THE EFFECTS OF A MACHINE FAILURE ON THE ROBUSTNESS OF JOB SHOP SYSTEMS - THE PREDICTIVE-REACTIVE APPROACH

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Abstract: The paper presents the classification of methods of dealing with uncertainty in scheduling problems. Two proactive approaches are identified: predictive-reactive (proactive with prediction) and proactive-reactive (proactive without prediction). In the first approach, researchers use prediction methods to predict maintenance time. Next, the influence of a disturbance on the schedule using the robustness measures is examined. In the second approach, the proactive schedule is achieved for the best sequence of idle times between jobs or batches taking the advantage of the simulation process. This paper presents the results of predictive-reactive approaches using both: the Hybrid Multi-Objective Immune Algorithm and heuristics based on priority rules. Two predictive heuristics are proposed in order to generate robust and stable schedules under uncertainity. The heuristics differ in the scheduling procedures applied for less flexible operations that are predicted to be disrupted by a machine failure. Computer simulations are conducted for job shop systems.
Key words: robustness; maintenance; proactive scheduling; predictive scheduling; immune algorithm; job shop.

1. INTRODUCTION

In the past decades, production and maintenance scheduling has been an interesting topic to many researchers. Both, production and maintenance tasks occupy machines capacity and deplete or restore machines reliability. Maintenance tasks can be treated as availability constraints of machines in scheduling problems. The unavailability interval for maintenance should be predicted in order to reduce idle time of a machine and thus increase its capacity. In related literatures, three important research tracks can be identified to deal with the uncertainty: predictive scheduling, proactive scheduling and reactive scheduling.

Predictive scheduling is implemented at the decision stage. A schedule of production and maintenance tasks, which guarantees machine reliability and a high utilization needs to be obtained. In other words, the schedule which can absorb the disturbance without affecting planned external activities, while maintaining a high system performance needs to be generated [7, 8]. Predictive schedule is achieved by introducing deterministic constraints for preventive maintenance. In the literature, there are two types of preventive maintenance (PM): a fixed time of PM [6] and flexible time [13], where PM must be executed in the time interval, which is longer than a time of PM. Researchers ignore a machine unexpected failure which makes the problem deterministic. They assume that PM performed at regular intervals is enough for machines to be available and reliable. The researchers are really dealing with the scheduling problems with constraints instead of the predictive scheduling since there is no prediction for failure-free time.

In many realistic situations, machines can be unavailable during the scheduling horizon for the reason of unexpected breakdown. Proactive scheduling considers the possibility of an unexpected machine failure in the production plan. This uncertainty causes the scheduling problem to be stochastic. Proactive scheduling is also implemented at the decision stage. The objective is to obtain a more robust schedule to minimize the effect of a disruption. The impact of an unexpected machine failure over the performance of the production system is researched [3]. Usually, the expectation of the system performance is compared using robustness criteria.

In the literature, two proactive approaches can be distinguished as: proactive with prediction (predictive-reactive) and proactive without prediction (proactive-reactive). In the first approach, proactive scheduling is treated as an expansion of the predictive scheduling. In the predictive-reactive approach, researchers use prediction methods in order to predict maintenance time. Next, the influence of the disturbance on the predictive schedule using the robustness measures is examined in order to select the best schedule [4]. In the proactive-reactive approach, only the impact of the disruption on the schedule using robustness criteria is investigated. The proactive schedule is achieved for the best sequence of idle times between jobs or batches taking the advantage of the simulation process [2, 14].

Reactive scheduling is implemented at execution time to adjust the schedule to the real-time situation [1]. The corrective maintenance is performed after the failure.

The authors of this paper intend to develop the existing studies via the comparison analysis of predictive-reactive methods using not only the advantage of computer simulation but also prediction. The presented predictive-reactive methods use the advantage of computer simulation by repeating following steps: generating a population / one basic schedule, conversion of basic schedule/s into predictive schedule/s, assessment of the impact of a disruption on reactive schedule/s using criteria: solution robustness (SR) and quality robustness (QR). After the disturbance, SR assesses how much the current schedule differs from the previously adopted one. QR assesses how much the current value of the quality indicator differs from the value of the previously adopted schedule. The first method uses the Multi Objective Immune Algorithm (MOIA) to generate the population of basic schedules [10, 11]. In the second method, a basic schedule is generated using one of priority rules. Next, predictive schedules taking the advantage of prognostic analysis are generated using the Minimal Impact of Disrupted Operation on the Schedule (MIDOS) rule [10]. The MIDOS rule transforms schedules so that they are more robust and stable in the event of disruptions. In the MIDOS rule, the job which is pre-assigned to be disturbed is rescheduled. The most flexible operation of the job is assigned to the bottleneck. The backward and forward scheduling are applied for remaining operations. The left shifting rule is used for backward scheduling and the right shifting rule is used for forward scheduling in the MIDOS I. In the MIDOS II rule, the backward scheduling and forward scheduling consists in assigning disrupted operations to the last and first available machines, respectively.

