FACTA UNIVERSITATIS
Series: **Mechanical Engineering**
https://doi.org/10.22190/FUME230927014B

Original scientific paper

AN INTEGRATED OPTIMIZATION OF PRODUCTION AND PREVENTIVE MAINTENANCE SCHEDULING IN INDUSTRY 4.0

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Abstract. *Preventive Maintenance (PM) plays an important role in maximizing machine reliability, improving production efficiency and reducing repair costs. Due to the importance of PM in manufacturing environments, it is necessary to develop an integrated model for scheduling production jobs and maintenance interventions on the machines. On the other side, with the advent of Industry 4.0 and the transformation of factories into smart factories, the production and maintenance processes generate huge volume of data on real-time basis. Despite the importance of the issue and the competitiveness of manufacturing companies in the world, past studies show that the integration of production scheduling and maintenance in Industry 4.0 platform has not been paid much attention. Therefore, in this paper, we propose an optimal parallel machine-scheduling problem with PM activities. A mathematical model is formulated to optimize the scheduling of production and maintenance operations. Industry 4.0 conceptual model is also presented in this paper, in which the smart sensors are considered as the real enablers for industrial digitalization. The optimization problem is solved using GAMS software and branch and bound algorithm. The results of the model provide a suitable schedule for scheduling production and maintenance, and the comparison of solution methods shows that the branch-and-bound algorithm achieves a suitable output in a shorter time.*

Keywords: *Production scheduling, Preventive maintenance (PM), Joint optimization, Industry 4.0*

Received: September 27, 2023 / Accepted March 15, 2024
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1. INTRODUCTION

Nowadays, manufacturing companies offer a variety of products to their customers at very competitive prices. Time-based manufacturing systems can help companies shorten their production and delivery lead times, minimize changeover, reduce spare parts inventory levels and respond instantly to market changes. Real-time decision-making can be considered as an important feature in time-based production and manufacturing systems. Real-time describes various operations or processes that respond to inputs reliably within a relatively fast. In other words, it means that it uses logic and mathematics to process the data just a few seconds after it becomes available so that users can get valuable information when they need it. It can help manufacturing businesses identify anomalies and sudden changes in production environment as they occur (like when a spike in product demand or an unexpected breakdown in manufacturing unit occurs) in order to take effective action to control the negative impacts of such changes [1].

The equipment failure is known as one of the main reasons for reduced production efficiency in many manufacturing industries [2]. There are various examples of equipment failure in different industry sectors such as the thermoplastic industry (e.g, the molds in hydraulic presses), the semiconductor industry [3], cutting tools in drilling (e.g, machines, cooling systems), and sensors [4]. In some of these failure cases, the equipment or machinery would need to be repaired or replaced, which can be costly and/or time consuming. The Preventive maintenance (PM) has been considered as one of the most effective strategies to avoid unexpected failures in production facilities and enhance the service life of machinery. Despite the many benefits of PM in manufacturing systems, repair activities may sometimes interfere with production processes and result in a complete shutdown of the production line. Furthermore, irregular PM actions may lead to safety hazards and huge losses to the company. Therefore, the PM activities must be scheduled in advance and performed on a routine basis to minimize production interruptions and ensure quality compliance.

In this paper, a new PM scheduling mathematical model is formulated for the integrated scheduling of parallel machine production and PM interventions such that the completion time as well as the expected cost are simultaneously minimized. An Industry 4.0 conceptual model is also presented in this paper, in which the smart sensors are considered as the real enablers for industrial digitalization. In addition to periodic PM activities, corrective maintenance is also performed to fix machines when they experience accidental failures. In order to optimize the timeliness of production and maintenance, reliability is considered for each machine. The reliability function is to estimate the production efficiency and estimate the useful life of parts to prevent their failure. Another innovation of this article is the simultaneous implementation of preventive and corrective maintenance in the production system with two parallel machines. Corrective maintenance and repairs are used when parts need to be replaced after estimating their useful life. In addition to the above, the conceptual model of the production system has been presented in the context of Industry 4.0. In today's competitive world, production data is very vital. To remain in the field of production, they must be analyzed. For this purpose, mastery of data science and its process is very significant. Industry 4 is used to analyze data and predict production and maintenance schedules. The optimization problem is solved using GAMS software and branch and bound algorithm. The results of each two cases have been compared.

