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A Makespan Minimization Problem of Job Dependent Risk Deterioration

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Abstract: In this study, different job deterioration rates with the position dependent learning rates were included in makespan minimization problem (MMP). Physical workloads and ergonomic design risks that the employee is exposed were considered. The European Assembly Worksheet (EAWS) was selected as a risk evaluation method and employed for determining risk deterioration rate, since it makes possible to assess awkward postures, action forces levels, material handlings and repetitive load of the upper limbs. EAWS risk assessments were made for 10 assembly jobs in a company in the manufacturing sector. It was proved and numerically shown that makespan minimization problem with job dependent risk deterioration and position dependent learning effect can be optimally solved by Smallest Deterioration Rule (SDR), only if common process time is used instead of basic process time. The results show that our approach is promising in terms of real life machine scheduling problems under ergonomic risk constraints. The contribution of this paper to the literature is the modeling musculoskeletal disorder risks with EAWS and calculation of deterioration rates by a hyperbolic tangent function for the first time. Furthermore, it was proved and numerically shown that makespan minimization problem can be optimally solved with SDR. As a future work, parallel machine scheduling or different deterioration functions could be employed for the ergonomic risks evaluations.

İşe Bağımlı Risk Bozulmasının Tamamlanma Zamanı Minimizasyonu

Anahtar Kelimeler
Ergonomi,
Makine çizelgeleme,
Avrupa Meclisi Çalışma Sayfası (EAWS),
Bozulma
Risk değerlendirmesi

Öz: Bu çalışmada, tamamlanma zamanı minimizasyon problemine (MMP) farklı iş bozulma oranları ile pozisyona bağlı öğrenme oranları dâhil edildi. Çalışanların maruz kaldığı fiziksel iş yükleri ve ergonomik tasarım riskleri göz önünde bulunduruldu. Uygun olmayan duruşları, faaliyet kuvvet seviyelerini, malzeme taşıma ve üst uzuv yüklenmelerini değerlendirmeyi mümkün kılması nedeniyle, Avrupa Meclisi Çalışma Sayfası (EAWS) bir risk değerlendirme yöntemi olarak seçilerek risk bozulma oranını belirlemesi için kullanıldı. İmalat sektöründeki bir şirkette 10 montaj işi için EAWS risk değerlendirmeleri yapıldı. İşe bağlı risk bozulması ve pozisyona bağlı öğrenme etkisi ile tamamlanma zamanı minimizasyon probleminin En Küçük Bozulma Kuralı (SDR) ile temel işlem zamanı yerine genel işlem zamanı kullanılarak en iyi şekilde çözülebileceği kanıtlandı ve sayısal örneklerle gösterildi. Sonuçlar, yaklaşımımızın ergonomik risk kısıtlamaları altında gerçek hayattaki makine çizelgeleme problemleri açısından umut verici olduğunu göstermektedir. Bu makalenin literatüre katkısı, EAWS ile kas-iskelet bozukluğu risklerinin modellenmesi ve bozulma oranlarının ilk kez hiperbolik tanjant fonksiyonu ile hesaplanmasıdır. Ayrıca, tamamlanma zamanı minimizasyon probleminin En Küçük Bozulma Kuralına göre en iyi şekilde çözülebileceği kanıtlanmış ve sayısal olarak gösterilmiştir. Gelecekteki çalışmalarda paralel makine çizelgelemesi ya da ergonomik risk değerlendirmelerinde farklı bozulma fonksiyonları kullanılabilir.