The following research point needs to be investigated: which approach of predictive-reactive scheduling achieves better solutions:

1. generating a population of basic schedules using HMOIA and quality assessment (using SR and QR) of predictive schedules after the disruption?
2. generating a basic schedule using a priority rule and quality assessment (using SR and QR) of the predictive schedule after the disruption?

The original contribution of this paper is threefold:

1. This paper proposes formulaes for the reliability characteristics used in the MIDOS rules:
   - the Mean Time Between Failures,
   - the period of a high probability of failure limited by points *b* and *a*,

   where the fialure-free time is described by Gamma distribution;
2. The comarition of both MIDOS rules: I and II;
3. The comparison of two approaches: generating basic schedules using HMOIA and priority rules.

On the basis of an overview of reference publications, the research on the following points is continuated:

1. heuristics of dealing with disruption and achieving the best predictive schedules, when the objective is to minimise: makespan, flow time, total tardiness and idle time.
2. heuristics of dealing with predicted or unexpected disruption that maximize stability and robustness of schedules.

The paper is organized as follows: predictive-reactive approaches are presented in the next Section. The job shop scheduling problem for experimental study is presented in Section 3. The criteria for the assessment of predictive and reactive schedules are also described in Section 3. Section 4 contains necessary analyses and experimental test results related to the research on the application of the MOIA and heuristics. The paper concludes with a brief summary of the results (Section 5).

2. THE PREDICTIVE-REACTIVE APPROACHES

The predictive-reactive approach consists of three stages. First, a basic schedule is generated, next is converted to a predictive schedule using the MIDOS rule. Finally, the impact of the bottleneck failure on the reactive schedule using the SR and QR criteria is assessed.

There are two approaches of generating basic schedules. The first approach generates a population of basic schedules using the metaheuristic based on immunological optimization - the MOIA [10, 11]. The second approach generates a basic schedule using one heuristic from:

- The Shortest Processing Time (SPT) rule favors the processes that require the shortest execution time.
- The Longest Processing Time (LPT) rule is applied because the makespan minimization criterion is used to evaluate schedules. The rule assigns the highest value of the priority indicator for the process which requires the longest execution time.
- The Earliest Due Date (EDD) rule assigns the highest value of the priority indicator for the most urgent process. This procedure is used because schedules are evaluated using timeliness criteria.

The Random Insertion Perturbation Scheme (RIPS) [12] is adopted in order to modify the basic schedule. This procedure is based on the local search of the space of solutions around the basic solution. Finally, the best solution from the neighborhood is selected (Figure 1).

Basic schedules are evaluated using:

$$FF(x) = \varpi_1 \cdot C(x) + \varpi_2 \cdot F(x) + \varpi_3 \cdot T(x) + \varpi_4 \cdot I(x) \quad (1)$$

subject to:

$$\varpi_1, \varpi_2, \varpi_3, \varpi_4 \in [0,1], \text{ and } \varpi_1 + \varpi_2 + \varpi_3 + \varpi_4 = 1 \quad (2)$$

where:

1. *C(x)* is makespan minimisation:

$$C(x) = \max\left[t_{z,V_j}\right] \quad (3)$$

–apply SPT/LPT/EDD rule to the sequence of processes;
–for 0 to ($2J$-2):
– select process j from the sequence;
– if the selected process is first or last in the sequence:
– randomly generate a number from (1, J) for $j = 0$ or a number from (0, J-1) for $j = J$;
– else if:
– randomly generate a number from (0, j-1) or (j+1, J);
– generate a new solution by replacing the processes indicated by the two numbers (positions) and assess the quality of the schedule;
–select the best schedule from the set of (2 J-2) solutions.

Fig. 1. The RIPS rule procedure

2. *F(x)* is flow time of processes minimisation:

$$F(x)=\sum_{j=1}^{J}\left(t_{z,V_j}-t_{r,1_j}\right) \tag{4}$$

3. *T(x)* is total tardiness of processes minimisation:

$$T(x)=\sum_{j=1}^{J}[0,D_j], \quad where \begin{cases} 0, & if \quad d_j-t_{z,V_j}\le 0 \\ D_i, & if \quad d_j-t_{z,V_j}>0 \end{cases} \tag{5}$$

4. *I (x)* is idle time of machines minimisation:

$$I(x)=\sum_{w=1}^{W} I_w \tag{6}$$

where: t_{z,v_j} is end time of operation v_j of process *j*, $v_j=1,\ldots,V_j$, $j=1,\ldots,J$, t_{r,v_j} is start time of operation v_j of process *j*, d_j is deadline for completing process *j*, D_j is delay in completing process *j*, I_w is idle time of machine *w*, $w=1,\ldots,W$.

Basic schedules are converted into predictive by applying the MIDOS rule. The MIDOS rule uses reliability characteristics which are estimated on the basis of historical data about the failure-free operation of the bottleneck.

