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Establishment of a maintenance plan based on quantitative analysis in the context of RCM in a JIT production scenario

Angélica Alebrant Mendes*, José Luis Duarte Ribeiro

Universidade Federal do Rio Grande do Sul. Departamento de Engenharia de Produção e Transportes. Av. Osvaldo Aranha, 99, Porto Alegre, RS, CEP 90035-190, Brazil

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ABSTRACT

This paper presents a quantitative method for supporting the preparation or review of an equipment maintenance plan in a Just-in-time production scenario. The proposed method includes the following steps: (i) identifying the parts that influence reliability; (ii) surveying the failure rates and times to repair the parts; (iii) classification of parts according to the effect of their failures; (iv) surveying the line occupation parameters; (v) identifying the probability distributions for time to failure, time to repair, and line occupation; (vi) simulating the production and maintenance using the Monte Carlo approach; (vii) conducting a sensitivity analysis concerning variations in demand, *MTTF*, and *MTTR*; and (viii) establishing optimized intervals for preventive maintenance. The method is illustrated through an application in a labeling and filling gallons line at a paints and dyes production company. This method allowed the identification of critical parts as it relates to the productive scenario in question. The results can support companies in their decision making regarding the need and/or type of maintenance investment that would best fit an expected demand scenario.

1. Introduction

The current economically globalized and highly competitive landscape requires that companies see maintenance as a strategic function to increase productivity. Since productivity is directly related to cost reduction and can increase profits, improvement in reliability and availability of production equipment can provide a sound contribution for enhancing the competitiveness of organizations [9, 8].

Traditionally, maintenance planning utilizes the experience of the staff involved and the instructions contained in manufacturers' equipment manuals [12,15]. However, experience may be limited and instructions contained in manufacturers' manuals are not always based on real data, because some equipment manufacturers advise clients to observe short inspection and replacement intervals to maximize part sales for manufacturers and/or minimize their level of responsibility [12]. Thus, collection and analysis of reliability data are crucial tasks in industrial plants.

According to Farrero et al. [7], the optimization of maintenance policy requires a cost-efficient balance of preventive, predictive, and corrective maintenance. The maintenance type and time interval between maintenance activities for each part depend on its failure rate and associated cost. Therefore, the use of quantitative data is important for the development of more effective maintenance plans [12,7,10].

Currently, one of the major challenges for maintenance planning is defining when and what kind of intervention must be taken for specific equipment parts. Although there is an abundance of material on product reliability, approaches from the perspective of manufacturers discussing the application of reliability in production lines are still scarce in literature [13].

Rao et al. [11] explain that qualitative approaches have been preferred to quantitative approaches due to a lack of historical data from plants along with a lack of appropriate statistical methods to interpret this data. Rausand [12] states that articles on maintenance optimization are written by mathematicians or statisticians who use a language incomprehensible for practitioners and propose models that are more complex than the reality found in maintenance practice. These claims have been made for over a decade and are still valid for most companies.

Thus, the objective of this paper is to present a method for developing a quantitative analysis to guide the preparation or review of a plan for equipment maintenance in a Just-in-time (JIT) production scenario. JIT production scenarios are characterized by reduced (or zero) inventories and the need to meet a production schedule in a single shift. In these scenarios, production scheduled for day d must be delivered in that day and should not be postponed for $d+1$. JIT systems have been widely applied to reduce the inventory costs of raw materials, semi-finished and finished products. For these systems to perform at the highest

* Corresponding author. Tel./fax: +55 51 33083491.
E-mail address: angelica@producao.ufrgs.br (A. Alebrant Mendes).

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level, production must be balanced over time and defective items should be eliminated. These assumptions can only be achieved through efficient maintenance planning and execution, eliminating the occurrence of defects, and avoiding unexpected equipment failures that would interrupt a steady process flow.

Using Monte Carlo simulation to analyze the production and maintenance in JIT scenarios permits the inclusion and consideration of variability, an important characteristic of all production systems. Monte Carlo simulation enables the analysis of system response to a production schedule, downtime, and overtime considering possible changes in demand, MTTF, and MTTR. These results may help companies in making decisions about the need for and/or type of maintenance investment that would best meet an expected demand scenario.

A maintenance plan prepared or revised based on quantitative analysis is essential to understand the best maintenance type and time interval considering the role and failure rate of each piece of equipment. Thus, it is possible to define an adequate maintenance strategy for each part, avoiding the use of unnecessary or inefficient tasks and adding activities that effectively contribute to increasing availability and promote cost reduction. It is worth noting that qualitative issues such as equipment access, operation rules, regulations, and training of maintenance personnel should also be considered.

This paper is organized into five sections. Section 2 presents a literature review positioning preventive maintenance and describing approaches to help determine optimum maintenance intervals. Section 3 describes the methods used to perform the study and solve the research problem. Results and discussion are presented in Section 4. Finally, Section 5 contains conclusions regarding the study and suggestions for future research.

2. Literature review

RCM is basically a management methodology that is being utilized more often, chiefly in equipment intensive industries. Recently, it has been successfully applied in power distribution systems [4, 17], railway networks [8,216] and steel companies [6,5].

The applications of RCM methodology are based on traditional approaches, using FMEA or FMECA, FTA, diagrams and algorithms. Quantitative approaches are scarce and are often applied just for cost evaluation, as described by Dehghanian et al. [4]. Some of the approaches used to create a maintenance plan (including maintenance strategy and time interval for preventive maintenance tasks) found in literature are presented below.

