

Integrating Reliability Centered Maintenance with Statistical Forecasting Techniques and Cost Engineering on Machine in Casting Plant of Automotive Parts

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Abstract

This paper describes the integration of reliability centered maintenance (RCM), Statistical Forecasting Techniques (SFT) and cost engineering to develop maintenance and cost management on Machine in Casting Plant of Automotive Parts. The main objective of RCM, SFT and cost engineering is the effective maintenance and cost management of the components of a machine inherent reliability value. Consequently, this research aims to manage the costs necessary to extend the service life of a machine through the use of probabilistic methods and simulation techniques in order to better identify the importance of every components in a machine with respect to maintenance costs. As a result of this research, our costing model allows to develop a methodology to determine maintenance costs which must be applied to some subsets of the elements of a machine, grouped according to their criticality and to identify the gap of costs between the true solution and the optimal maintenance interval.

Keywords: RCM, SFT, Cost engineering

1 Introduction

Cost engineering is the engineering practice devoted to the management of project cost, involving such activities as cost- and control- estimating, which is cost control and cost forecasting, investment appraisal, and risk analysis. Cost Engineers budget, plan and monitor investment projects. We seek the optimum balance between cost, quality and time requirements. Cost minimization has been always the traditional objective in maintenance planning; over the years, maintenance has been very often undervalued because of the strong business-oriented vision of firms managers who payed attention on production rather than on maintenance. Afterwards, the real advantages offered by the application of maintenance techniques have been understood giving them the right collocation inside the firm management. The present paper shows a costing

model to manage maintenance costs and improves it introducing simulation techniques to diversify the importance of the components of a plant by classifying their criticality with respect to maintenance costs.

Over the years, maintenance has been very often undervalued because of the strong business-oriented vision of firms managers who payed attention on production rather than on maintenance. Afterwards, the real advantages offered by the right application of maintenance techniques have been understood by reserving a branch of engineering to maintenance and by defining methodologies to manage it efficiently, among which RCM (Reliability Centered Maintenance).

RCM provides in fact an efficient and complete tool to improve maintenance policies involving service efficiency, plant reliability and budget and resources management. It allows to define maintenance plans of those activities which guarantee performances and

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reliability in a component considering its importance and its mission in the production context. In fact, the maintenance services and time intervals are optimized considering the real criticality of the parts, guaranteeing their availability. Clearly, the implementation of a maintenance plan is not a trivial or a zero-cost operation and in this sense a cost analysis must be developed.

2 Literature Reviews

Cost minimization has been the traditional objective in maintenance planning. Deterministic models [1] on preventive maintenance optimization have established minima in costs based on operating cost parameters (repair, maintenance and acquisition). The use of deterministic methods, however, does not provide information about potential risk that results in nonoptimal maintenance planning for process plants [2]. Probabilistic models, on the other hand, use probability distributions to describe and represent natural variability and uncertainty in parameter, model and scenario [3]. Probabilistic models of scheduling preventive maintenance also minimize objective functions that reflect repair, replacement and preventive maintenance costs [4]. The preventive maintenance interval is optimized when the increasing rate of corrective maintenance costs (with respect to time) equals the decreasing rate of preventive maintenance costs.

In conducting this type of analysis, some important maintenance parameters must be considered: in general terms, it is possible to state that the main goal of a maintenance plan is to improve the availability of a production line. By defining up-time as the functioning time of the line and down-time as the off-duty time of the line due to a failure, the availability can be defined as the ratio between the up time and the sum of up-time and down-time. To improve this performance, one of the possible chance is to reduce the Mean Time Waiting for Spares (MTWS), i.e. the time necessary to wait for a spare when a substitution operation occurs.

The classical model dealing with the maintenance costs defines the management procedure by which the *i*-th component is substituted when it reaches a critical age; this time is defined, in the case of electromechanical components, by the number of utilization hours with respect to the service life, or life expectancy of

its design. The substitution period, defined as t_c , is considered with respect to the last intervention of preventive or corrective maintenance independently. By defining ETTC (t_c) the average expected life for a component in the period t_c as the equation (1).

$$ETTE(t_c) = \int_0^{t_c} R(x)dx \tag{1}$$

Where $R(x)$ is the reliability function of the component

The total cost between two maintenance interventions can be so evaluated as the sum of the cost related to a planned and to an unplanned intervention because of a failure of the component; each of those is weighted with its probability represented by the reliability and unreliability functions respectively. So, the total provisioning cost per time unit is the equation (2).

$$E(C_i) = \frac{E(C_{pi}) \cdot R_i(t_c) + E(C_{ui}) \cdot [1 - R_i(t_c)]}{\int_0^{t_c} R(x)dx} \tag{2}$$

where:

$E(C_i)$ is the total expected cost of planned maintenance per time unit related to the *i*-th component;

$E(C_{pi})$ is the expected cost of a planned and preventive intervention for the *i*-th component;

$E(C_{ui})$ is the expected cost of an unplanned intervention due to a failure for the *i*-th component;

$R_i(t)$ is the cumulative distribution function of the reliability of the *i*-th component.

By deriving the cost function with respect to t_c time and setting to zero its first derivative, it is possible to evaluate the minimum of this equation (3) obtaining the optimal maintenance time which minimize the total costs:

$$\frac{d[E(C_i)]}{dt_c} = 0 \tag{3}$$

This work aims to generate a maintenance program that based on the RCM technique for the process-steam plant components. This technique should be able to minimize the downtime (DT) and improve the availability of the plant components. Also, it should benefits to decrease the spare parts

consumption system components. RCM is a systematic approach to determine the maintenance requirements of plant and equipment in its operating [5]. It is used to optimize preventive maintenance (PM) strategies.

The developed PM programs minimize equipment failures and provide industrial plants with effective equipment [6]. RCM is one of the best known and most used devices to preserve the operational efficiency of the steam system. RCM operates by balancing the high corrective maintenance costs with the cost of programmed (preventive or predictive) policies, taking into account the potential shortening of “useful life” of the item considered. But it is difficult to select suitable maintenance strategy for each piece of equipment and each failure mode, for the great quantity of equipment and uncertain factors of maintenance strategy decision [7,8]. RCM philosophy employs preventive maintenance, predictive maintenance (PdM), real-time monitoring (RTM), run-to-failure (RTF) and proactive maintenance techniques in an integrated manner to increase the probability that a machine or component will function in the required manner over its design life cycle with a minimum of maintenance [9,10].

It is currently believed the application of probabilistic maintenance models to determine the optimal inspection rates considering the tradeoff between reliability and cost; accordingly, practical solutions can be obtained for the optimal inspection rates with the careful selection of appropriate probabilistic maintenance models [11]. In addition, the Weibull parameters are estimated using a new analytical method. Based on the model for optimizing maintenance policy for power equipment, the optimal number of overhauls and the optimal overhaul interval for minimizing the expected total maintenance cost are also analytically determined [12]. Several study cases were designed in order to test the proposed model, demonstrating its applicability and simplicity to determine an optimal maintenance policy [11,12].

On the recent basis of researches conducted in their better ways, Quantitative forecasting methods, including time series methods and causal econometric approaches, are used widely in industrial demand forecasting. Likewise, combining statistical and judgmental forecasts via a web-based tourism demand forecasting system resulted that this combination of quantitative and judgmental forecasts improves the overall forecasting accuracy [13]. Moreover, show that



Figure 1: Sample main machines in the plant.



