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Procedia CIRP 104 (2021) 80–84

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54th CIRP Conference on Manufacturing Systems

Predictive maintenance key control parameters for achieving efficient Zero Defect Manufacturing

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Abstract

Predictive maintenance is a subbranch of Zero Defect Manufacturing concept. The goal is to achieve higher quality at the final product with the most optimum and efficient way. Predictive maintenance may be applied with various alternative ways for achieving the same goal. The current paper investigates and identifies the key control parameters for an effective predictive maintenance, such as prediction horizon. The identified parameters were implemented in a dynamic scheduling tool and simulations were performed for different manufacturing system layouts and the effect of the identified parameters to each layout were identified.

Keywords: zero defect manufacturing; ZDM; predictive maintenance; scheduling; simulation; quality

1. Introduction

Zero Defect Manufacturing (ZDM) is an emerging paradigm aiming to cross over the traditional six-sigma approaches in highly technology intensive and emerging strategic manufacturing sectors through applying knowledge-based and data-driven approaches [1-3]. With maturing technological capabilities of the Fourth Industrial Revolution, the concept of Zero Defect Manufacturing has become a topic of interest for researchers and industrial practitioners for improving productivity and process efficiency.

Currently adopted quality control strategies are mainly single stage strategies and do not consider the impact of quality monitoring actions on other traditional performance metrics of the multi-stage systems in which they are applied [4,5]. In the current manufacturing landscape, such dynamic adjustment of production targets of multi-stage systems is not well addressed, and researches on the topic are limited.

Guided by this challenge, there is a need to develop new approaches to overcome the limitations of traditional quality improvement tools in dealing with dynamically changing manufacturing contexts. On that regard, two important phenomena to be addressed are predictive maintenance and rescheduling of production. As stated by Psarommatis et al. [2] predictive maintenance is part of ZDM as part of the process oriented ZDM [2]. Maintenance processes of machines is an important aspect of quality as poorly maintained equipment could result in malfunctions and hence defected products. Subsequent maintenance actions to be performed based on this requirement could cause disruptions in production schedules, and thus it is important to address synergies and trade-offs between these three related concepts. Therefore, this study

10.1016/j.procir.2021.11.014

aims on defining the key parameters that are related predictive maintenance and have impact on the production schedule. Furthermore, a design of experiments methodology is used for the analysis of the defined predictive maintenance parameters, to understand the level of influence of each parameter as well as the interaction between the different factors regarding production scheduling.

2. State of the Art

In the pertinent literature, researchers addressed these topics of interest separately, and to the best of our knowledge, there are only a few studies combining all these three key phenomena, i.e. zero-defect manufacturing, predictive maintenance, and production scheduling. For instance, Psarommatis et al. (2020) [6] focused on re-scheduling flexible job shops for different types of unexpected events, one of these events being machine breakdown [7]. Besides, Dreyfus and Kiritsis (2018) [8] proposed an approach by combining these three deeply interconnected technologies to improve production capacity. Furthermore, Lindström et al. (2020) [9] developed and proposed a ZDM model integrating seven areas, which also include on-line predictive maintenance and re-scheduling of production, to improve overall performance of a manufacturing plant. Kumar et al. (2020) [10] proposed a next generation manufacturing planning system integrating four operations functions. Recently, Zheng et al. (2020) [11] developed a two-stage integrating optimization model of production scheduling, maintenance, and quality in a single machine system. Wang et al. (2019) [12] analyzed joint optimization of production, maintenance, and quality for batch production systems subject to varying operational conditions. Other attempts toward this direction include [13] that provided a scheduling model suitable for dealing with unforeseen events and [14] that designed a scheduler that can handle resource substitution taking into account historical data. Some other studies in literature dealt with scheduling and production quality. For instance, Hmida et al. (2014) [15] focused on a real-world production scheduling problem in a continuous manufacturing system involving multiple objectives including production and quality constraints. Other set of research papers investigated the integrated optimization of quality and maintenance. On that vein, Farahani and Tohidi (2020) [16] determined the increasing trend in research on integrated optimization of maintenance, quality, and production, and presented the gaps in this field. Bouslah et al. (2018) [17] studied the joint design of production, quality and maintenance control policies for production lines and found out that maintenance and quality control activities in preceding stages can play an important role in the reliability improvement of the subsequent machines.