Bevilacqua et al. [1] propose a method based on an integrated FMECA and modified Monte Carlo simulation to determine the most appropriate type of maintenance for each process machine. The risk priority number (RPN) is defined as the weighted product of six parameters: safety, machine importance for the process, maintenance costs, failure frequency, time to repair, and operating conditions. The weights established for each parameter were analyzed for their robustness by Monte Carlo simulation. The machines are classified into three groups according to their failure consequences and recommended maintenance strategy.

Carretero et al. [2] apply the RCM methodology in a railway network and use quantitative approaches to evaluate and classify lines criticality based on reliability factors and the failure consequences of each line.

Smith [14] defines the best maintenance strategy based on statistical evidence of equipment failure. By determining the parameters of the Weibull distribution, obtained by fitting failures data, it is possible to identify whether the equipment is in the stage of premature failures (monotonically decreasing failure rate, shape parameter <1), maturity (constant failure rate, shape parameter$=1$), or wear (monotonically increasing failure rate, shape parameter >1). Maintenance strategies are recommended as follows: (i) stage of premature failures – corrective maintenance, (ii) stage of maturity – predictive maintenance and management of good practices, (iii) wear stage – preventive maintenance.

Following a similar approach, Macchi et al. [8] and Yun et al. [17] use a Weibull distribution as an adequate approximation for their data and define the subsystem stage as infant mortality, useful life, and wear-out. By analyzing the current maintenance policy, the reliability level of each family of items is identified and subsystem failures can be predicted.

Rao et al. [11] present an algorithm to optimize maintenance intervals based on the lowest total cost of preventive and corrective maintenance. Santos et al. [13] propose a model for determining the optimal interval for preventive maintenance, also based on the optimal maintenance cost, but utilizing the Homogeneous and Non-Homogeneous Poisson Processes.

DAS et al. [3] propose a model to determine the optimal preventive maintenance interval, assuming that machine failure times follow a Weibull distribution. The optimal preventive maintenance interval (pmi) is obtained by solving the Weibull probability distribution function with respect to pmi, considering the restriction that failure probabilities of machines involved are held under an upper bound.

In summary, quantitative analysis used to support maintenance planning in a RCM context presented in literature are (i) used to define the most appropriate maintenance strategy: statistical analysis of parts failure rate, modified FMECA, and Monte Carlo Simulation; and (ii) used to determine the optimal time interval between maintenance tasks: optimization analysis considering maintenance cost or system availability.

3. Method

The case study documented in this paper is based on a set of assumptions established in Table 1, which presents the various aspects of the problem. The equipment under study is a labeling and filling gallons line arranged as a series system since the failure of any part results in system malfunction. Given that this is a series system of different machines that are not mechanically or electronically related, most component failures that are repaired do not result in a noticeable influence on other components. In this production line, the key aspects controlling failures are (i) part's manufacturing history, (ii) employee performance on operation procedures, and (iii) employee performance on maintenance procedures. Since parts come from different manufacturers and employee performance is random as it relates to operation and maintenance procedures, the key aspects controlling failures are essentially independent and are considered as such in this study.

The definition of maintenance activities most appropriate for each part was based on the experience of those responsible for the line maintenance and operation, stemming from recommendations contained in equipment manuals. Verification sheets were prepared containing information about parts maintenance activities and periodicity. Simple maintenance activities are carried out by operators (autonomous maintenance), while more complex tasks are performed by electrical and mechanical maintenance technicians.

It was verified that periodic preventive maintenance at intervals of 30 days is carried out on the equipment under study on top of emergency corrective maintenance. However, the intervals between maintenance were not optimized. As a result, the management's desire to obtain optimal intervals motivated this study.

Table 1
Overview of the case study and reasoning for the solution adopted.

Production scenario and premises	The labeling and filling gallons line at a paints and dyes production company is utilizing a Just-in-time production strategy, where all equipment parts are submitted to the same preventive maintenance interval. Daily demand must be met in the very same day. It takes an average of 12 h to meet the daily demand, but this is expected to increase to 15 h in the near future, following an approximate normal distribution with a standard deviation of 1.5 h
Maintenance scenario and premises	Spare time is used for maintenance. The equipment is relatively new, but free from infant mortality. All parts are composed of mechanical components and due to wear out failure rates increase as time passes. However, through cleaning, alignment, lubrication, and/or even replacement of components, preventive maintenance helps ensure the parts are good as new
Problem	It is necessary to reduce failures (time spent in corrective maintenance) and/or times to repair, which could become a major problem in the near future as demand increases
Solution	It is necessary to establish a more efficient preventive maintenance plan, which takes into account the times to failure and the times to repair for each specific part
Steps of adopted solution	Use of RCM concepts (1, identification of parts that influence reliability; 2, estimation of failure rates; 3, classification of parts according to the effect of their failures) and Monte Carlo simulation (4, estimation of line occupation parameters; 5, identification of probability distributions for occupation line, times to failure and times to repair; 6, simulation of production and maintenance using the Monte Carlo approach; 7, accomplishment of a sensitivity analysis concerning variations in demand, MTTF and MTTR) to establish optimized intervals for preventive maintenance.
Reasoning for the adopted solution	RCM concepts make it possible to focus on the parts relevant for reliability. Monte Carlo simulation is applied as an approach capable of dealing with stochastic variables such as daily demand, times to failure, and times to repair. The establishment of optimized maintenance intervals is necessary to reduce failure occurrence to an acceptable level that will not compromise Just-in-time delivery