The organization of this paper is as follows: Section 2 reviews the related work on the integration of production, maintenance and Industry 4.0. Section 3 presents new PM scheduling mathematical model. Section 4 presents the numerical example, followed by the conclusion and future directions for research in Section 5.

2. Literature Review

There are often two challenges, which should be taken into account in a production system. The first challenge is associated with the production planning, aiming to determine optimal production lot size and evaluate the required production capacity; and the second challenge is associated with the scheduling and sequence of production operations, which aims to allocate the existing production capacity to the jobs and determine the sequence of production operations and their start time. The literature review in this paper is divided into two parts. The first part is related to scheduling and maintenance, and the next part is related to the performance of sensors in the manufacturing system and how to determine the time of maintenance.

Maintenance of production systems is basically of two types. In the first type, known as corrective maintenance (CM), there is no control over the condition of production facilities, meaning that the machines are repaired only after they are broken down. In the second type of maintenance, known as Preventive maintenance (PM), there is a level of control over the condition of production facilities, meaning that the maintenance activities are performed to prevent the occurrence of failure. In this case, the scheduling of maintenance interventions plays a main role in production and operations management [5]. Optimal maintenance planning can help reduce the frequency of breakdowns and production stoppages [2]. On the other hand, non-optimal maintenance schedules may lead to increase in machine downtime, loss of production, and operating costs.

Another type of integrated models under time-based PM activities is the classical single machine-scheduling problem with tool replacement. Yazdani et al. [6] also studied the parallel machine-scheduling problem with tool change activities such that the makespan was minimized and the maximum makespan was kept below a certain level. Also researchers introduced a multi-objective optimization model that had two machines operating in parallel. They examined the breakdown from two resources [7]. The first resource is the machine and the second resource is the moulds. PM activity was considered flexible. The purpose of presenting the model was to minimize the completion time of jobs and the unavailability of machines and moulds. None dominated Sorting Genetic Algorithm (NSGA-II) was proposed to solves the model. Gara-Ali et al. [8] considered a general model for scheduling the production jobs on unrelated parallel-machines with PM interventions. The processing times were assumed to deteriorate according to their position in the production sequence and the goal of the maintenance was to help to restore good processing conditions. Yoo and Lee [9] determined a joint optimization of schedule for production jobs and PM activities on parallel machines such that the scheduling cost was minimized. Zhang et al. [10] studied an integrated scheduling production jobs and PM interventions for disrupted parallel machines. They assumed that machines might be unavailable at some particular times but they can resume operations. The objective function was to minimize the expected sum of completion times for both the reusable and non-reusable cases. Shen and Zhu [11] studied a parallel-machine scheduling problem with PM in which the processing and maintenance times were assume to be uncertain variables. Sin and Chung [12] studied a single machine-scheduling problem with the application to energy-aware scheduling with PM operations under time-of-use (TOU) pricing. The authors formulated the problem with a bi-objective mixed integer non-linear programming model and then solved it by meta-heuristic algorithm. Chen et al. [13] addressed the single machine-scheduling problem for a rotor production workshop and then solved the problem with a genetic algorithm (GA). The machine availability was evaluated by its reliability, which can be restored by a PM. Branda et al. [14] studied a flow shop scheduling problem in which machines might be unavailable at some times during the production planning horizon due to random failures. To solve the problem, they proposed two novel meta-heuristic algorithms, including a standard GA and a Harmony Search method. Bhattacharya and Chakraborty [15] presented a model for using a past CNC face milling dataset and employed a random forest (RF) regressor to effectively predict the response values of the said process for given sets of input parameters. Zhao and Yuan [16] considered constraints as product delivery time and changing machine failure rate, and established a multi-objective optimization model aiming to minimize the processing cost and the product processing time. The model includes the changing machine failure rate into the integrated optimization of job-shop production scheduling and predictive maintenance, and enables the prediction of the machine state according to the processing time of the current job, laying the basis for the decision-making of the machine activity and the reasonable and effective production planning.

