Using Overall Equipment Effectiveness (OEE) to Predict Shutdown Maintenance

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Abstract This research proposes an approach to predict equipment condition using OEE performance metrics. Statistical tools are used to correlate measurements of OEE factors and maintenance history from a real database. The results suggesting that there is a correlation between the Time Between Stoppages and the trend degree of the Mean and/or the Standard Deviation (SD) of cycle time. This approach intended to help the predictions of shutdowns for maintenance.

Keywords Condition-based maintenance · OEE · Trend analysis · Process mining

1 Introduction

Several maintenance strategies are proposed and applied to productive processes, for improving the operational capacity of processes, saving maintenance costs, and improving industrial competition (Kumar et al. 2013). An appropriate maintenance action, at the right moment, is necessary for reducing process failures and increasing equipment reliability (Wang 2012). In order to maximize preventive maintenance effectiveness, the Condition-Based Maintenance technique was proposed. The main motivation of this strategy is that equipment failures are preceded by signals, conditions or indications that the failure may occur (Ahmad and Kamaruddin 2012). According to Ahmad and Kamaruddin (2013), Overall Equipment Effectiveness (OEE) provides an estimation of the lifetime of the

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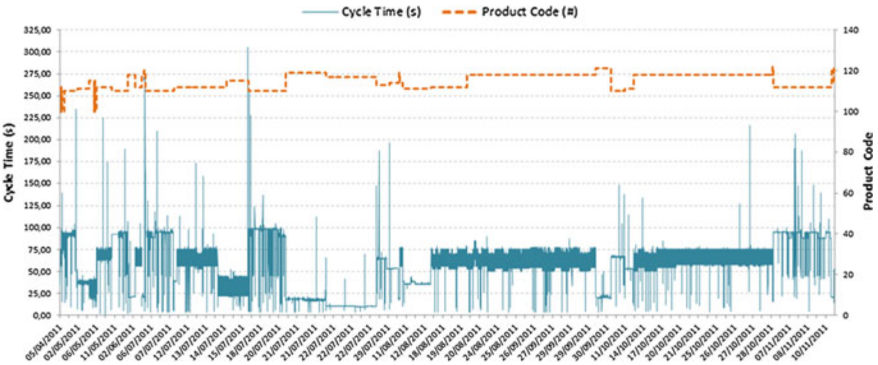

Fig. 2 Normal structure for production activities

case represents one production day. The equipment under analysis is used for the manufacturing of 13 types of products, with different cycle times and number of operations. Figure 2 graphically summarizes the cycle time variation according to the product type during the period under analysis. The curve represents the cycle time filtered, to eliminate incorrect events, e.g. production times higher than 1000 s. Nevertheless, a noise level was observed in the measures obtained, requiring its treatment for the conduction of the study object of this paper (Fig. 2).

5 Results and Discussion

Events registered by the FIS (taskID) were classified into Activities and Events, aiming to extract the process main structure represented by the Activities and identify the occurring deviations, represented by the Events. Events, in their turn, were classified into Production Events, Quality Events, and Maintenance Events. Table 1 summarizes the results obtained with the mining of the event log under analysis, identifying the four activities that compose the process and events classified as non-scheduled stoppages.

Four types of products were selected for the analysis, representing around 80 % of the production in the period considered, as pointed out in Table 2. Based on the execution time for activity “Machine Working”, the cycle times were obtained for each day of production and products selected in Table 2. In order to conduct the analyses, the outliers values were removed in order to keep the standard deviation of the cycle time acquisitions at about ±2 s for products #110 and #111, and about ±10 s for products #112 and #118. After that, days with 10 or less pieces produced were removed.

The DES method was employed, with mean smoothing factors and trend defined in 0.6 for the analysis of the respective cycle time trend (Mean and Standard Deviation). The compiled results are shown in Fig. 4, in which both the mean trend

Table 1 Structure activities and maintenance events

Activity description	Freq	Relative freq. (%)	Classification
Machine working	25,142	29.2928	Activity
Finished part	20,601	24.0161	Quality event
Product removal	20,437	23.8110	Activity
Short stoppage	18,662	21.7430	Activity
Adjustments	298	0.3472	Maintenance event
Tool wear	54	0.0629	Maintenance event
Autonomous maintenance	6	0.0070	Maintenance event
Electrical maintenance	2	0.0023	Maintenance event

Table 2 Selection of relevant products for analysis

Prod code	Quantity	Relative freq (%)	Cumulative (%)	Days of prod
118	9141	36.36	36.36	21
112	5494	21.85	58.21	20
110	3614	14.37	72.58	20
111	1697	6.75	79.33	9

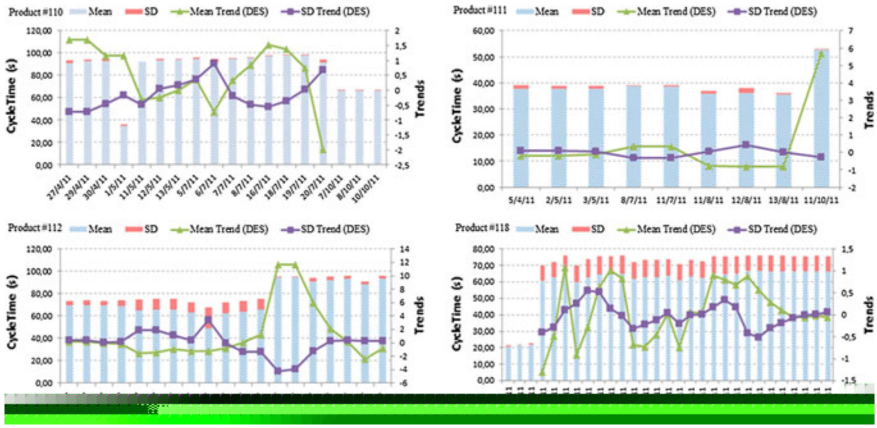

Fig. 3 Results of mean, SD and trending for each product

and the standard deviation follow normal distributions, at a reliability criterion of 95 %. It is possible to observe the occurrence of variations in the cycle time mean values of some products. Operation errors are regarded as factory-floor related, e.g. incorrect definition of the product type and/or acquisition errors of the events timestamp. The analysis is validated through the removal of those values for verification of trends and variations. As attested in the results shown in Fig. 3, the cycle times mean and/or standard deviation tend to increase in certain periods. Such

region, suggesting that there is a correlation between the Time Between Stoppages and the trend degree of the mean and/or the SD. In this analysis, the correlation with all Maintenance Events is considered, although the Electrical Maintenance event has almost no occurrence.

6 Conclusions

In this paper, we consider the hypothesis that any reduction in the equipment speed is due to factors such as degradation, aging or fatigue-related failures. With the results obtained, it is possible to attest the correlation between the mean and standard deviation trend of cycle time with the occurrence of maintenance events. Although measures present relative dispersion, most values obtained are grouped.

Indeed, the measurement quality of the cycle time, contributing for the accuracy of the methodology proposed by Kurscheidt Netto et al. (2014), can be emphasized. The existence of noise in the values acquired must be observed, increasing the factor variance and influencing the operational limits, thus impacting on the correct identification of the slope value. The main cause determined after the database analysis refers to event registration errors by the operator. In addition to the main objective of this paper, the need for the correct use of events for the explicit and well defined delimitation of the start and end working shifts, machine operation state and start/end of in-progress production. These events help employ mining algorithms, reducing the noise and contributing to the application of the proposed methodology.

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