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1. Introduction

Performing risk assessment is important in both business and service sector. Risk assessments make possible to take necessary precautions for potential risks. Risk assessment has been employed in different sectors from finance to the construction industry. Also many risk assessment tools and techniques were developed that can be grouped as quantitative, qualitative and hybrid. A few of these techniques can be used for risk assessment of repetitive tasks. Repetitive task is one of the major root causes of musculo-skeletal complaints and disorders. The European Assembly Worksheet (EAWS) has recently been developed as an outstanding technique and used for the risk assessment of musculo-skeletal disorders. EAWS was designed as a screening tool for physical workload in European region. EAWS consists of many sections which are body postures, action forces, material handlings and upper limb moves in repetitive tasks. These sections can be separated to sub-parts that allow evaluation of different aspects in risk assessment of musculo-skeletal disorders. These sub-parts are overall evolution, additional loads, comment, time aspects of repetitive loads, postures, forces, extract from force atlas, manual material handlings and repetitive loads [1].

In literature, many risk assessment techniques for musculo-skeletal disorders were presented. Most known risk assessment techniques are NIOSH (National Institute for Occupational Safety and Health), Work Practices Guide for Manual Lifting, Risk Assessment of Repetitive Movements of Upper Limbs (OCRA index), Quick Exposure Check (QEC), Rapid Entire Body Assessment (REBA) and European Assembly Worksheet (EAWS). Also a score table was designed for risk assessment of musculo-skeletal disorders [2-7].

Rapid Upper Limp Assessment (RULA), investigates the number of task movements; static muscle actions, force, body postures and duration of jobs without a break trigger musculo-skeletal disorders risk. This technique utilizes figure of body postures and score tables for evaluating exposure to risk factors [8]. Force required weight, load, center of gravity, frequency, stability, coupling, workplace geometry and environment are defined as risk factors by NIOSH. An algebraic equation is introduced for assessment of manual lifting [9]. REBA was developed for risk assessment of working postures in health care and service industries. This technique is a scoring system which uses score points belong to segment of body postures [5]. Although, EAWS has been widely used in Europe, it has not seen enough attention in Turkey. EAWS was defined as first level risk assessment technique for biomechanical load of the entire body and upper limbs. EAWS is divided into sections employing second level risk assessment techniques such as OWAS, RULA, Snook & Ciriello, NIOSH, OCRA index and Toyota System [10]. Although lots of software was developed for risk assessment, only a small number of risk assessment software employs pictures and video recording. WMSD-RA software is one of the exclusive software which has video recording [11].

Musculo-skeletal disorders were investigated in various problems and one of them is related with effect of ergonomic risk factors on assembly line assignment and balancing problem. OCRA index was used for another risk assessment problem named as Ergo-ALWABP [12]. In addition, ergonomics in lot-sizing was inspected as Ergo-Lot-Sizing problems. Energy expenditure was used for determining risks [13]. Furthermore, scheduling under ergonomic constraints was studied as Ergo-Scheduling problems. In another study, OCRA index was selected for risk assessment of musculo-skeletal disorders [14].

Actual process time was tried to be found by changing learning and deterioration rate or increasing and decreasing processing time parameters. The learning rate was modeled by Mosheiov and Sidney (2003), for the first time [15]. Different parameters were considered for scheduling problems of single machine. These parameters are constant beginning and finish time, early and tardy jobs, variable machine speed, reducible setup and processing times, step improvements [16-26]. On the other hand, weighted-tardiness, earliness, common due-date, total tardiness, time dependent processing times are inspected parameters on parallel machine scheduling [27-32]. In other studies, musculo-skeletal disorder risk factors modeled as deterioration rate in machine scheduling problems. OCRA index and RULA was employed as a risk assessment technique [33-36].

In this study, a model that inspects makespan minimization problem (MMP) with position-dependent learning effect and musculoskeletal disorders risk factors was improved. EAWS was selected as a risk assessment technique for the purpose of calculating actual process times, because it is a comprehensive analysis tool for evaluating the ergonomic risks that may arise due to biomechanical overload. Furthermore, EAWS provides detailed ergonomic risk assessment about body postures, action forces, manual material handling and upper body movements. It is applicable to all manufacturing industry from job shop production to mass production. For all the aforementioned reasons, EAWS was employed in this study. The job-dependent deterioration and the position-dependent learning rates were included in the Makespan Minimization Problem (MMP) model. In this study, hyperbolic tangent function was selected and employed for the first time in order to imitate deterioration rate in production process times. It was shown that MMP with job-dependent deterioration and the position-dependent learning rates on single machine can be optimally solved with Smallest Deterioration Rule (SDR), only if common process time is used in place of basic process time.