Table 2
Assemblies, parts, and computed MTTF, MTTR, and long-term availability

Assembly	Part	Part	MTTF (days)	MTTR (h)	Long-term Availability
Labeling system	Motor system A	A2	57.38	3.39	0.9971
	Clutch	A3	No record of failures		1.0000
	Sensors	A4	11.32	3.53	0.9846
Conveyor	Motor system B (motor, reducer, electric drive)	B5	No record of failures		1.0000
	Pulleys, bearings, conveyors and guides	B6	23.32	4.11	0.9913
	Control system	B7	34.00	2.15	0.9968
Filling system	Upper rotating union	C10	62.25	16.35	0.9870
	Filling nozzles	C11	96.45	4.18	0.9978
	Weighing-machine	C12	35.30	5.86	0.9918
	Brushes	C13	31.38	5.25	0.9917
	Inferior rotating union	C17	No record of failures		1.0000
	Washing system	C18	94.95	5.01	0.9974
	Motor system C	C19	98.63	3.00	0.9985
Lid system	Lid positioner	D14	26.06	4.99	0.9905
	Lid closer	D15	83.50	8.14	0.9952
Control panel	Control panel	E21	21.75	1.62	0.9963
Label printer	Label printer	F20	19.44	3.42	0.9913

Given the production and maintenance scenario presented in Table 1, an approach combining RCM and Monte Carlo simulation was utilized to solve the problem regarding the reduction of failures and time to repair. RCM is a classic approach used to improve the system availability through the identification of parts that influence reliability and classification of these parts according to the effect of their failures. However, to understand the whole scenario, it is necessary to take stochastic variables such as daily demand, times to failure, and times to repair into consideration. Monte Carlo simulation is a versatile method for analyzing the behavior of activities that involve uncertainty such as the scenario under study.

The study was accomplished through the following steps: (i) Identifying assemblies and parts that influence the reliability of the equipment under study; (ii) Surveying parts failure rates and times to repair; (iii) Classifying parts based on the effect of their failure (as downtime or accidents); (iv) Surveying line occupation parameters; (v) Identifying probability distributions for times to failure, times to repair, and line occupation; (vi) Conducting a production and maintenance simulation to define, through a stochastic approach, the probability of not achieving daily production demand; (vii) Conducting a sensitivity analysis for line overtime and downtime related to possible variations in demand, MTTF and MTTR, and (viii) Establishing optimized intervals for preventive maintenance. A detailed description of each step is presented in the following section.

4. Results and discussion

4.1. Identification of parts that influence reliability

The labeling and filling gallons line is composed of the assemblies and parts presented in Table 2. As a series system, all parts have a direct effect on reliability and the failure of any part results in system malfunction.

4.2. Estimation of failure rates and times to repair

The survey of failure rates was conducted by collecting data from maintenance work orders from 2008 to 2009 (failure description, time to repair and date of occurrence). Since many work orders did not have clear descriptions or comprehensive information about the maintenance work that was undertaken, data was organized and reviewed by the maintenance team. For all maintenance work orders, failure modes and associated assemblies, and parts were identified.

As a result, possible causes and consequences of each failure were identified and mean times to repair (MTTR), mean times to failure (MTTF), and the availability of each part were calculated. For parts that had no record of failure during the entire two year period, long-term availability = 1.0 was assumed, which is the equivalent of neglecting the eventual failures of corresponding parts. MTTF and MTTR were calculated respectively as the average of the observed times to failure (for each part) and as the average of the observed times to repair (for each part). Availability for each part was calculated as the stationary or long-term availability (see the following equation):

$$A = \frac{MTTF}{MTTF + MTTR} \quad (1)$$

For this production line, cleaning, alignment, and lubrication are required for the parts to continue operating as if they are as good as new. Replacement of pieces or even of full parts occurs if wear out is detected.

The results for mean time to failure, mean time to repair, and long-term availability for each part are shown in Table 2. According to Table 2, the sensors have the lowest long-term availability (0.9846). This is due to a lower MTTF, since this part is subject to corrective maintenance on an average of every 11.3 days. The upper rotating union has the second lowest long-term availability rate (0.9870). This is due to a higher MTTR, which is around 16 h. Thus, it is observed that actions are necessary to reduce the number of occurrences of failures in the sensors and to improve the maintenance routine for the upper rotating union. Since the production line is a series system, these actions would have a direct impact on line availability.

4.3. Classification of parts according to the effect of their failures

In this case study, failures are not associated with potential accidents where large financial losses or even human lives are involved. The effect of failures is restricted to downtime (line stoppage) associated with the necessary time to repair. Thus, all parts have the same failure classification: operational failure with no higher risks involved.

4.4. Survey of line occupation parameters

Data regarding line occupation was collected and included the daily and monthly hours of operation from January 2009 to July 2010.

