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ORIGINAL PAPER

Effects of OCRA parameters and learning rate on machine scheduling

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Abstract

In this paper, the effects of Occupational Repetitive Actions (OCRA) parameters, learning rate on process times, and machine scheduling were investigated. We propose that Work-Related Musculoskeletal Disorder (WMSD) risks should be taken into account in machine scheduling. To the best of our knowledge, none of the earlier methods simultaneously considered effects of WMSD risks and the learning rate on processing times. The OCRA index method was employed for WMSD risk assessments. In this context, OCRA parameters such as duration, recovery, force, posture, and repetitiveness were analyzed. Observed process times of each factor were obtained from video records. Statistical analysis (ANOVA) revealed a positive (r=0.616) relationship on processing times with OCRA indexes in independent t-tests at significance level 0.05. To investigate the effects of WMSD risk, our Scheduling with Learning Effect under Risk Deterioration (SLE&RD) model was compared with six existing machine scheduling models in the literature. Detailed machine scheduling instances of 9 jobs with WMSD risks revealed that job sequences and makespan varied under different scenarios. This means that WMSD risks and OCRA factors affect machine scheduling with a deterioration effect. The results confirmed that when WMSD risks are included, actual process time and makespan move closer to observed process times. To obtain more accurate machine scheduling, which is close to real-life applications, WMSD risks, and learning rates should be considered simultaneously. The SLE&RD model is promising in machine scheduling for real-life problems and presents a holistic view of machine scheduling and WMSD risks.

Keywords Machine Scheduling · Learning Rate · Risk Assessment · Risk Based Deterioration · WMSD · OHSAS · Ergonomics · OCRA · ANOVA

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1 Introduction

Occupational health and safety (OHSAS) regulations and risk assessment methods provide requirements that should be taken into account to protect labourers from occupational risks and accidents. Thus, risk assessments are employed to determine safety levels of machinery, improve ergonomics, labour efficiency, and performance. WMSD is one of the most common OHSAS risks encountered in the work environment. To the best of our knowledge, the effects of WMSD risks on processing times, which are caused by repeated activities, have not been studied in machine scheduling literature.

To achieve efficiency in production and to obtain more realistic and effective schedules, the actual processing time should be calculated more accurately. Three important variables that are employed in calculating the actual process time are the basic processing time, deterioration rate, and learning rate. Though the relationship between ergonomic risks and WMSD have mentioned in the literature, the scheduling problem, depending on basic processing times, WMSD risks based deterioration rate, and learning rate has not been considered simultaneously. In this study, the relationships between WMSD risks, learning rate, and processing times in the machine scheduling problem were investigated for the first time. We hypothesized that WMSD risks and learning rate should be considered synchronous in machine scheduling. Statistical analysis revealed a positive relationship between WMSD risks and processing times. There are significant differences in processing times concerning the OCRA index. Studies on machine scheduling under WMSD risks are limited in literature, so the approach offered here holds great promise for real-world applications.

The objective of this study was to analyze the relationship between WMSD risks with actual process times and to include the WMSD based deterioration rate, learning rate, and processing times simultaneously in machine scheduling to improve the efficiency of production systems. This paper has five sections. A literature review, methodology, purpose, and originality of the study are explained in Sects. 1 and 2. The methodology and innovation mechanisms of the research are presented in Sect. 3. Machine scheduling models are also explained in Sect. 3. OCRA parameters, such as duration, recovery, force, posture, repetitiveness, and additional factors affecting processing times were investigated. Processing times were gained from video records and the data was analyzed statistically. Section 4 devotes to the results and the discussions from statistical analysis and the machine scheduling models. The completion times of different processing types were compared by ANOVA. Statistical analysis revealed a relationship and significant differences in processing times concerning OCRA indexes. Our SLE&RD model was compared with six existing machine scheduling models in literature and process times were observed. Furthermore, machine scheduling instances showed that job sequences and makespan vary under different scenarios. This means that the learning effect and WMSD risks affect machine scheduling. The conclusion is presented in Sect. 5. It was shown that WMSD risks and learning rates have an effect on processing time and they should be considered in machine scheduling models.

2 Related works

In the literature, different WMSD risk assessment methods have been introduced and various risk assessments have been performed to prevent accidents and to ensure occupational health and safety Aven (2016). The most popular WMSD risk assessment methods are National Institute for Occupational Safety and Health (NIOSH) Thomas et al. (1993), Rapid Upper Limb Assessment (RULA) Valentim et al. (2017), Rapid Entire Body Assessment (REBA) Hignett and McAtamney (2000), European Assembly Worksheet (EAWS) Schaub et al. (2013), Rapid Office Strain Index (ROSA) Sonne et al. (2012), The Quick Exposure Check (QEC) Bidiawati and Eva Suryan (2015) and OCRA index Occhipinti (1998) and OCRA score table Colombini and Occhipinti (2017). The NIOSH equation was developed to evaluate risks exposed during lifting activities. The lifting index equality is employed for single tasks and the composite lifting index was calculated for the assessment of many tasks. Criteria such as weight, the height of the load, and carrying distance were also included in the assessment Thomas et al. (1993). RULA is a method that was developed for rapid risk assessment of the upper limbs and it uses the angle of repose, reaching, and lifting of a worker's upper limbs to analyze parts such as the body, neck, shoulder, arms, wrists, etc. Valentim et al. (2017). REBA was developed by Hignett and McAtamney to determine risks to the entire body. It was developed as a method of rapid assessment of the entire body and risk assessments performed in the field. A score table is used and Muscular-Skeletal Disorder (MSD) risks for the arm, elbow, neck, body, and wrists are included in the risk assessments Hignett and McAtamney (2000). The QEC method was developed by Bidiawati and Suryani and it includes MSD risks related to the back, shoulder/arm, wrist/hand, neck, vibration, and stress. Also, analysts and labourers give risk assessment points together Bidiawati and Eva Suryan (2015).

