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Multivariate Statistical Control Applied in a Marine Propulsion Engine

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ABSTRACT

Changes in the correlation structure between the variables that define a process, can cause deviations which are difficult to detect with the only use of univariate monitoring techniques. This paper applies a methodology based on Multivariate Statistical Process Control (MSPC), which takes into account the correlation between variables.

The combustion process of a 2T marine diesel engine was monitored through Hotelling's T2 multivariate technique for specific ship conditions. The control chart identified sudden changes in the process, which would not have been possible to detect through univariate monitoring. The variables that generated the signals in the process were identified through the technique of decomposition MYT.

1. Introduction.

Nowadays, the new ships have a high level of automation, this allows monitoring in real time a large number of signals (Ferrer 2003). However, the variables are monitored individually generating an alarm when its value exceeds a set threshold, without taking into account the condition of the engine for a particular operation of the ship.

When the variables are significantly correlated, it is not advisable to monitor the variables individually, because the changes in the correlation structure cannot be detected (Ryan 2011). These changes in the correlation structure can generate a setback in the process, even though it seems to be all the same.

The multivariate control charts are capable of detecting observations that cause the breakdown in the correlation structure and it is possible to anticipate the change in relation to the normal operating mode (Hossain, Masud 2016).

In this paper, we implemented multivariate monitoring of the combustion process of a 2T marine diesel engine, installed on a tanker ship, through Hotelling's T2 control charts for some specific working conditions.

In this case, eleven variables of the combustion process were monitored during its normal voyage from Africa to Europe. In the Phase I operation, the Historical Data Set (HDS) was created.

Further, in the Phase II, it was tested to see if a new entry of data generated a signal with respect to the HDS.

Finally, the main variable that caused the state out of range in the process was identified, through Mason, Young and Tracy (MYT) decomposition.

2. Material and Methods.

This section aims to provide a brief description of the LPG maritime transport, highlighting the main characteristics of the LPG as product and its trading, following it with a description of the LPG gas carriers.

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The combustion process of a 2T marine diesel engine with 19,620 kW, installed in a tanker ship was monitored (MAN 2016). Our study only focused on the loaded condition, monitoring the behavior of combustion process in the main engine during its voyage from Africa to Europe.

The analyzed variables were the following: Engine Load, Fuel Index, Turbocharger speed Rpm (they were measured in the local control), Fuel Plunge Stroke (it is the average of the value of all the injectors), Scavenge air cooler air inlet temperature (it was measure from inlet of intercooler), Exhaust gas temperature at turbine inlet (it was measure from inlet of turbocharger), P (scav) (air pressure inlet combustion chamber), Estimate Effective Power, Compression Pressure (Pcom) and Maximum Pressure (Pmax) (they were the average of the value of all the cylinders, measured in the combustion chamber) and SFOC (fuel oil consumed by the engine). For the selection of these, we have had the collaboration of the ship's engineers, and the manufacturer?s data.

There were taken 47 valid samples during one voyage, through monitoring systems and data acquisition of main engine, under the following conditions of normal operation mode: Speed over ground (SOG) between 12 and 14 knots with less than 18% slip, average temperature of sea water of 20 ºC, average ambient temperature in the engine room of 30 ºC and average temperature of the engine room of 37 ºC.

Because the number of acquired samples was not enough to apply the technique T^2, through cubic spline interpolation (McKinley, Levine 1998, n=599 samples were generated of each variable to create the preliminary database.

The minimum, maximum, mean and standard deviations values of each are listed in Table 1. Each variable was identified with a correlative numbering.

The first phase was to build Historical Data Set (HDS), from the selected variables.

The beta distribution was used in the purging's process of outliers (Mason, Chou et al. 2003), produced by measurements errors. Considering a purging procedure where a single vector of 599 samples of preliminary data base $X'=(x_1, x_2,...,x_p)$ is to be monitored for control of the process using a T^2 chart. We assume that the data follow a multivariate normal (MVN) distribution with an unknown mean vector μ and unknown covariance matrix Σ.