4.5. Identification of probability distribution for times to failure, times to repair and line occupancy

The research modeling for times to failure (TTF) deserved some consideration. Due to its flexibility and wide application, the Weibull distribution was chosen to represent the TTF. The production line has being used for some time, so it is free of infant mortality and a Weibull distribution seems appropriate to model its parts. However, since preventive maintenance was carried out monthly, TTF collected in the field was not appropriate for estimating the Weibull distribution shape parameter (preventive maintenance reduces failure rate slope, which would be more pronounced if components were not recuperated). Thus, the shape parameter was defined based on the characteristics of the parts under study. These are electromechanical parts that are subject to deterioration. Electronic systems are characterized by a constant failure rate and shape parameter equal to 1, while mechanical systems are characterized by increasing failure rate and a shape parameter higher than 1. Since this case study has no information concerning the natural behavior of the parts (by natural we mean the behavior of the parts without preventive intervention), an intermediate value of 1.5 was assumed for the shape parameter in order to model the parts. Due to lubrication losses, alignment losses, friction, and fatigue the parts of the equipment under study are subject to wear out and an increasing failure rate. Thus, technical consideration supports the choice of a Weibull distribution with an increasing failure rate (shape parameter greater than 1.0). Nevertheless, it is important to note that the method proposed here can easily deal with parts' failure times with any shape parameter or even any failure time distribution (the use of different distributions is a straightforward procedure in Monte Carlo simulation). This simplification is not part of the proposed method and it was carried out due to the lack of raw data concerning parts failure times in this case study. Whenever possible, we recommend modeling the shape parameters for the parts more precisely by basing into manufacturer information or by testing them. On the other hand, the Weibull distribution scale parameter (θ) was defined based on the MTTF of each part, according to the following equation, which is valid for shape parameter = 1.5.

$$\theta = 1.11 \times \text{MTTF} \quad (2)$$

Modeling the time to repair (TTR) was straightforward. It was observed that TTR for all parts approximately followed an exponential distribution (which is a special variation of the Weibull distribution). Thus, the exponential distribution was used to model times to repair for all parts. To validate this choice, statistical tests of Kolmogorov–Smirnov were applied for parts with less than 15 entries of data and Kolmogorov–Smirnov along with Chi square tests were applied for parts with 15 or more entries of data available. Parts presenting less than 5 entries of data could not be tested. Nevertheless, considering that these parts behave similarly, the same probability model was applied. Table 3 features statistical analysis that reveals that the hypothesis of exponential distribution for times to repair cannot be rejected (p-values larger than 0.05 for all tests). The memoryless property of the exponential distribution observed in this study implies that the remaining repair times are independent of previous repair times, which may not apply to other applications.

Next, line occupation data that included the daily and monthly hours of operation from January 2009 to July 2010 was collected. Based on this data, it was possible to fit a probability distribution

Table 3
Probability distribution tests.

Part Number	Part	Exponential distribution for TTRs		
		n	p-value $\chi 2$ test	p-value KS test
A2	Motor system A	3		
A3	Clutch			
A4	Sensors	27	0.281	0.271
B5	Motor system B	1		
B6	Pulleys, bearings, conveyors and guides	12		0.197
B7	Control system	9		0.070
C10	Upper rotating union	6		0.359
C11	Filling nozzles	6		0.256
C12	Weighing-machine	16	0.611	0.194
C13	Brushes	17	0.458	0.249
C17	Under rotating union			
C18	Washing system	6		0.225
C19	Motor system C	3		
D14	Lid positioner	20	0.417	0.076
D15	Lid closer	7		0.165
E21	Control panel	6		0.056
F20	Label printer	14		0.112

for daily work hours. A normal distribution with an average of 12.0 h a day and a standard deviation of 1.5 h per day was a proper fit for the data. Kolmogorov–Smirnov and Chi square tests were run, and they confirmed that the hypothesis of normal distribution for line occupation cannot be rejected.

4.6. Simulation of production and maintenance using Monte Carlo

After defining the appropriate probability distributions to model times to failure, times to repair, and line occupation, a Monte Carlo simulation study of production, failures, and maintenance was carried out. This simulation allowed the use of stochastic procedures to study the probability of production achieving daily demand. The simulation involved determining daily line occupation based on occupancy data, failure occurrence, and times to repair using their corresponding distributions.

To support the analysis, 1290 working days were simulated, which is the equivalent to five years of production (258 production days per year). Considering TTF values (Table 3), this is a period of time long enough to properly observe the system response. The simulation was divided into four steps as described next (see also Fig. 1):

Step 1 – Simulation of daily demand: random numbers were generated (adopted as percentiles) and were transformed into values for the daily demand distribution using the inverse normal function.
Step 2 – Simulation of failures: based on failure rate and the respective probability distribution of failure, failure probability for each part on a specific day after maintenance was identified. It is important to note that since the shape parameter adopted (1.5) is greater than the 1.0, failure rate and failure probabilities are increasing daily. The probability of failure on the second day after the last maintenance is greater than the probability of failure on the first day, and so forth. Next, random numbers were generated and the fault condition was reached whenever the random number generated for a given part was lower than the probability of failure for that part.
Step 3 – Simulation of times to repair (TTR): for each failed part, times to repair were generated using their respective distributions. Random numbers (representing percentiles) were generated and the values were transformed into times to repair using the inverse exponential distribution.
Step 4 – Overtime check: for each simulated day, the times to repair of failed parts were added to the daily demand hours. Whenever this sum exceeds the available production hours, overtime work is necessary. Overtime was generated daily, since the JIT scenario experienced by this company requires that daily demand should be met on that specific day. in situations where the sum of the available hours and overtime exceeded 24 h, surplus overtime was accounted for in the following working day (usually in these cases there is some contractual penalty inflicted on the manufacturer, but the quantification of any fines was not included in this study). Due to the relatively low occurrence of overtime, the possibility of failure while in overtime was not considered. Fig. 1 shows the algorithm of the simulation assuming known distributions of demand, times to failure, and times to repair.