Today, the Internet of Things, machine learning, big data and sensors can be used to further monitor manufacturing technologies and systems, for example, to predict, reduce costs, improve production, predict maintenance and repair operations, and etc. There are various researches related to surveillance systems based on the Internet of Things, which contain positive and significant results and feedback. One of the applications of Industry 4.0 in manufacturing is the use of sensors. Smart sensors or monitoring devices enable processing of lots of data points [17]. Cheung et al. [18] presented locations in manufacturing systems for monitoring by sensors. The basis of working with these sensors is that a set of sensor data is sent to a remote server. If an abnormal situation occurs, an alarm sounds and the process is executed with high precision.

According to the above literature reviewed, the following research gaps are extracted:

1. Lack of considering multiple objectives in decision making such as minimizing maintenance costs and the completion time;

2. Reliability of determining time to maintenance operations were not considered deeply and neither integrated with economic maintenance decisions. The estimation of the useful life of the parts in the production system in order to increase the reliability of the machines has not been investigated;

3. By evolution of industry 4.0, past works did not integrate the corresponding technologies into real-time maintenance scheduling.

To handle the aforementioned gaps, the contributions of this work are listed below:

1. Providing a multi-objective model of reliability-based maintenance scheduling considering the industry 4.0;

2. Developing an exact solution approach for the integrated maintenance scheduling within industry 4.0 paradigms;

3. Using real sensor data to predict maintenance operations.

3. THE PROPOSED MODEL

In this section, in addition to explaining the industry 4.0-based information flow management framework, we propose our integrated production and maintenance-scheduling model. Industry 4.0 describes an environment in which flexible and intelligent processes utilize data obtained from sensors connected to all parts of a value chain simultaneously with the occurrence of an event to optimize business processes. These cyber-physical systems use the power of big data analytics to translate complete operational vision into unprecedented speed and efficiency in production processes. At present, these machines and equipment can be programmed to interact with each other, with their higher and lower operating systems, and to make intelligent decisions independent of human intervention being exactly the definition of a modern smart factory.

In addition, a production system may fail due to various reasons, or the useful life of parts may end, in which case repair or replacement of parts is required. Since the production line is completely stopped when performing maintenance and repair operations, it is very essential to determine the right time for maintenance and repair operations to prevent the production of defective products, machine breakdowns, and also the costs caused by stopping the production line. The analysis of the data received from the sensors of industrial systems is of particular importance and they are entered into the model as parameters and primary data so that their results can be used to produce a suitable schedule. In the following, the characteristics of the problem are explained.

The problem involves $i=\{1,2,\dots, n\}$ independent job, which is in set $N=\{J_1,\dots, J_n\}$. There are $K=\{1,2,\dots, k\}$ machines in parallel and independent in each period to process these jobs. In other words, the presented model can be used for $K=\{1,2,\dots, k\}$ that are placed in parallel. At zero time and before the start of processing, all jobs and machines are available. The problem is that each machine is able to perform a maximum of one job at a time, and each job must be processed on only one machine. Preventive maintenance, $m_k=\{1,2,\dots, m\}$ is provided periodically. Moreover, after each maintenance operation, the machine becomes well in its new state. Because the machines in question are considered safe, no net operations are performed at the start of the schedule. If the machines break down between the two intervals intended for preventive maintenance operations, corrective maintenance operations must be performed on them. In this system, both machines can be stopped at the same time for maintenance operations, and this depends on the schedule and breakdown of the machines.