From the preliminary data base, we obtained estimates of mean vector $\overline{X}$ and covariance matrix S of μ and Σ. We began the purging process by making an initial pass through the preliminary data base. For a given α=0,05, all observation vectors whose T^2 values are less than or equal to the Upper Control Level (UCL) will remain in the data set, the T^2 values are computed (Hotelling 1947) as:

$$T^2=\left(X_i-\overline{X}\right)'\ S^{-1}\left(X_i-\overline{X}\right) \tag{1}$$

Where the upper control limit is determined by:

$$UCL=\left\{\frac{(n-1)^2}{n}\right\}\beta_{\{\alpha;\frac{p}{2};(n-p-1)/2\}} \tag{2}$$

Where p, is the number of variables; n, is the size of data set and $\beta\{\alpha; p/2; (n-p-1)/2\}$, is the upper αth quantile of the beta distribution $\beta\{p/2; (n-p-1)/2\}$.

If the value of T^2, which was monitored for an observation, exceeded the UCL, observation was purged from the preliminary data. With the remaining observations, we calculated new estimates of the mean vector and covariance matrix. Again, we removed all detected outliers and repeated the process until a homogeneous set of observations was obtained.

The final set of data was the HDS, the normal mode operation of the process, formed by 333 samples, listed in Table 2.

In the second phase, it was tested to see if a new entry of data generated a signal with respect to the HDS. Considering a continuous steady-state process where the observation vector is independent and the parameters of the underlying normal distribution are unknown and must be estimated. We assume the process is being monitored by observing a single vector of 13 new samples $X'=(x_1, x_2,..., x_p)$ on p variables at each point, listed in Table 3, acquired during one voyage in loaded condition, after having analyzed them according to the criteria of the normal condition of the operation.

The T^2 Hotelling´s value associated with X is given by:

$$T^2=\left(X_i-\overline{X}\right)'\ S^{-1}\left(X_i-\overline{X}\right) \tag{3}$$

Where, the common estimates $\overline{X}$ and S are obtained from the HDS. Here, the T^2 statistic (Mason, Young 2002) follows the F distribution. For a given α=0, 05, the UCL is computed as:

$$UCL=\left\{\frac{p\,(n+1)\,(n-1)}{n\,(n-p)}\right\}F_{\{\alpha;p;(n-p)\}} \tag{4}$$

Where: p, is the number of variables, n, is the size of the HDS and $\{\alpha; p; (n-p)\}$, is the upper αth quantile of the $F\{p; (n-p)\}$.

The values of T^2 which exceeded the UCL, were declared as signals and this concluded that the observation was out of range with respect to the mode of normal operation of the process.

Once the T^2 statistical detected samples which were out of range in the process from normal operating conditions, to identify the variables with more weight, responsible for state out of range for each sample, the MYT decomposition was used (Bersimis, Psarakis et al. 2007), (Agog, Dikko et al. 2014). The general decomposition for "p" variables of the Hotelling´s T^2 statistic, follows the equation:

$$T^2=T_1^2+T_{2.1}^2+T_{3.1,2}^2+T_{4.1,2,3}^2+\ldots T_{P.1,\ldots,P-1}^2=T_1^2\int_{j=1}^{P-1}T_{j+1.1,---,j}^2 \tag{5}$$

The final T^2 value, T_1^2, is Hotelling´s statistic for the first variable. It reduces to the square of the univariate t statistic for the initial variable:

$$T_1^2=\frac{\left(X_1-\overline{X}_1\right)^2}{S_1^2} \tag{6}$$

Table 1: Minimun, means and standard deviations.

