Opportunistic Maintenance Based on CUSUM Control Charts

S. Lampreia, V. Vairinhos, V. Lobo & R. Parreira

suzana.lampreia@gmail.com, Valter.vairinhos@sapo.pt, vlobo@isegi.unl.pt, ribeiro.parreira@marinha.pt, Centro de Investigação Naval (CINAV), Alfeite, 2810 Almada, Portugal

J. G. Requeijo

jfgr@fct.unl.pt, Faculty of Science and Technology of the Universidade Nova of Lisbon, Mechanical and Industrial Engineer Department, Lisbon. 2829-516, Caparica, Portugal

ABSTRACT: The use of a Ship Maintenance Management System is fundamental for the good performance of equipments and the entire platform. Over the systematic maintenance, the opportunistic maintenance is a concept that aims to minimize outages and costs preventing undesirable failures. To implement this kind of maintenance statistical methodologies must be used. The Cumulative Sum charts have a very good performance applied to processes control in quality control. We proposed the use of Modified Cumulative Sum control charts to equipment maintenance. The data under study are observations of cooling water and oil temperatures from a diesel generator. In the first phase, we will apply traditional control charts, and, in the second phase, the Cumulative charts with a certain Average Run Length will be used. Then we will compare the results and extract conclusions, presenting measures for improvement.

1. INTRODUCTION

1.1 *Maintenance*

Maintenance can be the secret of success for an industry and for a ship management.

In the last years, because of the crisis some industries, and even ships maintenance changed, sometimes from preventive maintenance to a contingency scenario. Many studies have been carried out aiming the prevention of failures and to enhance the interventions performance intervening equipments when it is imperative and when it is opportunistic.

Opportunistic maintenance can be corrective considering some level of failure allowance (Pham & Wang, 2000). This can be a good maintenance system for continuous equipment monitoring which is

[illegible] can be useful to an opportunistic maintenance management, considering that we can try to predict what´s the tendency of the equipment to suffer an anomaly and how long it will maintain its operational state.

For phase 1 of the study, traditional control charts are used and, for phase 2, the modified Cumulative Sum (CUSUM) control charts are proposed for online condition monitoring. The method is illustrated using observations of two variables on a diesel generator.

2. CONTROL CHARTS IN CONDITION MONITORING

2.1 *Phase 1*

Independent Data

In phase 1 for continuous and independent variables, X and MR control charts are implemented. To define working parameters charts must be in statistical control. To parameters calculation for individual observation 200 observations must be used on first phase considering the Quesenberry (Pereira & Requeijo, 2012) and Lampreia (2013).

Considering $X_t = \mu + \varepsilon_t$, with ε white noise. Where the X is the individual observation and $MR_i = |X_i - X_{i-1}|$

[illegible] (UCL) and the center line (CL) of those charts, are calculated respectively for X chart with $\overline{X}$ and $\overline{X} + 3\sigma_X$, and for MR chart with $\overline{MR}$ and $D_4\overline{MR}$. The parameters are estimated by $\hat{\mu} = \overline{X}$ and $\hat{\sigma} = \overline{MR}/d_2$. The constants D_3, D_4 and d_2 depend on the sample dimension and can be consulted in a table of Pereira & Requeijo (2012).

Autocorrelated Data

If the data is autocorrelated the ARIMA (Autoregressive Integrated Moving Average) models should be applied. The techniques to be applied are the same as those used for independent data in traditional charts, but applied to the residues from the adjustment. Based on the ARIMA model, adjusted by AR(p), MA(q) or ARMA(p,q)), the μ and dispersion σ parameters estimation must be calculated. If there is some outliers those observations must be replaced by the expected values for the corresponding instant; the new residues should be calculated and the same for the reviewed charts. (Pereira & Requeijo, 2012)

If the model is satisfactory, its residues are estimated with $e_t = X_t - \hat{X}_t$ ($\hat{X}_t$ is the expected value for the period *t*). Control charts are built from these residues, obtaining the mean and standard deviation For the model $AR(p)$, the parameters are estimated from the expressions:

$$\hat{E}(X) = \hat{\mu} = \xi \Big/ \left(1 - \sum_{j=1}^{p} \varphi_j \right) \tag{1}$$

and

$$V\hat{A}R(X) = \hat{\gamma}_0 = \sigma_\varepsilon^2 \Big/ \left(1 - \sum_{j=1}^{p} \rho_j \ \varphi_j \right) \tag{2}$$

Where $\hat{E}(X)$ is the estimated mean, ξ is mean process determination process from a *AR(p)* process, and ρ_j is the lag coefficient correlation, and φ_j is the order j parameters from a AR model.