The objective function includes minimizing the time to complete the jobs and minimizing the average cost of maintenance in two separate sections. Eqs. (1) and (2) represent the makespan and the cost of maintenance operations, respectively. Eq. (3) represents a linear weighted combination of two above objective functions:

$$\min z_1 = C_{\max} \tag{1}$$

where $C_{max} = max\ \{C_{ik}\}$ is completion time of the last job, t_{mk}, start time of maintenance operations on the machine k; C_{ik}: Completion time of the i^{th} job on machine k,

$$\min z_2 = \sum_{k=1}^{K} \frac{C_{pm} * R_k(t_{mk}) + C_{cm} * F_k(t_{mk})}{\mu_{pmk} * R_k(t_{mk}) + \mu_{cmk} * F_k(t_{mk}) \int_{m-1}^{m} R_k(u)du} \tag{2}$$

where C_{pm} is cost of a PM action, $R(t)$: $R(t) = 1- F(t)$ is machine reliability, $F(t)$ is probability distribution function for time to failure of machines, C_{pm} is cost of a CM action,

μ_{pmk} is the average time for executing a PM action, μ_{cmk} is the average time for executing a CM action,

$$\min z = W_1\left(\frac{z_1 - z_1^*}{z_1^*}\right) + W_2\left(\frac{z_2 - z_2^*}{z_2^*}\right) \tag{3}$$

where W_1 and W_2 are weights considered for the objective functions in order to use the LP metric method;

The model constraints are presented in the following equations:

$$C_{jk} \le C_{\max} \qquad \forall k \in \{1,2,3,...,k\} \text{ and } j \in \{1,2,3,...,n\} \tag{4}$$

$$\sum_{k=1}^{k}\sum_{i=0}^{n} x_{ijk} = 1 \qquad \forall i \ne j \text{ and } \mathrm{j} \in \{1,2,3,...,n\} \tag{5}$$

where x_{ijk}= 1 if job i precedes job j on machine k**,**

$$\sum_{k=1}^{k}\sum_{j=0}^{n} x_{ijk} \le 1 \qquad \forall i \ne j \text{ and } \mathrm{i} \in \{1,2,3,...,n\} \tag{6}$$

$$\sum_{h=0}^{n} x_{hik} \ge x_{ijk} \quad \forall i \ne j, i \ne h \text{ and i,}j \in \{1,2,3,...,n\}, k \in \{1,2,3,...,k\} \tag{7}$$

$$C_{0k} = 0 \qquad \forall k \in \{1,2,3,...,k\} \tag{8}$$

$$\begin{gathered} C_{jk} + M(1 - x_{ijk}) \ge C_{ik} + p_{jk} + (t_{m_k k} + g_{pm}(t_{m_k k}) * R(t_{m_k k})) + g_{cm_k}(t_{m_k k}) * F(t_{m_k k}) * Y_{i_{m_k k}} \\ \forall \mathrm{i} \in \{1,2,3,...,n\}, i \ne j, \forall j \in \{1,2,3,...,n\}, \forall k \in \{1,2,3,...,k\}, \forall m \in \{1,2,3,...,m\} \end{gathered} \tag{9}$$

where p_{ik} is processing time of the i^{th} job on machine k, M is a large positive number, $g_{pm}(t_{mk})$ is probability density function associated with the duration of a PM action, $g_{cm}(t_{mk})$ is probability density function associated with the duration of a CM action, y_{imk}, 1 if the m^{th} maintenance activity is performed prior to the i^{th} job on machine k**,**

$$\sum_{m_k}^{m} Y_{im_k k} \le 1 \qquad \forall \mathrm{i} \in \{1,2,3,...,n\}, \ k \in \{1,2,3,...,k\} \tag{10}$$

$$\sum_{i=1}^{n} Y_{im_k k} = 1 \qquad \forall k \in \{1,2,3,...,k\}, \ m_k \in \{1,2,3,...,m\} \tag{11}$$

where M_K is number of maintenance activities on machine k,

$$t_{mk} = L_{mk} \quad \forall k \in \{1,2,3,...,k\}, \ m_k \in \{1,2,3,...,m\} \tag{12}$$

where L_{mk} is the latest maintenance start time for the m^{th} maintenance activity on machine k,