N.º	Variables	Unit	N	Min. Value	Max. Value	Means(μ)	Standard deviations (σ)
1	Engine Load	%	599	54	61	56.81	1.42
2	Fuel Index	%	599	62.4	70.7	65.09	1.61
3	Fuel plunger stroke	mA	599	2.58	2.77	2.66	0.03
4	Scavenge air cooler air inlet Tª	ºC	599	142	160	149.24	4.11
5	Exhaust gas Tª at turbine inlet	ºC	599	353	408	372.43	14.93
6	Turbocharger speed	r.p.m.	599	10366	11206	10821.55	174.32
7	P (scav)	Bar	599	1.55	1.96	1.83	0.15
8	Estimate Effective Power	kW	599	10316	10936	10536.81	121.95
9	Pcom	Bar	599	109.18	129.72	123.94	5.42
10	Pmax	Bar	599	138.37	142.59	140.74	1.05
11	SFOC	g/kWh	599	154.28	164.36	158.48	1.96

Source: Authors.

Where, $\overline{X}_1$ and S_1 is the mean and standard deviation of variable X_1.

The statistic $T^2_{P.1,...,P-1}$ is the pth component of the vector X_i adjusted by the estimates of the mean and standard deviation of the conditional distribution of X_p given X_1, X_2, ..., X_{p-1}. It is given by

$$T^2_{P.1,...,P-1}=\frac{\left(X_{ip}-\overline{X}_{P.1,\ ...,\ P-1}\right)}{S_{p.1,\ ...,p-1}} \quad (7)$$

Where:

$$\overline{X}_{P.1,\ ...,\ P-1} = \overline{X}_P + b_p'(X_i^{(p-1)} - X^{(p-1)}),$$

$\overline{X}_P$ is the sample mean of n observations on the pth variable, $b_p = S^{-1}_{XX^s xX}$ is a (p-1) – dimensional vector estimating the regression coefficients of the pth variable regressed on the first p-1 variables, $S^2_{p.1,...,p-1} = S^2_X - S'_{xX} S^{-1}_{XX^s xX}$ and

$$S = \begin{pmatrix} S_{XX} & S_{xX} \\ S'_{xX} & S^2_X \end{pmatrix}.$$

3. Results.

Through Hotelling´s T^2 control chart were monitored eleven variables of the combustion process to detect changes significant in the normal operation condition. The UCL for the chart was 20.68, with α=0.05. Considering the data listed in Table 2 as the HDS, T^2 values were calculated according (3), for the 13 new incoming observations, and they were monitored in a T^2 control chart. See Fig. 1.

The control chart detected that all observations were out of range, above the UCL.

After this, through the technique of decomposition MYT, each T^2 value was decomposed for each one of the signals. The variables which had contributed most strongly to the value of T^2 being above the UCL were identified. The decomposition is listed in Table 4.

The SFOC was identified as the main variable that caused the deviation from its normal operation mode, using Mason, Young and Tracy decomposition (MYT).

Due to the fouling in the intercooler to keep the rpm of the engine it was generated an increase of fuel consumption.

Conclusions

Hotelling's T^2 multivariate control chart proved to be effective in detecting the existence of deviations in the combustion process of the propellant engine, even though the currently implemented system of univariate monitoring, indicated that the process did not show any kind of deviation.

The decomposition of the T^2 statistical through the MYT technique, facilitated the diagnosis of the changes in the process that gave rise to the deviation, giving the ship's engineers a set of indicators able to show which had been the variable that had broken the correlation between them defined by the HDS.

Table 2: Part of HDS.

