HAL open science

Heuristic approaches for scheduling manufacturing tasks while taking into account accumulated human fatigue

Nicola Berti, Christian Artigues, Olga Battaïa, Romain Guillaume, Daria Battini

To cite this version:

Nicola Berti, Christian Artigues, Olga Battaïa, Romain Guillaume, Daria Battini. Heuristic approaches for scheduling manufacturing tasks while taking into account accumulated human fatigue. 9th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2019, Aug 2019, Berlin, Germany. pp.963-968, 10.1016/j.ifacol.2019.11.319 . hal-02962577

HAL Id: hal-02962577

https://hal.science/hal-02962577v1

Submitted on 9 Oct 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Heuristic approaches for scheduling manufacturing tasks while taking into account accumulated human fatigue

Nicola Berti [*,**] **Christian Artigues** [**] **Olga Battaïa** [***]
Romain Guillaume [****] **Daria Battini** [*]

[*] *Department of Management and Engineering, University of Padova, Stradella San Nicola, 3, 36100 – Vicenza - Italy (e-mail: nicola.berti.5@studenti.unipd.it, daria.battini@unipd.it)*
[**] *LAAS-CNRS, Université de Toulouse, CNRS - Toulouse - France (e-mail: artigues@laas.fr)*
[***] *ISAE-SUPAERO, Université de Toulouse - Toulouse - France (e-mail: olga.battaïa@isae-supaero.fr)*
[****] *Université de Toulouse IRIT / UTM 5, 31058 - Toulouse - France (e-mail: Romain.Guillaume@irit.fr)*

Abstract: Human factors are often ignored in scheduling algorithms despite the fact that the majority of manufacturing systems still employ human operators. In particular, ergonomic studies shown that human fatigue has an important impact on worker performance and as a consequence it should be taken into account in the modelling of the system performance. This study investigates the problem of the integration of accumulated human fatigue into scheduling algorithms. A new optimization problem is defined and several constructive heuristics are developed to solve it. Their performances are evaluated through a numerical experiment. The conclusions of this analysis and future research directions are discussed.

Keywords: Scheduling, human factors, fatigue, constructive heuristics, optimization.

1. INTRODUCTION

Decision-making process behind the scheduling of manufacturing tasks plays a fundamental role in industrial environment. Nowadays its impact on the system performance is more and more investigated due to the availability of manufacturing data (Pinedo, 2016). The main purpose of scheduling is to organize the manufacturing process in the best way that a performance function is optimized and existing constraints of the manufacturing environment are respected (Pinedo, 2005). Such performance indicators can be expressed in different ways such as flow time, work in progress and throughput (Digiesi et al., 2009), but also makespan, total weighted completion time, maximum lateness, and the total number of tardy jobs (Ferjani et al., 2017). However, most of them are profit/cost oriented. Only recently new models were proposed in order to optimize the working conditions such as to reduce physical workload (Mossa et al., 2016; Otto and Battaïa, 2017). It shows an important gap in scheduling literature where the impact of scheduling decisions on human performance and health is usually ignored (Lodree et al., 2009).

To fill this gap, a significant effort on modelling of human factors has to be made. This study is dedicated to the integration of one of such factors, human accumulated fatigue in scheduling decision-making process. The objective is to assign (and schedule) a set of given tasks to a number of human operators taking into account their fatigue and their need to have a break.

The remainder of this article is organized as follows. Section 2 presents the existing mathematical models used to evaluate human fatigue in manufacturing. Section 3 provides the new optimization problem we introduce and a small example of the considered problem. Section 4 presents the algorithms that we have developed to solve the introduced optimization problem. Section 5 reports the results of the computational experiments. Finally, Section 6 provides conclusions and suggestions for future research.

2. STATE-OF-THE-ART

Lodree et al. (2009) stated that in scheduling literature human factors are often ignored although their impact on the performance of the manufacturing system is considerable. The authors even claimed that the scheduling research and the human factors research literature represent two disjoint sets because of the rarity of collaborations between researchers of these communities.

However, Grosse et al. (2017) showed that recently the number of studies that try to integrate human factors into decision support models have increased because of the awareness on the impact of these factors on the final performance of the manufacturing systems. In particular, such human factors as physical ergonomic risks are more and more integrated in such optimization problems as assembly line balancing and job rotation as revealed a recent survey (Otto and Battaïa, 2017).

Regarding the human fatigue, some studies have already been conducted to identify fatigue causing factors which reduce the performance of workers, and consequently, the productivity of the manufacturing system. In the following, we overview the mathematical models the most frequently used for evaluating fatigue in the literature on manufacturing systems.

Eilon (1964) presents two formulas modeling the loss in production due to fatigue and the gain in production rate due to a recovery time. They found the net gain (call it p) of production between these two conditions. Thus, a rest period is worthwhile if the gain exceeds the loss, then they found the maximum value of p. They also found at what point in time it is most beneficial to introduce a rest period.

Gentzler Jr et al. (1977) aim to maximize the function $W(x)$ which is

$$W(x) = \frac{\phi(x)}{x+\theta}$$

where $\phi(x)$ is the amount of work produced in one work period, x is the length of time of a work period and the length of a rest period and θ is a constant long enough to ensure that the work rate of the next work period starts at $v(0)$, the unfatigued state. Setting $W'(x) = 0$ states that the optimal time to introduce a rest period is when the average work rate of a cycle is equal to the instantaneous work rate.