Figure 2: Sample manufacturing process in the plant.

the proposed combination models can always provide desirable forecasting results compared to the existing traditional combination models [14]. In the same way, on many simulation results, a final combined approach that takes advantage of component forecasts should be better than the individuals, or at least equivalent to the best one, making it desirable to combine individuals to forecast wind-speed. Combined forecasting methodologies aggregate individual forecasting methods and take advantage of component models in order to improve the final forecasting performance [13,14].

3 Methodology

3.1 Our case study

This plant of foundry is capable of supplying top quality castings in a wide variety of alloyed cast irons, copper-based alloys, including aluminium bronzes and related alloys, as well as specially formulated aluminium alloys, for all types of glass moulds and machinery parts, all having material specifications equivalent to those originating from industrialized countries. All cast irons for glass moulds are chilled and annealed to the strictest quality standards to ensure the best possible glass production quality, and to maximize the life span of the moulds. The plant used main machines on electrical motors in Figure 1 about 100 units in manufacturing process in this plant in Figure 2.

3.2 RCM steps

The RCM steps are presented. The steps describe the systematic approach used to implement the preserves the system function, identifies failure mode, priorities failure used to implement the preserves the system function, identifies failure mode, priorities failure modes and performs PM tasks. The RCM steps are as follows [15]:

- Step 1: system selection and data collection
- Step 2: system boundary definition
- Step 3: system description and functional block
- Step 4: system function functional failures
- Step 5: failure mode effect analysis
- Step 6: logic tree diagram
- Step 7: task selection.

3.3 Criticality analysis

Criticality analysis is a tool used to evaluate how equipment failures impact organizational performance in order to systematically rank plant assets for the purpose of work prioritization, material classification, PM development and reliability improvement initiatives [16]. In general, failure modes, effects and criticality analysis (FMEA/FMECA) required the identification of the following basic information in Table 1. Criticality of each machine (MC) was calculated based on the following four criteria:

1. Effect of the machine downtime on the production process (EM).
2. Utilization rate of the machine (Bottleneck or not) (UR).
3. Safety and environmental incidence of machine failure (SEI).
4. Technical complexity of the machine and need of external maintenance resources (MTC).

Table 1: Sample of some values of machine criticality

Part No.	Weight	3	3	2	1	MC	Criticality Code
	Machine Code	SEI	EM	UR	MCT		
1	Motor & Pump 1	3	3	2	3	26	A
2	Motor 2	2	3	3	2	23	A
3	Motor 3	3	3	2	3	26	A

Each of the criteria was given a weight showing its importance relative to the criticality indices. The weight of each criterion ranges from zero (no effect) to three (very important effect). Machine criticality was then calculated in the equation (4) and criticality codes such as A (most critical machine): 20 to 27, B: 12 to 19, C: 0 to 11.

$$MC = 3*EM + 2*UR + 3*SEI + I*MTC \quad (4)$$

3.4 Failure Mode Effects Analysis (FMEA)

Failure modes and effects analysis (FMEA) is a step-by-step approach for identifying all possible failures in a design, a manufacturing or assembly process, or a product or service.

This is the severity rating, or S. Severity is usually rated on a scale from 1 to 10, where 1 is insignificant and 10 is catastrophic. If a failure mode has more than one effect, write on the FMEA table only the highest severity rating for that failure mode.

For each cause, determine the occurrence rating, or O. This rating estimates the probability of failure occurring for that reason during the lifetime of your scope. Occurrence is usually rated on a scale from 1 to 10, where 1 is extremely unlikely and 10 is inevitable. On the FMEA table, list the occurrence rating for each cause.

For each control, determine the detection rating, or D. This rating estimates how well the controls can detect either the cause or its failure mode after they have happened but before the customer is affected. Detection is usually rated on a scale from 1 to 10, where 1 means the control is absolutely certain to detect the problem and 10 means the control is certain not to detect the problem (or no control exists). On the FMEA table, list the detection rating for each cause.

The risk priority number, or RPN was then calculated in the equation (5).

$$RPN = (S) \times (O) \times (D) \quad (5)$$

Risk Evaluation such as Small Risk: RPN < 60, Medium Risk: RPN < 80 and High Risk: RPN < 100 and Crisis Risk: RPN > 100, then we should consider the RPN of components with the highest value first. Table 2 shows a sample of some valves of RPN.



Figure 3: Our meetings and brainstorming of staff members to rate scores and to classify RPN.

On our case study, we selected the way to rate scores and to classify RPN as small, medium, high or crisis by Meetings and brainstorming of staff members such as Managers, Engineers, Chiefs, Technicians and Workers in Figure 3.

3.5 Maintenance Assessment of Reliability Engineering

We applied Maintenance Assessment of Reliability Engineering to calculate the probability on the parameters of reliability. To begin with, we don't have the data of Time To Fail (TTF); therefore, we applied SFT on Non Linear Regression, to predict our machine's life time and TTF by the machine data of vibration in Table 3.

Table 3: Sample of machine data of vibration

	A	B	C	D
1		Motor & Pump 1	Motor 2	Motor 3
2	Time (hours)	G2 (rigid)	G2 (rigid)	G2 (rigid)
3		Vibration (mm/s rms)	Vibration (mm/s rms)	Vibration (mm/s rms)
4	200			
5	400			
6	600			
7	800			
8	1000		1.43	
9	1200		1.44	
10	1400		1.82	1.97
11	1600		1.88	1.97
12	1800		2.23	2.12
13	2000	2.49	2.51	2.45
14	2200	2.65	2.53	2.56
15	2400	2.74	2.87	2.89
16	2600	2.81	2.85	2.96
17	2800	2.86	2.89	3.12
18	3000	2.86	2.86	3.21
19	3200	2.88	3.12	3.24
20	3400	2.96	3.12	3.12
21	3600	3.12	3.31	3.31
22	3800	3.12	3.33	3.45
23	4000	3.22	3.32	3.55
24	4200	3.21	3.35	3.56
25	4400	3.22	3.38	3.62
26	4600	3.36	3.44	3.68
27	4800	3.36	3.56	3.81
28	5000	3.39	3.61	3.98
29	5200	3.41	3.62	4.47
30	5400	3.41	3.88	
31	5600	3.42	4.43	
32	5800	3.84		
33	6000	4.36		

Table 2: Sample of some values of RPN

No.	Machine Code	Features of Damage	Severity (SEV)		Occurrence (OOC)		Detection (DET)		RPN
			Information	Scores	Information	Scores	Information	Scores	
1	Motor & Pump 1	Having more vibration & higher temperature and unusual noise	It can not produce efficiently	6	Failure of bearing and gear	6	Temperature measurement, vibration analysis and unusual noise	6	216
		Motor stopped unexpectedly (burns)	To stop production	6	Using electrical overload	3	Daily monitoring	3	54
2	Motor 2	Having more vibration & higher temperature and unusual noise	It can not produce efficiently	6	Failure of bearing and gear	6	Temperature measurement, vibration analysis and unusual noise	6	216
		Motor stopped unexpectedly (burns)	To stop production	6	Using electrical overload	3	Daily monitoring	3	54
3	Motor 3	Having more vibration & higher temperature and unusual noise	It can not produce efficiently	6	Failure of bearing and gear	6	Temperature measurement, vibration analysis and unusual noise	6	216
		Motor stopped unexpectedly (burns)	To stop production	6	Using electrical overload	3	Daily monitoring	3	54

After that, we applied SFT on Decomposition Method in Non Linear Regression Analysis, to monitor vibration and to forecast vibration causes damage and TTF, by the machine data of vibration according to the standard of ISO 10816-3 in Figure 4. We used Statistical Software in Figure 5-7 to estimate the parameters and the equation in Table 4. So, we are able to forecast and to summarize the data of TTF in Table 5.