This paper is made up of four sections and the paper is organized as follows. Literature review, purpose and originality of the study are explained in Section-1. Methodology of the research with the EAWS risk assessment and problem definition is presented in Section 2. In Section-3, our proofs and numerical analysis are presented and the MMP with position-dependent learning effect and musculoskeletal disorders risk factors was inspected. EAWS risk assessments were made for 10 assembly jobs in a company in the manufacturing sector. Deterioration rate, actual process time and makespans were computed. It was proved and numerically shown that makespan minimization problem with job dependent risk deterioration and position dependent learning effect can be solved with SDR, on condition that common process time is used instead of basic process time, otherwise the problem can't be optimally solved. The results show that our approach is promising in terms of real life machine scheduling problems under ergonomic risk constraints. Proposed model makes possible to determine more accurate production plans. Also, it has a great potential in terms of bringing balance between musculoskeletal disorder risks and productivity. Discussions and conclusions are made in Section-4. Extensions of our approach for future research could be related with parallel machine scheduling or different deterioration functions could be employed for the ergonomic risks evaluations. Another extension may be developing a hybrid risk assessment method for musculo-skeletal disorders. Other problems such as the total flow time minimization, due date assignment or weighted due date minimization problems could also be investigated considering EAWS risk assessments as a future work.

The contribution of this paper to the literature is the modeling musculoskeletal disorder risks with EAWS and calculation of deterioration rates by a hyperbolic tangent function for the first time. Furthermore, it was proved and numerically shown that makespan minimization problem can be optimally solved with SDR.

2. Material and Method

2.1. EAWS risk assessments

The 'New Production Worksheet' (NPW) was developed by General Motors Europe Adam Opel. The Automotive Assembly Worksheet (AAWS) is the improved form of NPW and employed for evaluating risks by German car manufacturers. In Germany, it is compulsory to analyze the physical workload and the ergonomic conditions of hazardous jobs must be improved. Daimler and the Baden-Württemberg's Employers' Associations of Metal and Electrical Industries risk assessment technique (IAD-BkB) was designed for new employment contract and it is based on AAWS. The EAWS, the most current risk assessment method used by German automotive manufacturers, is the revised version of AAWS. EAWS enables risk assessment of upper limp and whole body that means postures, forces, manual handling etc. EAWS score point can be calculated by using Eq.1 [10].

$$EAWS = DS(\ Fo_m + Po_m +\ Ad_m) \tag{1}$$

DS: Duration score (up to shift duration)
Fo_m: Force frequency grip score
Po_m: Posture score
Ad_m: Additional factor score

EAWS provides a score point between 0 and 50. EAWS has tree risk levels which are low, possible and high as shown in Figure 1. EAWS score point can vary between 0 and 50. This score point can be used as a deterioration rate in machine scheduling problems if it is normalized.

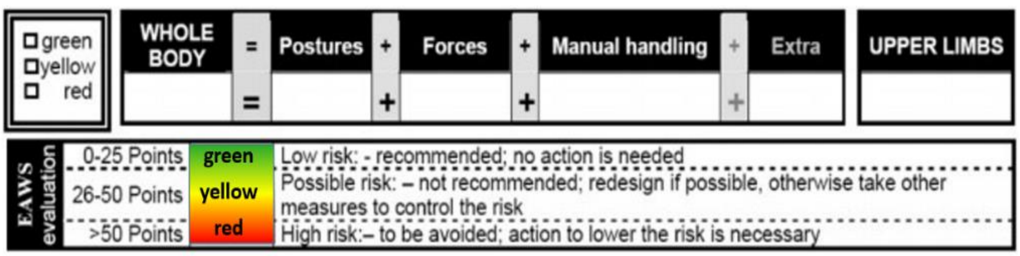

Figure 1. EAWS risk levels [6]