The control variables or inputs for simulation were the average demand in hours per day, the MTTF, and the MTTR in hours for

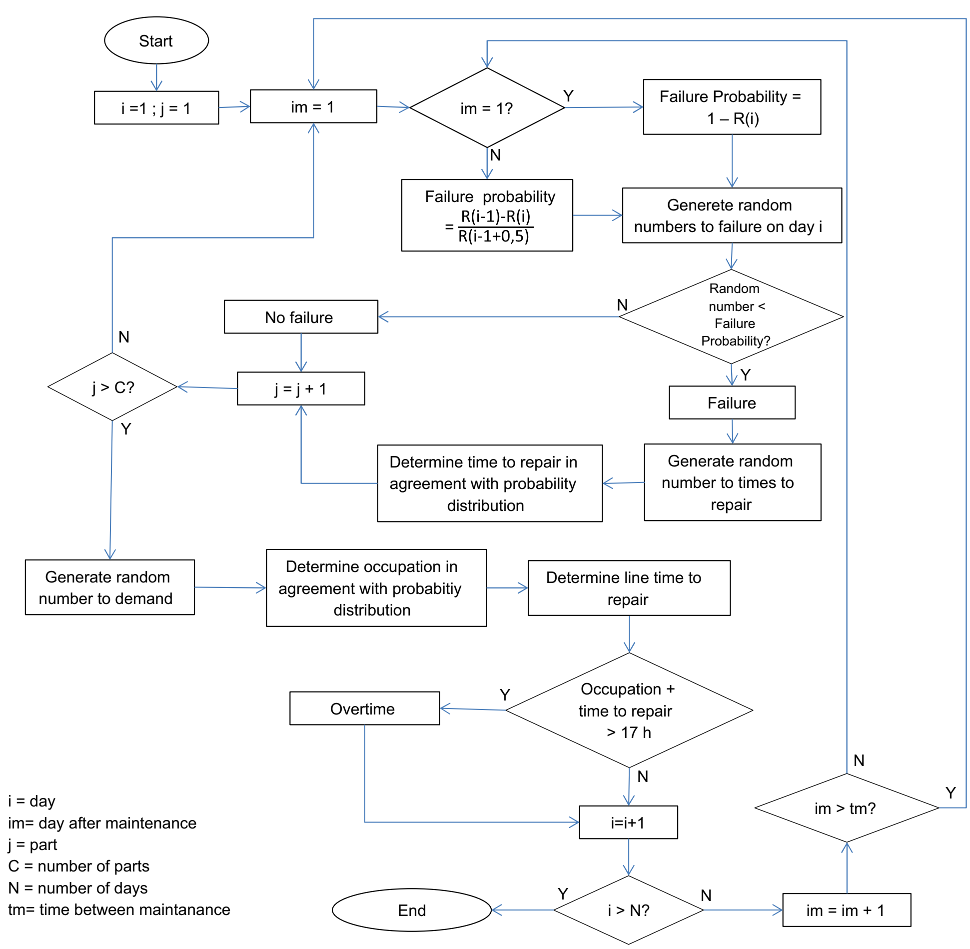

Fig. 1. Monte Carlo algorithm.

Tetha associated	1.108	Demand (h)	15

Part	Sensors	Label printer	Control panel	Pulleys, bearings, conveyors and guides	Lid positoner	Brushes	Control system	...
MTTF (days)	11.3	19.4	21.8	23.3	26.1	31.4	34	...
Theta (days)	12.5	21.5	24.1	25.8	28.9	34.8	37.7	...
Gamma	1.5	1.5	1.5	1.5	1.5	1.5	1.5	...
Time between prev maint (d)	30	30	30	30	30	30	30	...
MTTR (h)	3.5	3.4	1.6	4.1	5	5.3	2.2	...