In general, the RULA, REBA, and QEC methods provide MSD risk points for exposed labour and NIOSH presents a risk index for lifting. In these four methods, a risk point or index is obtained from a risk assessment. REBA is employed for ergonomic risk assessments. Video records are used for determining the exact pick-up time in REBA. Significant differences between pick up time and physical workload are reported (Hanson et al. 2018). Another assessment tool that gives risk scores is EAWS (Schaub et al. 2013). Occhipinti developed the OCRA score tables (Colombini and Occhipinti 2017; Rosecrance et al. 2017). The EAWS and OCRA score tables are very similar. However, the OCRA risk assessment method can provide an index and a score point, though EAWS cannot. Thus, the OCRA risk assessment method was suitable for our study. The OCRA index was used by Akyol and Baykasoglu in ergonomic assembly line balancing for solving assembly line worker assignment and balancing problems under ergonomic risk factors (Akyol and Baykasoğlu 2017, 2019) as well as in an occupation rotation problem by Boenzi et al. (2013). Baykasoglu et al. (2017) presented a solution for an assembly line balancing problem, which considered human factors. Tiacci and Mimmi (2018) proposed a model for ergonomic risks evaluation, balancing, and sequencing that allowed different assembly line configurations. A conceptual framework was presented by Goode et al. (2019). Yoon et al. (2016) proposed a job rotation scheduling model for reducing a cumulative workload from the successive use of the same body region. The model helps to reduce potential

WMSDs without additional cost for engineering work. Padula et al. (2017) a systematic review of job rotation problems and stated that studies on job rotation under ergonomic consideration in manufacturing industries were limited. To ensure production efficiency and reduce ergonomic risks, a mixed-integer programming model was proposed in Mossa et al. (2016). Rosecrance et al. (2017) compared the Strain Index (SI) and OCRA checklist and declared that both are similar. The OCRA Index is universally accepted to estimate WMSDs risk. In this concept, a new method, namely, the Predictive Risk Assessment for Safe Assembly Design (PRASAD) was proposed and verified by the OCRA index (Micheli and Marzorati 2018). The OCRA index was employed by Senyigit and Atici in themed scheduling under ergonomic risk factors where the OCRA index was taken as a constant number and an optimal schedule was obtained (Şenyiğit and Atici 2018).

The OCRA index is popular since it covers a wide range for risk assessment of WMSDs (Occhipinti 1998). It ensures a risk value based on observation related to a pathologic case percentage, which is expected among all of a working population (Micheli and Marzorati 2018). For these reasons, the OCRA index was selected as the risk assessment method for machine scheduling in this study.

Planning and scheduling activities have an important effect on the performance and productivity of enterprises. In many manufacturing companies, planning and scheduling processes require human support. Computers made the solution of complex planning and scheduling problems possible after the 1980s (MacCarthy et al. 2001). Due to these developments, interest in the machine scheduling problem has increased in literature and scheduling problems with various parameters and variables have been examined. The three variables of basic process time, learning rate, and deterioration rate have been employed for calculating actual process time (Panwalkar and Rajagopalan 1992). The basic process time is the time required to finish a process. It was assumed that the learning curve had an effect on basic process time, which means that the basic process time decreases with the number of repetitions (Biskup 1999). There are various machine scheduling studies in literature, including learning rates such as scheduling with the general learning rate (Wang 2008) group scheduling with the learning rate (Sun et al. 2020), position-dependent learning rate (Soleimani et al. 2020), sequence-dependent learning rate (Expósito-Izquierdo et al. 2019), job-dependent learning rate (Ji and Cheng 2010), DeJong's learning rate (Ji et al. 2016), time-dependent learning rate (Toksarı et al. 2009) and fuzzy learning rate (Toksari and Arık 2017), etc.

Furthermore, some parameters, such as setup times have a prolonging effect on process times and they are called as deterioration rates in scheduling literature. Time-dependent deterioration rate (Woo and Kim 2018), step-deterioration rate (Chung and Kim 2016), maintenance based deterioration rate (Abedi et al. 2020) job-dependent deterioration rate (Liu et al. 2019), sequence-dependent deterioration rate (Ding et al. 2019), linear-deterioration rate (Chen et al. 2020), and proportional deterioration (Chen et al. 2017) are different deterioration rates investigated in literature. The innovation of this study was to analyze the relationship between WMSDs. The objective of this study was to analyze the relationship between the OCRA index, learning rate, and processing times to improve machine scheduling. Statistical analysis showed that WMSD risk and learning rate affects processing times in the machine scheduling problem.