Maximum endurance time (MET) is the duration for which a specific body posture (or muscular effort) can be sustained by a worker before his/her capability limits are reached. In Jaber et al. (2013), it is a function of the level of the force being applied i.e., f_{MVC}, which is a fraction of the muscle's maximum voluntary contraction (MVC) when performing a specific task. $MET = \beta_0 \cdot e^{\beta \cdot f_{MVC}}$ or power forms, e.g., $MET = \alpha_0 \cdot f_{MVC}^{-\alpha}$ where α_0, α, β_0 and β are model-specific parameters and MET is measured in minutes. The model used in (Jaber et al., 2013) to evaluate fatigue is as follows:

$$F_{i+1}(t) = R(\tau_i) + (1 - R(\tau_i))(1 - e^{-\lambda(t_n - t_i)}) \quad (1)$$

- $R(\tau_i)$ is the residual fatigue carried forward into cycle $i+1$;
- λ is a fatigue exponent, specifying fatigue rate;
- t_n is the production time of the cycle i;
- t_i is determined by projecting the value of $R(\tau_i)$ on the fatigue curve as:

$$t_i = \frac{-ln(1 - R(\tau_i))}{\lambda} \quad (2)$$

Glock et al. (2019) use the description of fatigue accumulation above for developing a biomechanical model to estimate the expected fatigue-recovery parameters in manual packaging process. Moreover, the authors perform a sensitivity analysis of the fatigue parameter λ evaluating how the value of this parameter changes for modifications of $\%MVC$ by 10% and 20% (plus/minus).

The study of Perez et al. (2014) proposes the following behavior of fatigue accumulation while trying to simulate a dynamic process using static MET models:

$$F_t = fF_{t-1} + \frac{\Delta t}{MET_i} + \frac{\Delta t}{R_j} \quad (3)$$

The fatigue accumulation after $task_i(F_i)$ is calculated as follows:

$$F_{i+1} = (F_{i-1} + fF_i) \cdot (1 - fR_i) \quad (4)$$

- F_i is the fatigue rate after $task_i$;
- fF_i is the fraction of fatigue contribution per $task_i$;
- fR_i is the fraction of recovery received after $task_i$;
- R_i is the recovery time (in seconds) needed after $task_i$ to bring fatigue down to 0.

In Givi et al. (2015), the fatigue accumulation in the "learning–forgetting–fatigue–recovery model" (LFFRM), is modelled by an exponential model of the following form:

$$F(t_i) = R(t_{i-1}) + (1 - R(t_{i-1})(1 - exp(\lambda t_i))) \quad (5)$$

where $F(t)$ is the accumulated fatigue over time t_i, $R(t_{i-1})$ is the residual fatigue after a break carried along cycle $i-1$, and λ is the fatigue index describing the severity of the work performed, t_i is the length of the current production cycle and t_{i-1} is the length of the previous one. At time $t = 0$, fatigue is zero and as time increases, fatigue converges asymptotically to 1. A recovery function can be also defined.

Fruggiero et al. (2017) propose the following model to evaluate the amount of physical stress L_t accumulated by a worker L_t after time t.

$$L_t = \sum f_i \cdot t_i - \frac{L_{max}}{RA_i \cdot MET_i} \cdot b_i \quad (6)$$

where f_i is the amount of physical stress for executing task i of duration t_i, b_i is the break time following task i, L_{max} is the maximum fatigue index, RA_i (Rest Allowance) required for task i as a fraction of MET_i.

Ferjani et al. (2017) associate a penalty coefficient d_j to each machine j to model the difficulty of work on that machine, such that $0 \leq d_j \leq 1$. This coefficient d_j expresses the speed of fatigue accumulation. The value of $G_i(\theta)$ characterizes how the level of fatigue of a worker increases. $G_i(\theta) = 1 - e^{-d_j \cdot \theta}$ where θ is the duration. $F_i(t_i)$ is the worker initial fatigue at time t_i. $\Delta_{ij}(t_i, t)$ expresses the increase of fatigue generated during a new task on machine j, between its beginning t_i and the current time t, which can be expressed as follows:

$$\Delta_{ij}(t_i, t) = (1 - F_i(t_i))(1 - e^{-d_j(t - t_i)}) \quad (7)$$

As a consequence, from time t to t_i, the level of fatigue is updated as follows:

$$F_i(t) = F_i(t_i) + \Delta_{ij}(t_i, t) \quad (8)$$

Since the aim is to correct the theoretical processing times to take the fatigue level into account, they suggest that these processing times increase according to a logarithm function, i.e. $T'_{kj}(t_i)$ represents corrected processing time of the task waiting in the k-th position on machine j to which the worker i can be assigned at the instant t_i, as follows:

$$T'_{kj}(t_i) = T_{kj}(1 + \delta d_j(ln(1 + F_i(t_i)))) \quad (9)$$

The parameter δ represents the influence of fatigue. Typically, it allows a maximum degradation time to be considered, given that when it is zero then fatigue does not influence the task duration. They also develop an heuristic to dynamically assign workers to machines so as to reduce the mean flowtime. The proposed approach takes the impact of fatigue into consideration.

Visentin et al. (2018) measure the physical fatigue through the energy expenditure rate. Considering their exponential trends, the fatigue $F(t_w)$ and the recovery $R(\tau)$ related to a certain task i are modelled as follows:

$$F(t_w)_i = \dot{E}_{w_i} + (\dot{E}_R - \dot{E}_{w_i}) \cdot e^{-\lambda t_{w_i}} \tag{10}$$

The value of $F(t_w)_i$ is linked to:

- the duration of task w is t_w;
- the energy expenditure rate at rest $\dot{E}_R$ (The energy expenditure rate at rest $\dot{E}_R$, as stated by (Battini et al., 2017), is 1.86 Kcal/min for a standard worker);
- the maximum energy expenditure rate $\dot{E}_{w_i}$;
- λ, which is the parameter of fatigue accumulation of the specific operator.