Overtime (hours/month)	**32.83**
Time to repair (h/month)	**45.48**

Day	Sensors			Label printer			Control panel			Pulleys, bearings, conveyors and guides			Lid positoner			Brushes			Control system			...
	Day after maint	Failure Prob.	Failure	Day after maint	Failure Prob.	Failure	Day after maint	Failure Prob.	Failure	Day after maint	Failure Prob.	Failure	Day after maint	Failure Prob.	Failure	Day after maint	Failure Prob.	Failure	Day after maint	Failure Prob.	Failure	...
1	1	0.02		1	0.01		1	0.01		1	0.01		1	0.01		1	0.00		1	0.00		...
2	2	0.04		2	0.02		2	0.02		2	0.01		2	0.01		2	0.01		2	0.01		...
3	3	0.05		3	0.02		3	0.02		3	0.02		3	0.02		3	0.01		3	0.01		...
4	4	0.06		4	0.03		4	0.02		4	0.02		4	0.02		4	0.01		4	0.01		...
5	5	0.07		5	0.03		5	0.03		5	0.02		5	0.02		5	0.02		5	0.01		...
6	6	0.08		6	0.04		6	0.03		6	0.03		6	0.02		6	0.02		6	0.02		...
7	7	0.09		7	0.04		7	0.03		7	0.03		7	0.02		7	0.02		7	0.02		...
8	8	0.09		8	0.04		8	0.03		8	0.03		8	0.03		8	0.02		8	0.02		...
9	9	0.10	1	9	0.04		9	0.04		9	0.03		9	0.03		9	0.02		9	0.02		...
10	10	0.10		10	0.05		10	0.04		10	0.04		10	0.03		10	0.02		10	0.02		...
11	11	0.11		11	0.05		11	0.04		11	0.04		11	0.03		11	0.02		11	0.02		...
12	12	0.11		12	0.05		12	0.04		12	0.04		12	0.03	1	12	0.02		12	0.02		...
13	13	0.12		13	0.05		13	0.04		13	0.04		13	0.03		13	0.03		13	0.02		...
14	14	0.12		14	0.06		14	0.05		14	0.04		14	0.04		14	0.03	1	14	0.02		...
15	15	0.13		15	0.06		15	0.05		15	0.04		15	0.04		15	0.03		15	0.02		...
16	16	0.13		16	0.06		16	0.05		16	0.05		16	0.04		16	0.03		16	0.03		...
17	17	0.14		17	0.06		17	0.05		17	0.05		17	0.04		17	0.03		17	0.03		...
18	18	0.14		18	0.06		18	0.05		18	0.05		18	0.04		18	0.03		18	0.03		...
19	19	0.15	1	19	0.06		19	0.05		19	0.05		19	0.04		19	0.03	1	19	0.03		...
20	20	0.15		20	0.07		20	0.06		20	0.05	1	20	0.04		20	0.03		20	0.03		...
21	21	0.15		21	0.07		21	0.06		21	0.05	1	21	0.04		21	0.03		21	0.03		...
22	22	0.16		22	0.07		22	0.06		22	0.05		22	0.04		22	0.03		22	0.03		...
23	23	0.16		23	0.07		23	0.06		23	0.05		23	0.05		23	0.03		23	0.03		...
24	24	0.16		24	0.07		24	0.06		24	0.06		24	0.05		24	0.04		24	0.03		...
25	25	0.17		25	0.07		25	0.06		25	0.06		25	0.05		25	0.04		25	0.03		...
26	26	0.17	1	26	0.08		26	0.06		26	0.06		26	0.05		26	0.04		26	0.03		...
27	27	0.17		27	0.08		27	0.07		27	0.06		27	0.05		27	0.04		27	0.03		...
28	28	0.18		28	0.08		28	0.07		28	0.06		28	0.05		28	0.04		28	0.03		...
29	29	0.18		29	0.08		29	0.07		29	0.06		29	0.05		29	0.04		29	0.03		...
30	30	0.18		30	0.08		30	0.07		30	0.06		30	0.05		30	0.04		30	0.04		...
31	1	0.02		1	0.01		1	0.01		1	0.01		1	0.01		1	0.00		1	0.00		...
32	2	0.04		2	0.02		2	0.02		2	0.01		2	0.01		2	0.01		2	0.01		...
33	3	0.05		3	0.02		3	0.02		3	0.02		3	0.02		3	0.01		3	0.01		...
34	4	0.06		4	0.03		4	0.02		4	0.02		4	0.02		4	0.01		4	0.01		...
35	5	0.07		5	0.03		5	0.03		5	0.02		5	0.02		5	0.02		5	0.01		...

Day	Sensors TTR (h)	Label printer TTR (h)	Control panel TTR (h)	Pulleys, bearings, conveyors and guides TTR (h)	Lid positoner TTR (h)	Brushes TTR (h)	Control system TTR (h)	...	Occupation (h)	Time to repair (h)	Overtime (h)
1								...	13.88		
2								...	14.87		
3								...	15.22		
4								...	14.85	31.80	29.65
5								...	13.89		
6								...	15.83		
7								...	15.89		
8								...	15.25		
9	1.15							...	15.84	1.15	
10								...	13.86		
11								...	14.16		
12					14.16			...	14.03	14.16	11.19
13								...	13.80		
14						7.05		...	17.00	7.05	7.05
15								...	14.93	0.59	
16								...	16.41		
17								...	15.32		
18								...	14.83	8.29	6.12
19	0.66					7.95		...	15.40	11.56	9.95
20				1.73				...	12.08	1.73	
21				10.31				...	15.90	10.31	9.22
22								...	15.24		
23								...	15.41		
24								...	13.30		
25								...	16.05		
26	1.65							...	15.96	1.65	0.61
27								...	14.78		
28								...	15.24	30.03	28.27
29								...	14.03		
30								...	15.50		
31								...	13.62		
32								...	14.51		
33								...	15.76		
34								...	16.17		
35								...	15.06		

Fig. 2. Summary of simulation spreadsheet.

each part. The simulation results provided an estimation of downtime hours per month and overtime hours required to meet the monthly demand. Fig. 2 summarizes the simulation spreadsheet.

The simulation estimates the amount of overtime that would be necessary to meet determined daily demand using established values for MTTF and MTTR. The Monte Carlo approach allows the inclusion of variability, inherent in the stochastic variables, which generates realistic results representative of the system under study.

As a series system, long-term availability of equipment may be computed as the product of parts availability. Considering data presented in Table 2, system long-term availability results in 91.1%, which implies 32 h per month of downtime. For the current scenario, simulation indicates 17 h of overtime (see next subsection, Fig. 3 (c), demand = 12 h/day, 1 × MTTF, 1 × MTTR). This matches the computed system downtime, since a fraction of downtime (roughly 50%) is carried out during regular production hours while the remaining fraction leads to overtime.

