A New Intelligent Approach in Predictive Maintenance of Separation System

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ABSTRACT: Reducing contaminant emissions is an important task of any industry, included the maritime one. In fact, in April 2018, IMO (International Maritime Organization) adopted an Initial Strategy on reduction of Greenhouse gas (GHG) emissions from ships. An essential part responsible for producing these emissions is the diesel engine. For that reason vessels include separation systems for heavy fuel oils. The purpose of this work is to improve the predictive maintenance techniques incorporating new intelligent approaches. An analysis of vibrations of this separation system was made and their characteristics were used in a Genetic Neuro-Fuzzy System in order to design an intelligent maintenance based on condition monitoring. The achieved results show that the proposed method provides an improvement since it indicates if a maintenance operation is necessary before the schedule one or if it could be possible extend the next maintenance service.

1 INTRODUCTION

Recently, relevant advances in predictive maintenance have been developed, since it has been demonstrated that it is the most suitable and efficient method (Muszynska, 2005; Wang et al., 2017; White, 2010). This technique is based on the basis that machinery will show unusual behavior before of failing. In the maritime industry is especially useful (Gkerekos et al., 2017; Go et al., 2013; Jakovlev et al., 2017) owing to the fact that any unexpected failure during a journey can make a danger.

One of the most interesting predictive maintenance is which based on vibration analysis given that it is the non-destructive tests that provides the greatest amount of information about internal functioning of a machine (Martini and Troncossi, 2016; White, 2010). Therefore, knowing its normal signature of vibration, it is possible to prevent a breakdown by monitoring. In this way, vibrations are indicator of a potential problem. Therefore, to count on indirect monitoring systems would be very advantageous to preventively maintain aboard and hence to avoid damages. Separation systems for heavy fuel oils are considered to be complex mechanical systems and their reparation is usually difficult. Owing to its complexity, a wide monitoring of its behavior is essential in order to detect incipient failures. Thus, a sensor that can measure vibrations should be incorporated. The maintenance of these systems is based on preventive maintenance scheduled from their working hours. In other words, when a certain number has been achieved, a preventive scheduled maintenance is carried out. Nevertheless, with a monitoring, it could be possible to extend the next maintenance service if the system is healthy or make it scheduled ahead of time if the separator system shows failure indications. For this, it is essential to design a technique in order to conveniently extract and process this amount of information.

The application of artificial intelligence (AI) in machine diagnosis has been widely investigated in different fields (M. Samhouri , A. Al-Ghandoor , S. Alhaj Ali , I. Hinti, 2009; Simani et al., 2003). Recently, there is a tendency for the use of genetic algorithms (Baojia et al., 2018; Cerrada et al., 2015; Gou et al., 2018; He et al., 2017). The purpose of this work is to combine predictive maintenance based on condition monitoring, with a genetic neuro-fuzzy system. The proposed intelligent algorithm intends to process the measured vibrations and provides information about the internal state of the heavy fuel oil separators. For that, several actual measurements were carried out on board separators of Ro-Pax vessel.

In Section 2 a description of the heavy fuel oil separation system used in the actual experimental tests and an explanation of the measurement procedure are explained. In Section 3 the signal processing method based on artificial intelligence techniques is exposed. Section 4 shows the results and finally in Section 5 conclusions are presented.

2 EXPERIMENTAL STUDY

With the purpose of collecting vibration data from separators, several actual measurements were carried out on board centrifugal heavy fuel oil separators of Ro-Pax vessels to transport passengers and freight. Figure 1 shows the model Alfa Laval SA 861 separator used in this work, which technical characteristics are exposed in Table 1.

Figure 1. Marine Fuel Separators Alfa Laval SA 861.