Nº. Obs	Variable identification number										
	1	2	3	4	5	6	7	8	9	10	11
1	55.81	64.53	2.67	145.2	401.1	10490.52	1.59	10395.79	110.97	139.82	154.98
2	56.3	65.04	2.68	145.81	401.61	10504.45	1.59	10418.04	111.14	140.04	155.2
3	56.81	65.55	2.69	146.44	402.14	10518.42	1.6	10441.52	111.31	140.25	155.43
4	57.3	66.04	2.7	147.08	402.68	10532.25	1.6	10465.55	111.47	140.46	155.67
5	57.77	66.49	2.71	147.7	403.2	10545.74	1.61	10489.41	111.64	140.65	155.9
6	58.19	66.9	2.71	148.31	403.7	10558.70	1.61	10512.39	111.79	140.81	156.11
7	58.54	67.23	2.72	148.88	404.16	10570.92	1.61	10533.79	111.93	140.95	156.29
8	58.82	67.47	2.72	149.4	404.57	10582.22	1.62	10552.89	112.06	141.06	156.44
9	59	67.6	2.72	149.87	404.92	10592.39	1.62	10569.00	112.17	141.13	156.55
10	59.07	67.61	2.72	150.27	405.2	10601.27	1.62	10581.57	112.26	141.16	156.61
11	59.04	67.52	2.71	150.59	405.4	10608.76	1.62	10590.72	112.32	141.15	156.63
12	58.93	67.33	2.71	150.85	405.54	10614.82	1.63	10596.76	112.36	141.1	156.61
13	58.74	67.07	2.7	151.03	405.62	10619.40	1.63	10599.97	112.38	141.02	156.57
14	58.49	66.75	2.69	151.13	405.65	10622.42	1.63	10600.65	112.38	140.92	156.5
15	58.2	66.38	2.68	151.16	405.63	10623.83	1.62	10599.08	112.36	140.8	156.42
16	57.88	65.99	2.67	151.11	405.56	10623.58	1.62	10595.57	112.32	140.67	156.34
17	57.53	65.59	2.66	150.98	405.46	10621.61	1.62	10590.40	112.27	140.52	156.25
18	57.18	65.19	2.65	150.78	405.33	10617.85	1.62	10583.87	112.19	140.37	156.18
19	56.84	64.82	2.64	150.49	405.17	10612.27	1.62	10576.28	112.1	140.22	156.12
20	56.52	64.49	2.64	150.12	404.98	10604.79	1.62	10567.90	111.99	140.08	156.09
21	56.24	64.21	2.63	149.67	404.79	10595.35	1.61	10559.05	111.86	139.94	156.08
22	56	64	2.63	149.14	404.58	10583.91	1.61	10550.00	111.72	139.82	156.12