If after task i the operator has to perform consecutively another task $i+1$ without taking a rest, the fatigue is accumulated. Moreover, the task can have a higher or a lower value of $\dot{E}_{w_i}$ than the previous one. Considering this, the trend of fatigue accumulation for this second task is formulated as:

$$\int_0^{t_{w_i}} F(t_w)_i = \dot{E}_{w_i} \cdot t_{w_i} + \begin{cases} +(F(t_w)_{i-1} - \dot{E}_{w_i}) \cdot \dfrac{e^{-\lambda \cdot t_{w_i}}}{-\lambda} + \dfrac{(F(t_w)_{i-1} - \dot{E}_{w_i})}{\lambda} \\ \qquad if\ \dot{E}_{w_i} \geq F(t_w)_{i-1} \\ +(F(t_w)_{i-1} - \dot{E}_{w_i}) \cdot \dfrac{e^{-\mu \cdot t_{w_i}}}{-\mu} + \dfrac{(F(t_w)_{i-1} - \dot{E}_{w_i})}{\mu} \\ \qquad if\ \dot{E}_{W_i} < F(t_W)_{i-1} \end{cases} \tag{11}$$

$F(t_w)_i$: fatigue reached after the end of the first task. Parameters λ and μ are related to the personal characteristics of the operator, which respectively indicate how the fatigue is accumulated (λ) and alleviated (μ). Moreover, with this RA (rest allowance) it is possible to calculate the total time the operator needs to execute all tasks including the time necessary for the recovery:

$$t_{tot} = \sum_{i=1}^{n} t_{w_i} + \sum_k \tau_{r_k} + RA \cdot (\sum_{i=1}^{n} t_{w_i} + \sum_k \tau_{r_k}) \tag{12}$$

where τ_{r_k} is the time necessary to reach 1.86 Kcal/min. The value of RA is estimated as a percentage of the working time the operator needs to stay at $\dot{E}_R$ i.e. at total recovery.

Baucells and Zhao (2018) present a model for marginal productivity decreasing because of fatigue, where $Y_0 \geq 0$ is the initial fatigue level, and $\gamma > 0$ is the fatigue recovery rate:

$$Y(t) = Y_0 \cdot e^{-\gamma t} + \int_0^t e^{-\gamma(t-s)} dX(s) \tag{13}$$

The literature analysis shows that except the heuristic developed in Ferjani et al. (2017) and used to minimize the flowtime, no scheduling procedure takes into consideration the fact that operators' performances often decline because of the fatigue generated during task execution.

This study proposes a set of constructive heuristics capable of taking this into account while scheduling a set of tasks with the objective to minimize the makespan. The optimization problem is formally defined in the next section.

3. PROBLEM DEFINITION

We consider the problem of scheduling of a given set of tasks in a manufacturing cell. The set of operators with their personal characteristics (λ and μ) are known. The set of tasks $w \in W$ to be scheduled with their energy expenditure rate E_w is known as well. Index i is used to enumerate the tasks performed in sequence by the same operator. The operators perform their tasks independently. The typical scheduling constraints have to be respected:

- All tasks have to be scheduled;
- Each task has to be scheduled once;
- Each operator can perform one single task per time;
- Preemption of tasks is forbidden.

The objectives considered is this study are the makespan and the fatigue accumulation by the operators. Each time an operator accumulates the fatigue to the level of rest allowance, a break is imposed which duration has an impact on the final makespan. The fatigue models used are discussed here below.

3.1 Fatigue evaluation

We use a model derived from the proposition of (Visentin et al., 2018), where fatigue is accumulated after each task i performed according to eq. 14.

$$\int_0^{t_{w_i}} F(t_w)_i = \int_0^{t_{w1}} F(t_w)_1 + \cdots + \int_{t_{w_{i-1}}}^{t_{w_i}} F(t_w)_i \tag{14}$$

The fatigue caused by the first task after a total recovery break is calculated with formula 15:

$$\int_0^{t_{w1}} F(t_w)_1 = \dot{E}_{w1} \cdot t_{w1} + (\dot{E}_R - \dot{E}_{w1}) \cdot \frac{e^{-\lambda \cdot t_{w_1}}}{-\lambda} + \frac{(\dot{E}_R - \dot{E}_{w1})}{\lambda} \tag{15}$$

Then, formula (16) is used to evaluate the accumulation of the fatigue after task i taking into account the difference between the energy expenditure rate of the current and previous tasks.

$$\int_{t_{w_{i-1}}}^{t_{w_i}} F(t_w)_i = \dot{E}_{w_i} \cdot t_{w_i} + \begin{cases} +(\dot{E}_{wi-1} - \dot{E}_{w_i}) \cdot \dfrac{e^{-\lambda \cdot t_{w_i}}}{-\lambda} + \dfrac{(\dot{E}_{wi-1} - \dot{E}_{w_i})}{\lambda} \\ \qquad if\ \dot{E}_{w_i} \geq \dot{E}_{w_{i-1}} \\ +(\dot{E}_{wi-1} - \dot{E}_{w_i}) \cdot \dfrac{e^{-\mu \cdot t_{w_i}}}{-\mu} + \dfrac{(\dot{E}_{wi-1} - \dot{E}_{w_i})}{\mu} \\ \qquad if\ \dot{E}_{w_i} < \dot{E}_{w_{i-1}} \end{cases} \tag{16}$$

The main difference between the model used in (Visentin et al., 2018) and our model is between equations (11) and (16). In our model, the fatigue is calculated for each task i and the accumulated fatigue is evaluated by (14). The value of accumulated fatigue is generated by the sum of the different contributions of tasks performed by the same operator. It is a key variable of our model used in order to guarantee the fairness in task distribution among operators.

Each time an operator accumulates the fatigue to the level of rest allowance, a break is imposed which duration is calculated according to formula:

$$\tau_{r_k} = \frac{-\ln(\dot{E}_R) + \ln F(t_w)_k}{\mu} \tag{17}$$

It represents the time necessary to reach 1.86 Kcal/min from the value of energy the operator reaches when the threshold is exceeded. While the operator is restoring energy until the value of $\dot{E}_R$, a small amount of fatigue has to be considered in the total value of accumulated fatigue. This value is calculated with the formula:

$$\int_{t_{w_k}}^{t_{w_k}+\tau_{r_k}} R(\tau)_k = \frac{F(t_w)_k}{-\mu} \cdot e^{-\mu \cdot t_{w_k}} \cdot (e^{(-\ln F(t_w)_k) + \ln(\dot{E}_R)} - 1) \tag{18}$$

This amount of fatigue "accumulated during a break" can be considered as negligible, a fixed value is added each time an operator needs a break, for a precise estimation of the total accumulated fatigue.