4.7. Sensitivity analysis

Subsequently, a sensitivity analysis of overtime and downtime caused by variations in demand, times to failure, and times to repair was conducted. Graphs were generated representing scenarios with different demands, MTTF, and MTTR. These graphs allow the evaluation of the impact of these variables in overtime.

To analyze the results generated by the simulation, a sensitivity analysis of overtime and downtime was performed. The sensitivity analysis was conducted by taking into account changes in demand, MTTF, and MTTR for parts simultaneously. Thus, different scenarios comprising of variations in demand, MTTF, and MTTR were tested and the results are presented in Fig. 3. Each graph corresponds to a simulated level of MTTR, and each curve in the graph represents a different level of MTTF. Each point in each graph represents the estimated overtime corresponding to the scenario generated by the combination of demand, MTTF, and MTTR for all parts simultaneously.

It is worth noting that the response to variations in demand was the main interest for the company under study since management expects a demand increase next year. Variations in MTTF would be the result of changes in the current policy of preventive and predictive maintenance. For example, intensifying activities of predictive and preventive maintenance will typically promote an increase in MTTF. Variation of MTTR would be the result of changes in training and staff resources dedicated to maintenance. For example, increasing the amount or quality training for mechanical and electrical technicians and improvements in the tools and spare parts inventory will typically result in MTTR reduction.

The graphs show that as demand grows, the amount of overtime required also increases. Even when average demand is lower than production capacity, the stochastic profile results in days with demand higher than production capacity, which generates some overtime. This occurs more frequently when failures require emergency repairs and/or cause production interruption.

Fig. 3 also clarifies the effect of improvements on MTTF and MTTR. The higher the MTTF level, the lower the number of system failures which results in less time spent on repair activities. This allows better use of production capacity. Similarly, lower MTTR leads to less time spent on corrective maintenance which increases system availability.

In spite of MTTF and MTTR having similar effects on system productive capacity, both are independent. MTTF is associated with failures frequency while MTTR refers to time spent to repair each failure. Fig. 3 shows that percentage changes in MTTR produce greater impacts on overtime than corresponding percentage changes in MTTF. Considering the equipment under

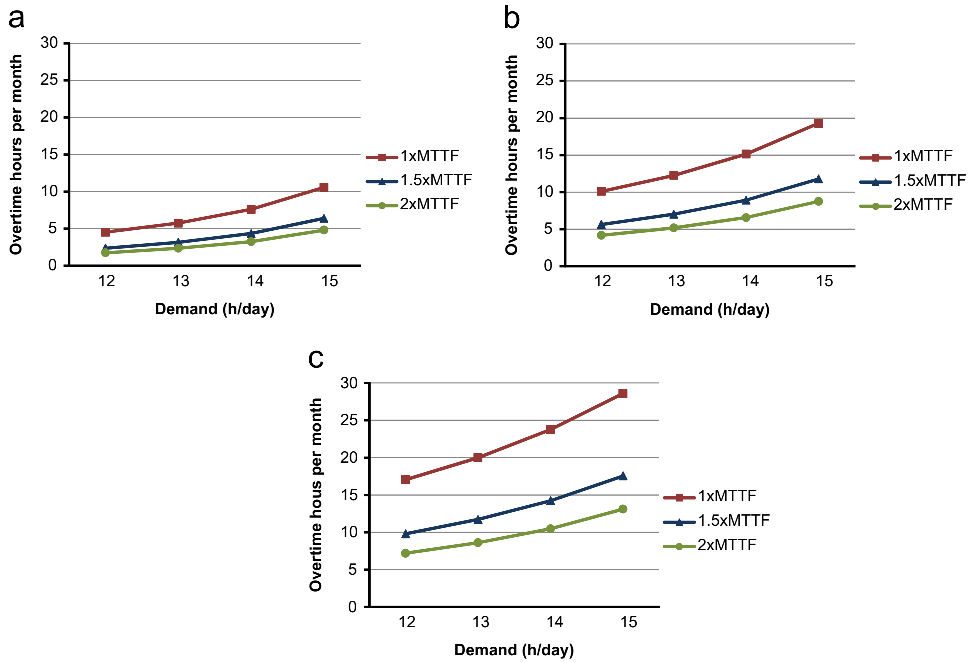

Fig. 3. Overtime sensitivity analysis to variations in demand, MTTR, and MTTF of all parts simultaneously.

Table 4
Calculated time and package recommended interval for maintenance

Assembly	Part		Calculated interval (days)	Package average interval (days)	Recommended interval
A	4	Sensors	2.5	2.8	Three times a week
F	20	Label printer	4.3	7	Once a week
E	21	Control panel	4.9	7	
B	6	Pulleys, bearings, conveyors and guides	5.2	7	
D	14	Lid positioner	5.8	7	
C	13	Brushes	7.0	7	
B	7	Control system	7.6	7	
C	12	Weighing-machine	7.9	7	
A	2	Motor system A	12.8	14	Once every two weeks
C	10	Upper rotating union	13.9	14	
D	15	Lid closer	18.6	21	Once every three weeks
C	18	Washing system	21.2	21	
C	11	Filling nozzles	21.5	21	
C	19	Motor system C	22.0	21	
A	3	Clutch	178.5	180	Once a semester
B	5	Motor system B	178.5	180	
C	17	Inferior rotating union	178.5	180	

study, improvements in MTTR would be more effective to reduce monthly overtime hours. Improvements in MTTR can be accomplished by enhancing management and maintenance practices. It is also noted that as MTTR decreases, actions to increase MTTF become less effective in promoting overtime reduction.