Velocity threshold values ISO 10816-3

		Velocity threshold values				ISO 10816-3	
		1.1	1.6	2.2	3.1	4.5	6.3
Velocity	2.44	Red	Red	Red	Red	Red	Red
	2.08	Red	Red	Red	Red	Red	Red
	1.71	Red	Red	Red	Red	Red	Red
	1.35	Red	Red	Red	Red	Red	Red
2.00 to 2.50 mm/s	2.00	Red	Red	Red	Red	Red	Red
	1.75	Red	Red	Red	Red	Red	Red
	1.50	Red	Red	Red	Red	Red	Red
	1.25	Red	Red	Red	Red	Red	Red
0.50 to 1.00 mm/s	0.50	Red	Red	Red	Red	Red	Red
	0.45	Red	Red	Red	Red	Red	Red
	0.40	Red	Red	Red	Red	Red	Red
	0.35	Red	Red	Red	Red	Red	Red
0.10 to 0.20 mm/s	0.10	Red	Red	Red	Red	Red	Red
	0.09	Red	Red	Red	Red	Red	Red
	0.08	Red	Red	Red	Red	Red	Red
	0.07	Red	Red	Red	Red	Red	Red
0.03 to 0.05 mm/s	0.03	Red	Red	Red	Red	Red	Red
	0.025	Red	Red	Red	Red	Red	Red
	0.02	Red	Red	Red	Red	Red	Red
	0.015	Red	Red	Red	Red	Red	Red
0.005 to 0.01 mm/s	0.005	Red	Red	Red	Red	Red	Red
	0.0045	Red	Red	Red	Red	Red	Red
	0.004	Red	Red	Red	Red	Red	Red
	0.0035	Red	Red	Red	Red	Red	Red

Machine Type	Group 1	Group 2	Group 3	Group 4
Large machines	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW
Medium size machines	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW
Small machines	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW
Motor driven	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW
Integrated drive	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW
Motor driven	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW
Motor driven	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW
Motor driven	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW	15 kVv > 1000 kW

Group	Color	Description
Group 1	Blue	Very good condition
Group 2	Green	Good condition
Group 3	Yellow	Warning condition
Group 4	Red	Alarm condition

Figure 4: ISO 10816-3.

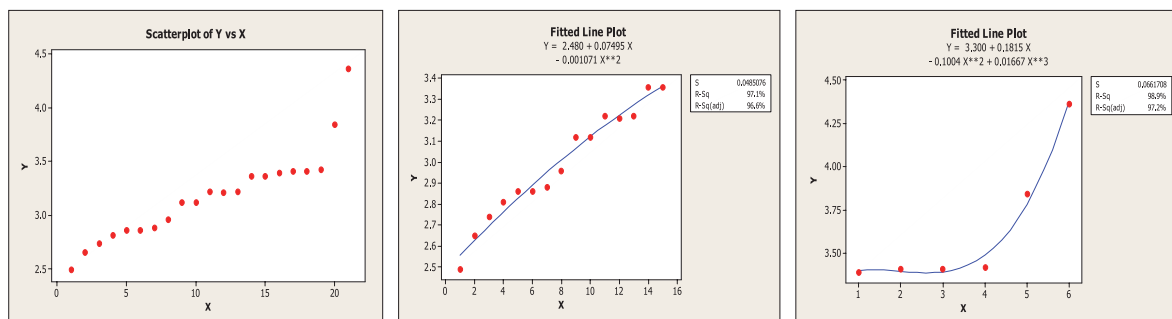


Figure 5: Decomposition Method in Non Linear Regression Analysis of Motor & Pump 1.

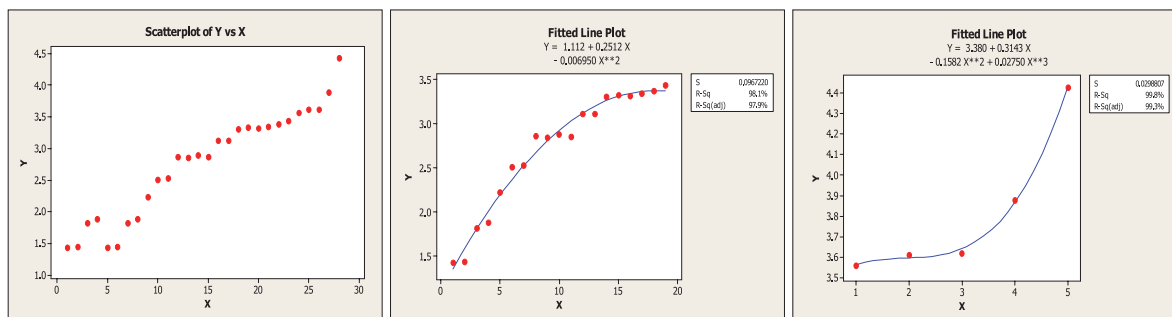


Figure 6: Decomposition Method in Non Linear Regression Analysis of Motor 2.

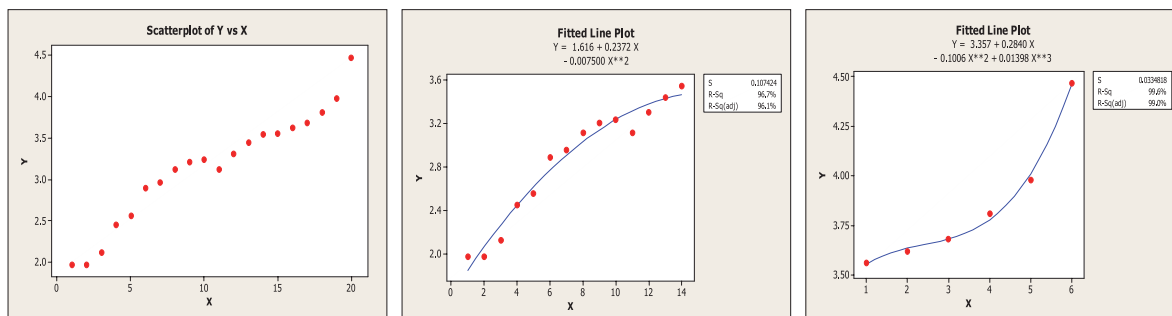


Figure 7: Decomposition Method in Non Linear Regression Analysis of Motor 3.