For more details to independent and autocorrelated data Pereira & Requeijo (2012) should be consulted.

2.2 *Phase 2*

Independent Data

"Modified CUSUM" charts are built on cumulative sum –C - defined by (Perry & Pignatiello, 2011):

$$C_t = max\left(0, C_{t-1} + (Z_t - k)\right) \ ; \ C_0 = 0 \tag{3}$$

where $Z_t = \left(\left(\overline{X}_t - T_L\right) / \sigma_{\overline{X}}\right)$, $\sigma_{\overline{X}} = \sigma / \sqrt{n}$, $\Delta = \delta \, \sigma_{\overline{X}}$, $k = \delta/2$ e $T_L = (T_L)_{Standard} - \Delta_S$ and $\Delta_S = \delta_1 \, \sigma$, where δ_1 is constant.

$\overline{X}_t$ is the sample mean at t, T_L is the maximum admissible value, specified by normative or by the manufacturer, σ the process standard deviation, n the sample dimension, Z_t is the reduced form of $\overline{X}_t$, k the reference value and Δ_s is the safety factor. (Barbosa, 2012)

The "Modified CUSUM" chart has two limits; one is the Alert Level (AL), and the second is the Upper Control Level (UCL). The AL and UCL calculations are based on Gan (1991) abacus, in function of ARL (Average Run Length) value for both situations and the reference value k. In this study a significance level $\alpha = 1\%$ ($ARL = 100$) will be considered to define AL and $\alpha = 0{,}2\%$ ($ARL = 500$) to define UCL.

Autocorrelated Charts

For second phase with autocorrelated data, the Modified CUSUM are built based on the C statistic, both calculated by the prediction errors e_t. The prediction errors are estimated at the time τ by $e_\tau(T) = X_{T+\tau}(T) - \hat{X}_{T+\tau}(T)$, where $X_{T+\tau}(T)$ is the value for that time, and $\hat{X}_{T+\tau}(T)$ the predicted value for time τ; the prediction for the present time is the same as the final value of phase 1.

For predicted, values the T_L expression should include the mean so it becomes: $T_L = (T_L)_{Norma} - \mu - \Delta_S$. (Lampreia, 2013)

The CUSUM charts has a higher and consistent sensibility to parameters values variation. (Sibanda & Sibanda, 2007)

3. METHODOLOGY

The proposed methodology is to be applied to repairable systems using statistical control charts, considering both independent and autocorrelated data. Specifically, the following steps must be taken:

- Collect 200 samples of each variable with the diesel generator operational and in a good state (Lampreia, 2013). Check its independence, normality and calculate the functioning parameters:
  - For independent data, build the traditional control charts (X and MR charts).
  - For autocorrelated data fit an ARIMA Model, build $e - MR$ Charts from the residues.
- To monitor vibration process, build the Modified CUSUM chart for independent or autocorrelated data, using the values collected after the anomaly simulation
- Define the standard limits of the variables, and specify the change in the mean to be detected.
- Set the two control limits - AL and UCL.
- Define the intervention rules:
  - Proceed to an inspection, when 6 consecutive points are above the AL.
  - Proceed to a maintenance intervention when 3 consecutive points are above the UCL.

4. CASE STUDY

For the case study two variables will be considered, one represents the generator cooling water temperature (Var1) and the other the Lub oil temperature(Var2); the maximum allowed values are 89ºC and 100ºC respectively.

4.1 *Phase 1*

Studying the variables, using the STATISTICA software, we obtain Var1 autocorrelated and Var2 independent.