In the next section, we present the constructive heuristics that we developed in order to find a compromise between the total makespan and the distribution of the fatigue among the operators.

4. CONSTRUCTIVE ALGORITHMS

Algorithm 1 Calculate $Makespan_{max}$

op, task - read input data
L is the list of unscheduled tasks, initialized with the set of given tasks
while L is not empty **do**
  $j \leftarrow$ select Task (L, *op*, *task*)
  $o \leftarrow$ select Operator (j, *op*, *task*)
  Schedule (j, o, L, *op*, *task*), Update L
end while
return $Makespan\ \forall o \in op$
return $AccumulatedFatigue\ \forall o \in op$

The pseudo-code of the general algorithm is represented by Algorithm 1. This algorithm uses 8 different rules for selecting next task. All of them use two criteria, if a tie occurs according to the first criterion, the second one is applied to select a task.

(1) Max task duration & Min task energy
(2) Max task energy & Min task duration
(3) Min task duration & Min task energy
(4) Min task energy & Min task duration
(5) Max task duration & Max task energy
(6) Max task energy & Max task duration
(7) Min task duration & Max task energy
(8) Min task energy & Max task duration

Algorithm 1 uses 9 different rules for selecting next operator: the criteria are applied in the specified order.

(1) Min operator makespan & Min value of λ
(2) Min operator makespan & Max value of λ
(3) Min number of tasks already assigned & Min operator makespan & Min value of λ
(4) Min number of tasks already assigned & Min value of λ & Min operator makespan
(5) Min number of tasks already assigned & Min value of fatigue & Min value of λ
(6) Min number of task already assigned & Min operator makespan & Max value of λ
(7) Min value of fatigue & Min Number of tasks already assigned & Min value of λ
(8) Min value of accumulated fatigue & Min number of tasks already assigned & Max value of λ
(9) Min value of accumulated fatigue & Min number of tasks already assigned & Min value of λ & Max value of μ

In the next section, we study the performances of these rules in a numerical experiment.

5. COMPUTATIONAL EXPERIMENTS

5.1 Example of solution

Figure 1 presents a short example of scheduling of 12 tasks and 5 operators following the rule 1 for task selection and rule 1 for operator selection. Parameters of tasks are given in Table 1. The personal characteristics of 5 operators are given in Table 2 as well as the makespan and total accumulated fatigue obtained as results of scheduling. The maximal difference in the accumulated fatigue among the operators is equal to 358.85-127.01=231.84.

Task	1	2	3	4	5	6
t_w	15.0	8.7	12.6	17.5	6.8	10.5
$\dot{E}_w$	3.2	5.3	2.7	7	5.2	6.1
Task	7	8	9	10	11	12
t_w	9.7	13.6	18.3	15.9	7.7	16.5
$\dot{E}_w$	4.8	4.1	2.6	8.1	6.3	4.9

Operator	λ	μ	Makespan	Accumulated fatigue
1	4.0	1.5	39.78	358.85
2	3.5	2.0	38.32	127.01
3	2.5	1.5	41.22	299.47
4	6.0	2.5	39.28	315.73
5	4.5	1.0	43.01	158.52

Table 1. Task and Operators' parameters

Figure 1 shows the obtained schedule of 12 tasks including the breaks required by Rest Allowance when the energy threshold is exceeded (value > 4.3). Final short breaks show how long should be the rest to return the energy expenditure rate to the initial value of 1.86 Kcal/min.

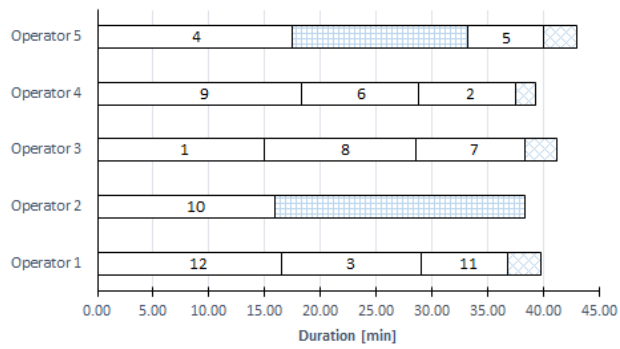

Fig. 1. Example of scheduling of 12 tasks

5.2 Instance generation

Fifteen problem instances have been randomly generated for this numerical experiment. Each problem instance contains 24 tasks to be assigned to 5 operators. Each operator

has different values of parameters λ and μ expressing their personal characteristics, they are reported in Table 2. The values of $\dot{E}_w$ have been randomly generated on interval [2-8] $Kcal/min$. The duration of tasks has been also generated randomly on interval [5-20] minutes. These 15 problem instances were solved with heuristics obtained by all combinations of task and operator selection rules, i.e. with 8×9=72 heuristic rules. The obtained results are reported in Tables 3-7.

5.3 Results and analysis

Table 3 reports the rules that provided the best values of makespan (BestM) and accumulated fatigue (BestF) for P1-P15 problem instances solved. The rules are encoded in the following way: T1O1 corresponds to the first rule of task (T) selection and to the first rule for operator (O) selection. The best results summarized for task and operator selection rules are also reported.

