	7	3	12	1	6	5	8	3	5	2
5	o13	7	`0	4	5	6	3	5	15	2	6
	o14	5	6	3	9	8	2	8	6	1	7
	o15	6	1	4	1	10	4	3	11	13	9
6	o16	8	9	10	8	4	2	7	8	3	10
	o17	7	3	12	5	4	3	6	9	2	15
	o18	4	7	3	6	3	4	1	5	1	11
7	o19	1	7	8	3	4	9	4	13	10	7
	o20	3	8	1	2	3	6	11	2	13	3
	o21	5	4	2	1	2	1	8	14	5	7
8	o22	5	7	11	3	2	9	8	5	12	8
	o23	8	3	10	7	5	13	4	6	8	4
	o24	6	2	13	5	4	3	5	7	9	5
9	o25	3	9	1	3	8	1	6	7	5	4
	o26	4	6	2	5	7	3	1	9	6	7
	o27	8	5	4	8	6	1	2	3	10	12
10	o28	4	3	1	6	7	1	2	6	20	6
	o29	3	1	8	1	9	4	1	4	17	15
	o30	9	2	4	2	3	5	2	4	10	23

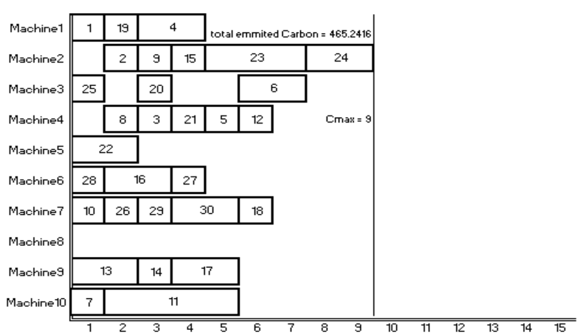

Figure 6: Gant chart of result for MCT algorithm (Total emitted carbon=465.2415, C-max=9)

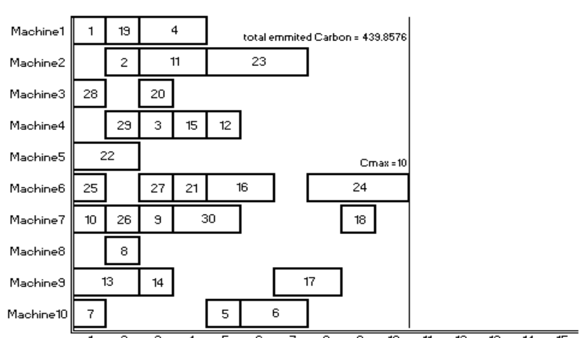

Figure 7: Gant chart of result for MCE algorithm (Total emitted carbon=439.8576, C-max=10)

Table 4: Processing times of instance "Total 15X10"