2.2. Problem Definition

In other studies actual process time was modeled considering deterioration rate, time depended process rate and position depended jobs [37-39]. In this study, makespan with job dependent risk deterioration of musculoskeletal disorders and position dependent learning rate was investigated. Actual process time was calculated considering deterioration and learning rates, where the process time decreases by the number of repetitions or learning and increases by exposed ergonomic risks or the deteriorations. Here, p_{jr} is the actual process time of job j provided that it is scheduled in the position r of a sequence. Learning effect is represented by a ($a < 0$) and it is calculated with the equation $a = \log\alpha/\log 2$. Here, α is the learning rate and if α=0.8 then a=-0.312 [40].

Furthermore we used a different function for deterioration rate. In artificial neural networks, there are two "s" shaped transfer functions, which are sigmoid and hyperbolic tangent functions [41-43]. Though sigmoid function is "s" shaped and used as a transfer function, it cannot imitate the deterioration in production process times. But hyperbolic tangent function, which is an increasing "s" shaped function, can imitate the deterioration in production process times. Thus hyperbolic tangent function ($\sigma_x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$) was selected and employed for the first time in this study in order to imitate deterioration rate in production process times.

Deterioration rate (β_{jr}) and actual process time (p_{jr}) values can be determined with the help of Eq.2 and Eq.3, respectively. EAWS was selected as a risk assessment technique for the purpose of calculating actual process times. Deterioration rate (β_{jr}) in Eq.2 is the normalized EAWS score point of job j in hyperbolic tangent function. EAWS provides a score point between 0 and 50, thus EAWS score is multiplied by 0.02 for normalization in Eq.2. In order to calculate actual process time (p_{jr}) deterioration rate (β_{jr}) is multiplied with the basic process time ($p_{[j]}$) and with the position dependent learning rate (r^a) in Eq.3. Objective function of makespan minimization problem is defined in Eq.4.

$$\beta_{jr} = 1 + \frac{e^{[DS_j(Fo_{mj}+Po_{mj}+Ad_{mj})0.02]} - e^{-[DS_j(Fo_{mj}+Po_{mj}+Ad_{mj})0.02]}}{e^{[DS_j(Fo_{mj}+Po_{mj}+Ad_{mj})0.02]} + e^{-[DS_j(Fo_{mj}+Po_{mj}+Ad_{mj})0.02]}} \tag{2}$$

$$p_{jr} = p_{[j]}\, \beta_{jr} r^{a} \tag{3}$$

$$min \sum_{j=1}^{n} \sum_{r=1}^{n} p_{jr} \tag{4}$$

3. Results

In this section the MMP with position-dependent learning effect and musculoskeletal disorders risk factors was inspected. Our proofs and numerical analysis show that MMP with job-dependent deterioration and the position-dependent learning rates on single machine can be solved with respect to smallest deterioration rule, only if common process time is used in place of basic process time.

3.1 Proofs

According to the shortest process time (SPT) rule optimal machine schedule can be obtained by sorting process times in increasing order. Also two adjacent jobs can be interchanged and compared with actual time. If job's processing times can be determined, the optimal schedule can be obtained by using SPT rule.

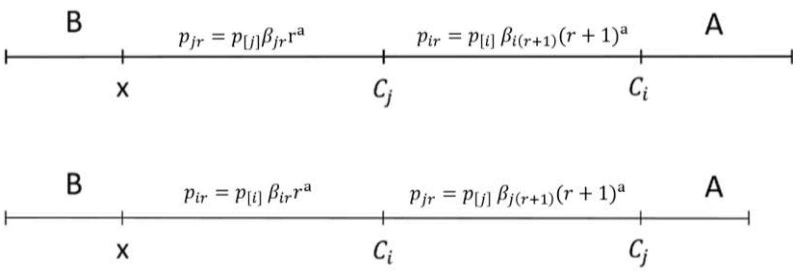

Figure 2. Interchange of adjacent jobs adapted from [37]

Lemma-1

If ($a < 0$ and $\beta_j > \beta_i$) basic process time is used, makespan minimization problem with job dependent risk deterioration and position dependent learning effect can't be optimally solved with SPT rule.