	BestM	BestF
P 1	T1O2, T5O2	T1O8, T5O8
P 2	T1O9, T5O9	T1O1, T5O1
P 3	T2O1, T6O1	T2O1
P 4	T1O8, T5O8	T1O1, T5O1
P 5	T2O8, T6O8	T1O8, T5O8
P 6	T2O9, T6O9	T2O3, T6O3
P 7	T2O2, T6O2	T2O2, T6O2
P 8	T2O1	T2O2
P 9	T2O2, T6O2	T2O2, T6O2
P 10	T2O2, T6O2	T5O6
P 11	T1O8, T5O8	T1O8, T5O8
P 12	T2O9, T6O9	T1O2, T5O2
P 13	T2O2, T6O2	T5O1
P 14	T2O8, T6O8	T2O8, T6O8
P 15	T1O2, T5O2	T1O9

Rule	BestM	BestF	Tot
T1	5	7	12
T2	10	6	16
T5	5	8	13
T6	9	4	13
O1	3	6	9
O2	12	7	19
O3	0	2	2
O6	0	1	1
O8	8	8	16
O9	6	1	7
Tot	58	50	108

Table 3. Rules that provided the best makespan / accumulated fatigue

We can notice that the best rules for task selection are T2 and T6 for makespan and T1 and T5 for accumulated fatigue. These rules give the priority to the most longest (T1, T5) or to the most difficult tasks (T2, T6). The best rules for operator selection are O2 and O8 both for makespan and accumulated fatigue (they select as the first criterion the operator with minimum makespan and the minimum accumulated fatigue, respectively). Rule O9 performed well only for makespan.

Table 4 reports, for the rules that provided at least one best solution ether for makespan or accumulated fatigue: the number of best obtained values (NBM and NBF) respectively for makespan and accumulated fatigue and maximal, average and minimal values of the gap from the best values for makespan and accumulated fatigue.

We can notice that different heuristic rules are the most efficient for different problem instances: the maximal frequency of best makespan is 4 and accumulated fatigue 3. These values are reached by the T202 combination (in green), which gives priority to the most difficult task and assigns it to the operator with the minimal makespan. However, the average gaps are quite small for all reported combinations. We can also notice that the majority of heuristic rules were capable of providing both best values

	NBM	MaxGapM	AvGapM	MinGapM	NBF	MaxGapF	AvGapF	MinGapF
T1O1	0	11.8	3.6	0.2	2	73.3	26.5	0
T1O2	2	9.0	2.7	0	1	64.2	32.4	0
T1O8	2	14.7	6.0	0	3	34.7	12.1	0
T1O9	1	15.9	6.1	0	1	20.5	11.2	0
T2O1	2	4.3	1.7	0	1	68.5	18.2	0
T2O2	4	5.9	2.1	0	3	63.0	18.3	0
T2O3	0	24.6	13.0	3.5	1	70.4	41.6	0
T2O8	2	5.6	2.1	0	1	31.5	9.8	0
T2O9	2	7.0	2.5	0	0	26.7	8.9	0.3
T5O1	0	11.8	3.7	0.2	3	73.3	28.1	0
T5O2	2	9.0	2.8	0	1	64.2	32.4	0
T5O6	0	33.1	15.0	1.8	1	65.8	38.4	0
T5O8	2	14.7	6.1	0	3	34.7	13.4	0
T5O9	1	14.2	6.8	0	0	20.5	12.3	1.9
T6O1	1	4.3	1.8	0	0	68.5	19.2	1.4
T6O2	4	5.9	2.1	0	2	63.0	18.4	0
T6O3	0	24.6	13.2	3.5	1	70.4	41.5	0
T6O8	2	5.6	2.0	0	1	31.5	9.8	0
T6O9	2	7.0	3.1	0	0	26.7	9.0	0.3

Table 4. Gaps from the best values of makespan and accumulated fatigue

of makespan and accumulated fatigue. This means that the working conditions of workers can be improved with no or little impact on total completion time due to a fairer task distribution among the workers.

Table 5 reports the maximal, average and minimal values of makespan among all problem instances solved with the heuristic rules proposed.

		1st rule	2nd rule	3rd rule	4th rule	5th rule	6th rule	7th rule	8th rule	9th rule
1st rule	Max	130.63	127.89	131.96	170.77	170.77	136.19	183.12	133.46	130.01
	Average	104.22	103.32	114.05	125.71	127.05	114.97	132.90	106.60	106.68
	Min	84.40	83.01	87.29	96.68	100.50	87.11	100.50	84.82	86.25
2nd rule	Max	120.17	123.46	139.53	168.13	168.13	137.13	147.24	121.30	120.24
	Average	102.28	102.75	113.67	123.61	123.75	114.19	120.93	102.73	103.13
	Min	83.79	84.79	87.91	99.65	99.65	89.44	99.65	82.58	81.80
3rd rule	Max	143.20	143.20	153.68	168.98	168.98	150.65	220.64	138.08	149.77
	Average	118.85	118.84	123.48	125.07	127.85	121.25	168.17	117.50	122.40
	Min	92.07	91.62	89.54	95.90	101.84	90.30	128.61	91.58	93.23
4th rule	Max	145.11	144.79	148.57	170.17	159.21	151.98	391.77	149.13	147.28
	Average	119.96	119.83	123.98	124.77	125.97	123.71	191.26	122.92	122.99
	Min	91.33	88.40	96.62	101.17	104.08	96.62	124.36	88.40	90.24
5th rule	Max	130.63	127.89	133.19	170.77	170.77	137.47	202.17	133.46	130.01
	Average	104.36	103.44	114.58	125.57	126.92	115.60	135.82	106.69	107.38
	Min	84.40	83.01	87.29	96.68	100.50	87.11	100.50	84.82	86.25
6th rule	Max	120.17	123.46	139.53	168.13	168.13	137.13	147.24	121.80	121.93
	Average	102.37	102.76	113.84	124.32	124.06	114.32	121.40	102.63	103.68
	Min	83.79	84.79	87.91	99.65	99.65	89.44	99.65	82.58	81.80
7th rule	Max	143.20	143.20	153.68	168.98	168.98	150.65	254.95	138.95	149.77
	Average	119.16	118.98	123.47	125.62	128.47	121.48	169.09	117.47	122.70
	Min	92.07	91.62	89.54	95.90	101.84	90.30	128.61	91.58	93.23
8th rule	Max	145.11	144.79	148.57	170.17	159.21	151.98	391.77	149.13	147.28
	Average	119.79	119.12	124.92	124.05	125.25	124.12	190.91	122.55	122.26
	Min	91.33	88.40	96.62	101.17	104.08	96.62	124.36	88.40	90.24