3 Method

3.1 OCRA risk assessments

Considering the effect of the OCRA index on processing time, the related OCRA index formulation is given in Eq. (1) with the related notations in Table 1. The main feature of the OCRA index in Eq. (1) is the consideration of the cumulative effect of repetitive tasks (Boenzi et al. 2013). While calculating the OCRA index in this study, all constant values were taken from Occhipinti (Occhipinti 1998).

$$OCRA = \frac{\sum_{k=1}^{n} f_j t_j}{k_f Rc_m t_m \sum_{k=1}^{n} Fo_m Po_m Re_m Ad_m t_j} \tag{1}$$

Technical standards and publications of the machines were used to determine the foreseeable duration of the cycle time (FCT). All technical activities needed to be completed within the FCT. The cycle times of the machines were equal to the FCT which was determined by experts (e.g. production planning department and industrial engineers) in an electrical household appliance manufacturing plant in Kayseri. Musculoskeletal activities of the upper limbs were counted to determine the number of technical activities during the cycle time (NCT). These activities were multi-joint movements.

Complex movements involve simple technical activities as positioning an object, putting in or pulling out a spare part, and using force. For example, three times rotation are counted as three technical activities, and two times hitting with a hammer are counted as two technical activities. Awkward postures were classified for all process types to determine the posture multiplier (Po_m) before the experiments and Po_m was noted for each process type. The ratio of the awkward posture period to the cycle time was revealed for each process type. Repetitive task duration lasts 240 minutes to 480 minutes per shift and there are two breaks (each break lasts 10 minutes) per shift. Therefore the recovery periods multiplier (Rc_m), duration of repetitive task multiplier (t_m), and frequency constant of technical work (k_f) equal 0.6, 1, and 30, respectively.

Table 1 Notation

Notation	Explanation
f_j	Frequency of actions per minute [min^{-1}] of job j
t_j	The net duration of job j in the shift [min]
k_f	Frequency constant of technical work
Rc_m	Recovery multiplier
t_m	Duration multiplier
Fo_m	Force multiplier
Po_m	Posture multiplier
Re_m	Repetitiveness multiplier
Ad_m	Additional factor multiplier

Additional risk factors (Ad_m) such as the use of vibrating tools, gloves, precision tools, or sudden movements were considered. Factor multipliers (Po_m, Re_m, Fo_m, Rc_m , t_m, and Ad_m) were considered in normal working conditions to determine how processing times were affected by these multipliers. Work-related musculoskeletal disorder risk assessment (WMSD-RA) software was employed for computing the OCRA index and for determining exact process times. WMSD-RA provides a single framework to employ ergonomic risk assessment methods, which are prevalent in literature. The data used in this study was obtained from observations in an electrical household appliance manufacturing plant in Kayseri, Turkey. Participants were workbench operators and components employed in the observations were spare parts to be processed in a normal shift. All spare parts followed a certain procedure during each shift. The gender, machine type, process type, processing time, cycle time, number of technical activities, and OCRA parameters (posture multiplier, force multiplier, etc.) were recorded in the WMSD-RA and the OCRA index was computed. The relationship between actual process times and OCRA index parameters were determined by statistical analysis. The significance level of the independent t-test was 0.05, commonly used in the relevant literature. The effects of the OCRA Index parameters, including Po_m, Re_m, Fo_m, Rc_m, t_m, and Ad_m on processing times were investigated.

3.2 Scheduling

We developed the single-machine SLE&RD for the first time. This paper shows how process times are deteriorated (increased) and machine scheduling is affected under WMSD risks. Detailed SLE&RD instances are presented in Sect. 4.2. The machine scheduling under the WMSD risk problem is a combination of a model, which was proposed by Biskup (1999) and Occhipinti (1998). The learning effect was represented by a ($a < 0$) and formulated as $a = \log \alpha / \log 2$, where α is the learning rate. This study assumed the same learning rate ($\alpha = 0.8$) proposed by Biskup (1999). The actual processing time p_{jr}, which was calculated for the position of jobs, learning rate, basic process time, and job dependent deterioration rate was defined by Eq. (2) where β_j and p_j are the deterioration rate and basic processing time of job j and r is the position of job j. The deterioration rate, which was calculated concerning OCRA index parameters including t_j, k_f, t_m, Rc_m , fj, Fo_m, Po_m, Re_m, Ad_m, was defined by Eq. (3). The rationale behind computing this parameter with Eq. (3) was to obtain a more accurate actual process time.

$$p_{jr} = p_j r^a (1 + \beta_j) \tag{2}$$

$$\beta_j = \frac{\sum_{k=1}^{n} f_j t_j}{k_f Rc_m t_m \sum_{k=1}^{n} Fo_m Po_m Re_m Ad_m t_j} 1/OCRA_{max} \tag{3}$$

The optimal scheduling of jobs and machines can be considered as an assignment problem. In this model, the investigated production environment was a single machine and the objective function minimizes makespan in Eq. (4). Three constraints were written to assign jobs. Each job position ($r, r = 1 \ldots n$) should be assigned to a job ($j, j = 1 \ldots n$) in Eq. (5). Only one job ($j, j = 1 \ldots n$) can be assigned to a position

$(r, r = 1 \ldots n)$ in Eq. (6). Let x_{jr} be a 0/1 variable such that $x_{jr} = 1\ (j, r = 1 \ldots n)$ if job j is assigned to position r and otherwise $x_{jr} = 0\ (j, r = 1 \ldots n)$ in Eq. (7).