Suppose that operation times $X_{i,1},\ldots,X_{i,N_i}$ in the *i*th historical period $[(i-1)T,iT)$, $i=1,\ldots,m+1$ have a Gamma distribution with probability density function $f_i(\cdot)$ of the form (7), where $p_i>0$, $\lambda_i>0$, thus each parameter of the distribution depends on the number of period and is the same in each period separately.

$$f_i(t)=\begin{cases} \dfrac{\lambda_i^{p_i}}{\Gamma(p_i)}t^{p_i-1}\exp(-\lambda_i t), & t>0, \\ 0, & t\le 0, \end{cases} \tag{7}$$

where $\Gamma(p_i)=\int_0^\infty x^{p_i-1}e^{-x}dx$, $\Gamma(p_i)$ is read from statistical tables.

N_i denotes a random number of disturbances observed in $[(i-1)T,iT)$. At the end of operation time $X_{i,k}$, as the failure occurs, a repair time $Y_{i,k}$ begins immediately and so on. It is assumed that repair times $Y_{i,1},\ldots,Y_{i,N_i}$ for $i=1,\ldots,m+1$ are exponentially distributed.

Estimators $\hat{p}_i$ and $\hat{\lambda}_i$ of Gamma distributions are obtained for scheduling periods $i=1,\ldots,m$ by applying approaches: maximum likelihood or empirical moments [5]. After achieving estimators $\hat{p}_1,\ldots,\hat{p}_m$ and $\hat{\lambda}_1,\ldots,\hat{\lambda}_m$ one can extrapolate values $\hat{p}_{m+1}$ and $\hat{\lambda}_{m+1}$ for the next planning period $[mT,(m+1)T)$, by applying the regression method. The following reliability characteristics used in the MIDOS rule are calculated:

1. The maintenance task is assigned to the bottleneck at the time determined by the Mean Time Between Failures (MTBF)

$$MTBF=E\{X_{m+1,1}+Y_{m+1,1}\}=\frac{\hat{p}_{m+1}}{\hat{\lambda}_{m+1}}+\frac{1}{\alpha_{m+1}} \tag{8}$$

where: $\alpha_{m+1}>0$ is predefined.

2. The risk of inconsistent prediction of machine failure-free time is minimized by assigning the most flexible operations to the period limited by points *b* and *a*, where:

a is estimated on the assumption that the probability of the failure-free time of the bottleneck described by the Gamma distribution with parameters $\hat{p}_{m+1}$ and $\hat{\lambda}_{m+1}$ is higher than *a* equalling 40%, $P\{X_{m+1,1}>a\}=0.4$

thus $P\{X_{m+1,1} < a\} = 0.6$ and $1 - e(-\lambda \cdot a^p) = 0.6$ and we have $e(-\lambda \cdot a^p) = 0.4$ and taking the property $\ln e(r) = r$ we achieve $a^p = -\ln(0.4)/\lambda$ and finally

$$a = \sqrt[p]{-\ln(0.4)/\lambda} \tag{9}$$

b is estimated on the assumption that the probability of the failure-free time described by Gamma distribution with parameters $\hat{p}_{m+1}$ and $\hat{\lambda}_{m+1}$ is less than b equalling 70%, $P\{X_{m+1,1} < b\} = 0.7$ thus $1 - e(-\lambda \cdot b^p) = 0.7$ and we have $e(-\lambda \cdot b^p) = 0.3$ and taking the property $\ln e(r) = r$ we achieve $b^p = -\ln(0.3)/\lambda$ and finally

$$b = \sqrt[p]{-\ln(0.3)/\lambda} \tag{10}$$

The following criteria are assessed after the disturbance (for reactive schedule x^*):

1.The objective function which equals to the weighted sum of values of criteria (3-6) :

$$FF(x^*) = \varpi_1 \cdot C(x^*) + \varpi_2 \cdot F(x^*) + \varpi_3 \cdot T(x^*) + \varpi_4 \cdot I(x^*) \tag{11}$$

2.The quality robustness criterion:

$$QR(x^*) = |FF(x) - FF(x^*)| \tag{12}$$

The QR measures the degradation of the performance (efficiency measures) of the predictive schedule due to disturbance.

3.The solution robustness criterion:

$$SR(x^*) = \sum_{j=1}^{J} \sum_{v_j=1}^{V_j} \left| st_{j,v_j}(x) - st_{j,v_j}(x^*) \right| \tag{13}$$

where $st_{j,v_j}(x)$ – start time of operation v_j of process j in predictive schedule x; $st_{j,v_j}(x^*)$ – start time of operation v_j of process j in reactive schedule x*;

The SR measures the sum of absolute deviations of operation start times in the reactive and predictive schedule.

4.The total robustness function which equals to the weighted sum of values of criteria: QR and SR:

$$TR(x^*) = \omega_1 \cdot QR_1(x^*) + \omega_2 \cdot SR_2(x^*) \tag{14}$$

where: $\omega_1 = 0.5$ and $\omega_2 = 0.5$.

Reactive schedules are generated by shifting the disrupted operation to the right or to the machine first available from a set of parallel machines. The best schedule is selected using the TR (14) in the MIROS rule - Minimal Impact of Rescheduled Operation on the Schedule.

Computer simulations are conducted for a job shop scheduling problem presented in the next Section.