Jobs	15X10	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
1	o1	1	4	6	9	3	5	2	8	9	4
	o2	1	1	3	4	8	10	4	11	4	3
	o3	2	5	1	5	6	9	5	10	3	2
	o4	10	4	5	9	8	4	15	8	4	4
2	o5	4	8	7	1	9	6	1	10	7	1
	o6	6	11	2	7	5	3	5	14	9	2
	o7	8	5	8	9	4	3	5	3	8	1
	o8	9	3	6	1	2	6	4	1	7	2
3	o9	7	1	8	5	4	9	1	2	3	4
	o10	5	10	6	4	9	5	1	7	1	6
	o11	4	2	3	8	7	4	6	9	8	4
	o12	7	3	12	1	6	5	8	3	5	2
4	o13	6	2	5	4	1	2	3	6	5	4
	o14	8	5	7	4	1	2	36	5	8	5
	o15	9	6	2	4	5	1	3	6	5	2
	o16	11	4	5	6	2	7	5	4	2	1
5	o17	6	9	2	3	5	8	7	4	1	2
	o18	5	4	6	3	5	2	28	7	4	5
	o19	6	2	4	3	6	5	2	4	7	9
	o20	6	5	4	2	3	2	5	4	7	5
6	o21	4	1	3	2	6	9	8	5	4	2
	o22	1	3	6	5	4	7	5	4	6	5
	o23	0	0	0	0	0	0	0	0	0	0
	o24	0	0	0	0	0	0	0	0	0	0
7	o25	1	4	2	5	3	6	9	8	5	4
	o26	2	1	4	5	2	3	5	4	2	5
	o27	0	0	0	0	0	0	0	0	0	0
	o28	0	0	0	0	0	0	0	0	0	0
8	o29	2	3	6	2	5	4	1	5	8	7
	o30	4	5	6	2	3	5	4	1	2	5
	o31	3	5	4	2	5	49	8	5	4	5
	o32	1	2	36	5	2	3	6	4	11	2
9	o33	6	3	2	22	44	11	10	23	5	1
	o34	2	3	2	12	15	10	12	14	18	16
	o35	20	17	12	5	9	6	4	7	5	6
	o36	9	8	7	4	5	8	7	4	56	2
10	o37	5	8	7	4	56	3	2	5	4	1
	o38	2	5	6	9	8	5	4	2	5	4
	o39	6	3	2	5	4	7	4	5	2	1
	o40	3	2	5	6	5	8	7	4	5	2
11	o41	1	2	3	6	5	2	1	4	2	1
	o42	2	3	6	3	2	1	4	10	12	1
	o43	3	6	2	5	8	4	6	3	2	5
	o44	4	1	45	6	2	4	1	25	2	4
12	o45	9	8	5	6	3	6	5	2	4	2
	o46	5	8	9	5	4	75	63	6	5	21
	o47	12	5	4	6	3	2	5	4	2	5
	o48	8	7	9	5	6	3	2	5	8	4
13	o49	4	2	5	6	8	5	6	4	6	2
	o50	3	5	4	7	5	8	6	6	3	2
	o51	5	4	5	8	5	4	6	5	4	2
	o52	3	2	5	6	5	4	8	5	6	4
14	o53	2	3	5	4	6	5	4	85	4	5
	o54	6	2	4	5	8	6	5	4	2	6
	o55	3	25	4	8	5	6	3	2	5	4
	o56	8	5	6	4	2	3	6	8	5	4
15	o57	2	5	6	8	5	6	3	2	5	4
	o58	5	6	2	5	4	2	5	3	2	5
	o59	4	5	2	3	5	2	8	4	7	5
	o60	6	2	11	14	2	3	6	5	4	8

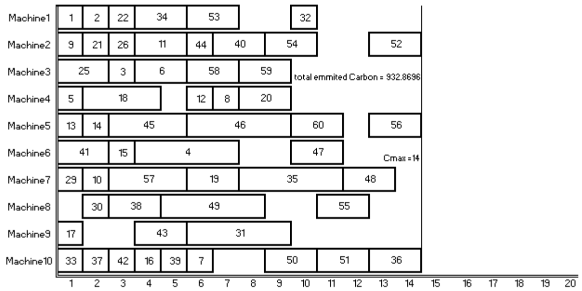

Figure 8: Gant chart of result for MCT algorithm (Total emitted carbon=932.8696, C-max=14)

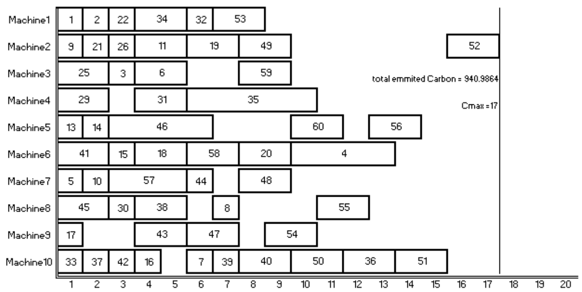

Figure 9: Gant chart of result for MCE algorithm (Total emitted carbon=940.9864, C-max=17)

4 Discussions

4-1 Instance "Total 4X5"

All machines in this total flexible system were capable of processing all operations; there were five options for each. As it has shown in figures 1 and 2, completion times were 12 and 13, respectively. The fifth machine, because of its smaller power usage, was completely idle for both models. Despite reducing workloads was not the prior objective, still has been calculated for both algorithms (MCT: M1=12, M2=6, M3=11, M4=4, M5=0 and MCE: M1=10, M2=11, M3=6, M4=6, M5=0).

Machines idle-time has been calculated by reducing machine workloads from C-max (MCT: M1=0, M2=6, M3=1, M4=8, M5=12 and MCE: M1=3, M2=2, M3=7, M4=7, M5=13). The power consuming indexes (Table 5) were extracted from literature and multiplied by 0.76 to find the carbon emission per kilowatt [6]; which were 278.2 and 266.6 respectively.

Some standard instances have been taken from [35] to verify the quality of the solution. They have suggested a hybrid Genetic Algorithm to tackle the FJSP. Later their results have been compared to the collected answers of proposed algorithms.