Scheduling Model:

$$\min \sum_{j=1}^{n} \sum_{r=1}^{n} p_j (1 + \beta_j) r^a x_{jr} \tag{4}$$

$$\sum_{j=1}^{n} x_{jr} \quad r = 1 \ldots n \tag{5}$$

$$\sum_{r=1}^{n} x_{jr} \quad j = 1 \ldots n \tag{6}$$

$$x_{jr} = 0 or 1 \quad j, r = 1 \ldots n \tag{7}$$

4 Results and discussion

4.1 Statistical analysis

Effects of the OCRA index parameters on processing times, such as posture, repetitiveness, force, recovery, duration (e.g. Po_m, Re_m, Fo_m, Rc_m , t_m, and Ad_m) were separately investigated and determined from video records for each factor. The completion times of different jobs were compared with ANOVA. Data were analyzed by using SPSS Statistic 20 software. The OCRA index has five risk levels, which are high, medium, low (slight), borderline (uncertain), and acceptable. The score point of the high-risk level is greater than 9. The score point of medium, slight, borderline, and acceptable risk levels are between "4.6 and 9", "3.6 and 4.5", "2.3 and 3.5", and "0 and 2.2", respectively Colombini and Occhipinti (2017). In our research, the risk levels of jobs range from acceptable to medium with risk scores ranging from 0 to 9 in Figure 1. Thus, in this study, the OCRA risk levels were divided into the four groups of the acceptable, borderline, medium, and slight.

Considering the OCRA indexes, significant differences in processing times were detected by independent t-tests. The OCRA index was included as a factor variable and processing time was included as a dependent variable in the analysis. Table 2 shows one way ANOVA analysis of the OCRA index and processing time. Significant differences in processing times for different OCRA risk levels were revealed (sig., $p < 0.05$). To find out which groups were different, the homogeneity of variances of OCRA and processing times were checked. Table 3 shows the variance homogeneity test results.

Tamhanes's T-2 post hoc test was employed to reveal which groups differ since the variance homogeneity test (Levene statistic, $p < 0.05$) was rejected. Significant differences were observed in 404 of 650 different jobs by Tamhanes's T-2 post hoc test results (Table 3).

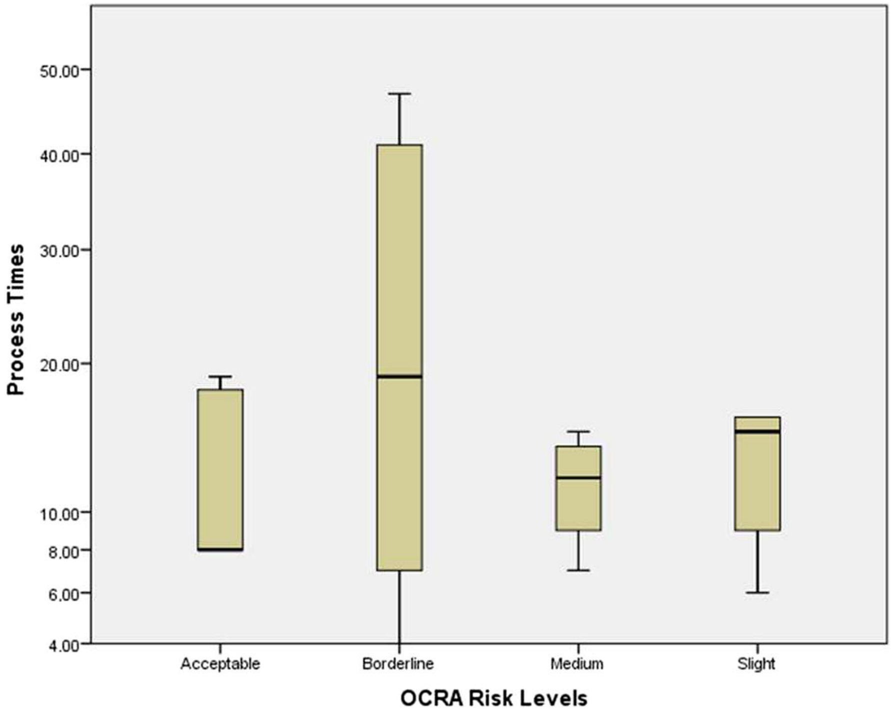

Fig. 1 OCRA risk levels and processing time boxplots

Table 2 ANOVA results, OCRA index, and processing time

	Sum of squares	df	Mean square	f	Sig.
Between groups	34080.701	25	1363.228	29.657	0.05
Within groups	15306.943	333	45.967		
Total	Number	49387.643	358		

Table 3 Test of Homogeneity of Variances

Levene statistics	df1	df2	Sig.
22.411	25	333	0.05

ANOVA analyses were performed to determine how the process times (dependent variables) were affected by each OCRA index (independent variables) parameter. A summary of the results is shown in Table 4.