$$L_{m+1,k} = t_{m+1,k} + g_{p(m)}(t_{(m)k}) * R(t_{(m)k}) + L_k \quad \forall k \in \{1,2,3,...,k\}, m_k \in \{1,2,3,...,m_k - 1\} \tag{13}$$

$$p(\varepsilon \ge L_k) = \beta \tag{14}$$

where β is a positive number between 0 and 1, ε is instant of failure in the machine,

$$x_{ijk} \text{ and } Y_{im_k k} \in \{0,1\} \text{ and } t_{mk} \geq 0 \quad \forall k \in \{1,2,3,...,k\}, m_k \in \{1,2,3,...,m\}, j \in \{1,2,3,...,n\} \quad (15)$$

Eq. (4) indicates the maximum time, when the processing of jobs is completed. Eq. (5) states that each job must only be processed on one machine. Eq. (6) ensures that the maximum number of successors of every job to be one. Eq. (7) limits the number of successors of each job to a maximum of one on each machine. Eq. (8) states that the zero job ends in zero time, in other words, no processing time is set for the zero job. Eq. (9) shows how to calculate the processing time of jobs on machines. Therefore, if job *j* is performed after job *i* to machine *k*, the processing time of job *j* will be greater than job *i*. Eq. (10) indicates that after processing each job, a maximum of one maintenance operation can be performed on the machine. Eq. (11) states that a maximum of one maintenance operation can be performed on each machine after each job and at any time interval. Eqs. (12) and (13) explain how to calculate the latest maintenance time on machines. In Eq. (14) to obtain the L_k for maintenance on each machine, the maximum production efficiency of each machine must be considered, which is indicated here by β and is considered as a parameter. Then, with efficiency and integration, the value of the upper limit of the integration interval indicates the latest start time of maintenance operations, which is given in Eq. (14). Eq. (15) indicates decision variables.

4. Numerical Example

In this section, a numerical solution algorithm is provided to illustrate the proposed model. The following provided a numerical method for determining decision variables that minimizes completion time and total maintenance costs per unit time. Since the proposed model is NP-hard, solving it with GAMS software would be so times consuming. For solving in small scale, GAMS software has been used, and for large scale, branch and bound method has been used in MATLAB software. Initially, after introducing the parameters, the upper limit of the integral (L_k) shown in Eq. (13) is calculated. Then the latest maintenance time on each machine can be calculated. Because by calculating the latest time of maintenance operations, it is possible to periodically determine the time of preventive maintenance. In the next step, the jobs are assigned to the machines and the time of preventive maintenance and repairs is determined. After processing each job, the system checks whether it is time for maintenance and corrective repairs. If it is time for maintenance, maintenance operations will be performed. After the maintenance operations are completed, job processing starts again and will be returned to Eq. (13). If the condition fails, the allocation of jobs to the machines will continue. If all the jobs are assigned to the machines, the calculation of the objective function is performed and finally the output of the algorithm and the schedule of production, maintenance and repairs are reached. The branch and bound algorithm is used to schedule jobs and preventive maintenance.

In this section, the input data for solving the model by the proposed algorithm is given. This model is solved by 10 problems with different processing times. In this section, the parameters are given. Job execution times are generated using random data. However, for the duration of maintenance and repairs and their cumulative distribution, another article and previous studies have been used. In problem number 1, seven jobs J_1, J_2, J_3, J_4, J_5, J_6 and J_7 are defined to run the model and obtain the solution.

- Costs: cost of PM = 2$, cost of CM = 4$.
- The duration of PM task ~LogNorm (mean μ_p=10, standard deviation δ_p=1.5).
- The duration of CM task ~LogNorm (mean μ_C=20, standard deviation δ_c=2).
- The time to machine failure ~ Weibull distribution (shape parameter=2, scale parameter =100), i.e., the average lifetime is μ=8.86-time units.
- β=90%
- Number of machines =2.
- The number of jobs and their processing times is given in Table 1.
- In this example, the jobs are assigned to machines and there are different sequences between the jobs of each machine.

Random numbers in accordance with previous articles have been used to calculate the proposed model. This model was run with 10 jobs each time by the proposed algorithm and in MATLAB software and 7 jobs by GAMS software.