Table 5: Power consumption indexes for "Total 4X5"

4X5	M1	M2	M3	M4	M5
work	8.12	8.29	12.4	7.14	11.4
idle	2.41	2.57	1.95	2.75	1.23

The calculations on data extracted from [35] revealed a higher carbon emission comparing both MCT and MCE methods (carbon=278.198 and C-max=12); which proves the quality of the proposed algorithms. Figure 10 clarified the final schedule, and all calculations have displayed in Table 6.

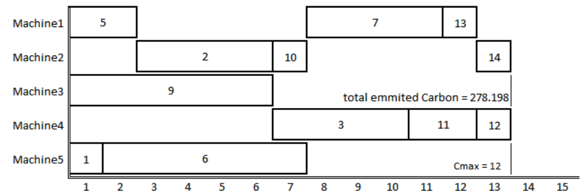

Figure 10: Gant chart of result for [35] (Total emitted carbon=278.198, C-max=12)

Table 6: Reported emitted carbon for [35]–Total 4X5

	time		energy cons.	
	idle	work	idle	work
Machine1	6	7	14.46	56.84
Machine2	7	6	17.99	49.74
Machine3	7	6	13.65	74.4
Machine4	6	7	16.5	49.98
Machine5	6	7	7.38	79.8
results:	Sum:		69.98	310.8
	Total energy cons:		380.74	
	Emitted Carbon:		289.3624	

4-2 Instance "Partial 8X8"

A partial flexible job shop, with six or more machines for every operation, has been studied here. Other than second, fifth, and eighth jobs, all others have received a dummy. In addition, a big constant has been performed to code the incapability of some machines; by forcing the algorithm to neglect to assign this machine to the current operation.

Figures 4 and 5 demonstrated that the seventh machine has the lowest workload among all. Completion times were 18 and 17, and the carbon emissions have been calculated as 766.3 and 752.5, respectively. Further, for evaluating the carbon emission, the power consumption index has been shown in Table7.

Table 7: Power consumption indexes for "Partial 8X8"

8X8	M1	M2	M3	M4	M5	M6	M7	M8
work	7.45	17.81	15.5	12.98	11.57	5.7	7.82	11.05
idle	1.38	2.61	1.94	2.44	1.12	2.99	2.4	2.98

Despite the proper balance of workloads, the total workload of all machines (83) was 10 minutes more than both offered algorithms. Predicting more energy consumption and carbon emission as well resulted by a higher total workload was not that surprising. Then a 55-kilowatt idle-consumption plus a 950.8-kilowatt processing consumption results in a 764.38 carbon emission. Comparing MCT and MCE with the presented GA has confirmed that MCE produced a better schedule regarding emission reduction. As mentioned before, MCT has a time-concerned nature while MCE focused on carbon emission; and this has justified 766.3 emitted carbon in MCT and 752.5 for MCE. Table 8 exposes the details of calculating carbon emission for "Partial 8X8" using [17].

Table 8: Reported emitted carbon for [17]– "Partial 8X8"

	time		energy cons.	
	idle	work	idle	work
Machine1	10	4	13.8	29.8
Machine2	0	14	0	249.34
Machine3	4	10	7.76	155
Machine4	5	9	12.2	116.82
Machine5	4	10	4.48	115.7
Machine6	0	14	0	79.8
Machine7	2	12	4.8	93.84
Machine8	4	10	11.92	110.5
results:	Sum:		54.96	950.8
	total energy cons:		1005.76	
	Emitted Carbon:		764.3776	

4-3 Instance "Total 10X10"

In the first method, the eighth machine was completely idle; on the other hand, in the second method, it has been processed only one minute. Then, C-max and carbon emission were 9 and 465.2 for MCT vs. 10 and 439.9 for MCE. Table 8 has presented the detailed data needed to find the reported carbon emission for the GA algorithm. And Table 9 has elicited the multipliers for power consumption.

Table 9: Power consumption indexes for "Total 10X10"

10X10	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
work	7.45	17.81	15.5	12.98	11.57	5.7	7.82	11.05	11.05	11.05
idle	1.38	2.61	1.94	2.44	1.12	2.99	2.4	2.98	2.98	2.98

4-4 Instance "Total 15X10"

All machines in this total flexible system have been available for all operations. Then C-max has been counted 9 and 10 for both models in order. Despite neglecting the machine workloads, yet MCT showed a balanced allocation, except the 52nd (the last operation of the 13th job) in MCE, has been placed on the second machine behind an enormous gap. This extended C-max and idle-time, so the emitted carbon increases from 932.9 in MCT to 941.0 in MCE. The reason for this failure could be a wrong selection among two candidates with a similar value of selecting criterion. A random selection of the candidate in these circumstances may work. Table 10 illustrates the power consumption indexes regarding this instance.