Table 5. Makespan obtained

		1st rule	2nd rule	3rd rule	4th rule	5th rule	6th rule	7th rule	8th rule	9th rule
1st rule	Max	399.38	430.94	399.38	491.65	491.65	430.94	535.79	395.76	387.09
	Average	340.14	346.03	341.36	379.23	378.15	351.18	395.66	325.80	324.83
	Min	265.75	298.72	278.78	302.54	302.54	278.78	302.54	276.81	280.04
2nd rule	Max	411.81	377.39	415.54	503.36	503.36	418.68	435.39	370.47	370.32
	Average	331.88	331.99	355.29	377.88	377.01	353.48	368.74	323.50	322.54
	Min	268.73	285.29	276.84	308.65	308.65	287.21	308.65	281.62	275.01
3rd rule	Max	440.86	532.80	450.99	493.99	493.99	477.80	671.13	444.95	436.35
	Average	370.00	379.41	374.93	379.25	383.15	375.80	501.69	367.29	367.44
	Min	295.37	296.36	295.24	295.51	300.17	300.98	396.23	279.53	285.94
4th rule	Max	461.37	471.22	461.37	501.41	469.40	471.22	1179.04	436.78	439.60
	Average	381.96	379.49	381.10	390.39	392.67	386.10	581.81	371.92	371.17
	Min	274.65	279.75	299.23	321.09	321.09	299.23	382.81	275.69	272.73
5th rule	Max	399.38	430.94	399.38	491.65	491.65	430.94	580.86	395.76	387.09
	Average	341.78	346.11	344.82	375.86	376.31	352.10	402.05	327.04	325.98
	Min	265.75	298.72	278.78	302.54	302.54	278.78	302.54	276.81	280.04
6th rule	Max	411.81	377.39	415.54	503.36	503.36	418.68	434.40	370.47	370.32
	Average	332.89	332.02	355.16	379.87	378.30	353.96	370.29	323.50	322.67
	Min	268.73	277.17	276.84	308.65	308.65	287.21	308.65	281.62	275.01
7th rule	Max	462.62	532.80	450.99	493.99	493.99	477.80	720.57	444.95	436.35
	Average	371.64	384.84	376.05	382.66	386.12	376.05	502.80	368.94	367.53
	Min	295.37	296.36	295.24	295.51	300.17	300.98	396.23	279.53	285.94
8th rule	Max	461.37	471.22	461.37	501.41	469.40	471.22	1179.04	436.78	439.60
	Average	379.13	377.50	383.33	388.40	390.68	387.74	580.64	275.69	370.78
	Min	274.65	279.75	299.23	321.09	321.09	299.23	382.81	371.04	272.73

Table 6. Max values of Accumulated Fatigue

Table 6 reports the maximal, average and minimal values of accumulated fatigue among all problem instances

solved. The best values are highlighted in green. One sees again the good results of the T2O2 combination (along others). Especially O8 and O9 rules that considers the selection of the operator with the minimum accumulated fatigue as well as T5 (that selects the most difficult task as the secondary criterion, the main criterion being the max task duration) and T6 (variant of T2 with max task duration instead of min task duration as the secondary criterion) perform also well.

Table 8 reports the maximal, average and minimal values of differences in the accumulated fatigue among all operators in the same problem instance. Not surprisingly, the rules that lead to the minimum of maximal fatigue accumulated lead also to the fairest distribution of fatigue.

		1st rule	2nd rule	3rd rule	4th rule	5th rule	6th rule	7th rule	8th rule	9th rule
1st rule	Max	114.04	107.96	138.77	299.41	250.95	134.99	492.24	46.88	42.72
	Average	55.57	65.83	71.94	143.30	137.26	78.28	214.42	33.98	28.93
	Min	15.15	36.85	41.89	72.35	72.35	24.80	72.35	15.55	3.90
2nd rule	Max	100.49	96.17	166.84	320.98	320.98	161.01	255.78	62.34	54.50
	Average	47.13	47.79	120.25	161.67	164.24	117.00	149.66	34.88	33.45
	Min	15.45	19.06	72.90	55.71	55.71	51.25	55.71	10.19	10.01
3rd rule	Max	161.77	230.99	254.23	301.75	301.75	221.31	671.13	160.69	158.36
	Average	111.06	121.93	121.96	140.76	160.69	121.04	448.06	98.01	101.60
	Min	45.21	62.86	47.35	45.22	66.80	46.89	128.87	36.81	37.79
4th rule	Max	190.85	198.19	215.72	319.03	330.71	226.22	1162.54	162.82	166.47
	Average	124.57	119.14	136.87	165.46	175.99	148.71	546.86	109.23	104.47
	Min	50.31	45.77	43.82	57.35	83.36	79.42	152.94	47.69	33.18
5th rule	Max	114.04	107.96	138.77	299.41	250.95	134.99	532.10	46.88	42.72
	Average	57.07	68.10	77.35	136.71	137.42	80.85	223.08	35.31	28.99
	Min	12.06	38.17	41.89	55.05	55.05	9.08	55.05	15.55	3.90
6th rule	Max	100.49	96.17	166.84	320.98	320.98	161.01	255.78	62.34	54.50
	Average	46.82	48.86	121.57	162.16	163.86	118.96	152.82	35.46	32.87
	Min	15.45	19.06	72.90	55.71	55.71	53.74	55.71	10.19	10.01
7th rule	Max	187.76	230.99	254.23	301.75	301.75	221.31	707.02	160.69	158.36
	Average	114.57	128.38	119.86	150.93	167.43	122.00	449.18	99.99	99.90
	Min	45.21	62.86	47.35	49.35	70.09	46.89	128.87	36.81	37.79
8th rule	Max	190.85	198.19	215.72	319.03	330.71	226.22	1162.54	162.82	166.47
	Average	120.10	117.15	139.74	164.89	175.23	150.51	545.69	108.72	104.03
	Min	50.31	45.77	80.80	57.35	83.36	79.42	152.94	47.69	33.18

Table 7. Difference between Max value of Accumulated Fatigue and Min value of Accumulated Fatigue

5.4 Multi-start heuristic

Other results have been provided thanks to the creation of a multi-start heuristic which has been obtained from the initial model. A random selection criteria is used to choose an operation selection rule and an operator selection rule every time a new task is assigned in order to find better performance results in terms of makespan reduction and lower value of maximum accumulated fatigue. Random task selection have been carried on for 1000 iterations for each of 15 instances already used previously.