Table 4: Summary on Decomposition Method in Non Linear Regression Analysis

No.	Machine Code	Decomposition Method on Regression Analysis: (X: Time); (Y: Vibration)			Coefficient of Determination		Applications
		Durations (hours)	X: Time (200 hours)	Equations	R-Sq	R-Sq (adj)	
1	Motor & Pump 1	2000 to 4800	1 to 15	$Y = 2.48 + 0.07495 X - 0.001071 X^2$	97.1%	96.6%	To monitor vibration
		5000 to 6000	1 to 6	$Y = 3.3 + 0.1815 X - 0.1004 X^2 + 0.01667 X^3$	98.9%	97.2%	To forecast vibration causes damage
2	Motor 2	1000 to 4600	1 to 19	$Y = 1.112 + 0.2512 X - 0.00695 X^2$	98.1%	97.9%	To monitor vibration
		4800 to 5600	1 to 5	$Y = 3.38 + 0.3143 X - 0.1582 X^2 + 0.0275 X^3$	99.8%	99.3%	To forecast vibration causes damage
3	Motor 3	1400 to 4000	1 to 14	$Y = 1.616 + 0.2372 X - 0.0075 X^2$	96.7%	96.1%	To monitor vibration
		4200 to 5200	1 to 6	$Y = 3.357 + 0.284 X - 0.1006 X^2 + 0.01398 X^3$	99.6%	99.0%	To forecast vibration causes damage

Table 5: Summary of the data of Time To Fail: TTF (unit: hours)

No.	Machine Code	Time To Failure: TTF (hours)				
		Period 1	Period 2	Period 3	Period 4	Period 5
1	Motor & Pump 1	6800	13600	20400	27200	34000
2	Motor 2	6300	12600	18900	25200	31500
3	Motor 3	6100	12200	18300	24400	30500

Therefore, we applied Excel Simulation to calculate the equation on Decomposition Method in Non Linear Regression Analysis such as Motor & Pump 1, Motor 2 and Motor 3 in Figure 8 to 10.

After that, we adopted Reliability Engineering for the calculation by using graph probability (Probability Plotting) with Statistical Software in Figure 11-13 to estimate the parameters.

In addition, we tested conditions about Goodness of Fit Test to confirm that a hypothesized distribution fits a data set by Kolmogorov-Smirnov Test for the small population using the equation (6)-(9). Then we created Excel Simulation to calculate the equation (6)-(9) in Figure 14 and the results on Goodness of Fit are summarized in Table 6.

Table 6: Sample of the summarized results on Goodness of Fit

No.	Machine Code	Parameters		K-S Test ($\alpha = 0.05, n$)			Hypothesis test:
		β	η	max d	d_α	n	
1	Motor & Pump 1	1.64093	23892.7	0.2239	0.563	5	accepted H_0
2	Motor 2	1.64093	22135.9	0.2239	0.563	5	accepted H_0
3	Motor 3	1.64093	21433.1	0.2239	0.563	5	accepted H_0

	A	B	C	D	E	F	G	H	I	J	K	L
1												
2			To forecast vibration causes damage in Motor & Pump 1									
3	Hours	X	X ²	X ³	3.3	0.1815	0.1815*X	0.1004	0.1004*X ²	0.01667	0.01667*X ³	Y
4	6200	7	49	343	3.3	0.1815	1.2705	0.1004	4.9196	0.01667	5.7178	5.3687
5	6300	7.5	56.25	421.875	3.3	0.1815	1.3613	0.1004	5.6475	0.01667	7.0327	6.0464
6	6400	8	64	512	3.3	0.1815	1.4520	0.1004	6.4256	0.01667	8.5350	6.8614
7	6500	8.5	72.25	614.125	3.3	0.1815	1.5428	0.1004	7.2539	0.01667	10.2375	7.8263
8	6600	9	81	729	3.3	0.1815	1.6335	0.1004	8.1324	0.01667	12.1524	8.9535
9	6700	9.5	90.25	857.375	3.3	0.1815	1.7243	0.1004	9.0611	0.01667	14.2924	10.2556
10	6800	10	100	1000	3.3	0.1815	1.8150	0.1004	10.04	0.01667	16.6700	11.7450
11	6900	10.5	110.25	1157.63	3.3	0.1815	1.9058	0.1004	11.0691	0.01667	19.2976	13.4343
12	7000	11	121	1331	3.3	0.1815	1.9965	0.1004	12.1484	0.01667	22.1878	15.3359
13	7100	11.5	132.25	1520.88	3.3	0.1815	2.0873	0.1004	13.2779	0.01667	25.3530	17.4623
14	7200	12	144	1728	3.3	0.1815	2.1780	0.1004	14.4576	0.01667	28.8058	19.8262
15	7300	12.5	156.25	1953.13	3.3	0.1815	2.2688	0.1004	15.6875	0.01667	32.5586	22.4398
16	7400	13	169	2197	3.3	0.1815	2.3595	0.1004	16.9676	0.01667	36.6240	25.3159
17	7500	13.5	182.25	2460.38	3.3	0.1815	2.4503	0.1004	18.2979	0.01667	41.0145	28.4668
18	7600	14	196	2744	3.3	0.1815	2.5410	0.1004	19.6784	0.01667	45.7425	31.9051
19	7700	14.5	210.25	3048.63	3.3	0.1815	2.6318	0.1004	21.1091	0.01667	50.8206	35.6432
20	7800	15	225	3375	3.3	0.1815	2.7225	0.1004	22.59	0.01667	56.2613	39.6938
21	7900	15.5	240.25	3723.88	3.3	0.1815	2.8133	0.1004	24.1211	0.01667	62.0770	44.0691
22	8000	16	256	4096	3.3	0.1815	2.9040	0.1004	25.7024	0.01667	68.2803	48.7819

Figure 8: Excel Simulation to calculate the equations on Decomposition Method in Non Linear Regression Analysis of Motor & Pump 1.

	A	B	C	D	E	F	G	H	I	J	K	L
23	To forecast vibration causes damage in Motor 2											
24	Hours	X	X^2	X^3	3.38	0.3143	0.3143*X	0.1582	0.1582*X^2	0.0275	0.0275*X^3	Y
25	5800	6	36	216	3.38	0.3143	1.8858	0.1582	5.6952	0.0275	5.9400	5.5106
26	5900	6.5	42.25	274.625	3.38	0.3143	2.0430	0.1582	6.6840	0.0275	7.5522	6.2912
27	6000	7	49	343	3.38	0.3143	2.2001	0.1582	7.7518	0.0275	9.4325	7.2608
28	6100	7.5	56.25	421.875	3.38	0.3143	2.3573	0.1582	8.8988	0.0275	11.6016	8.4401
29	6200	8	64	512	3.38	0.3143	2.5144	0.1582	10.1248	0.0275	14.0800	9.8496
30	6300	8.5	72.25	614.125	3.38	0.3143	2.6716	0.1582	11.4300	0.0275	16.8884	11.5100
31	6400	9	81	729	3.38	0.3143	2.8287	0.1582	12.8142	0.0275	20.0475	13.4420
32	6500	9.5	90.25	857.375	3.38	0.3143	2.9859	0.1582	14.2776	0.0275	23.5778	15.6661
33	6600	10	100	1000	3.38	0.3143	3.1430	0.1582	15.8200	0.0275	27.5000	18.2030
34	6700	10.5	110.25	1157.63	3.38	0.3143	3.3002	0.1582	17.4416	0.0275	31.8347	21.0733
35	6800	11	121	1331	3.38	0.3143	3.4573	0.1582	19.1422	0.0275	36.6025	24.2976
36	6900	11.5	132.25	1520.88	3.38	0.3143	3.6145	0.1582	20.9220	0.0275	41.8241	27.8966
37	7000	12	144	1728	3.38	0.3143	3.7716	0.1582	22.7808	0.0275	47.5200	31.8908
38	7100	12.5	156.25	1953.13	3.38	0.3143	3.9288	0.1582	24.7188	0.0275	53.7109	36.3009
39	7200	13	169	2197	3.38	0.3143	4.0859	0.1582	26.7358	0.0275	60.4175	41.1476
40	7300	13.5	182.25	2460.38	3.38	0.3143	4.2431	0.1582	28.8320	0.0275	67.6603	46.4514
41	7400	14	196	2744	3.38	0.3143	4.4002	0.1582	31.0072	0.0275	75.4600	52.2330
42	7500	14.5	210.25	3048.63	3.38	0.3143	4.5574	0.1582	33.2616	0.0275	83.8372	58.5130
43	7600	15	225	3375	3.38	0.3143	4.7145	0.1582	35.5950	0.0275	92.8125	65.3120

Figure 9: Excel Simulation to calculate the equations on Decomposition Method in Non Linear Regression Analysis of Motor 2.