Table 10: Power consumption indexes for Total 15X10

15X10	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
work	7	18	16	13	12	6	8	11	11	11
idle	1	3	2	2	1	3	2	3	3	3

The mentioned instances have been investigated precisely along with some well-known meta-heuristics. Then the results have been compared with the proposed algorithms. Tables 11 and 12 had summarized all comparisons.

The stated meta-heuristics had focused on makespan and machine workloads. Therefore using available data on idle-times and workloads, the emitted carbon of each model, has been calculated subsequently. Data mostly has been extracted from [35]; then solution 1 and 2 (3rd and 4th raw) refers to their recommended solutions. Fifth to eighth rows, however, refer to methods investigated by [17]. Furthermore, the last row, has been addressed a PSO algorithm offered by [36].

Table 11: Data on Makespan and Maximum Workload

METHODS	MAKESPAN				CRITICAL MWL			
	4X5	8X8	10X10	15X10	4X5	8X8	10X10	15X10
solution1 MCT	13	17	10	17	11	13	8	14
solution2 MCE	12	18	9	14	12	16	8	13
Solution1	13	14	7	11	7	11	5	11
Solution2	12	14	8	12	8	12	5	10
A1: 'Temporal Decomposition	-	19	16	-	-	-	16	-
A2: 'Classic' GA	-	16	7	-	-	-	7	-
A3: Approach by Localization	-	16	8	-	-	-	6	-
A4: 'AL+CGA'	16	14/15/16	7	24/23	10	14/13/13	5	11/11
A6: 'PSO+SA'	11	15/16/14	7	12	10	12/13/2012	6	11

According to Table 11, the reported makespan was acceptable in most cases. However, the critical machine workload, which did not consider as a primary objective, was not promising.

On the other hand, in Table 12, the results for total machine workload have presented; that is crucial regarding power consuming. Investigating machine workloads reveals that the results were proper and better than most of the reviewed meta-heuristics. Furthermore, the standard deviation, which refers to line balancing, has been calculated for studied methods.

Table 12: Data on Total Workload and Standard Deviation

METHODS	TOTAL MWL				Standard Deviation			
	4X5	8X8	10X10	15X10	4X5	8X8	10X10	15X10
solution1 MCT	33	73	42	95	0.131	0.033	0.051	0.0247
solution2 MCE	33	73	43	100	0.151	0.044	0.05	0.0226
Solution1	33	78	43	91	0.017	0.023	0.029	0.0217
Solution2	32	75	42	93	-	-	-	-
A1: 'Temporal Decomposition	-	91	59	-	-	-	-	-
A2: 'Classic' GA	-	77	53	-	-	-	-	-
A3: Approach by Localization	-	75	46	-	-	-	0.018	-
A4: 'AL+CGA'	34	83/79/75	45	91/95	-	0.038/-/-	0.015	-
A6: 'PSO+SA'	32	75/73/77	44	91	-	0.101/0.103	0.029	0.0173

As illustrated in Table12, albeit machine workload and line balancing were not the priority of the proposed method, still results were in an acceptable range. Considering solutions created by proposed algorithms have been founded less than a minute, while results of these meta-heuristics collected due 100, 1000, or even more iterations, significantly assures the quality of MCT and MCE algorithms.

5 Conclusions and future recommendations

Two fast algorithms, called MCT and MCE, have been proposed, to reduce carbon emission along C-max and total machine workload. Results had compared with some well-known meta-heuristics. The original MCT was a time concern dispatching rules, while MCE is a novel method that has contributed to reducing carbon emissions. This method was significantly faster than meta-heuristics, while results comparing to most of them were better. For instance, the total machine workload in the "Partial 8X8" instance (72 and 73) was the best among all investigated approaches. And the emitted carbon was lower than both [35], and [17]. Moreover, the calculated standard deviation for each instance has proven that machine workloads balance were satisfying. Thus, this MCE method strongly suggested for carbon emission minimization problems in FJSP due to its quick performance and accuracy.

However, as future work, a random operator in the phase of selection can improve the performance of the proposed MCE algorithm. Hybridizing these algorithms with a meta-heuristic or applying it as an initializer also seems promising. On the other hand, dynamic environment is another challenging field to examine the efficiency of these algorithms.

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