Then, it is presented a comparison between multi-start heuristics: one which can select randomly among 24 (4×6) best selection rules already founded before in the article (4 best rules to select operation and 6 best rules to select operator) and the other which can randomly select among all 72 available rules (8×9).

	max makespan	min maxmakespan	max acc fatigue	min max acc fatigue	max difference	min max difference
Instance 1	154,23	86,53	448,00	273,93	277,16	11,94
Instance 2	182,32	102,40	533,80	315,19	325,51	14,28
Instance 3	199,91	121,67	584,36	373,92	352,20	22,32
Instance 4	147,74	84,74	444,96	260,88	271,28	15,99
Instance 5	179,82	103,13	519,27	317,35	317,64	15,42
Instance 6	157,14	81,04	467,34	269,68	286,79	12,76
Instance 7	217,23	116,60	627,18	348,31	452,27	8,75
Instance 8	162,68	93,69	488,63	298,39	288,95	15,36
Instance 9	203,40	106,95	597,63	335,07	404,14	17,19
Instance 10	167,59	98,66	485,51	302,95	304,11	11,14
Instance 11	161,64	90,54	470,32	279,13	281,21	11,49
Instance 12	193,21	101,88	563,21	315,21	366,53	18,45
Instance 13	202,62	112,16	584,20	344,28	367,48	5,71
Instance 14	169,37	88,83	508,69	291,93	340,02	10,33
Instance 15	221,39	113,21	634,42	342,46	410,21	13,47

Table 8. Multi-start heuristic results with 72 rules available to be selected

	max makespan	min maxmakespan	max acc fatigue	min max acc fatigue	max difference	min max difference
Instance 1	110,09	84,79	378,72	269,25	138,36	4,32
Instance 2	137,09	101,07	443,68	308,77	150,40	6,09
Instance 3	146,84	119,75	502,94	365,88	161,63	4,47
Instance 4	100,38	82,93	371,25	256,06	137,45	5,87
Instance 5	141,77	100,73	398,50	307,50	136,83	4,02
Instance 6	123,55	80,10	486,60	256,12	247,62	4,86
Instance 7	140,00	113,12	434,26	346,67	125,41	4,67
Instance 8	140,10	92,31	432,31	291,08	174,29	5,69
Instance 9	138,84	106,22	443,70	328,43	159,46	10,47
Instance 10	124,09	96,68	371,09	296,83	103,49	5,17
Instance 11	112,58	88,68	355,52	275,57	108,52	4,32
Instance 12	135,07	99,15	471,21	309,57	196,02	5,55
Instance 13	142,06	111,89	403,71	338,30	111,76	3,21
Instance 14	116,29	86,09	372,96	278,60	119,01	3,42
Instance 15	146,15	110,88	508,39	336,26	206,25	7,87

Table 9. Multi-start heuristic results with 24 rules available to be selected

The conclusion is that the model which run with only 24 best selection criteria provides better results than the model which run with all 72 rules of selection.

In order to show that multi-start heuristic, which is allowed to randomly choose every time a new task has to be assigned among 24 possibilities, can provide better results than the heuristic initially presented in the article which has to follow the same criteria until the assignment of all tasks, following table are presented to demonstrate that for every single parameter (makespan, accumulated fatigue and difference in accumulated fatigue) multi-start heuristic is able to present at least one better solution in almost all instances.

	Instance 1	multi-start	Instance 2	multi-start	Instance 3	multi-start	Instance 4	multi-start	Instance 5	multi-start
Max	154,22	110,09	134,04	137,09	183,12	146,84	151,52	100,38	178,13	141,77
Min	85,19	84,79	104,28	101,07	120,17	119,75	86,64	82,93	103,12	100,73
	Instance 6	multi-start	Instance 7	multi-start	Instance 8	multi-start	Instance 9	multi-start	Instance 10	multi-start
Max	391,77	123,55	1788,56	140,00	143,86	140,10	238,80	138,84	168,56	124,09
Min	81,80	80,10	117,28	113,12	93,20	92,31	108,31	106,22	100,18	96,68
	Instance 11	multi-start	Instance 12	multi-start	Instance 13	multi-start	Instance 14	multi-start	Instance 15	multi-start
Max	137,19	112,58	187,49	135,07	212,95	142,06	222,74	116,29	279,36	146,15
Min	91,13	88,68	100,40	99,15	114,96	111,89	88,66	86,09	113,94	110,88

Table 10. Makespan comparison between 72 heuristics and multi-start heuristic

	Instance 1	multi-start	Instance 2	multi-start	Instance 3	multi-start	Instance 4	multi-start	Instance 5	multi-start
Max	454,15	378,72	398,62	443,68	551,85	502,94	447,58	371,25	531,99	398,50
Min	276,81	269,25	323,92	308,77	368,98	365,88	265,75	256,06	316,19	307,50
	Instance 6	multi-start	Instance 7	multi-start	Instance 8	multi-start	Instance 9	multi-start	Instance 10	multi-start
Max	1179,04	486,60	518,09	434,26	461,41	432,31	713,07	443,70	519,78	371,09
Min	276,84	256,12	351,66	346,67	300,33	291,08	341,76	328,43	303,31	296,83
	Instance 11	multi-start	Instance 12	multi-start	Instance 13	multi-start	Instance 14	multi-start	Instance 15	multi-start
Max	419,76	355,52	571,39	471,21	633,32	403,71	725,35	372,96	808,19	508,39
Min	285,85	275,57	323,44	309,57	345,16	338,30	281,62	278,60	343,33	336,26