Table 1 Time required processing each job on both machines

	Problem Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Processing times for the jobs on both machines*(s)* (p_{ik})	1	10	7	11	6	12	5	12	-	-	-
	2	6	10	7	12	18	17	5	-	-	-
	3	6	20	7	19	8	19	20	-	-	-
	4	11	8	5	6	10	6	13	-	-	-
	5	18	20	18	9	12	14	5	8	18	16
	6	6	11	8	12	6	7	14	12	17	5
	7	5	10	16	20	17	15	15	14	6	14
	8	13	12	15	15	15	17	20	15	16	10
	9	19	10	9	5	12	19	15	14	19	8
	10	11	13	7	9	17	5	5	15	20	14

The number of preventive maintenance operations was initially set equal to the number of jobs. In the worst case, after each job processing, a maintenance operation is performed on the machine and the required number is determined after the model is run. The results obtained from the proposed algorithm and GAMS software are given in Table 2. Schedule of jobs and anticipated is given in Fig. 1.

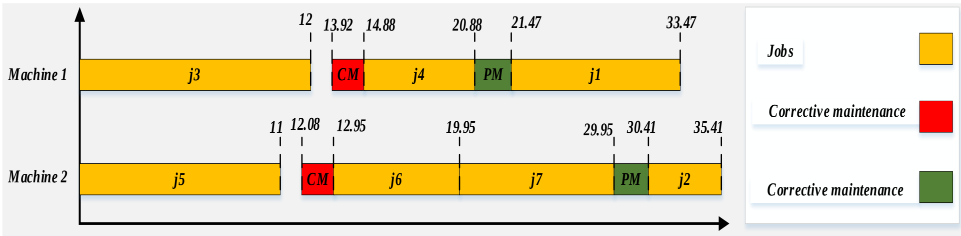

Fig. 1 Initial scheduling of the seven jobs on two parallel machines

Table 2 The obtained results

Problem Number	Objective Function	Cmax GAMS	Cmax (Branch and Bound)	Solution Time (Branch and Bound)	Solution Time (GAMS)
1	17.623	35.41	35.41	121.18	524.12
2	19.713	39.23	39.23	99.89	335.92
3	26.273	52.35	52.35	101.22	529.32
4	15.723	31.25	31.25	133.37	658.18
5	33.995	-	66.53	143.269	-
6	37.043	-	72.58	187.191	-
7	47.478	-	93.45	135.594	-
8	48.373	-	95.24	258.427	
9	33.328	-	65.15	227.686	-
10	40.448	-	79.39	167.517	-

In this section, the proposed model is solved using parameters. The output of the model is a schedule that, in addition to the production schedule, optimizes the maintenance and repair schedule in an integrated manner. This model is very serious to save time and money. According to the current conditions, many manufacturing plants still do not integrate the production schedule with the maintenance and repair schedule. Each unit tries to optimize individually. In addition, due to today's competitive world, in order to optimize and remain in the field of competition, they must update themselves with the latest science. Organizations, in addition to needing a comprehensive plan for production, also need to analyze data and use it in order to increase quality and competition. Therefore, it is very necessary to provide a model that can optimize all these things and can use data science for data analysis.

5. CONCLUSION

In this paper, an optimization model was presented to schedule production operations as well as preventive maintenance interventions on multiple parallel machines in an integrated way. A conceptual model was presented in order to understand how industry 4.0 works. Then the proposed model was solved by GAMS software and branch-and-bound algorithm. The output of the model was the integrated schedule of production and maintenance and repairs. This model is essential from the point of view that it optimizes both programs (scheduling and maintenance) simultaneously. In addition, the results show that for a high number of scales, the branch-and-bound algorithm provides better results in the shortest time. For future studies, online analytical processing (OLAP) tools can be used to examine changes in machines, as well as condition-based maintenance. Furthermore, some other decision variables such as pricing, batch size, etc. can also be considered in our model.