3. A JOB SHOP SCHEDULING PROBLEM

This Section presents a job shop scheduling problem with disruptions for experimental study. The job shop scheduling problem presented in [9] is investigated in order to compare the results of computer simulations for the predictive-reactive approaches. 15 jobs have to be performed on 10 machines (15x10). The objective is to achieve a feasible schedule for four objective functions: $C_{max} \rightarrow \min$; F $\rightarrow$min; T$\rightarrow$min and I$\rightarrow$min. A decision maker defined the priorities of criteria in order to make possible the comparison of the two algorithms. The priority (weight) of 1st and 3rd criterion equals 0.3, the priority of 2nd and 4th criterion equals 0.2. The first machine is the most heavily loaded. The failure-free time of the bottleneck *MTTF* equals 66. The repair time of the bottleneck *MTTR* equals 6. The increased probability of the bottleneck failure occurs in time horizon [a,b+*MTTR*] where: a = 60 and b = 72.

In the next Section the results of computer simulations are presented. The influence of the quality of predictive schedules over the quality of reactive ones is investigated. The objective is to find an approach which is able to generate stable and robust schedules in the event of the bottleneck failure.

4. RESULTS OF COMPUTER SIMULATIONS

Two approaches were compared for generating basic schedules: metaheuristic and heuristic. Two approaches were compared for generating predictive schedules: MIDOS I and MIDOS II. Reactive schedules were generated using the MIROS rule.

In the paper [9] predictive schedules were generated using the MOIA for basic scheduling and MIDOS I for predictive scheduling. Predictive schedules were generated only for the best basic schedules achieved for two sets of control parameters: the affinity threshold *affthres* and the stimulation threshold *stimthres*. The *affthres* was used to determine if one antibody is similar to another, *affthres* = 8 and 80. The stimulation threshold *stimthres* was used to define the number of similar solutions that can exist in a population, *stimthres* = 3. This paper is a continuation of the comparative analysis using the same parameter values: *affthres* and *stimthres.* The experiments were performed on a PC with Inel Pentium CPU B970, 2.3GHz and 6GB RAM. The heuristics were coded in Borland C++.

4.1 Predictive-reactive approach (HMOIA and MIDOS I)

First, computer simulations were run using the MOIA (for *affthres* = 8) for basic schedules generation. Predictive schedules were generated using the MIDOS I. The impact of the bottleneck failure was evaluated using the objective function FF (11) and the total robustness TR (14). For example, in the first simulation, the predictive and reactive schedules were generated for the basic schedule with the sequence of tasks: {2 5 14 1 3 0 4 6 7 10 8 9 11 12 13}. The objective function of the first predictive schedule was FF(1) =276.3 with the components of $C_{\max}$ = 115, F = 597, I = 612 and T = 0. The objective function of the first reactive schedule was FF(1*) =275.9 with the components of $C_{\max}$ = 115, F = 598, I = 609 and T = 0. The total robustness of the first reactive schedule was TR(1*) = 0.2 with the components of QR = 0.4 and SR = 0. Quality of the remaining solutions is described in Table 1. Also, computer simulations were run for *affthres* = 80. Quality of the solutions is described in Table 2.

The best basic schedule dealing with the uncertainty was generated for the first sequece of tasks when *affthres* = 8 (Table 1) and for the first sequece of tasks when *affthres* = 80 (Table 2). The total robustness was TR(1*) = 0.2 with the components of QR = 0.4 and SR = 0 when *affthres* = 8 (Table 1). The total robustness was TR(1*) =2.2 with the components of QR = 0.4 and SR = 4 when *affthres* = 80 (Table 2).

Let us consider the results achieved in the paper [9]. The best basic schedule dealing with the uncertainty was generated for the sequence of tasks: {10 14 2 5 3 1 0 4 7 8 9 6 11 12 13} when *affthres* = 8 and for the sequence of tasks: {2 5 14 1 0 4 8 9 3 6 7 10 12 11 13} when *affthres* = 80. TR(x*) = 7.3 with the components of QR = 2.6 and SR = 12 for the first sequence. TR(x*) =10.1 with the components of QR = 1.2 and SR = 19 for the second sequence. Taking into account the results of both papers the following conclusion can be proven. Generating subsequent simulations increases the chance of finding a better solution by the metaheuristic algorithm.

Let us consider the results achieved in the paper [11]. The average total robustness of schedules equals 13.71 achieved for *affthres* = 8 and 12.49 for *affthres* = 80. Thus, a better approach of dealing with uncertainty is to generate the best schedule, modify it using the MIDOS I and evaluate it using the MIROS than to generate a basic schedule, modify and evaluate it.