	A	B	C	D	E	F	G	H	I	J	K	L
45	To forecast vibration causes damage in Motor 3											
46	Hours	X	X^2	X^3	3.697	0.284	0.284*X	0.1006	0.1006*X^2	0.01398	0.01398*X^3	Y
47	5400	7	49	343	3.357	0.284	1.988	0.1006	4.9294	0.01398	4.7951	5.2107
48	5500	7.5	56.25	421.875	3.357	0.284	2.13	0.1006	5.6588	0.01398	5.8978	5.7261
49	5600	8	64	512	3.357	0.284	2.272	0.1006	6.4384	0.01398	7.1578	6.3484
50	5700	8.5	72.25	614.125	3.357	0.284	2.414	0.1006	7.2684	0.01398	8.5855	7.0881
51	5800	9	81	729	3.357	0.284	2.556	0.1006	8.1486	0.01398	10.1914	7.9558
52	5900	9.5	90.25	857.375	3.357	0.284	2.698	0.1006	9.0792	0.01398	11.9861	8.9620
53	6000	10	100	1000	3.357	0.284	2.84	0.1006	10.0600	0.01398	13.9800	10.1170
54	6100	10.5	110.25	1157.63	3.357	0.284	2.982	0.1006	11.0912	0.01398	16.1836	11.4314
55	6200	11	121	1331	3.357	0.284	3.124	0.1006	12.1726	0.01398	18.6074	12.9158
56	6300	11.5	132.25	1520.88	3.357	0.284	3.266	0.1006	13.3044	0.01398	21.2618	14.5805
57	6400	12	144	1728	3.357	0.284	3.408	0.1006	14.4864	0.01398	24.1574	16.4360
58	6500	12.5	156.25	1953.13	3.357	0.284	3.55	0.1006	15.7188	0.01398	27.3047	18.4929
59	6600	13	169	2197	3.357	0.284	3.692	0.1006	17.0014	0.01398	30.7141	20.7617
60	6700	13.5	182.25	2460.38	3.357	0.284	3.834	0.1006	18.3344	0.01398	34.3960	23.2527
61	6800	14	196	2744	3.357	0.284	3.976	0.1006	19.7176	0.01398	38.3611	25.9765
62	6900	14.5	210.25	3048.63	3.357	0.284	4.118	0.1006	21.1512	0.01398	42.6198	28.9436
63	7000	15	225	3375	3.357	0.284	4.26	0.1006	22.6350	0.01398	47.1825	32.1645
64	7100	15.5	240.25	3723.88	3.357	0.284	4.402	0.1006	24.1692	0.01398	52.0598	35.6496
65	7200	16	256	4096	3.357	0.284	4.544	0.1006	25.7536	0.01398	57.2621	39.4095

Figure 10: Excel Simulation to calculate the equations on Decomposition Method in Non Linear Regression Analysis of Motor 3.

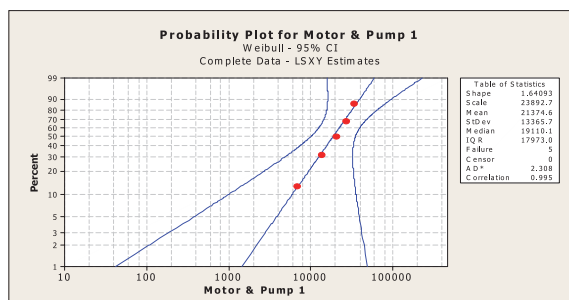


Figure 11: Probability Plotting with Statistical Software of Motor & Pump 1.

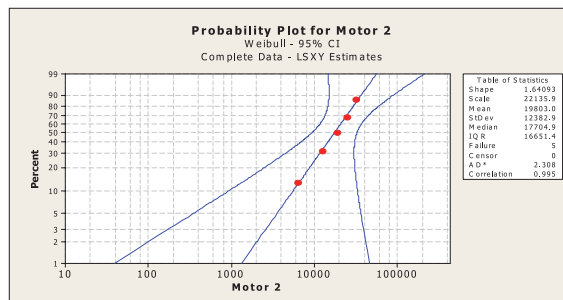


Figure 12: Probability Plotting with Statistical Software of Motor 2.

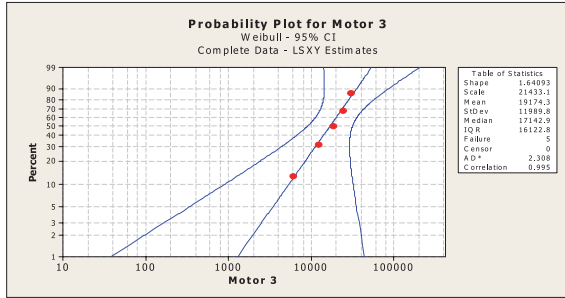


Figure 13: Probability Plotting with Statistical Software of Motor 3.

Statistical Hypothesis:

Test Statistics by Kolmogorov-Smirnov Test :

$$d = \max\left\{\left|F(t_i) - \hat{F}(t_i)\right|, \left|F(t_i) - \hat{F}(t_{i-1})\right|\right\} \quad (6)$$

$$F(t_i) = 1 - e^{-\left(\frac{t_i}{\eta}\right)^\beta} \quad (7)$$

$$\hat{F}(t_i) = \text{Opportunity of Breakdown by Table 7} \quad (8)$$

d_α = Critical Values of Komogorov-Smirnov Tests by Table 8 (9)

Decision criteria on Significance level (α): Accept H_0 if $d < d_\alpha$

Table 8: Critical Values of Komogorov-Smirnov Tests [17]

Sample Size	Level of Significance (d_α)				
	0.2	0.1	0.05	0.02	0.01
1	0.900	0.950	0.975	0.990	0.995
2	0.684	0.776	0.842	0.900	0.929
3	0.565	0.636	0.708	0.785	0.829
4	0.493	0.565	0.624	0.689	0.734
5	0.447	0.509	0.563	0.627	0.669
6	0.410	0.468	0.519	0.577	0.617
7	0.381	0.436	0.483	0.538	0.576
8	0.358	0.410	0.454	0.507	0.542
9	0.339	0.387	0.430	0.480	0.513
10	0.323	0.369	0.409	0.457	0.489
11	0.308	0.352	0.391	0.437	0.468
12	0.296	0.338	0.375	0.419	0.449
13	0.285	0.325	0.361	0.404	0.432
14	0.275	0.314	0.349	0.390	0.418
15	0.266	0.304	0.338	0.377	0.404
16	0.258	0.295	0.327	0.366	0.392
17	0.250	0.286	0.318	0.355	0.381
18	0.244	0.279	0.309	0.346	0.371
19	0.237	0.271	0.301	0.337	0.361
20	0.232	0.265	0.294	0.329	0.352
25	0.208	0.238	0.264	0.295	0.317
30	0.190	0.218	0.242	0.270	0.290
35	0.177	0.202	0.224	0.251	0.269
40	0.165	0.189	0.210	0.235	0.252
Over 40	$1.07/\sqrt{n}$	$1.22/\sqrt{n}$	$1.36/\sqrt{n}$	$1.52/\sqrt{n}$	$1.63/\sqrt{n}$