Table 11. Accumulated fatigue comparison between 72 heuristics and multi-start heuristic

	Instance 1	multi-start	Instance 2	multi-start	Instance 3	multi-start	Instance 4	multi-start	Instance 5	multi-start
Max	402,94	138,36	226,22	150,40	508,87	161,63	433,89	137,45	518,65	136,83
Min	16,24	4,32	25,67	6,09	12,88	4,47	24,80	5,87	15,55	4,02
	Instance 6	multi-start	Instance 7	multi-start	Instance 8	multi-start	Instance 9	multi-start	Instance 10	multi-start
Max	1162,54	247,62	472,38	125,41	443,08	174,29	687,70	159,46	498,12	103,49
Min	35,53	4,86	19,06	4,67	18,08	5,69	26,29	10,47	9,08	5,17
	Instance 11	multi-start	Instance 12	multi-start	Instance 13	multi-start	Instance 14	multi-start	Instance 15	multi-start
Max	419,76	108,52	554,80	196,02	622,98	111,76	715,02	119,01	794,64	206,25
Min	31,03	4,32	22,12	5,55	12,06	3,21	3,90	3,42	16,07	7,87

Table 12. Difference in accumulated fatigue comparison between 72 heuristics and multi-start heuristic

6. CONCLUSION

In this study, we propose a new scheduling problem where human fatigue affecting operator performance is taken into consideration while assigning and scheduling a given set of tasks to a set of operators of a manufacturing cell. All operators work in parallel and execute the tasks independently each from other. All tasks are characterized by a certain level of difficulty having a different impact on each operator taking into account his/her personal characteristics. Each time the fatigue level exceeds a defined level, a break is imposed to the operator at the end of the task. Its duration contributes to the total makespan. In

order to solve this scheduling problem with the objectives to minimize the makespan and the maximal accumulated fatigue, 72 constructive heuristics have been developed and evaluated through a numerical experiment. The obtained results showed that the best task selection rules mix the most longest and the most difficult task selection. However, this approach has to be further developed in several directions. First of all, the heuristic rules can be integrated in a metaheuristic or hyperheuristic approach. Secondly, the impact of variability of personal characteristics of operators and difficulty of their exact measurement should be evaluated and this uncertainty should be integrated in the problem model.

REFERENCES

Battini, D., Glock, C.H., Grosse, E.H., Persona, A., and Sgarbossa, F. (2017). Ergo-lot-sizing: An approach to integrate ergonomic and economic objectives in manual materials handling. *International Journal of Production Economics*, 185, 230–239.

Baucells, M. and Zhao, L. (2018). It is time to get some rest. *Management Science*.

Digiesi, S., Kock, A.A., Mummolo, G., and Rooda, J.E. (2009). The effect of dynamic worker behavior on flow line performance. *International Journal of Production Economics*, 120(2), 368–377.

Eilon, S. (1964). On a mechanistic approach to fatigue and rest periods. *The International Journal of Production Research*, 3(4), 327–332.

Ferjani, A., Ammar, A., Pierreval, H., and Elkosantini, S. (2017). A simulation-optimization based heuristic for the online assignment of multi-skilled workers subjected to fatigue in manufacturing systems. *Computers & Industrial Engineering*, 112, 663–674.

Fruggiero, F., Fera, M., Lambiase, A., Maresca, P., and Caja, J. (2017). The role of human fatigue in the uncertainty of measurement. *Procedia Manufacturing*, 13, 1320–1327.

Gentzler Jr, G., Khalil, T., and Sivazlian, B. (1977). Analytical and computer modeling of work scheduling. *Computers & Industrial Engineering*, 1(3), 163–174.

Givi, Z., Jaber, M., and Neumann, W. (2015). Modelling worker reliability with learning and fatigue. *Applied Mathematical Modelling*, 39(17), 5186–5199.

Glock, C., Grosse, E., Kim, T., Neumann, W., and Sobhani, A. (2019). An integrated cost and worker fatigue evaluation model of a packaging process. *International Journal of Production Economics*, 207, 107–124.

Grosse, E.H., Calzavara, M., Glock, C.H., and Sgarbossa, F. (2017). Incorporating human factors into decision support models for production and logistics: current state of research. *IFAC-PapersOnLine*, 50(1), 6900–6905.

Jaber, M., Givi, Z., and Neumann, W. (2013). Incorporating human fatigue and recovery into the learning–forgetting process. *Applied Mathematical Modelling*, 37(12-13), 7287–7299.

Lodree, J., Emmett, J., Geiger, C.D., and Jiang, X. (2009). Taxonomy for integrating scheduling theory and human factors: Review and research opportunities. *International Journal of Industrial Ergonomics*, 39(1), 39–51.

Mossa, G., Boenzi, F., Digiesi, S., Mummolo, G., and Romano, V. (2016). Productivity and ergonomic risk in human based production systems: A job-rotation scheduling model. *International Journal of Production Economics*, 171, 471–477.

Otto, A. and Battaïa, O. (2017). Reducing physical ergonomic risks at assembly lines by line balancing and job rotation: A survey. *Computers and Industrial Engineering*, 467–480.

Perez, J., De Looze, M., Bosch, T., and Neumann, W. (2014). Discrete event simulation as an ergonomic tool to predict workload exposures during systems design. *International Journal of Industrial Ergonomics*, 44(2), 298–306.

Pinedo, M. (2005). *Planning and scheduling in manufacturing and services*. Springer.

Pinedo, M.L. (2016). *Scheduling: theory, algorithms, and systems*. Springer.

Visentin, V., Sgarbossa, F., Calzavara, M., and Persona, A. (2018). Fatigue accumulation in the assignment of manual material handling activities to operators. *IFAC-PapersOnLine*, 51(11), 826–831.