Proof.

Let $C_j(S)$ be the completion time of job *j* in the schedule *S.*
Let $\Delta C(S)$ be the difference between the completion time of two jobs *i, j*.

$$C_j(S) = B + p_j\beta_j r^a \tag{5}$$

$$C_i(S) = B + p_j\beta_j r^a + p_i\beta_i(r+1)^a \tag{6}$$

$$C_i(S') = B + p_i\beta_i r^a \tag{7}$$

$$C_j(S') = B + p_i\beta_i r^a + p_j\beta_j(r+1)^a \tag{8}$$

$$\Delta C(S) = C_i(S) - C_j(S') = \quad B + p_j\beta_j r^a + p_i\beta_i(r+1)^a - [\,B + p_i\beta_i r^a + p_j\beta_j(r+1)^a] \tag{9}$$

Let's distribute the minus sign in front of the square brackets, so variable B is subtracted from equality.

$$\Delta C(S) = \quad B + p_j\beta_j r^a + p_i\beta_i(r+1)^a - B - p_i\beta_i r^a - p_j\beta_j(r+1)^a \tag{10}$$

Let's distribute the minus sign in front of the parenthesis Eq.(10).

$$\Delta C(S) = \quad p_j\beta_j r^a + p_i\beta_i(r+1)^a - p_i\beta_i r^a - p_j\beta_j(r+1)^a \tag{11}$$

Let's group the Eq.11 by r^a and $(r+1)^a$

$$\Delta C(S) = \quad p_j\beta_j r^a - p_i\beta_i r^a + p_i\beta_i(r+1)^a - p_j\beta_j(r+1)^a \tag{12}$$

Let's put the Eq.13 in the parentheses r^a and $(r+1)^a$.

$$\Delta C(S) = \quad (p_j\beta_j - p_i\beta_i)r^a + (p_i\beta_i - p_j\beta_j)(r+1)^a \tag{13}$$

Let's put the Eq.14 in the parentheses $(p_j\beta_j - p_i\beta_i)$.

$$\Delta C(S) = \quad (p_j\beta_j - p_i\beta_i)(r^a - (r+1)^a) \tag{14}$$

Any comment cannot be done whether $\Delta C(S) > 0$ or not. Thus, makespan minimization problem with job dependent risk deterioration and position dependent learning effect can't be optimally solved with SPT rule if basic process time is used.

Lemma-2

If ($p_{[i]} = p_{[j]} = p > 0$, $a < 0$ and $\beta_j > \beta_i$) common process time is used instead of basic process time, makespan minimization problem with job dependent risk deterioration and position dependent learning effect can be optimally solved with SDR.

Proof.

$$\Delta C(S) = \quad B + p\beta_j r^a + p\beta_i (r+1)^a - [B + p\beta_i r^a + p\beta_j (r+1)^a] \tag{15}$$

The sign of negativity in front of the schedule S' is distributed in parentheses.

$$\Delta C(S) = \quad B + p\beta_j r^a + p\beta_i (r+1)^a - B - p\beta_i r^a - p\beta_j (r+1)^a \tag{16}$$

Since the completion time constants of previous operations are $B - B = 0$, the expression of r^a, $(r+1)^a$ and p is distributed in parentheses. Equality reorganizes.

$$\Delta C(S) = \quad p\beta_j r^a - p\beta_i r^a + p\beta_i (r+1)^a - p\beta_j (r+1)^a \tag{17}$$

Equality is rearranged by order pr^a, $p(r+1)^a$ and $p(r+1)^a$.

$$\Delta C(S) = \quad pr^a(\beta_j - \beta_i) + p(r+1)^a(\beta_i - \beta_j) \tag{18}$$

Equality is rearranged by order $(\beta_i - \beta_j)$

$$\Delta C(S) = \quad p(\beta_j - \beta_i)(r^a - (r+1)^a) \tag{19}$$

$p > 0$, $a < 0$ and $\beta_j > \beta_i$ hence $\Delta C(S) > 0$. Thus, makespan minimization problem with job dependent risk deterioration and position dependent learning effect can be optimally solved with SDR.