Based on the current scenario, the simulation allows the company to define if investments in maintenance would pay off by helping focus on what would be more efficient to increase production line availability. Scenarios where demand is low do not justify investment in maintenance improvement since the need for overtime to meet demand will also be low. On the other hand, cases where demand is high definitely require better management practices and maintenance performance.

Considering the demand growth predicted by this company, the simulation study showed that the current system lacks sufficient capacity to satisfy daily demand. Demand growth will require a high amount of overtime which significantly increases production costs. For example, a demand forecast of 15 h per day would require about 29 h of overtime a month. In order to reduce overtime through improvements in maintenance management, an initial task that could be taken is to revise the maintenance intervals for parts as stated in the next step.

4.8. *Optimized intervals for preventive maintenance*

Considering the results of the simulation study and the company's forecast pointing to an increase in demand for next year, a new maintenance plan was established that reviewed the preventive maintenance intervals.

Maintenance intervals for each part were defined in alignment with the maintenance and operation staff. Due to the lack of a costing system that is sufficiently structured to assess costs related to equipment maintenance and unavailability, the team adopted a reliability reference of 80%. More specifically, the team accepts a 20% probability that failure occurs prior to the preventive maintenance visit. Isolating time (t) in the reliability equation for a Weibull distribution, it is possible to obtain the estimated time interval to perform periodic maintenance visits (tm) for each part:

$$\text{for } R(t) = 0.8 \text{ we have } tm = \theta \times [-\ln(0.8)]^{1/\beta} \quad (3)$$

In Eq. (5), the θ and β are the Weibull scale and shape parameters respectively. Intervals for preventive maintenance (tm) were calculated using Eq. (5). However, to facilitate maintenance scheduling, maintenance activities were grouped into maintenance packages that were carried out at the same time and treated as an entity. Thus, parts with similar maintenance intervals were grouped into a common average interval and these intervals were recommended for preventive maintenance. Table 4 shows the calculated and recommended maintenance intervals for all parts.

After combining reliability and practical aspects, it is recommended to execute periodic maintenance visits: (i) three times a week for sensors; (ii) every week for the label printer, control panels, pulleys, bearings, conveyors and guides, lid positioner, brushes, control system, and weighing-machine; (iii) every 14 days for motor system A and upper rotating union; (iv) every 21 days for lid closer, washing system, filling nozzles, and motor system C; (v) every 6 months for clutch, motor system B, and inferior rotating union. These intervals of periodic maintenance are recommended to ensure a reliability level of approximately 80% for each part which was the reference adopted by this company. If a higher reliability target was established, intervals would be shorter and preventive maintenance costs would be higher. On the other hand, if a lower reliability target was established, failures (and their associated costs) would be more frequent. The reliability level of 80% was considered a reasonable compromise.

It is important to note that recommended preventive maintenance must be used to check the operating condition of parts, conduct cleaning, ensure appropriated level of lubrication, retight parts, and even replace components when necessary.

In this particular application, the standard used for defining maintenance intervals tm was the same for all parts since all the parts were classified as having “operational failure with no higher risks involved” in step (iii). In other applications, if some parts share a different classification, such as being associated with potential accidents, then a more rigorous criterion (a higher reliability target) should be used for these parts.

5. Conclusion

The main objective of this study was to present a quantitative method for supporting the preparation or review of a maintenance plan in a Just-in-time production scenario. JIT production scenarios are characterized by reduced (or zero) inventories and the need to meet production schedule in a single shift.

The proposed method features the identification of parts that influence the reliability of the studied equipment followed by the computation of their failure rates, times to failure, times to repair, and availability. Next, production line occupation data and its probability distribution are obtained, as well as the time to failure and time to repair probability distributions. Later, a simulation comprising production, failures, and maintenance using the Monte Carlo approach is conducted using stochastic procedures to define the probability that production does not achieve daily demand.

The results grant the ability to perform a sensitivity analysis of downtime and overtime considering changes in demand, MTTF, and MTTR. The method was applied to a paint and dyes company. Combining the simulation results with the growth in demand predicted by the company management, the need for improvement on maintenance management was identified. To improve line availability and reliability, new preventive maintenance intervals were determined for the parts.

Besides being able to determine the proper maintenance intervals, the study of TTF and TTR allowed the identification of critical parts and provided sound information for choosing the most appropriate action to improve their performance. Parts with lower MTTF need improvements in maintenance policy, while parts with higher MTTR need improvements in training and resources for the maintenance team.

This simulation allowed a precise analysis of system response concerning downtime and overtime as it relates to variations in demand, MTTF, and MTTR. The use of the Monte Carlo approach allowed the natural system variability to be taken into consideration. These results helped the company in the decision making process regarding the need and type of investment in maintenance that would be best for that specific future demand scenario.

Finally, it is worth noting the limitations of this study. The proposed method was applied to the study of a production scenario where demand must be met in the same work day and it is possible to use overtime to compensate for peak demand or downtime. Other scenarios, where it is not possible to use overtime or there is stock that reduces reliability problems may require different approaches and are suggested for future research. The consideration of global costs in the model, such as maintenance and unavailability costs, is also recommended for future work. Moreover, the inclusion of dependent failures would also extend the application of the proposed method. The consideration of different scenarios, global costs, and dependent failures would help to increase the broadness and accuracy of the simulation study.

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