REFERENCES

1. Kazimieras Zavadskas, E., Turskis, Z., Stevic, Z., Mardani, A., 2020, *Modelling procedure for the selection of steel pipes supplier by applying fuzzy AHP method*, Operational Research in Engineering Sciences: Theory and Applications, 3(2), pp. 39-53.
2. Bajestani, M.A., Banjevic, D., Beck, J.C, 2014, *Integrated maintenance planning and production schedulingwith Markova deteriorating machine conditions*, International Journal of Production Research, 52(24), pp. 7377–7400.
3. Sloan, T. W., Shanthikumar, J.G., 2000, *Combined production and maintenance scheduling for a multiple product, single- machine production system*. Production and Operations Management, 9(4), pp. 379–399.
4. Bajestani, M.A., 2014, *Integrating maintenance planning and production scheduling: Makingoperational decisions with a strategic perspective*, PhD thesis, Department of Mechanical and Industrial Engineering, University of Toronto, Canada.
5. Rahmati, S.H.A., Ahmadi,A., Govindan, K., 2018, *A novel integrated condition-based maintenance andstochastic flexible job shop scheduling problem: Simulation-based optimization approach*, Annals of Operations Research, 269(1–2), pp. 583–621.
6. Yazdani, M., Khalili, S. M., Jolai, F., 2016, *A parallel machine scheduling problem with two-agent and tool change activities: An efficient hybrid metaheuristic algorithm*, International Journal of Computer Integrated Manufacturing, 29(10), pp. 1075–1088.
7. Wang, S., Liu, M., 2015, *Multi-objective optimization of parallel machine scheduling integrated with multi resources preventive maintenance planning*, Journal of Manufacturing Systems, 37(1), pp. 182–192.
8. Gara-Ali, A., Finke, G., Espinouse, M.-L., 2016, *Parallel-machine scheduling with maintenance: praising the assignment problem*, European Journal of Operational Research, 252(1), pp. 90–97.
9. Yoo, J., Lee, I.S., 2016, *Parallel machine scheduling with maintenance activities*, Computers and Industrial Engineering, 101, pp. 361–371.
10. Zhang, X., Liu, S., Lin, W., Wu, G., 2020, *Parallel-machine scheduling with linear deteriorating jobs and preventive maintenance activities under a potential machine disruption*, Computers and Industrial Engineering, 145, 106482.
11. Shen, J., Zhu, Y., 2019, *A parallel-machine scheduling problem with periodic maintenance under uncertainty*, Journal of Ambient Intelligence and Humanized Computing, 10, pp. 3171-3179.
12. Sin, I.H., Chung, B.D., 2020, *Bi-objective optimization approach for energy aware scheduling considering electricity cost and preventive maintenance using genetic algorithm*, Journal of Cleaner Production, 244, 118869.
13. Chen, L., Wang, J., Yang, W., 2021, *A single machine scheduling problem with machine availability constraints and preventive maintenance*, International Journal of Production Research, 59(9), pp. 2708–2721.
14. Branda, A., Castellano, D., Guizzi, G., Popolo, V., 2021, *Dataset of meta heuristics for the flow shop scheduling problem with maintenance activities integrated*, Data in Brief, 36, 106985.
15. Bhattacharya, S., Chakraborty, S., 2023, *Prediction of Responses in a CNC Milling Operation using Random Forest Regressor*. Facta Universitatis-Series Mechanical Engineering, 21(4), pp. 685-700.
16. Zhao, Z. Y., Yuan, Q. L., 2022, *Integrated multi-objective optimization of predictive maintenance and production scheduling: Perspective from lead-time constraints*, Journal of Intelligent Management Decision, 1(1), pp. 67-77.
17. Friedemann, M., Trapp, T.U., Stoldt, J., Langer, T., Putz, M., 2016, *A framework for information-driven manufacturing*, Procedia CIRP, 57, pp. 38-43.
18. Cheung, W.F., Lin, T.H., Lin, Y.C, 2018, *A real-time construction safety monitoring system for hazardous gas integrating wireless sensor network and building information modeling technologies*. Sensors, 18, 436.