For example the data normality for Var1 was verified with the Kolmogorov-Smirnov test, Figure 1, where $D_{Crítico} = \frac{0,886}{\sqrt{N}} = \frac{0,886}{\sqrt{200}} = 0,06265$ for $\alpha = 5\%$,and $d = 0,04659$. Because $d < D_{Crítico}$ the normality condition is accepted.

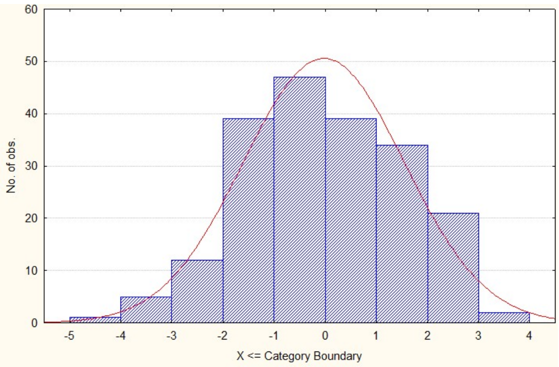

Figure 1. Var1 - Normality Study

Figures 2 and 3 present the autocorrelation function and partial autocorrelation function for variable 1. We are in the presence of an AR4, because we can see a peak in a lag of order 4, the other one´s we´ll be ignored because it has less significance, $p=0,0000$.

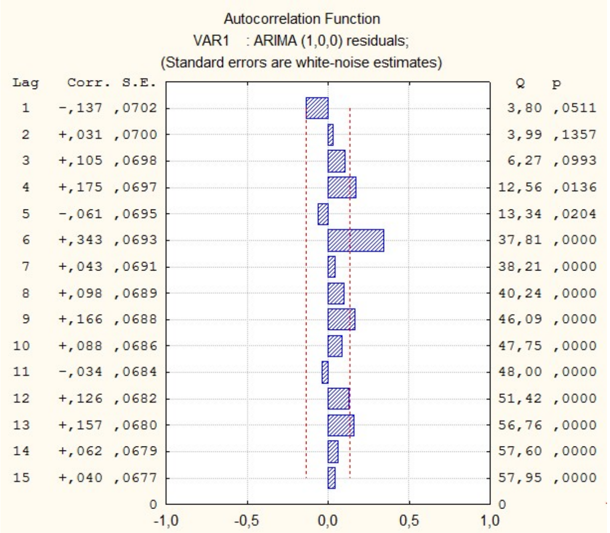

Figure 2. Var1 – ACF with review data

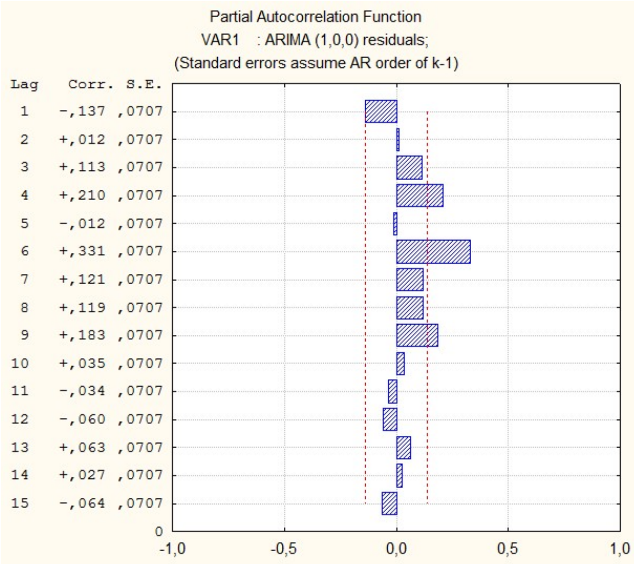

Figure 3. Var1 – PACF with review data

We also calculate the residues using STATISTICA and built the *e –MR* Control charts. In figure 4 we can observe the residues of Var1 without review, and for MR we see two outliers. So the outliers should be substituted with the values calculated from ARIMA model.