Table 7: Median Rank [17]

i \ n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	50.000	29.289	20.630	15.910	12.945	10.910	9.428	8.300	7.412	6.697	6.107	5.613	5.192	4.830	4.516	4.240	3.995	3.778	3.582	3.406
2		70.711	50.000	38.573	31.381	26.445	22.849	20.113	17.962	16.226	14.796	13.598	12.579	11.702	10.940	10.270	9.678	9.151	8.677	8.251
3			79.370	61.427	50.000	42.141	36.412	32.052	28.624	25.857	23.578	21.669	20.045	18.647	17.432	16.365	15.422	14.581	13.827	13.147
4				84.090	68.619	57.859	50.000	44.015	39.308	35.510	32.380	29.758	27.528	25.608	23.939	22.474	21.178	20.024	18.988	18.055
5					87.055	73.555	63.588	55.984	50.000	45.169	41.189	37.853	35.016	32.575	30.452	28.589	26.940	25.471	24.154	22.967
6						89.090	77.151	67.948	60.691	54.831	50.000	45.951	42.508	39.544	36.967	34.705	32.704	30.921	29.322	27.880
7							90.572	79.887	71.376	64.490	58.811	54.049	50.000	46.515	43.483	40.823	38.469	36.371	34.491	32.795
8								91.700	82.038	74.142	67.620	62.147	57.492	53.485	50.000	46.941	44.234	41.823	39.660	37.710
9									92.587	83.774	76.421	70.242	64.984	60.456	56.517	53.059	50.000	47.274	44.830	42.626
10										93.303	85.204	78.331	72.472	67.425	63.033	59.177	55.766	52.726	50.000	47.542
11											93.893	86.402	79.955	74.392	69.548	65.295	61.531	58.177	55.170	52.458
12												94.387	87.421	81.353	76.061	71.411	67.296	63.629	60.340	57.374
13													94.808	88.298	82.568	77.525	73.060	69.079	65.509	62.289
14														95.169	89.060	83.635	78.821	74.529	70.678	67.205
15															95.484	89.730	84.578	79.976	75.846	72.119
16																95.760	90.322	85.419	81.001	77.033
17																	96.005	90.849	86.173	81.945
18																		96.222	91.322	86.853
19																			96.418	91.749
20																				96.590

	B	C	D	E	F	G	H	I	J	K	L	M
1	To calculate "d" of Motor & Pump 1											
2	η (scale)	t/η	β (Sharpe)	$(t/\eta)^\beta$	$e = 2.7182$	$e^{(t/\eta)^\beta}$	$1/e^{(t/\eta)^\beta}$	$F(t_i) = 1 - (1/e^{(t/\eta)^\beta})$	$F(t_i)$ by Median Rank Table	$ F(t_i) - F(t_i) $	$ F(t_i) - F(t_{i-1}) $	d
3	23892.7	0.2846	1.64093	0.1272	2.7182	1.13563	0.8806	0.1194	0.12945	0.0100		0.0100
4	23892.7	0.5692	1.64093	0.3967	2.7182	1.48684	0.6726	0.3274	0.31381	0.0136	0.1980	0.1980
5	23892.7	0.8538	1.64093	0.7716	2.7182	2.16312	0.4623	0.5377	0.50000	0.0377	0.2239	0.2239
6	23892.7	1.1384	1.64093	1.2371	2.7182	3.44537	0.2902	0.7098	0.68619	0.0236	0.2098	0.2098
7	23892.7	1.4230	1.64093	1.7841	2.7182	5.95382	0.1680	0.8320	0.87055	0.0385	0.1459	0.1459
8											max d =	0.2239
9												
10	To calculate "d" of Motor 2											
11	η (scale)	t/η	β (Sharpe)	$(t/\eta)^\beta$	$e = 2.7182$	$e^{(t/\eta)^\beta}$	$1/e^{(t/\eta)^\beta}$	$F(t_i) = 1 - (1/e^{(t/\eta)^\beta})$	$F(t_i)$ by Median Rank Table	$ F(t_i) - F(t_i) $	$ F(t_i) - F(t_{i-1}) $	d
12	22135.9	0.2846	1.64093	0.1272	2.7182	1.13563	0.8806	0.1194	0.12945	0.0100		0.0100
13	22135.9	0.5692	1.64093	0.3967	2.7182	1.48684	0.6726	0.3274	0.31381	0.0136	0.1980	0.1980
14	22135.9	0.8538	1.64093	0.7716	2.7182	2.16312	0.4623	0.5377	0.50000	0.0377	0.2239	0.2239
15	22135.9	1.1384	1.64093	1.2371	2.7182	3.44536	0.2902	0.7098	0.68619	0.0236	0.2098	0.2098
16	22135.9	1.4230	1.64093	1.7841	2.7182	5.95380	0.1680	0.8320	0.87055	0.0385	0.1459	0.1459
17											max d =	0.2239
18												
19	To calculate "d" of Motor 3											
20	η (scale)	t/η	β (Sharpe)	$(t/\eta)^\beta$	$e = 2.7182$	$e^{(t/\eta)^\beta}$	$1/e^{(t/\eta)^\beta}$	$F(t_i) = 1 - (1/e^{(t/\eta)^\beta})$	$F(t_i)$ by Median Rank Table	$ F(t_i) - F(t_i) $	$ F(t_i) - F(t_{i-1}) $	d
21	21433.1	0.2846	1.64093	0.1272	2.7182	1.13563	0.8806	0.1194	0.12945	0.0100		0.0100
22	21433.1	0.5692	1.64093	0.3967	2.7182	1.48684	0.6726	0.3274	0.31381	0.0136	0.1980	0.1980
23	21433.1	0.8538	1.64093	0.7716	2.7182	2.16313	0.4623	0.5377	0.50000	0.0377	0.2239	0.2239
24	21433.1	1.1384	1.64093	1.2371	2.7182	3.44538	0.2902	0.7098	0.68619	0.0236	0.2098	0.2098
25	21433.1	1.4230	1.64093	1.7841	2.7182	5.95386	0.1680	0.8320	0.87055	0.0385	0.1459	0.1459
26											max d =	0.2239

Figure 14: Excel Simulation to calculate the equation (6)-(9).