Significant differences in process times between FCT, NCT, Po_m, Ad_m, and Fo_m were detected at the significance level of 0.05, but no statistic was computed for k_f, t_m, and Rc_m since they are constants in Occhipinti (1998) for the company. It was accepted that k_f, t_m, and Rc_m equalled 30, 1, and 0.6 respectively. k_f can take a single value that equals 30. Repetitive task duration lasts 240 minutes to 480 minutes,

Table 4 OCRA index multiplier ANOVA analyses results

OCRA In. parameters	Dependent variables	Sig. Dif. level	Dif. is Sig.	Variance homogeneity	Post hoc test	Number of groups	Number of different groups	Explanation
FCT			Accepted	Rejected	T T-2	90	84	
NCT			Accepted	Rejected	T T-2	182	138	
Po_m			Accepted	Rejected	T T-2	12	10	
Ad_m			Accepted	Rejected	T T-2	12	12	
Fo_m	Process		Accepted	Rejected	T T-2	6	6	
	Times	0.005						
k_f			Accepted	Rejected	T T-2	–	–	No statistics are computed.
t_m			Accepted	Rejected	T T-2	–	–	
Rc_m			Accepted	Rejected	T T-2	–	–	
Re_m			Accepted	Rejected	T T-2	–	–	Post hoc tests are not performed

so t_m equals 1. There are two tea breaks and one lunch break per shift, so Rc_m equals 0.6.

If the same technical actions of the upper limbs take 50% of cycle time or if the cycle time is shorter than 15 seconds, Re_m is equal to 0.7 otherwise Re_m is equal to 1. The hypothesis that there is a significant difference between Re_m and process time was accepted. However, post hoc tests were not performed because there were fewer than three groups.

Partial correlation analyses were conducted to determine the strength of the relationship between the OCRA index and process times. FCT values were selected as control variables and two-tailed significance tests were applied. Correlation between the OCRA index and process times was calculated as 0.616. The relationship between the OCRA index and processing time was statistically significant at $p < 0.05$ level, which means the OCRA index and process times have a strong positive relationship ($r = 0.616$). If the relationship between the OCRA index and process time is higher than 0.7, it means that the OCRA index has a very strong positive effect on process time. However, the relationship between the OCRA index and process time was determined as $r = 0.616$. This result can be interpreted as different parameters affect process time in addition to the OCRA index. We think that there is also a relationship between process times and other parameters such as gender, age, and medical history and these relationships may be investigated in another study. When other possible parameters, which have effects on process time, were considered, the revealed relationship level supported the validity of the study. This result confirms the reliability of the study.

4.2 Machine scheduling examples

Different jobs, which must be processed in the same shift, were employed in scheduling examples. Basic process times were obtained from technical publications of the jobs. Observed process times (OPT) were measured by video records and the average observed process times were calculated. The actual process (p_{jr}) and time parameters of the jobs are given in Table 5. These parameters were based on Occhipinti (1998). The rationale behind computing this parameter with Eq. (3) was to obtain a more accurate actual process time. OCRAmax is equal to 9 (Boenzi et al. 2013). If job 5 is assigned to position-1, actual process time and makespan can be calculated as follows by using data in Table 5.

Position-1

Job 5- left upper limb

$13.3*1^{(-0.322)}+13.3*1^{(-0.322)}*[(18*13.3)/(30*0.6*1*(1*1*0.7*1*13.3))]*1/9 = 15.4$

Job 5- right upper limb

$13.3 * 1^{(-0.322)} + 13.3 * 1^{(-0.322)} * [((36 * 13.3))/(30 * 0.6 * 1 * (0.85 * 0.7 * 0.7 * 1 * 13.3))] * 1/9 = 20.4$

Makespan of job-5 is equal to 20.4 (min) and the actual process time of job 5 is equal to 20.4 (min). If job 7 is assigned to position 2, the actual process time and makespan can be calculated as follows by using data in Table 5.

Table 5 Parameters of OCRA and (p_{jr}) Occhipinti (1998)

Jobs		j-1	j-2	j-3	j-4	j-5	j-6	j-7	j-8	j-9
Cycle Time (sec)		45	35	25	16	10	50	40	12	20
Number of Cycle		50	150	148	200	80	80	40	400	100
t_j (min)		37.5	87.5	61.7	53.3	13.3	66.7	26.7	80	33.3
OPT		32.7	55.7	48.3	55.1	20.4	46.3	33.2	63	34.6
k_f		30	30	30	30	30	30	30	30	30
t_m		1	1	1	1	1	1	1	1	1
Rc_m		0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
NCT	L	20	9	12	9	3	15	10	8	11
	R	37	30	22	15	6	42	34	12	16
f_j	L	26.7	15.4	28.8	33.8	18	18	15	40	33
	R	49.3	51.4	52.8	56.3	36	50.4	51	60	48
Fo_m	L	1	1	1	1	1	1	1	1	1
	R	1	1	1	1	0.85	1	1	1	1
Po_m	L	1	1	1	1	1	1	1	1	1
	R	1	1	0.7	0.7	0.7	1	0.7	1	0.7
Re_m	L	1	1	1	1	0.7	1	1	0.7	1
	R	1	1	1	1	0.7	1	1	0.7	1
Ad_m	L	1	0.95	1	0.8	1	1	1	1	1
	R	0.95	0.95	0.8	0.8	1	0.8	0.8	1	1