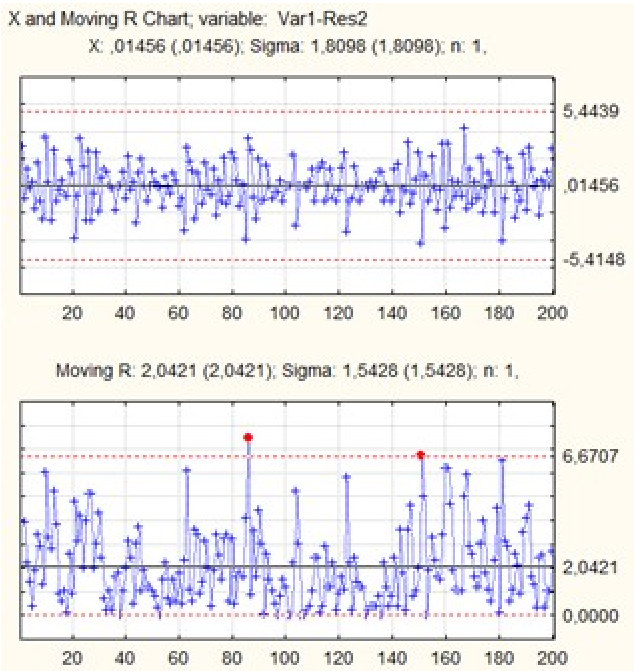

Figure 4. Var1 - Residues *e –MR* Control chart with none review data

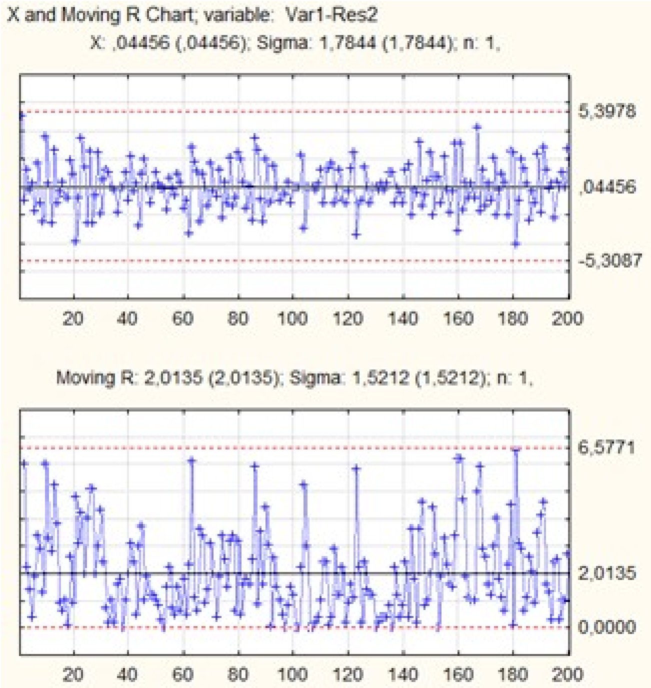

Figure 5. Var1 - Residues *e* –*MR* Control chart with review data

The Var2 parameters calculated are in table 1:

Table 1. Var 2 parameters

μ	ϕ_1	d_2	ξ
72,84	0,6441	1,128	25,92

For Var2 already with the replaced outliers:

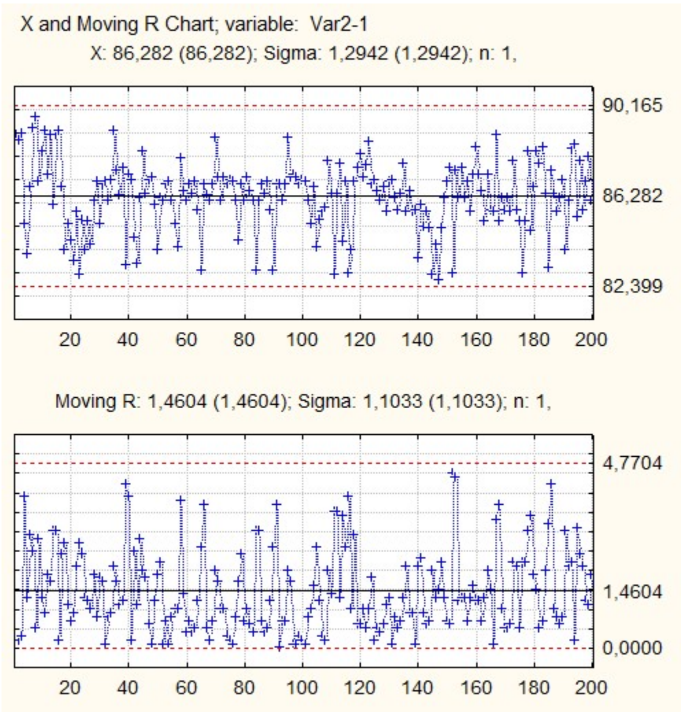

Figure 6. Var2 - *e* –*MR* Control chart with reviewed data

For Var2 the parameters are: μ=86,282, σ=1,9242.

4.2 *Phase 2*

To accomplish this equipment study, because it is operational the data on phase 2 is simulated, considering three anomaly progression steps (1, 2, and 3). For variable 1 we obtained the following limits:

			$K=\delta/2$		
			0.25	0.5	0.75
ARL	500	UCL With α=0,2%	8.5	5.1	3.5
	100	AL with α=1%	5.51	3.5	2.5

For progression 1 none observation above zero it is registered, both for Var1 and Var2.

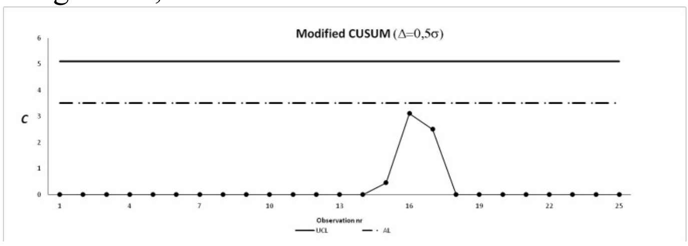

Figure 7. Var1 – Modified CUSUM chart with Δ=0,5σ - 2ªProgressão

In figure 7, we can see the second progression for variable 1, where there isn´t any need of intervention.

Figures 8 and 9 show the third progression where for Δ=0,5σ the sensibility is higher, and it shows a need for inspection on 23 observation.

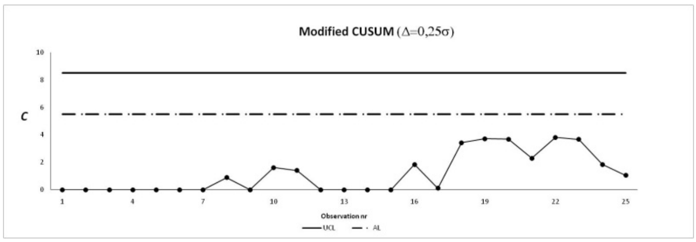

Figure 8. Var1 – Modified CUSUM chart with Δ=0,25σ - 3ªProgressão

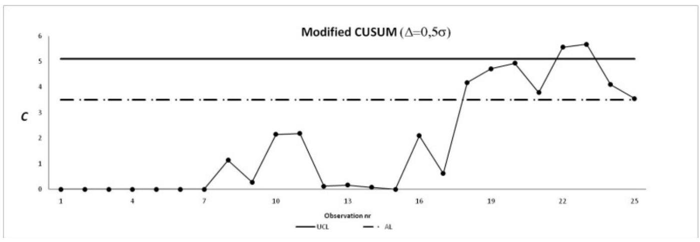

Figure 9. Var1 – Modified CUSUM chart with Δ=0,5σ - 3ªProgressão

Figure 10 show the third progression for Δ=0,75σ and we can observe the need of a maintenance action on observation nr 20. For higher Δ we have higher sensibility.