4.2 Predictive-reactive approach (HMOIA and MIDOS II)

Next, computer simulations were run using the MOIA (for *affthres* = 8) for basic schedules generation and the MIDOS II for predictive schedules generation. The best predictive schedule was generated for the basic schedule with the sequece of tasks: {5 2 13 14 0 3 4 6 7 1 8 9 10 11 12}. The objective function of the predictive schedule was FF(4) =276.1 with the components of $C_{\max}$ = 121, F = 527, I = 672 and T = 0. The objective function of the reactive schedule was FF(4*) =275.5 with the components of $C_{\max}$ = 121, F = 527, I = 669 and T = 0. The total robustness of the reactive schedule was TR(4*) = 1.3 with the components of QR = 0.6 and SR = 2. Quality of the remaining solutions is described in Table 3.

Table 1. The schedules generated using the MIDOS I and MIROS for the best basic schedules achieved by the MOIA and *affthres* = 8.

No	Job shop scheduling problem *(15x10)*													
	The sequece of tasks:the basic schedule	The quality of the predictive schedule x					The quality of the reactive schedule x*							
		C_{max}	F	T	I	FF(x)	C_{max}	F	T	I	FF(x*)	QR	SR	TR(x*)
1	**2 5 14 1 3 0 4 6 7 10 8 9 11 12 13**	**115**	**597**	**0**	**612**	**276.3**	**115**	**598**	**0**	**609**	**275.9**	**0.4**	**0**	**0.2**
2	10 14 2 5 3 1 0 4 7 8 9 6 11 12 13**	110	611	0	562	267.6	110	601	0	559	265	2.6	12	7.3
3	**2 5 8 0 14 1 4 3 6 7 9 10 11 12 13**	**111**	**652**	**0**	**572**	**278.1**	**111**	**653**	**0**	**569**	**277.7**	**0.4**	**0**	**0.2**
4	5 2 13 14 0 3 4 6 7 1 8 9 10 11 12	121	542	0	672	279.1	121	532	0	669	276.5	2.6	48	25.3
5	2 10 5 14 0 1 3 4 7 8 9 6 11 12 13	110	639	0	562	273.2	110	630	0	559	270.8	2.4	12	7.2
6	2 5 8 14 1 3 0 4 6 7 10 11 12 9 13	109	693	0	552	281.7	109	692	0	549	280.9	0.8	20	10.4
	average					**276**					**274.46**			**8.43**

**the best basic schedule dealing with the uncertainty, achieved in [9]

Table 2. The schedules generated using the MIDOS I and MIROS for the best basic schedules achieved by the MOIA and *affthres* = 80.

No	Job shop scheduling problem *(15x10)*													
	The sequece of tasks:the basic schedule	The quality of the predictive schedule x					The quality of the reactive schedule x*							
		C_{max}	F	T	I	FF(x)	C_{max}	F	T	I	FF(x*)	QR	SR	TR(x*)
1	**5 14 6 3 2 0 4 7 1 8 9 10 11 12 13**	**111**	**558**	**0**	**572**	**259.3**	**111**	**559**	**0**	**569**	**258.9**	**0.4**	**4**	**2.2**
2	2 5 14 1 0 4 8 9 3 6 7 10 12 11 13**	111	669	0	572	281.5	111	666	0	569	280.3	1.2	19	10.1
3	2 14 3 8 7 13 5 10 6 4 1 0 9 11 12	119	610	9	652	290.8	119	607	9	649	289.6	1.2	21	11.1
4	2 5 1 13 14 10 0 3 6 4 7 8 9 11 12	117	591	0	632	279.7	117	580	0	629	276.9	2.8	20	11.4
5	2 10 5 0 14 4 3 7 1 8 9 6 11 12 13	110	623	0	562	270	110	622	0	559	269.2	0.8	4	2.4
6	2 5 8 14 1 0 3 4 7 9 6 10 11 12 13	114	648	0	602	284.2	114	634	0	599	280.8	3.4	15	9.2
	average					**277.58**					**275.95**			**7.7**

Table 3. The schedules generated using the MIDOS II and MIROS for the best basic schedules achieved by the MOIA and *affthres* = 8.

No	Job shop scheduling problem *(15x10)*													
	The sequece of tasks:the basic schedule	The quality of the predictive schedule x					The quality of the reactive schedule x*							
		C_{max}	F	T	I	FF(x)	C_{max}	F	T	I	FF(x*)	QR	SR	TR(x*)
1	2 5 14 1 3 0 4 6 7 10 8 9 11 12 13	115	607	0	612	278.3	115	617	0	609	279.7	1.4	32	16.7
2	10 14 2 5 3 1 0 4 7 8 9 6 11 12 13	111	617	0	572	271.1	111	618	0	569	270.7	0.4	4	2.2
3	2 5 8 0 14 1 4 3 6 7 9 10 11 12 13	111	619	0	572	271.5	111	630	0	569	273.1	1.6	21	11.3
4	**5 2 13 14 0 3 4 6 7 1 8 9 10 11 12**	**121**	**527**	**0**	**672**	**276.1**	**121**	**527**	**0**	**669**	**275.5**	**0.6**	**2**	**1.3**
5	2 10 5 14 0 1 3 4 7 8 9 6 11 12 13	111	636	0	572	274.9	111	637	0	569	274.5	0.4	4	2.2
6	2 5 8 14 1 3 0 4 6 7 10 11 12 9 13	109	648	0	552	272.7	109	647	0	549	271.9	0.8	18	9.4
	Average					**274.1**					**274.23**			**7.18**

Table 4. The schedules generated using the MIDOS II and MIROS for the best basic schedules achieved by the MOIA and *affthres* = 80.