As it was mentioned previously, vibration measurements were used in order to detect changes in the behavior of machinery. For this reason, a triaxial accelerometer sensor, Bruel & Kjaer 4504A (Bruel & Kjaer, Naerum, Denmark) was attached to separator system. In each separator ten consecutive vibration measurements were made for 2 seconds with a sampling frequency (Fs) of 2560 Hz. The used sensor has three independent outputs for simultaneous high-level measurements in three mutually perpendicular directions. The sensitivity of the accelerometer is 10 mV/g, and it measures a range of up to 9.0 KHz, and its lower bound of the sensing frequency range is 1 Hz. The orientation of the accelerometer is as shown in Figure 2: the X axis is vertical, the Y axis goes through from right to left, and the Z axis traverses the device from front to back. Figure 2 shows the final assembly where it can be seen that the accelerometer was connected to a Brüel&Kjaer PHOTON+ dynamic signal analyzer and this one to a laptop where the measurements were recorded [30]. The PHOTON+ consists of data acquisition hardware and PC software able to measure, to record, to analyze and to post-process. It allows for real-time signal analysis. In fact, it could be used as a FFT analyzer with a measurement dynamic range of 115 dB and an 84 kHz real-time rate.

Table 1. Technical characteristics of Marine Fuel Separators Alfa Laval SA 861.

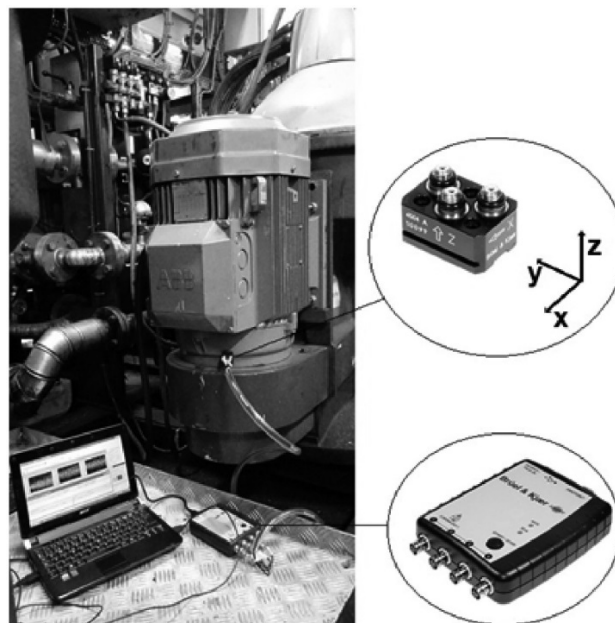| Characteristics	Values
Belt transmission	UFT-21
Electrical current frequency	50 HZ
Motor power (50 Hz)	18.5 kW
Motor speed synchronous (50Hz)	3000 rpm
Max. density of feed/sediment	1100 / 2057 kg/m³
Max. density of operating liquid	1000 kg/m³
Feed temperature, min./max.	0°C to 100°C
Max. viscosity of operating liquid	700 cSt at 50°C.

Figure 2. Final assembly of accelerometer and PHOTON+ analyzer.

3 INTELLIGENT APPROACH

The maintenance of majority of machineries onboard is based on the number of hours. Particularly, the separator systems are revised when they has been working 12000h. This kind of maintenance is not efficient, since it is often possible to keep the device working as long as it does not show sign of failure.

On the other hand, it is also possible that a maintenance operation should be done before a scheduled one because of a failing piece. For this reason, this work tries to find an efficiency-based maintenance method for the oil separators through intelligent condition monitoring. The number of working hours has been considered as a key parameter in this work. In this sense, it would be convenient to associate this factor with the internal state of the system, that in this paper it is studied through the vibration signature.