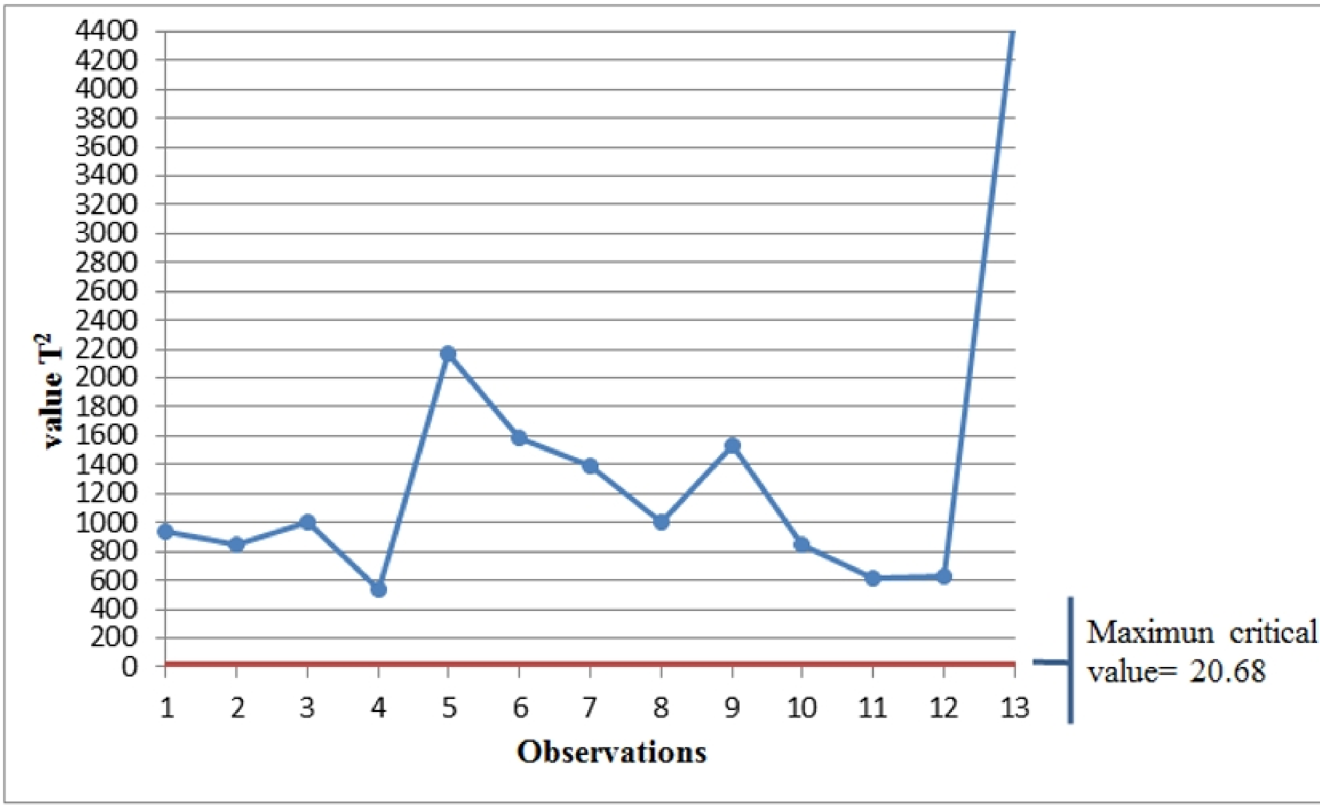
Source: Authors.

Table 3: New observations.

Nº. Obs	Número de identificación de variables										
	1	2	3	4	5	6	7	8	9	10	11
1	57	64.7	2.67	155	373	10992	1.89	10808	126.98	140.8	176.27
2	57	66.3	2.73	155	373	11052	1.89	10782	127.17	141.8	176.35
3	58	64.5	2.73	155	372	10960	1.9	10758	127.3	141.8	175.55
4	61	68.4	2.77	160	378	11260	2.01	11128	130.32	142.1	175.53
5	59	66.3	2.73	160	375	11076	2.06	11229	130.47	142.1	177.71
6	60	65.7	2.75	160	381	11159	2.01	11144	128.45	141.4	177.63
7	61	69	2.83	150	369	10987	2.03	11173	130.6	143.1	179.27
8	57	66.9	2.78	155	370	11048	1.95	10947	128.98	142.5	178.86
9	57	64.7	2.7	150	369	10906	1.93	10849	127.72	141.9	179.21
10	62	69.5	2.75	155	369	11139	2.02	11267	131.63	143.2	180.57
11	60	65.4	2.8	155	368	11154	2.07	11410	133.03	144.5	175.27
12	58	64.3	2.73	155	369	11070	1.99	11111	130.42	142.8	175.22
13	59	65.9	2.8	150	352	10141	2.04	11195	135.1	145.6	162.86

Source: Authors.

Figure 1: T^2 Multivariate Control Chart.



Source: Authors.

Table 4: T^2 decomposition.

N.º Observations	Variable identification number	Variables
1	11	*SFOC*
2	11	*SFOC*
3	11	*SFOC*
4	11	*SFOC*
5	11	*SFOC*
6	11	*SFOC*
7	11	*SFOC*
8	11	*SFOC*
9	11	*SFOC*
10	11	*SFOC*
11	11, 8	*SFOC*, Estimate Effective Power
12	11	*SFOC*
13	8, 10	Estimate Effective Power, Pmax

Source: Authors.

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