No	Job shop scheduling problem *(15x10)*													
	The sequece of tasks:the basic schedule	The quality of the predictive schedule x					The quality of the reactive schedulexy*							
		C_{max}	F	T	I	FF(x)	C_{max}	F	T	I	FF(x*)	QR	SR	TR(x*)
1	**5 14 6 3 2 0 4 7 1 8 9 10 11 12 13**	**113**	**572**	**0**	**592**	**266.7**	**113**	**573**	**0**	**589**	**266.3**	**0.4**	**4**	**2.2**
2	2 5 14 1 0 4 8 9 3 6 7 10 12 11 13	111	666	0	572	280.9	111	672	0	569	281.5	0.6	28	14.3
3	2 14 3 8 7 13 5 10 6 4 1 0 9 11 12	119	596	9	652	288	119	596	9	649	287.4	0.6	12	6.3
4	2 5 1 13 14 10 0 3 6 4 7 8 9 11 12	118	563	0	642	276.4	118	567	0	639	276.6	0.2	14	7.1
5	2 10 5 0 14 4 3 7 1 8 9 6 11 12 13	111	647	0	572	277.1	111	648	0	569	276.7	0.4	4	2.2
6	2 5 8 14 1 0 3 4 7 9 6 10 11 12 13	114	623	0	602	279.2	114	625	0	566	272,4	6,8	4	5.4
	average					**278.05**					**276.81**			**6.25**

Also, computer simulations were run for *affthres* = 80. Quality of the solutions is described in Table 4.

Taking into account the results achieved using the MOIA and both heuristics: MIDOSI and MIDOSII the following conclusion can be drawn. The best predictive schedule which best deals with uncertaininty was achieved using the MIDOS I heuristic for the basic schedule achieved for the *affthres* = 8 (Table 1, Figure 2). But, considering the average total robustness of reactive schedules, the best reactive schedules were generated using the MIDOS II heuristic and the *affthres* = 80. The choice of the MIDOS rule depends on the decision-maker's preferences.

4.3 Predictive-reactive approach (heuristics: SPT, LPT, EDD, RIPS, MIDOS I and II)

Next, computer simulations were run using heuristics: SPT, LPT, EDD and RIPS for basic schedules generation and the MIDOS I and II for predictive schedules generation. A prerequisite for accepting the schedule is that the tasks be completed without delay. Solutions achieved using the SPT and LPT rules are not acceptable. The best predictive schedule was generated for the EDD heuristic and MIDOS I or II.

The best predictive schedule was for the sequece of tasks: {2 5 1 0 3 4 6 7 8 9 10 11 12 13 14}. The objective function of the predictive schedule was FF(x) = 288,1 with the components of $C_{\max}$ = 111 , F = 702, I = 572 and T = 0. The objective function of the reactive schedule was FF(x*) = 287,9 with the components of $C_{\max}$ =111 , F = 704, I = 569 and T = 0. The total robustness was TR(x*) = 1.6 with the components of QR = 0.2 and SR = 3. Heuristics: EDD+RIPS do not improve the quality of the predicticve schedule. Quality of the remaining solutions is described in Table 5.

The following research point was investigated in this paper: which construction of predictive-reactive algorithms provides a more robust schedule: MOIA, SPT, LPT, EDD, SPT+RIPS, LPT+RIPS, EDD+RIPS for a basic schedule generation, MIDOS I or II for a predictive schedule generation?. Using only heuristics: SPT, LPT or EDD to generate a schedule gave poor solutions. Many changes were made to the schedule to update it after the disruption (see SR in Table 5). The quality of schedules was slightly reduced (see QR in Table 5). The average total robustness equaled 105,9. But, much better solutions were obtained after supporting the SPT, LPT or EDD heuristics by the MIDOS I or II. The average weighted function of SR and QR equals 8.33