In order to collect data, real vibrations were measured over on board separators systems. These recorded vibrations are analyzed by a signal processing stage with the purpose of obtaining their internal characteristic parameters. In this research, a FFT is applied in order to get the frequency domain of the separator vibrations. The first five frequencies with greater amplitude were collected, along with their corresponding amplitudes as indirect parameters. With the aim of linking these pair of data, that is, the internal state of the separator, with the number of working hours, an intelligent method based on training was used. Specifically, a three layers genetic neuro-fuzzy system (Cordón et al., 2004; Marichal et al., 2016; Nobre, 1995), with an analogous structure to the one proposed by Jang (Jang, 1993). System inputs are introduced to the first layer, which represent the membership functions, and the outputs of this layer are expressed by Equation 1.

$$\varphi_{ij} = \exp\left(\frac{-\left(U_i - m_{ij}\right)^2}{\sigma_{ij}^{\ 2}}\right) \begin{array}{l} i= 1,2,\ldots, N_1 \\ j=1,2,\ldots,N_2 \end{array} \tag{1}$$

where N_1=input number; N_2=number of nodes of the intermediate layer; u_i= i-th input, m_{ij}=center of the membership function; σ_{ij}=the width of the membership function, φ_{ij}= output neuron with the i-th input and the output connected to the j-th node of the intermediate layer.

The second layer outputs correspond to the rule system, and it is shown in Equation 2.

$$\varepsilon_i = \min\left|\varphi_{1j}, \varphi_{2j},\ldots,\varphi_{N_1 j}\right| \quad j = 1,\ldots, N_2 \tag{2}$$

Finally Equation 3 represents the global output,

$$Y_k = \frac{\sum_{j=1}^{N_2} sv_{jk}\varepsilon_j}{\sum_{j=1}^{N_2}\varepsilon_j} \quad k=1,\ldots,N_3 \tag{3}$$

where N_3= genetic neuro-fuzzy output number; sv_{jk}=estimated value of the k-th output given by the j-th node.

As Equations (1)–(3) show, the genetic neuro-fuzzy system depends on the center and width of the membership function, the estimated system outputs and the number of nodes of the intermediate layer. These parameters are fixed through a three-phase learning algorithm. Initial values and an optimization of the number of nodes of the hidden layer are

established in the first two phases. Then at the third phase these parameters are reset.

3.1 Fist Level: Unsupervised Learning Phase

In this first phase, the initial values to m_{ij} and sv_{jk} are provided by a Kohonen's self-organizing [37] map, where their inputs are:

$$V = \left(U_1 U_2 \ldots U_{N_1} Y_1 Y_2 \ldots Y_{N_3}\right) \tag{4}$$

The vector (U_1 U_2…U_{N1}) is the input vector to the genetic neuro-fuzzy system, and (Y_1 Y_2…Y_{N3}) is the desired output vector. Equation (5) shows the necessary initial weight vector of the self-organizing map and it is acquired by the mean between the maximum and minimum of the input set by the user.

$$W_j = \left(w_{1j} w_{2j} w_{3j} \ldots w_{N_1+N_3, j}\right) j = 1, 2, \ldots, N_2 \tag{5}$$

An update of the weights is achieved after a monodimensional Kohonen self-organizing map is applied, since it provide the winner node.

$$m_{ij} = w_{ij}; j = 1, 2, \ldots, N_2; i = 1, 2 \tag{6}$$

This algorithm is an unsupervised learning algorithm; therefore, once the process has been completed and the winner node has been obtained, the center of the membership functions (m_{ij}) is fixed, and then the estimated system outputs (sv_{jk}) will be carried out.

This phase is crucial, since the initial assignment establishes the starting point. In the following learning phases, these parameters will be modified from the initial ones.

3.2 Second Level: The Genetic Algorithm Phase

In this phase a genetic neuro-fuzzy system is built, since in the previous one N_2, m_{ij}, and sv_{jk} were obtained, but then there are still values for the parameters σ_{ij} missing. Moreover, an optimization process is necessary in order to obtain a minimum number of rules. Then, in this phase will be accomplish a more reduced number of nodes in the hidden layer.

The genetic algorithm (Cordón et al., 2004; Nobre, 1995; Rajasekaran and Pai, 2003) used in this phase is based on the biological model of genetic evolution. On the one hand, there is an individual with basic information, particularly a vector; on the other hand, there are genes, in this work they are the vector components. Therefore, the components of each vector represent the hidden nodes by a Boolean parameter and the width of the membership functions. Following, a fitness function is defined, taking into account the difference between the real outputs and the individual outputs. Once the genetic neuro-fuzzy algorithm is applied, individual

satisfactory values for σ_{ij}, and an adequate set of N_2 rules (nodes on the hidden layer) can be reached.