3.2 Numerical Analysis

In this section a numerical example is given for the case in Lemma-1 and Lemma-2. EAWS risk assessments were made for the following 10 assembly jobs in a company in the manufacturing sector. Deterioration rate was computed with respect to Eq.2 and actual process time was calculated in regard to Eq.3. Then makespans were computed by employing Eq.4 and Table 1-4 was gathered.

Numerical example for Lemma-1

In Lemma-1 it was stated that if basic process time is used, makespan minimization problem with job dependent risk deterioration and position dependent learning effect can't be solved with SDR or SPT. We will explain this case with numerical examples in Table 1-2. In Table 1, *B* and *A* values were calculated as 308.8 and 150.1, respectively. The makespans for the job 5 in row 5 and job 6 in row 6 were calculated as 367.8 and 444.92 minutes in the S schedule in Table 1.

Table 1. *S* schedule for Lemma-1

Jobs	1	2	3	4	5	6	7	8	9	10
Position	1	2	3	4	5	6	7	8	9	10
Basic Process Time ($p_{[j]}$)	60	88	56	45	90	80	78	35	50	32
Actual Process Time ($p_{jr} = p_{[j]}\beta_{jr}r^a$)	71.8	124.0	64.3	48.7	59.0	77.1	53.8	28.8	41.0	26.5
Makespan ($\min\sum_{j=1}^{n}\sum_{r=1}^{n} p_{jr}$)	B=308.8				367.8	444.9	A=150.1			

Let's get the S' schedule by interchanging jobs 5 and 6 in the Table 1 according to the SPT rule similar to the Figure-1. As shown in Table 2, the B' and A' values of the S' schedule were computed as 308.8 and 150.1 minutes, respectively and they are equal to *B* and *A* values in the *S* schedule in Table 1. The makespans for the job 6 in row 5 and job 5 in row 6 were calculated as 390.6 and 446.2 minutes in the S' schedule in Table 2 and these values are greater than the makespan values 367.8 and 444.9 in Table 1. Although S' schedule was gathered with SPT rule, a shorter completion time could not be achieved as it was proposed in Lemma-1. Thus, makespan minimization problem with job dependent risk deterioration and position dependent learning effect can't be optimally solved with SDR or SPT rule if basic process time is used.

Table 2. S' schedule for Lemma-1

Jobs	1	2	3	4	6	5	7	8	9	10
Position	1	2	3	4	**5**	**6**	7	8	9	10
Basic Process Time ($p_{[j]}$)	60	88	56	45	80	90	78	35	50	32
Actual Process Time ($p_{jr} = p_{[j]} \beta_{jr} r^a$)	71.8	124.0	64.3	48.7	81.7	55.6	53.8	28.8	41.0	26.5
Makespan ($\min \sum_{j=1}^{n} \sum_{r=1}^{n} p_{jr}$)	B'=308.8				390.6	446.2	A'=150.1			

Numerical example for Lemma-2

In Lemma-2 it was stated that if common process time is used instead of basic process time, makespan minimization problem with job dependent risk deterioration and position dependent learning effect can be solved with SDR. We will explain this case with numerical examples in Table 3-4. The average of basic process times of the 10 jobs ($p = \sum_{i=1}^{10} \frac{p_{[j]}}{10} = 61{,}4$) in Table 1 was taken and it was accepted as common process time. Actual Process Times (p_{jr}) were calculated with respect to common process times. In Table 3, B and A values were calculated as 295.06 and 192.8, respectively. The makespans for the job 5 in row 5 and job 6 in row 6 were calculated as 357.4 and 395.1 minutes in the S schedule in Table 1.