3.6 Maintenance period analysis

On $\beta \sim 1$: Constant Failure Mode regarded as Exponential Distribution, we applied the technique of Failure Finding by calculating the inspection interval in the equation (10) [17]. Also, we created Excel Simulation to calculate the equation (10) in Figure 15, and the results on Assessment Guidelines for the maintenance of Reliability Engineering are summarized in Table 9.

$$A = 1 - \frac{FFI}{2M} \tag{10}$$

A = Availability of the protective device (Ex. $A \geq 0.90$)

FFI = The inspection interval (t_i)

M = MTTF

Table 9: Sample of Assessment Guidelines in Maintenance and Reliability Engineering

No.	Machine Code	Parameters		Type of maintenance	Period of Maintenance (hours)	$A \geq 0.90$
		β	η			
1	Motor & Pump 1	1.64093	23892.7	PM	4,600	0.9037
2	Motor 2	1.64093	22135.9	PM	4,400	0.9006
3	Motor 3	1.64093	21433.1	PM	4,600	0.9037

	A	B	C	D	E
1	1. A of Motor & Pump 1				
2	t_i	η	$2M = 2\eta ; (\text{if } \beta \sim 1)$	$t_i / 2M$	$A = 1 - (t_i / 2M)$
3	3000	23892.7	47785.4	0.062781	0.937219
4	3200	23892.7	47785.4	0.066966	0.933034
5	3400	23892.7	47785.4	0.071151	0.928849
6	3600	23892.7	47785.4	0.075337	0.924663
7	3800	23892.7	47785.4	0.079522	0.920478
8	4000	23892.7	47785.4	0.083708	0.916292
9	4200	23892.7	47785.4	0.087893	0.912107
10	4400	23892.7	47785.4	0.092078	0.907922
11	4600	23892.7	47785.4	0.096264	0.903736
12	4800	23892.7	47785.4	0.100449	0.899551
13	5000	23892.7	47785.4	0.104634	0.895366
14	5200	23892.7	47785.4	0.108820	0.891180
15	5400	23892.7	47785.4	0.113005	0.886995
16	5600	23892.7	47785.4	0.117191	0.882809
17	5800	23892.7	47785.4	0.121376	0.878624
18	6000	23892.7	47785.4	0.125561	0.874439
19	6200	23892.7	47785.4	0.129747	0.870253
20	6400	23892.7	47785.4	0.133932	0.866068
21	6600	23892.7	47785.4	0.138118	0.861882
22	6800	23892.7	47785.4	0.142303	0.857697
23	7000	23892.7	47785.4	0.146488	0.853512

Figure 15: Excel Simulation to calculate the equation (10).

In addition, we are able to develop the maintenance planning for the plant of Hard Chrome Plating in Figure 16 by applying reliability centered maintenance of the plant components inherent reliability value.

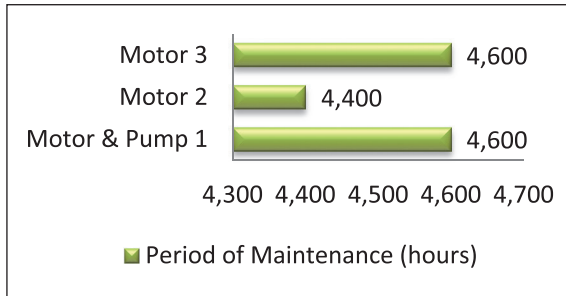


Figure 16: Sample of maintenance planning for the plant of Hard Chrome Plating.

3.7 Our model for cost engineering

The aim of the work is to develop a new equation representing the model to determine and optimize the maintenance costs which could be applied not only to the single component but to a set of components grouped in a particular way, i.e. to their criticality. At the same time, this new model allows to overcome some limits in the application of the classical one, when dealing with big dimensions plants. One of the problem is in fact due to the application of the classical model to a complex plant; the model forces to divided the plant by a very detailed tree-structure which is a very difficult task dealing with machines rich in components [18]. Another problem is represented by the meaning of the integral in the denominator of the equation; it represents an estimate of the service life of a component over a fixed time interval which must be the same for every component. Its meaning is in fact the substitution period provided by the analysis of the data sheets of the component i.e. without considering the real use in the plant or for example without considering repairs whereas possible [19]. So, the classical model does not take into account an historical study of all of the past conditions of the component to be analyzed, determining a loss of precision in the determination of the total maintenance costs and so providing a result in term of optimal maintenance interval which may be quite far from the true one [20].

As said, the proposed method tries to overcome these limits by a re-elaboration of the classical model; it introduces two important features represented by the possibility to apply the model to the whole machine and by the combination of the maintenance statistics of the firm and the probabilistic analysis about the components.

It is possible to manipulate the classical equation of maintenance costs to define a new model. As said, the classical equation (11) is as follows [21]:

$$E(C_i) = \frac{E(C_{pi}) \cdot R_i(t_c) + E(C_{ui}) \cdot [1 - R_i(t_c)]}{\int_0^{t_c} R(x) dx} \quad (11)$$

The first step is to split this equation since it will be applied to a group of components rather than to a single one. Then, we need to define the equation (12) to (14).

$$E_A(C_A) = \text{The equation of maintenance costs on Motor \& Pump 1} \quad (12)$$

$$E_B(C_B) = \text{The equation of maintenance costs on Motor 2} \quad (13)$$

$$E_C(C_C) = \text{The equation of maintenance costs on Motor 3} \quad (14)$$

At the same way, Total $E(C)$ must be redefined as the equation (15).

$$\text{Total } E(C) = E_A(C_A) + E_B(C_B) + E_C(C_C) \quad (15)$$

So it is necessary to find some reliability function $R(t)$ which represents the average of the $R(t)$ functions of machinery on the equation (16) to (18).

$$R_{Ai}(t_A) = h_A(t_A) = e^{-\left(\frac{t_A}{\eta_A}\right)^{\beta_A}} \quad (16)$$

$$R_B(t_B) = h_B(t_B) = e^{-\left(\frac{t_B}{\eta_B}\right)^{\beta_B}} \quad (17)$$

$$R_C(t_C) = h_C(t_C) = e^{-\left(\frac{t_C}{\eta_C}\right)^{\beta_C}} \quad (18)$$

Moreover, by substituting and putting in evidence, we are able to state $E_A(C_A)$, $E_B(C_B)$, and $E_C(C_C)$ on the equation (19) to (21).

$$E_A(C_A) = \left[E(C_{pA}) \cdot \left(e^{-\left(\frac{t_A}{\eta_A}\right)^{\beta_A}} \right) \right]$$

$$+ E(C_{uA}) \cdot \left[1 - \left(e^{-\left(\frac{t_A}{\eta_A}\right)^{\beta_A}} \right) \right] \Bigg] \Bigg] \div \left(\int_0^{t_{cA}} \left(e^{-\left(\frac{t_A}{\eta_A}\right)^{\beta_A}} \right) dt \right) \tag{19}$$

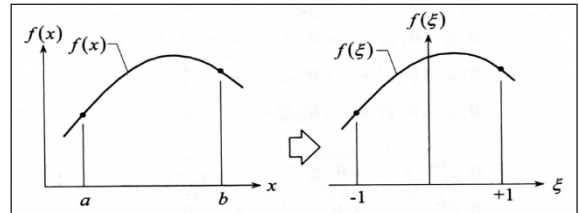


Figure 17: Converting coordinates from x to ξ .

$$E_B(C_B) = \left[E(C_{pB}) \cdot \left(e^{-\left(\frac{t_B}{\eta_B}\right)^{\beta_B}} \right) + E(C_{uB}) \cdot \left[1 - \left(e^{-\left(\frac{t_B}{\eta_B}\right)^{\beta_B}} \right) \right] \right] \div \left(\int_0^{t_{cB}} \left(e^{-\left(\frac{t_B}{\eta_B}\right)^{\beta_B}} \right) dt \right) \tag{20}$$

$$\int_0^{t_c} R(x) dx = \int_0^{t_c} \left[e^{-\left(\frac{x}{\eta}\right)^{\beta}} \right] dx = \int_0^{u_c} \left[(e^{-u}) \left(\frac{\eta}{\beta} u^{\left(\frac{1}{\beta}-1\right)} \right) \right] du = \left[\frac{\eta}{\beta} \right] \cdot \int_0^{u_c} \left[(e^{-u}) \left(u^{\left(\frac{1}{\beta}-1\right)} \right) \right] du; u_c = \left(\frac{t_c}{\eta} \right)^{\beta}$$

$$E_C(C_C) = \left[E(C_{pC}) \cdot \left(e^{-\left(\frac{t_C}{\eta_C}\right)^{\beta_C}} \right) + E(C_{uC}) \cdot \left[1 - \left(e^{-\left(\frac{t_C}{\eta_C}\right)^{\beta_C}} \right) \right] \right] \div \left(\int_0^{t_{cC}} \left(e^{-\left(\frac{t_C}{\eta_C}\right)^{\beta_C}} \right) dt \right) \tag{21}$$

Accordingly, we used Gauss Integration (Gaussian quadratures) for solving $\int_0^{u_c} \left[(e^{-u}) \left(u^{\left(\frac{1}{\beta}-1\right)} \right) \right] du$ in the following steps [23].