3.3 *Third Level: Supervised Learning Phase*

The last phase attempts to improve the initial values for the m_{ij}, σ_{ij}, and sv_{jk} parameters. Owing to the fact that the system used in this work is similar to a three layer neural network, the same mathematical expression as the neurons in a radial basis neural network (Chen et al., 1991) has been used to express the nodes on the input layer of the genetic neuro-fuzzy system. Furthermore, the least mean squared learning algorithm has been also applied. Finally, the criterion function (Equation 8), defined as the error function between the outputs of the genetic neuro-fuzzy system (ψ_k) and the real outputs (Y_k), is intended to minimize.

$$E = \frac{1}{2}\sum_{k=1}^{N_3}\left(Y_k - \psi_k\right)^2 \qquad (8)$$

4 RESULTS

As it was mentioned in previous sections, vibration signals were collected in the vessel and a signal processing was carried out in order to extract the information about the state of the system. In this work, a traditional FFT was applied and the five dominant frequencies were obtained in each measurement. An example of a vibration measurement is shown in Figure 3. This graph displays a vibration measured on the Y axis.
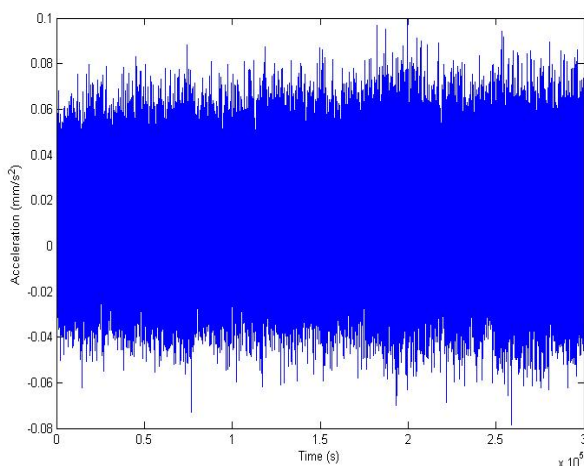

Figure 3. An example of vibration signal on the *Y* axis.

Figure 4 displays the corresponding frequency spectrum of previous vibration. At this point is necessary to remark that every measurement including in this work was carried out in a real vessel in the middle of actual journeys.

The main purpose of this work is to reach that the exposed intelligent method allows relating the vibration signature with the corresponding working hours. For that reason, the five dominant frequencies

with their corresponding amplitude FFTs were used as input vectors to the genetic neuro-fuzzy system. The output intelligent system would be the number of hours of the oil separator had been running at the moment that vibration signal was measured. With this input-output data set, once the system has been trained, it will be able to provide the number of hours that it had been working.
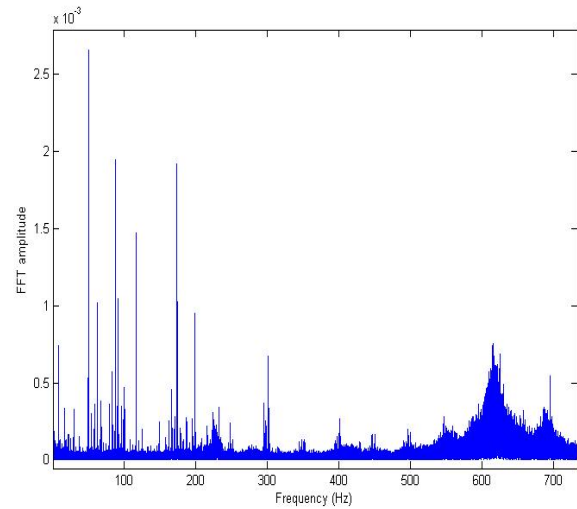

Figure 4. Frequency spectrum of the signal shown in Figure 3.