Table 3. S schedule for Lemma-2

Jobs	1	2	3	4	5	6	7	8	9	10
Position	1	2	3	4	5	6	7	8	9	10
Common Process Time (p)	61.4	61.4	61.4	61.4	61.4	61.4	61.4	61.4	61.4	61.4
Deterioration rate (β_{jr})	0,20	1,00	0,75	0,85	0,90	0,10	0,30	0,70	0,80	0,95
Actual Process Time ($p_{jr} = p_{[j]} \beta_{jr} r^a$)	73	85,97	70	66	62,36	37,68	42	50	50	51
Makespan ($\min \sum_{j=1}^{n} \sum_{r=1}^{n} p_{jr}$)	B=295.06				357,4	395,1	A=192.8			

Let's get the S' schedule by interchanging jobs 5 and 6 in the Table 3 according to the SDR similar to the Figure-1. As shown in Table 4, the B' and A' values of the S' schedule were computed as 295.06 and 192.8 minutes, respectively and they are equal to B and A values in the S schedule in Table 3. The makespans for the job 6 in row 5 and job 5 in row 6 were calculated as 335.01 and 393.82 minutes in the S' schedule in Table 4 and these values are smaller than the makespan values 357.4 and 395.1 in Table 3. S' schedule was gathered with SDR and a shorter completion time was achieved as it was proposed in Lemma-2. Thus, makespan minimization problem with job dependent risk deterioration and position dependent learning effect can optimally be solved with SDR rule if basic process time is used.

Table 4. S' schedule for Lemma-2

Jobs	1	2	3	4	6	5	7	8	9	10
Position	1	2	3	4	5	6	7	8	9	10
Common Process Time ($p_{[j]}$)	61.4	61.4	61.4	61.4	61.4	61.4	61.4	61.4	61.4	61.4
Deterioration rate (β_{jr})	0,20	1,00	0,75	0,85	0,10	0,90	0,30	0,70	0,80	0,95
Actual Process Time ($p_{jr} = p_{[j]} \beta_{jr} r^a$)	73	85,97	70	66	39.96	58.81	42	50	50	51
Makespan ($min \sum_{j=1}^{n} \sum_{r=1}^{n} p_{jr}$)	B'=295.06				335.01	393.82	A'=192.8			

4. Discussion and Conclusion

In this study, makespan minimization problem with job dependent risk deterioration and learning effect was introduced. Musculoskeletal disorder risks were modeled with respect to EAWS which has a common use in German automotive and truck manufacturing industry. It was assumed that deterioration rate is a hyperbolic tangent function of EAWS and varies with jobs. Position dependent learning rate was included in the problem.

It was proved and numerically shown that makespan minimization problem with job dependent risk deterioration and position dependent learning effect can be optimally solved by using smallest deterioration rule, on condition that common process time is used instead of basic process time, otherwise the problem can't be optimally solved. The results show that our approach is promising in terms of real life machine scheduling problems under ergonomic risk constraints. Proposed model makes possible to determine more accurate production plans. Also, it has a great potential in terms of bringing balance between musculoskeletal disorder risks and productivity. The contribution of this paper to the literature is the modeling musculoskeletal disorder risks with EAWS and calculation of deterioration rates by a hyperbolic tangent function for the first time. Furthermore, it was proved and numerically shown that makespan minimization problem can be optimally solved with SDR.

For future research, parallel machine scheduling could be studied. Furthermore different deterioration functions could be employed for the ergonomic risks evaluations. In addition, a hybrid evaluation method including state of the art approaches in the literature could be developed for the risk assessment of musculo-skeletal disorders. Our approach could be applied to different problems such as the total flow time minimization problem, due date assignment problem or weighted due date minimization problems.

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