3.8 Solving techniques on our mathematical problems

We tried to solve mathematical problems [22] of style in the equation (22).

$$E(C_1) = \frac{E(C_{p1}) \cdot e^{-\left(\frac{t_c}{\eta}\right)^{\beta}} + E(C_{u1}) \cdot \left[1 - e^{-\left(\frac{t_c}{\eta}\right)^{\beta}} \right]}{\int_0^{t_c} \left[e^{-\left(\frac{x}{\eta}\right)^{\beta}} \right] dx} \tag{22}$$

After that, we applied Numerical Methods for solving

$$\int_0^{t_c} \left[e^{-\left(\frac{x}{\eta}\right)^{\beta}} \right] dx$$

Let $u = \left(\frac{x}{\eta}\right)^{\beta}$ and $x = \eta u^{\frac{1}{\beta}}$
 $dx = \frac{\eta}{\beta} u^{\left(\frac{1}{\beta}-1\right)} du$

1. Converting coordinates from x to ξ before the integration by using Gauss Legendre formulas in Figure 17.

2. The Gaussian quadratures provide the flexibility of choosing not only the weighting coefficients (weight factors) but also the locations (abscissas) where the functions are evaluated. When the function is known and smooth, the Gaussian quadratures usually have decisive advantages in efficiency [24].

3. All Gaussian quadratures share the following the equation (23).

$$\int_b^a f(x) dx = \sum_{k=1}^n w(x_k) f(x_k) + R_n(x) \tag{23}$$

Where:

x_k , associated with zeros of orthogonal polynomials, are the integration points.

$w(x)$ is the weighting function related to the orthogonal polynomials.

4. Gauss-Legendre Formula: The Gauss-Legendre integration formula is the most commonly used form of Gaussian quadratures in the equation (24).

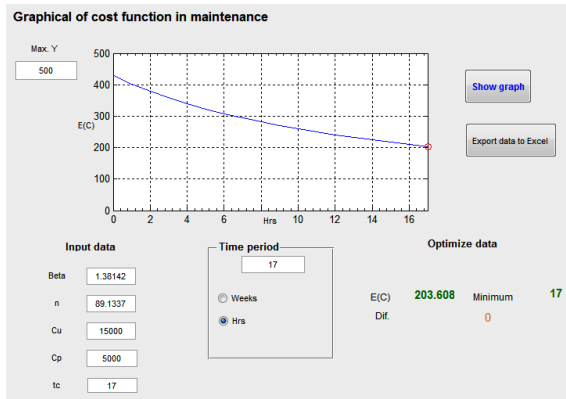


Figure 18: Sample MATLAB for $E(C)$ Calculation.

$$\int_a^b f(x) dx = \int_{-1}^1 f\left(\frac{b-a}{2}\xi + \frac{b+a}{2}\right) \left[\frac{b-a}{2} d\xi\right]$$

$$= \frac{b-a}{2} \int_{-1}^1 g(\xi) d\xi = \frac{b-a}{2} \sum_{k=1}^n w(\xi_k) g(\xi_k) + R_n(\xi)$$

$$= \frac{b-a}{2} \sum_{k=1}^n w(\xi_k) f\left(\frac{b-a}{2}\xi_k + \frac{b+a}{2}\right) + R_n(\xi) \quad (24)$$

Where:

$$\xi = \frac{2x-b-a}{b-a}, \text{ i.e., } x = \frac{b-a}{2}\xi + \frac{b+a}{2}, -1 < \xi < 1,$$

ξ_k is the k^{th} zero of $P_n(\xi)$,

$$w(\xi_k) = \frac{2}{(1-\xi_k^2)[P_n'(\xi_k)]^2},$$

$$g(\xi) = f\left(\frac{b-a}{2}\xi_k + \frac{b+a}{2}\right),$$

$$R_n(\xi) = \frac{2^{2n+1}(n!)^4}{(2n+1)[(2n)!]^3} g^{(2n)}(\xi).$$

5. Thus, we applied MATLAB and Excel about Gauss Integration for solving this model $E(C)$ in Figure 18 and The total expected cost of planned maintenance per time: Total $E(C)$ in Figure 19 [25].

	A	B	C	D	E	F	G	H
1	No.	Machine Code	β	η	tc	Cp	Cu	E(C)
2	1	Motor & Pump 1	1.64093	23,892.70	4,600	15,000.00	350,000.00	532.1
3	2	Motor 2	1.64093	22,135.90	4,400	10,000.00	250,000.00	397
4	3	Motor 3	1.64093	21,433.10	4,600	10,000.00	200,000.00	300.8
5							Total E(C)	1229.9
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7								
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12								
13								
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18								

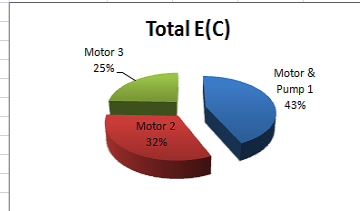


Figure 19: Excel simulation to calculate Total $E(C)$.

4 Case Study Result

The model has been applied to the previous case study by the use of MATLAB and Excel software to generate simulation results. The analysis has been focused on the determination of the maintenance costs over a time period of 36 months after the data history analysis of the treated components of the plant, it is possible to show that Total $E(C)$ consisted of 43% of $E(C)$ on Motor & Pump 1, 32% of $E(C)$ on Motor 2, and 25% of $E(C)$ on Motor 3 in the trend of the reliability function for each criticality class. It can be said that, in spite of their main criticality, the element belonging to Motor & Pump 1 has higher maintenance costs; therefore, the element belonging to Motor 3 has low maintenance costs on analyzing costs which together contribute to generate the total maintenance costs from planned and unplanned maintenance costs.

5 Conclusions

We can make a comprehensive analysis of maintenance strategy and reliability requirements throughout the lifecycle of maintenance. The model has been applied to the previous case study by the use of integrated Reliability Theory on Hazard Rate for optimal cost of maintenance with the number of components in a semi automatic machine of coating to generate suitable results. The analysis has been focused on the determination of the cost throughout the lifecycle of maintenance.

The present work focused on the definition of a model to manage the costs necessary to extend the service life of a plant through the use of probabilistic

methods and Reliability Theory on Hazard Rate in order to better identify the importance of every components in a plant with respect to maintenance costs.

The new model is able to develop a methodology to determine maintenance costs which must be applied to some subsets of the elements of a plant, grouped according to their criticality.

The model allows also to overcome some limits of the classical model, providing a more precise determination of the costs. In fact, the previous data history of the components and the previous maintenance plans together with a probabilistic study are considered in the model to enhance the model to be more accurate [26].

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