Based on the analysis of the previous literature and relevant challenges to be addressed, in this study we provide key control parameters of predictive maintenance to be considered for achieving an efficient and effective zero-defect manufacturing system. The paper is structured as follows: Section 2 provides and explains in detail research framework and method, as well as predictive maintenance control parameters and KPIs used for simulations. Next, Section 3 presents results of the simulations performed in the study and discusses these results. Finally, Section 4 concludes by highlighting the main findings and outcomes of the study.

3. Methodology

The current section is devoted to presenting the framework and the methodology used. The framework used in the current research is aligned with the ZDM framework presented in [2]. Predictive maintenance is a complex but effective process. It relies on data analytics and knowledge in order to predict the end of life of machine components or the transition of a machine from normal to out-of-control state. Based on these predictions, manufacturers need to take actions, i.e. maintenance, in order to avoid unexpected breakdowns or poor product quality. The implementation of predictive maintenance can create undesired implications to the schedule and the performance of production. Therefore, it is important to identify the key parameters that are imposed by predictive maintenance and affect the schedule. In this research work, we define seven control parameters for predictive maintenance, Table 1. Those parameters were defined using the methodology and approach presented in [18].

Table 1: Predictive maintenance control factors

Factor Name	Description
Prediction Accuracy (PA)	**PA** is a percentage depicting how accurate the prediction algorithm is.
Prediction horizon (PH)	**PH** is a time unit showing how far ahead in time the prediction algorithm looks for patterns changes with PA accuracy.
Horizon Standard deviation (HSTD)	**HSTD** is the standard deviation of the PH, which denotes the repeatability of the prediction algorithm
Reaction Time (RT)	**RT** is the time that is required in preparation in order to perform maintenance
Maintenance Cost (MC)	**MC** is the cost of maintenance (labor, raw materials)
Maintenance Time (MT)	**MT** is the time required in order to perform maintenance
Maintenance Effectiveness (ME)	**ME** is a percentage showing how accurately the prediction maintenance algorithm identifies the root of the problem and suggests the correct type of maintenance

The simulations were performed using the design of experiments methodology developed by Taguchi presented in [17]. This method was used in order to decode the effect that these parameters may have on the scheduling and by extent to the performance of the overall production [20]. The effects of the defined factors (Table 1) and 16 interactions were studied in order to acquire deep insights regarding the defined predictive maintenance parameters. The current problem has 7 main factors and 16 interactions and using 2-level factors the total degrees of freedom of the problem are 23. Therefore, the L_{32} standard orthogonal array is used for the experiments, which denotes that 32 experiments are required for extracting the desired information. Table 2 presents the factor levels, the interactions to be examined and the corresponding column of L_{32} that each factor was assigned. The column assignment procedure was performed using the linear graph of L_{32} in order to properly design the experiments and be able to extract the required results. The factor levels were selected in order to represent the extreme limits. The analysis of the L_{32} results was performed using the analysis of means (ANOM) and analysis of variance (ANOVA) methodologies.