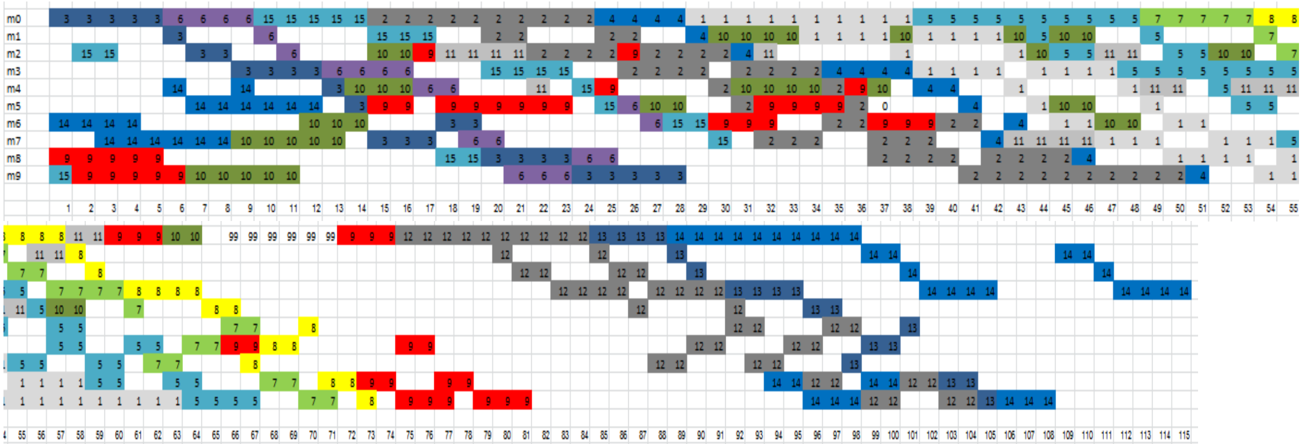

Fig. 2. The best predictive schedule obtained by the MOIA (*affthres* = 8) and MIDOS I, where (i = {0,2,..,9} - no. of machine, (j = {1,2,..,15} - no. of job, 99- predicted technical inspection at time 66.

Table 5. The schedules generated using heuristics: SPT, LPT, EDD and RIPS, MIDOS and MIROS.

Heuristic	Job shop scheduling problem *(15x10)*													
	The sequece of tasks	The quality of the basic/predictive schedule x					The quality of the reactive schedule x^*							
		C_{max}	F	T	I	FF(x)	C_{max}	F	T	I	FF(x*)	QR	SR	TR(x^*)
SPT	5 2 3 14 11 1 6 12 4 10 8 9 0 13 7	120	512	17	668	277,1	120	541	17	662	281,7	4,6	226	115,3
LPT	7 13 9 0 10 8 4 12 6 1 14 11 2 3 5	129	514	165	758	342,6	129	527	182	752	349,1	0,6	228	114,3
EDD	2 5 1 0 3 4 6 7 8 9 10 11 12 13 14	119	591	0	658	285,5	119	608	0	652	287,7	2	174	88,1
	average					**301,73**					**306,16**			**105,9**
SPT+ MIDOS I	5 2 3 14 11 1 6 12 4 10 8 9 0 13 7	114	601	5	602	276,3	114	598	5	599	275,1	1,2	26	13,6
LPT+ MIDOS I	7 13 9 0 10 8 4 12 6 1 14 11 2 3 5	129	617	162	752	361,1	129	602	162	749	357,5	3,6	16	9,8
EDD+ MIDOS I	**2 5 1 0 3 4 6 7 8 9 10 11 12 13 14**	**111**	**702**	**0**	**572**	**288,1**	**111**	**704**	**0**	**569**	**287,9**	**0,2**	**3**	**1,6**
	average					**308,5**					**306,83**			**8,33**
SPT+ MIDOS II	5 2 3 14 11 1 6 12 4 10 8 9 0 13 7	114	594	5	602	274,9	114	594	5	599	274,3	0,6	17	8,8
LPT+ MIDOS II	7 13 9 0 10 8 4 12 6 1 14 11 2 3 5	129	603	162	752	358,3	129	603	162	749	357,7	0,6	1	0,8
EDD+ MIDOS II	2 5 1 0 3 4 6 7 8 9 10 11 12 13 14	111	709	0	572	289,5	111	711	0	569	289,3	0,2	3	1,6
	average					**307,56**					**307,1**			**3,73**
SPT+ RIPS+ MIDOS I	8 2 3 14 11 1 6 12 4 10 5 9 0 13 7	112	632	2	582	277	112	683	40	579	298	21	96	58,5
LPT+ RIPS+ MIDOS I	3 1 5 14 6 2 12 9 13 7 11 10 4 0 8	120	604	4	662	290,4	120	610	4	659	291	0,6	24	12,3
EDD+ RIPS+ MIDOS I	8 5 1 0 3 4 6 7 2 9 10 11 12 13 14	111	714	35	572	301	111	716	35	569	300,8	0,2	3	1,6
	average					**289,46**					**296,6**			**24,13**
SPT+ RIPS MIDOS II	8 2 3 14 11 1 6 12 4 10 5 9 0 13 7	112	692	2	582	289	112	680	40	579	297,4	8,4	96	52,2
LPT+ RIPS+ MIDOS II	3 1 5 14 6 2 12 9 13 7 11 10 4 0 8	120	608	4	662	291,2	120	614	4	659	291,8	0,6	24	12,3
EDD+ RIPS+ MIDOS II	8 5 1 0 3 4 6 7 2 9 10 11 12 13 14	111	714	35	572	301	111	716	35	569	300,8	0,2	3	1,6
	average					**293,73**					**296,66**			**22,03**

for MIDOS I and 3.73 for MIDOS II.

The use of the metaheuristics MOIA allows for generation of non-delayed solutions (except for one solution in Table 2). Also, predictive solutions are robust and stable. The average total robustness equals 8.43 (Table 1) and 7.7 (Table 2) for MIDOS I, 7.18 (Table 3) and 6.25 (Table 4) for MIDOS II. The best predictive schedule was obtained by the MOIA (*affthres* = 8) and MIDOS I (Table1).