Position-2

Job 7- left upper limb

$26.7 * 2^{(-0.322)} + 26.7 * 2^{(-0.322)} * [((18 * 13.3) + (15 * 26.7))/(30 * 0.6 * 1 * (1 * 1 * 0.7 * 1 * 13.3 + 1 * 1 * 1 * 1 * 26.7))] * 1/9 = 23.7$

Job 7- right upper limb

$26.7 * 2^{(-0.322)} + 26.7 * 2^{(-0.322)} * [((36 * 13.3) + (51 * 26.7))/(30 * 0.6 * 1 * (0.85 * 0.7 * 0.7 * 1 * 13.3 + 1 * 0.7 * 1 * 0.8 * 26.7))] * 1/9 = 33.2$

The longest makespan of upper limbs for each job was accepted as the makespan. The makespan of job 7 is equal to 53.6 (min) and the actual process time of job 5 is equal to 33.2 (min). The complexity of an assignment problem of size n is $O(n^3)$. The assignment problem was coded using LINGO software. The model was solved by using the sample data set in Table 5. Pseudo-code for makespan minimization on a single machine is given in Table 6.

Table 7 provides the actual processing times at different positions, the optimal solution, and each job's OCRA index for the SLE&RD. Each job has a different cumulative OCRA index. The actual process time with risk deterioration and learning effect was calculated (see Eq. (3)). The optimal sequence according to the SLE&RD is job 5, job 7, job 9, job 1, job 4, job 6, job 3, job 2, job 8, and makespan- SLE&RD equals 419.7.

Table 6 Pseudo-code for makespan minimization

1: **INPUT** Cycle Time, t_j, k_f, t_m, Rc_m, f_j, Fo_m, Po_m, Re_m, Ad_m, Learning Rate (LE) parameter
2: **Set** Constraints
  Each job can be assigned to one position
  Each position can be assigned to one job
  Sum X(j,r) can be equal to "1"
3: **WHILE** the Calculation Time Limit is reached or Global Optimum Value is found
  Generate solution Assign all jobs to positions
  IF jobs assigned to a position **THEN**
  X(j,r)=1
  ELSE
  (j,r)=0
  END IF
  IF solution meet constraints **THEN**
  Calculate Jobs' OCRA index value for left and right upper limb
  END IF
  IF Left Upper Limb OCRA index value> Right Upper Limb OCRA index value **THEN**
  Job OCRA index value= Left Upper Limb OCRA index value
  ELSE
  Job OCRA index value= Right Upper Limb OCRA index value
  END IF
  CALCULATE Makespan Value and Jobs Sequence
  SET
  Makespan Value= Current Makespan Value
  Jobs Sequence = Current Jobs Sequence
  IF Current Makespan Value < Best Makespan Value **THEN**
  Best Makespan Value= Current Makespan Value
  Best Jobs Sequence= Current Jobs Sequence
  END IF
END WHILE
4: **STOP**
5: **OUTPUT** Best Makespan Value, Best Jobs Sequence

Table 7 Makespan minimization on a single machine with SLE&RD

Positions	1	2	3	4	6	5	7	8	9
Jobs	J-5	j-7	j-9	j-1	j-6	j-4	j-3	j-8	j-2
Basic Process Time	13.3	26.7	33.3	37.5	53.3	66.7	61.7	87.5	80.0
OCRA index	4.8	5.0	4.3	3.3	4.1	4.2	4.2	3.7	3.7
Actual Process Time	20.4	33.2	34.6	32.7	46.3	55.1	48.3	63.0	55.7

4.3 Comparison of SLE&RD with SWL, SED, STDL, SL&D, SPJ&PL, SPT&JPL, and OPT

To investigate the effects of WMSD risk, our SLE&RD model was compared with six existing machine scheduling models from the literature. Detailed machine scheduling examples of 9 jobs were investigated to show changes in schedules for six different policies. The SLE&RD jobs sequence and makespan value were compared with the existing models, which are scheduling with learning (SWL) considerations (Biskup 1999), scheduling jobs with values exponentially deteriorating (SED) (Voutsinas and Pappis 2002), scheduling with a time-dependent learning (STDL) effect (Kuo and Yang 2006), scheduling with the effects of learning and deterioration (SL&D) (Wen-Chiung 2004), scheduling processed jobs time and position-dependent learning (SPJ&PL) effect (Chin-Chia and Wen-Chiung 2008), and scheduling with sum-of-processing-times-based and job-position-based learning (SPT&JPL) effects (Cheng et al. 2008). The actual process times (p_{jr}, p_{jt}) in six different machine scheduling models are explained below.