Table 2: Factors levels and experiment information

Factor Name	Level 1	Level 2	L_{32} column	Interactions
PA	0.85%	0.98%	1	PAxPH, PAxHSTD, PAxRT, PAxMC, PAxMT, PHxHSTD, PHxRT, PHxMC, PHxMT, HSTDxRT, HSTDxMC, MCxME HSTDxMT, RTxMC, RTxMT, MCxMT
PH	30 min	500 min	2	
HSTD	10 min	100 min	4	
RT	15min	400 min	8	
MT	60 min	500 min	15	
MC	500€	5000€	16	
ME	0.88%	0.99%	19	

For the evaluation of the 32 experiments imposed by L_{32} orthogonal array, nine different key performance indicators (KPIs) were used as presented in Table 3. These KPIs were selected in order to study as accurate as possible the effects of the defined factors to the performance of the production. The first three KPIs makespan, tardiness and production cost are those which are indicating the performance of specific schedule in the traditional scheduling problem. Makespan and tardiness are measuring the time aspects of the schedule were as the production cost the financial. The rest of the KPIs are related to the ZDM concept, customer satisfaction and to the implementation of predictive maintenance. It is critical to include to the KPIs list the ZDM related KPIs because the normal KPIs used in the traditional scheduling problem cannot capture the quality aspects arising from the implementation of predictive maintenance. Quality loses is a critical and difficult KPI to measure since it may include the costs from the customers' dissatisfaction. In the current study those costs are not considered. As quality losses are considered the costs within the production facility which are related to product poor quality. In order to combine all the KPIs into one single value and be able to compare the alterative scenarios, a methodology was used for the normalization and the weighted summation of the KPIs [18]. The product of the weighted summation formula, named Utility Value, is a value between [0,1] with 1 to be the best.

Table 3: KPIs used for simulations

KPIs	Description
Makespan	The completion time of the last job to leave the production [22]
Tardiness	$T = DueDate - Makespan$ [22]
Production Cost (PC)	The total production cost includes the machine operational, labor, raw material and setup costs [18]
Defects ratio	$DR = DefectedParts/TotalParts$
Maintenance Cost (MT)	The total cost required for performing maintenance, labor and spare parts needed
Quality losses (QL)	$QL = CostPerProduct * DefectedParts$
Number of breakdowns	Indicates how many times there was a breakdown
Delay cost (DC)	The cost that arises because of a delay from the agreed due date [18]
Cost per product	$CpP = (PC + MT + QL + DC)/TotalParts$ [18]

The experiments were conducted using data from a European industry in the hard metal domain. In this research work, we used a specific part of the factory including 10 individual machines configured in open-shop configuration [19]. The simulation period covers an entire year and considers the production of 16,000 parts. The demand profile used is the average from the past three years. The specific part of the factory is responsible for producing 20 different products with various cycle times.

4. Results & Discussion

Using the factor combinations that the L_{32} imposes, the required simulation scenarios were created and conducted using a ZDM oriented dynamic scheduling tool acting as a simulation engine [6][20]. Fig. 1 and Fig. 2 illustrate the results from the ANOM analysis and in both figures, the y-axis represents the utility value. More specifically, Fig. 1 presents the ANOM graphs of the factors' main effects, whereas in Fig. 2 the interactions between the factors are presented. Furthermore, Table 4 presents the ANOVA table. Looking at the overall results from ANOM analysis, it can be observed that besides the main factor effects there are also some strong interactions between the factors verifying that the implementation of predictive maintenance is a complex process and requires careful design prior the implementation.

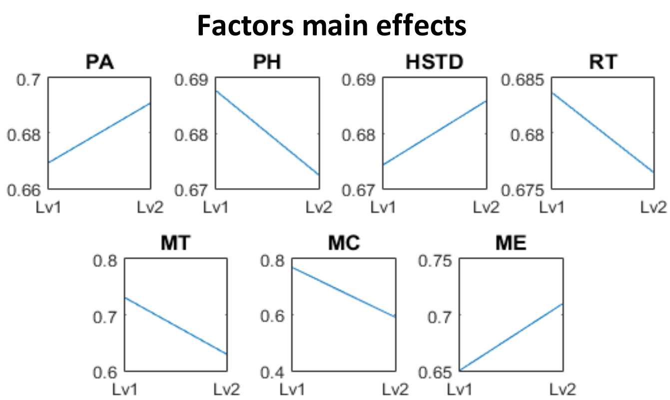

Fig. 1. ANOM factors main effects

More specifically, based on the results in Fig. 1 PA, HSTD and ME affect the utility value positively when transitioning from level one to level two while the rest of the factors affect it negatively. The factor with the highest effect to the solution is the MC with 26.02% relative difference from level one to level two, followed by MT, ME and PA with 14.79%, 8.75% and 3.15% respectively. PH, HSTD and RT are below 3%. It is important to not disregard the factors with low percentage of effect to the utility value because Fig. 2 illustrates that they have strong interactions.