5. CONCLUSIONS

Two proactive approaches were identified: predictive-reactive (proactive with prediction) and proactive-reactive (proactive without prediction). In the predictive-reactive approach researchers use prediction methods in order to predict maintenance time and built predictive schedule. Next, the influence of disturbance on the predictive schedule using robustness measures is examined. In the proactive-reactive approach the impact of disruption on a proactive schedule using robustness criteria is investigated. The proactive schedule is achieved for the best sequence of idle times between jobs or batches taking the advantage of the simulation process. This paper presented the compatiotion of the results of computer simulations for the predictive-reactive approaches using priority rules and metaheuristics. The main conclusions based on the study presented are:

- Using only heuristics: SPT, LPT or EDD to generate a schedule gives poor solutions. Much better solutions were obtained after supporting the SPT, LPT or EDD heuristics by the MIDOS I or II taking the solution and quality robustness into consideration.
- The meta-heuristic MOIA achieves better solutions than heuristics: SPT, LPT or EDD taking the solution robustness and robustness into consideration.
- A better predictive-reactive approach of dealing with uncertainty is to generate the best basic schedule, modify it using the MIDOS I and evaluate it using the MIROS than to generate a basic schedule, modify and evaluate it.
- The best predictive schedule which best deals with uncertaininty was achieved using the MIDOSI. Considering the average total robustness of reactive schedules the best reactive schedules were generated using the MIDOS II heuristic.

It is necessary to compare two approaches that are popular in the literature on maintenance scheduling: predictive-reactive and proactive-reactive. The paper entitled "*On the effect of a machine failure on the robustness of a job shop system. Proactive approaches*" [11] continues the research. In the paper, the predictive-reactive approach is compared with other proactive approaches.

6. REFERENCES

1. Alag, Azizoglu, (2003). *Rescheduling of identical parallel machines under machine eligibility constraints*. European Journal of Operational Research, **149**, 523-532.
2. Cui, W.,W., Lu, Z., Pan, E., (2014). *Integrated production scheduling and maintenance policy for robustness in a single machine*. Computers & Operations Research, **47**, 81-91.
3. Cui, W.W., Lu, Z., Li, Ch., Han, X., (2018). *A proactive approach to solve integrated production scheduling and maintenance planning problem in flow shops*. Computers & Industrial Engineering, **115**, 342-353.
4. Kamrul, Hasan, S. M., Sarker, R., Essam, D., (2011). *Genetic algorithm for job-shop scheduling with machine unavailability and breakdowns*. *Int J of Production Research*, **49**(16), 4999-5015.
5. Kempa, W.M.**,** Paprocka, I., Kalinowski, K., Grabowik, C., (2014). *Estimation of reliability characteristics in a production scheduling model with failures and time-changing parameters described by Gamma and exponential distributions*, Advanced Materials Research, **837**, 116-121.
6. Lei, D., (2011). *Scheduling fuzzy job shop with preventive maintenance through swarm-based neighborhood search*. Int J Adv Manuf Technol, **54**, 1121-1128.
7. Liu, Q.M., Dong, M., Peng, Y., (2013). *A dynamic predictive maintenance model considering spare parts inventory based on hidden semi-Markov model*. Proc. Inst. Mech. Eng. Part C **227**(9), pp. 2090-2103.
8. Mehta, S.V., Uzsoy, R.M., (1998). *Predictable scheduling of a job subject to breakdowns*. IEEE Transaction on Robotics and Automation, **14**, pp. 365-378.
9. Paprocka, I., (2016). *On the quality of basic schedules influencing over the performance of predictive and reactive schedules. Proceedings of 37th International Conference on Information Systems Architecture and Technology–ISAT 2016–Part IV, Karpacz, Poland, 18–20 September 2016*; Advances in Intelligent Systems and Computing; Springer: New York, NY, USA, **524**, pp. 243–253.
10. Paprocka, I., Skołud, B., (2017). *A Hybrid - Multi Objective Immune Algorithm for predictive and reactive scheduling*. *J. Sched.*, **20**, iss. 2, pp. 65-182.
11. Paprocka, I., (2019). *Evaluation of the Effects of a Machine Failure on the Robustness of a Job Shop System—Proactive Approaches*. Sustainability, **11**(1), 65; https://doi.org/10.3390/su11010065
12. Ponnambalam, S., G., Ramkumar, V., Jawahar N., (2004). *A TSP-GA multi-objective algorithm for flowshop scheduling*. Int J Adv Manuf Technol, **23**, 909-915.
13. Wang, S., Yu, J., (2010). *An effective heuristic for flexible job-shop scheduling problem with maintenance activities*. Computers & Industrial Engineering, **59**, 436-447.
14. Xia, T., Jin, X., Xi, L., Ni, J., (2015). *Production-driven opportunistic maintenance for batch production based on MAM-APB scheduling*. European Journal of Operational Research, **240**, 781-790.

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