A NEW APPROACH TO FAULT DIAGNOSIS IN AGRICULTURAL TRACTOR MECHANICAL GEARBOX

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Abstract
This paper proposes a new expert system tool in order to diagnose with a great accuracy and speed the existence of faults – failures in an agricultural tractor mechanical gearbox. In addition, the system is able to diagnose which of the bearings is not operational so that the repair becomes selective and the maintenance cost-effective. The research showed that such problems could be dealt with using Neural Networks. The Bayesian Multilayer Perceptron Neural Network with Automatic Relevance Determination (MLP-ARD) makes a good approach. Time and frequency-domain vibration signals of normal and faulty bearings are processed for feature extraction. These features from all the signals are used as input to the MLP-ARD. The experimental results show that the proposed approach is highly accurate regarding different bearing fault detection. This approach will be extended with regards to real-time fault detection of rotating parts in agricultural vehicles where the anticipation of detection of incipient failure can lead to reduced downtime.

Key words: condition monitoring, expert system, bearings, reliability, MLP-ARD neural network.

INTRODUCTION

In our days, agricultural tractors are the most important part of agricultural machinery. Without them agricultural operations such as plowing, planting and harvesting would not be feasible. Hence, agricultural tractors should be maintained correctly in order to ensure that they work effectively for a long period without any serious breakdown. A tractor that breaks down and must be prematurely maintained incurs large expenses.

The gearbox is one of the most important components of an agricultural tractors mechanical transmission system. Its function is to transfer power of revolution from one shaft to another. Therefore, the gearbox fault diagnosis is crucial to prevent the mechanical system from malfunctioning that could cause serious damages or the entire system to halt, even personnel casualties (LOUTRIDIS, 2008). So, it is very important to detect and diagnose early faults that may arise in such gearboxes.

The gearbox has a significant number of moving components (axles, gears and bearings). These components give rise to vibration. Every component has a unique – specific vibration signature related to the construction and the operating condition of it. If the operating condition of the component changes, the vibration signature will also change. This change in combination with acoustic emission can be used to detect faults before they become critical.

Bearing as one of the basic gearbox components, plays an important role in many transmission systems. Early fault diagnosis of bearing may prevent unnecessary failures of most of the rotating machinery system and thereby increase operational reliability and availability of the machine. It is well known that when a fault appears at a single gearbox bearing, all bearings are replaced even though most of them are still operational. This happens because it is impossible for the technician to diagnose exactly which bearing is faulty. As a result, every bearing of the gearbox is replaced, increasing the total repair costs.

In the last decades, many researchers have developed different fault diagnosis methods. One of the principal tools for diagnosing bearing faults is the vibration-based analysis (HENG AND NOR, 1998; RANDALL ET AL., 2001; STACK ET AL., 2006; DU AND YANG, 2006). Using signal processing techniques in vibration signals, it is possible to obtain vital diagnostic information (LEI ET AL., 2008). Fault signal detection and recognition are often accomplished by pattern recognition using a neural network (BROTHERTON AND POLLARD, 1992; YANG ET AL., 2002), RBF network (LEONARD AND KRAMER, 1991), Gaussian mixture model network (CHOW ET AL., 1993; HECK AND CHOU, 1994), fuzzy logic network (CHOW ET AL., 1993), Bayesian classifier (MEYER AND TUTHILL, 1995), vector correlation or vector distance measure (BAUGH, 1993). Commonly used feature generation methods including the short-time Fourier transform (STFT) (BROTHERTON AND POLLARD, 1992), wavelet time-scale decomposition (BROTHERTON AND POLLARD, 1992; CHOE ET AL., 1995; PENG ET AL., 2001), cumulant spectrum (BAUGH, 1993), etc.

The aim of this paper is to present an expert system tool which gives a solution to the above problem. The system can diagnose with great accuracy and speed the existence of faults – failures. In addition, the system is able to diagnose which of the bearings is not operational so the repair becomes selective and the maintenance cost-effective. The originality of the developed system focuses on the accurate determination of the faulty bearing that needs to be replaced. The absence of large scale data to be used for training and verification of the system's effectiveness, led to the design and the construction of an experimental device in order to take the measurements required.

Research showed that such problems could be dealt with effectively using Neural Networks. The Bayesian Multilayer Perceptron Neural Network with Automatic Relevance Determination (MLP-ARD) is a very good approach. The developing system is based on the performance of two Bayesian multilayer neural networks with automatic relevance determination (Multilayer Perceptron Neural Network with Automatic Relevance Determination, MLP-ARD) that combine data from mono-axial and tri-axial accelerometers positioned at selected locations on the gearbox.

MATERIALS AND METHODS

Work area and soil

In order to develop and validate the expert system an experimental test rig was used. This test rig was designed and constructed entirely at the Department of Biosystems Engineering, Technological Educational Institute of Thessaly, Greece (Fig. 1).