SWL actual process times can be calculated by Eq. (8). Actual process time (p_j), is the processing time of job j if it is scheduled in position r in Eq. (8). The learning effect was represented by $a(a < 0)$ and it was formulated as $a = log\alpha/log2$, where a is the learning rate. $\alpha = 80\%$, thus $a = -0.322$ (Biskup 1999).

$$p_{jr} = p_j r^a \tag{8}$$

SED was adapted from scheduling jobs with the values exponentially deteriorating overtime model, which was proposed in Voutsinas and Pappis (2002). In Eq. (8), t is the starting time for job j, k_j is the value of j, and β_j is the value deterioration rate for job j. Risk value $OCRA_j$ for job j was accepted as the deterioration rate. SED actual process time can be calculated by Eq. (9).

$$p_{jt} = p_j r^a + K_j t^{(\beta_j)} \tag{9}$$

STDL is scheduling with a time-dependent learning effect and was adapted from Kuo and Yang (2006). The basic process time of job j is $p_{[k]}$ (Kuo and Yang 2006). STDL actual process time can be calculated by Eq. (10).

$$p_{jr} = p_j (1 + \sum_{j=1}^{n} p_{[k]})^a \tag{10}$$

Scheduling with the effects of the learning and deterioration model was proposed by Wang (2007) and Wen-Chiung (2004), . SL&D was adapted from Lee's study and combines learning effect and linear deterioration Wen-Chiung (2004). SL&D actual process time can be calculated by Eq. (11). t is the starting time for job j and β_j is the value deterioration rate for job j $(OCRA_j)$. SL&D actual process time can be calculated by Eq. (11).

$$p_{jr} = p_j + \beta_j t r^a \tag{11}$$

SPJ&PL was adapted from a study by Chin-Chia and Wen-Chiung (2008). SPJ&PL is based on processed job times and a position-dependent learning effect (Chin-Chia and Wen-Chiung 2008). a_1 and a_2 represent the learning effect ($a_1 < 0$, $a_2 < 0$). Actual processing times depend on both position and processed jobs' time. $a_1 = \log\alpha/\log 2$ and $a_2 = \log\alpha/\log 2$ where α is the learning rate. $a = 80\%$, thus $a_1 = a_2 = -0.322$. SPJ&PL actual process time can be calculated by Eq. (12).

$$p_{jr} = p_j(1 + \frac{\sum_{j=1}^{r-1} p_{[k]}}{\sum_{j=1}^{n} p_{[k]}})^{a_1} r^{a_2} \tag{12}$$

SPT&JPL is scheduling with the sum-of-processing-times-based and job-position-based learning effects. It is based on a model, which was proposed by Cheng et al. (2008). a_1 and a_2 represent the learning effect ($a_1 \geq 1$, ($a_2 \leq 0$) (Cheng et al. 2008). Learning effect was formulated as $a_2 = \log\alpha/\log 2$ where α is the learning rate. $a = 80\%$, thus $a_2 = -0.322$ (Cheng et al. 2008). We accepted $a_1 = |a_2|^{-1}$, thus $a_1 = 3.105$. SPT&JPL actual process time can be calculated by Eq. (13).

$$p_{jr} = p_j(1 - \frac{\sum_{j=1}^{r-1} p_{[k]}}{\sum_{j=1}^{n} p_{[k]}})^{a_1} r^{a_2} \tag{13}$$

The scheduling models (e.g. SWL, SED, STDL, SL&D, SPJ&PL, SPT&JPL) were set as an assignment problem and coded using LINGO software. To make a fair comparison of the SLE&RD model with the results of other scheduling models and OPT, all of the models were solved for the same sample data set in Table 5. When the makespan values of scheduling models were compared with OPT, SLE&RD yielded the closest results to OPT than the other scheduling models SWL, SED, STDL, SL&D, SPJ&PL, SPT&JPL.

The comparison of machine scheduling models is presented in Table 8. If the jobs are sequenced by SWL, the positions of the jobs are job 5, job 7, job 9, job 1, job 4, job 3, job 6, job 8, job 2, and the makespan of SWL are 268.2. If the jobs are sequenced by SED, the positions of the jobs are job 8, job 9, job 7, job 6, job 4, job 3, job 2, job 1, job 5, and the makespan of SED is 1.4×10^{14} (min). If the jobs are sequenced by STDL, the positions of the jobs are job-8, job-9, job-7, job-6, job-4, job-3, job-2, job-1, job-5 and the makespan of STDL is 148.2. If the jobs are sequenced by SL&D, the positions of the jobs are job 5, job 7, job 9, job 1, job 4, job 6, job 3, job 2, job 1, and the makespan of SL&D is 3209.5. If the jobs are sequenced by SPJ&PL, the positions of the jobs are job 5, job 7, job 9, job 1, job 4, job 3, job 6, job 8, job 2, and the makespan of SPJ&PL is 840.4. If the jobs are sequenced by SPT&JPL, the positions of the jobs are job 5, job 7, job 9, job 1, job 4, job 3, job 6, job 8, job 2, and the makespan of SPT&JPL is 840.4. The results show that job sequences and makespan vary under different scenarios, as seen in Table 8.