The ANOM analysis of the factors interactions (Fig. 2) revealed that 10 out of 16 interactions studied show the presence of interaction. Five of them show synergistic behavior and the rest five anti-synergistic. More specifically, anti-synergistic behavior is observed for PA*PH, PA*MC, PH*MC and HSTD*RT. PA*PH, PA*RT and HSTD*RT have strong anti-synergistic behavior, meaning that when one factor is changing level, the direction of effect of the other factor is changing to the other direction. The synergistic interaction is when one factor is changing level and the effect of the other factor does not change direction but the slope between the two lines is increased. Interactions PA*MT, PH*HSTD, PH*MT, HSTD*MT, HSTD*MC, and MT*ME show very small or no interactions, and therefore, are excluded from further analysis.

Moving forward, from the interpretation of the interaction results, some interesting insights can be drawn. An increase to the PH combined with low PA affect the solution negatively but when PA is at high level then the increase of the PH affects the solution positively. The same trend is observed also for the HSTD*RT interaction, which shows that when prediction maintenance algorithms have high HSTD they can achieve high RT. In PA*RT, the higher the PA the less impact to the solution for different values of RT, but lower PA values combined with high RT values can significantly negatively affect the solution. Therefore, when PA is low RT should be low in order to achieve good results. Furthermore, in PA*HSTD, PA affects the solution in different way, and with any level of HSTD there is a positive effect of the solution which is intensifying, and hence producing much better results when the PA is high. Finally, the solution is not affected by RT values when PH has low values, whereas when PH is high the produced solution is worst with high RT values.

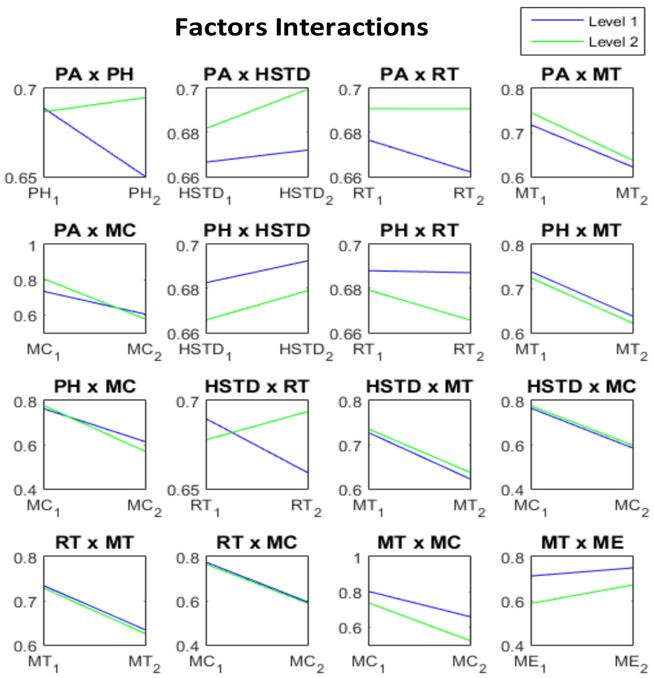

Fig. 2. ANOM factor interactions

Table 4 presents the results from the ANOVA analysis performed to the experiments results. The ANOVA results showed that almost half (12/23) of the factors and interactions studies can be characterized as statistically significant, since their probability F is lower than 0.05. Furthermore, the significant factors and interactions also shows the highest percentages of contribution to the final solution (Table 4, column 3). More specifically, MC shows the highest contribution with 25.098% followed by MT, MC*ME, HSTD*RT with 15.571%, 11.163% and 8.517% accordingly. The rest of the significant factors and interactions are between either 4%-8% or 1%-3%. The insignificant ones contribution is lower than 1%.