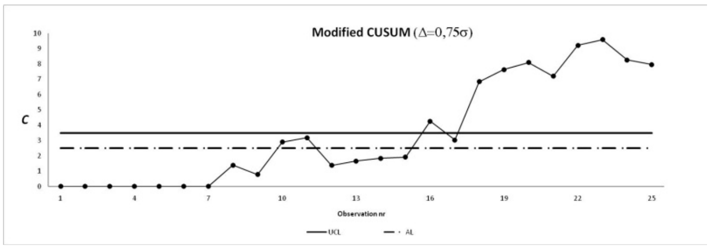

Figure 10. Var1 – Modified CUSUM chart with Δ=0,75σ - 3ªProgressão

For variable 2 in figure 11 we have some values registered but none above the AL, so there´s no need of intervention.

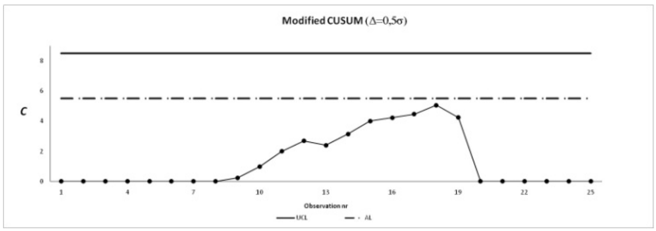

Figure 11. Var2 – Modified CUSUM chart with Δ=0,5σ - 2ªProgression

Analyzing figures 12 and 13, we can observe that, for third progression for variable 1 with Δ=1,0σ, the sensibility is higher than for Δ=0,5σ.

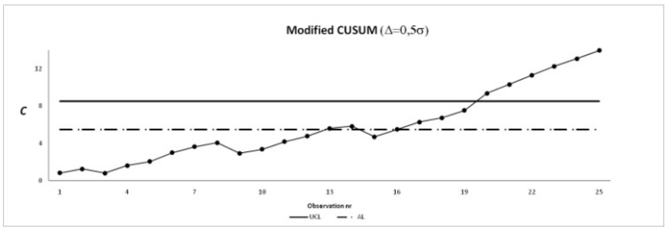

Figure 12. Var2 – Modified CUSUM chart with Δ=0,5σ - 3ªProgressão

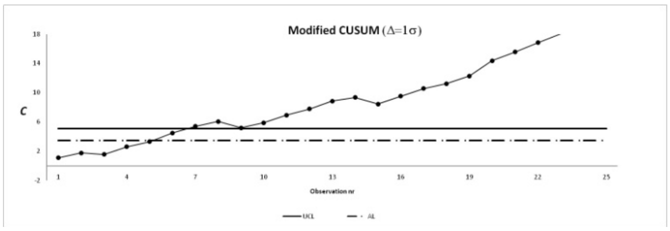

Figure 13. Var2 – Modified CUSUM chart with Δ=1,0σ - 3ªProgressão

Figure 12, in observations 21st, shows that there is a need for inspection and, on 22nd, an intervention action is needed, according to defined rules. Also according to those rules, Figure 13 shows that, since the 11th observation, both an inspection and an intervention action are needed, opportunity maintenance should occur accordingly the equipment availability.

Observing the original data, and the results of the charts, in this case we believe that the Δ=0,5σ is more accurate than for higher values, not showing excessive sensibility.

5. CONCLUSIONS

For the same equipment we obtained one variable independent and other dependent.

For higher Δ we get higher chart sensibility for this variables monitoring.

For autocorrelated data the residues should be used in phase 1 and the expected values in phase 2.

The parameters should be calculated based on a good equipment state data.

The ARL value should be flexible considering the application and the owner specifications and requisites.

The limits of the CUSUM charts and rules for intervention should be adequate to the equipment state and fabricant and owner requisites.

The modified CUSUM control chart can be used for online condition monitoring and in a system submitted to an opportunistic maintenance policy.

We expect that modified CUSUM charts allied to an opportunistic maintenance policy can reduce maintenance costs, planning equipment intervention for the right moment.

6. FUTURE WORK

Test this equipment data with modified multivariate CUSUM charts.

Test other generator variables applying modified CUSUM charts.

Develop software that allows the online monitoring with various variables.

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