If the jobs are sequenced by SLE&RD, which includes the OCRA index, WMSD risks, and learning rate, the positions of the jobs are job 5, job 7, job 9, job 1, job 4, job 6, job 3, job 2, job 8 and the makespan of SLE&RD is 389.2. If the jobs are sequenced by OPT, for the shortest process times rule, the positions of the jobs are job 5, job 7,

Table 8 Actual process time (p_{jr}) and jobs' sequence of SWL, SED, STDL, SL&D, SPJ&PL, SPT&JPL, SLE&RD, and OPT

Scheduling Models		Positions 1	2	3	4	5	6	7	8	9	Makespan (min)
SWL	Jobs	j-5	j-7	j-9	j-1	j-4	j-3	j-6	j-8	j-2	268.2
	p_{jr}	13.3	21.3	23.4	24	31.8	34.6	35.6	41	43.1	
SED	Jobs	j-8	j-9	j-7	j-6	j-5	j-4	j-3	j-2	j-1	$1.4x10^{14}$
	p_{jr}	80	$6.8x10^{8}$	$2.0x10^{9}$	$7.0x10^{8}$	$6.6x10^{11}$	$3.7x10^{13}$	$9.9x10^{13}$	$1.4x10^{10}$	$5.7x10^{8}$	
STDL	Jobs	j-8	j-9	j-7	j-6	j-4	j-3	j-2	j-1	j-5	148.2
	p_{jr}	80	8.1	5.8	13.5	9.6	10.3	13.6	5.4	1.9	
SL&D	Jobs	j-5	j-7	j-9	j-1	j-4	j-6	j-3	j-2	j-8	3209.5
	p_{jr}	13.3	79.9	154	190.1	324.9	458.2	577.7	635.9	775.5	
SPJ&PL	Jobs	j-5	j-7	j-9	j-1	j-4	j-3	j-6	j-8	j-2	840.4
	p_{jr}	13.3	23.3	30.3	38	62.1	89.3	123.1	188.8	272.1	
SPT&JPL	Jobs	j-5	j-7	j-9	j-1	j-4	j-3	j-6	j-8	j-2	93.1
	p_{jr}	13.3	19.5	17.6	14	13.5	8.8	4.4	1.8	0.2	
SLE&RD	Jobs	j-5	j-7	j-9	j-1	j-4	j-6	j-3	j-2	j-8	**389**.**2**
	p_{jr}	20.4	33.2	34.6	32.7	46.3	55.1	48.3	63	55.7	
OPT	Jobs	j-5	j-7	j-9	j-1	j-6	j-4	j-3	j-8	j-2	**419**.7
	p_{jr}	15	25	32	40.4	51.5	54	55.8	70.4	75.6	

job 9, job 1, job 6, job 4, job 3, job 8, job 2 and the makespan of OPT is 419.7. The SLE&RD model yielded results closest to OPT when considering makespan values because our model includes WMSD risks and learning rate in the work environment. This means that machine scheduling is affected by learning rates and WMSD risks.

The makespan-OPT is greater than makespan- SLE&RD due to deterioration. WMSD risks should be considered in machine scheduling to have better results in real-world scenarios. To obtain a schedule, which is close to real life, parameters such as learning rate and WMSD risks should be considered in machine scheduling models. The results in Table 7 show that when WMSD risks are included in scheduling problems, makespan moves closer to observed results and real-world scenarios.

5 Conclusion and future works

This is the first study that includes WMSD risks and the learning rate in a machine scheduling problem. In this study, effects of WMSD risks and learning rates on processing time and machine scheduling were studied to increase productivity and to improve occupational health and safety. The OCRA index was employed to assess the WMSD risks. It was shown that WMSD ergonomic risks like duration, recovery, force, posture, repetitiveness, additional factors and OCRA factors affect processing times. Besides, the relationship between WMSD risks and processing time was proven statistically. Significant differences in processing times for different OCRA indexes, FCT, NCT, Po_m, Ad_m, and Fo_m were detected in independent t-tests at significance level 0.05. Correlation between the OCRA index and processing time was calculated as $r = 0.616$. The relationship between the OCRA index and processing time was statistically significant at $p < 0.05$ level, which means that the OCRA index and processing time have a positive relationship. Different machine scheduling problem instances from the literature were presented. It was shown that job sequences and makespan vary under different scenarios, which means that machine scheduling is affected by learning effect and WMSD risks. The result shows that when ergonomic risks (e.g. WMSD) are included in scheduling problems, makespan moves closer to the observed results. Thus, WMSDs risks should be included in machine scheduling problems as a parameter and the scheduling problem should be solved more realistically, considering real-life constraints. Due to the positive relationship between the OCRA index and processing times, WMSD risks should be included as a deterioration effect. As future works other risk assessment methods and different mathematical functions can be employed while calculating deterioration. Other effects of widely used WMSD risk assessment techniques on processing time will be compared and some heuristics will be employed during the solution.

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