Table 4: ANOVA table

Source	Sum Sq.	Contribution %	F	Prob>F
PA	0.01468	2.825%	9.97	0.0196
PH	0.02185	4.205%	5	0.0496
HSTD	0.00106	0.204%	2.87	0.1413
RT	0.00041	0.079%	1.12	0.3307
MT	0.0809	15.571%	219.14	0
MC	0.1304	25.098%	678.72	0
ME	0.03232	6.221%	76.73	0.0001
PA*PH	0.0354	6.813%	3.56	0.0025
PA*HSTD	0.0003	0.058%	0.81	0.4036
PA*RT	0.0404	7.776%	1.09	0.0336
PA*MC	0.02919	5.618%	51.99	0.0004
PH*HSTD	0.00002	0.004%	0.06	0.8093
PH*RT	0.00032	0.062%	0.86	0.3889
PH*MC	0.00674	1.297%	18.25	0.0053
HSTD*RT	0.04425	8.517%	11.52	0.0146
HSTD*MT	0.00009	0.017%	0.25	0.6379
HSTD*MC	0.00001	0.002%	0.02	0.8898
HSTD*ME	0.00107	0.206%	2.89	0.1403
RT*MT	0.00002	0.004%	0.05	0.8246
RT*MC	0.00002	0.004%	0.06	0.8079
RT*ME	0.00004	0.008%	0.11	0.7545
MT*MC	0.01987	3.824%	26.75	0.0021
MC*ME	0.058	11.163%	76.46	0.0001
Error	0.00221	0.425%		
Total	0.51957	100.00%		

5. Conclusions and Future steps

In this research work, we defined seven key control parameters for predictive maintenance, and performed simulations to investigate the effect of these parameters on production scheduling. Besides the effects of the defined parameters on production scheduling, we found out that there is a significant trade-off between these identified factors, highlighting the complexity of predictive maintenance approaches and criticality and importance of its proper design. If the design of the predictive maintenance process is not correct the produced schedule will not have acceptable quality.

Some other key findings of the study are as follows:

- As expected, high level prediction accuracy of the prediction algorithm combined with an increasing prediction horizon leads to better results.
- An alignment should exist between PH and RT, more specifically the following statement should be fulfilled RT<PH, otherwise predictive maintenance is not having the desired results.

- The effect of the defined factors to the solution is not simple and certainly not straight forward. There is presence of strong interactions between factors, which makes the implementation of predictive maintenance a difficult task.

The implications of this study are manifold. First off, the key control parameters that are linking predictive maintenance with the scheduling of a manufacturing system were defined. Further to that, simulations and the analysis performed in this research work revealed several interactions among the key control parameters of predictive maintenance. Further to that revealed which factors are affecting the most in order to pay attention more to them. The outcome that should be kept out of the current research is that the implementation of predictive maintenance has significant impact to the scheduling of the system and attention should be given to the control parameters defined that have strong influence on the final quality of the schedule. The experiments revealed that besides the main effects of the control parameters there are also some strong first level interactions that should be taken into consideration when designing a predictive maintenance tool. Also, the usability of the current results is when incorporating a predictive maintenance tool to a manufacturing system in order to achieve efficient schedules.

Future steps will include the utilization of the finding for expanding the predictive maintenance model further. Using the finding perform a more detailed design of experiments, with more factor levels for understanding deeper the effect of each factor. Also, the finding of the current study will be used for designing properly and efficiently predictive maintenance tools for specific industrial use cases and incorporate them to the production schedule with minimum performance loss.

Acknowledgements

The present work was partially supported by EU H2020 funded projects Eur3ka (101016175) and QU4LITY (825030). The paper reflects the authors' views only and not the Commission's.

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