Several trials were carried out with the input–output data set in each training phase previously explained, in order to obtain the parameters that provide an satisfactory error value. The training process has been developed with 70% of the data, since the other 30% was reserved to check the generalization capability of the algorithm. If the genetic neuro-fuzzy system provides adequate outputs to unknown input values (data that had not been used in the training process), then a suitable level of generalization has been reached.

After all training phases have been concluded, one with a minimum error function is chosen. Figure 5 shows the results of the genetic algorithm phase. After 12 generations, the best fitness value was quite similar to the mean, and after 48 generations, the average value between individuals was zero; this means that the genetic neuro-fuzzy system has achieved good training.
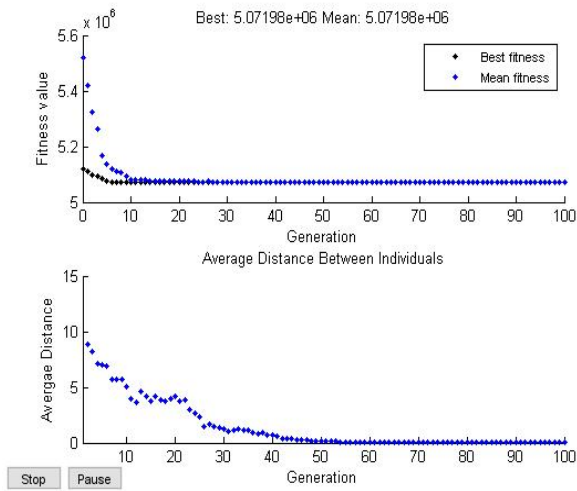
Figure 5. Evolution of the fitness value and the average distances between individuals.

Moreover, if more particular results were evaluated, satisfactory parameters were obtained as well. In this case, the genetic neuro-fuzzy system reached a training error of 2277 h, and a generalization error of 1872.8 h. Analyzing these error, it could be said that are acceptable, since the on board heavy fuel oil separators used for this work had been working between 3196 and 12236 hours.

As a final point, a comparative table is presented in order to ensure that the genetic algorithm reached a suitable generalization level. Table 2 shows a comparison between the real value of the working hours corresponding to a separator system and the value provided by the trained genetic neuro fuzzy system. It is essential to highlight that the input values used for generating this table are unknown for the system, that is, they were not included to the training.

Table 2. Comparison between outputs provided by the genetic neuro-fuzzy system, and the real values of the working hours.

Real Working Hours	Working Hours Provided by Genetic Neuro Fuzzy
3196	2776
3090	4338
3078	4231
6300	6411
12236	10145
5621	4725
6476	4996

5 CONCLUSIONS

The exposed research presents an intelligent condition-based maintenance for heavy fuel oil separators based on genetic neuro-fuzzy system. Vibration measurements were carried out on board real vessels with the purpose of to relating these vibrations and the internal state of the separation systems. The collected data were processed in order to obtain their characteristic parameters. In this work, a Fast Fourier Transform allowed for extracting the frequency domains of the separator vibrations and their corresponding amplitudes. This packet of data was used as input set for the training algorithm. Each input vector was fixed with the number of working hours that each fuel oil separator had been running for until the measurement moment.

Once the training process has been finished, it is possible to conclude that there is a vibration signature capable of providing useful information in order to preventing damages. This is because of there is a relationship between vibration and the internal state, and, therefore, a trained system can indicate the number of working hours that the system have been running for. The fact that a monitoring and a trained system are included presents an advance over the traditional preventive scheduled maintenance. Whereas the preventive maintenance is carried out when a certain number of hours has been achieved, the proposed method can indicate whether it is possible to extend the next maintenance service if the separator is healthy, or if it is required to execute maintenance ahead of time if any failure indications are shown. This potential is an advantage to shipowners, since it can prevent breaks or delay a revision, and consequently, it would involve an economic improvement.

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