The test rig consists of a 6-speed manual transmission gearbox (5 forward and 1 reverse) with 4 bearings (Fig. 4), a three phase AC motor (5,5 Hp), a hydraulic dynamometer for gearbox loading and a complete vibration recording system of Brüel & Kjær company (Fig. 2). In order to collect the vibration data, which is used as input to the expert system, two types of accelerometers (2 tri-axial and 4 mono-axial) were placed at selected locations on the gearbox. Specifically, as shown in Fig. 3, 5 and 6 of the tri-axial accelerometers were placed on the gearbox at the front and at the rear vertical axis and the mono-axial accelerometers were placed on the gearbox at the front and the rear horizontal axis.

Fig. 1. – (a) Gearbox test rig, (b) Data acquisition system, (c) Bearing fault (inner race)

Fig. 2. – Vibration recording system

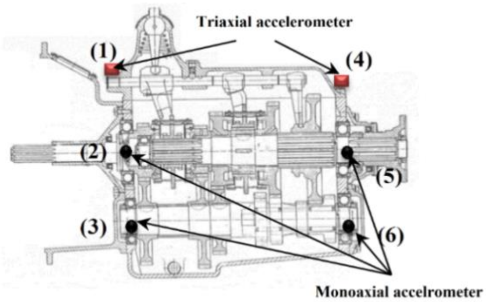

Fig. 3. – Locations where the accelerometers were placed on the gearbox**.**

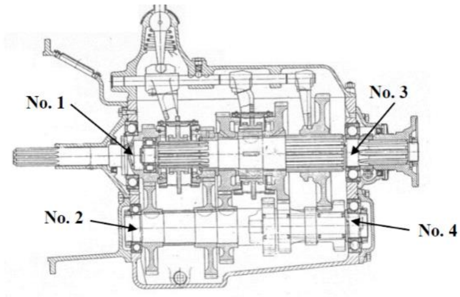

Fig. 4. – Gearbox cut section - four bearings locations (No 1 to 4).

Fig. 5. – Locations where the mono-axial accelerometers were placed on the gearbox

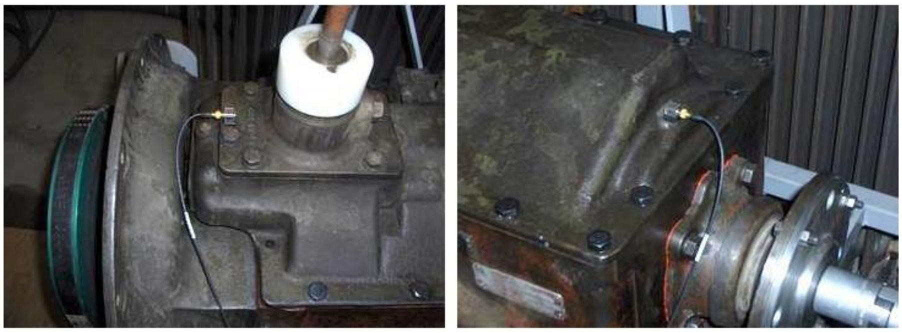

Fig. 6. – Locations where the tri-axial accelerometers were placed on the gearbox

Feature extraction

The first and maybe the most important step in any fault diagnosis problem, is the feature extraction from the raw signal. The aim of this is to reflect the general changes of the machine operation conditions. However, though some features are closely related to the fault, others are not. In this paper, twenty-four (24) features parameters, twelve (12) time-domain (T_1-T_{12}) and twelve (12) frequency-domain (F_1-F_{12}) were selected.

Time-domain features

The first eleven features were introduced by LEI ET. AL (2008). These were Mean value (T_1), Standard deviation (T_2), (T_3), Root mean square (T_4), Peak (T_5), Skewness (T_6), Kurtosis (T_7), Crest factor (T_8), Clearance factor (T_9), Shape indicator (T_{10}) and Impulse Indicator (T_{11}). The twelfth one was introduced by MOSHOU ET AL. (2010) and regards the linear integral of the acceleration signal (Line integral, T_{12}). All the used features provide statistical information about the nature of data, and were found to be reasonably good features for bearing fault detection. These features are presented in Tab. 1.

The new feature (Line Integral) is based on the observation that the higher frequencies are presented in a signal, the higher density of the signal is. The signal path due to its direct correlation to the signal variation affected by this. This parameter is sufficient to give an accurate indication of changing frequency content reflecting the total length of the signal. For high sampling rates the approximation can be simplified.

Tab. 1. – Time-domain feature parameters

Time-domain feature parameters			
$T_1=\frac{\sum_{n=1}^{N}x(n)}{N}$	(1)	$T_7=\frac{\sum_{n=1}^{N}\left(x(n)-T_1\right)^4}{(N-1)T_2^4}$	(7)
$T_2=\sqrt{\frac{\sum_{n=1}^{N}(x(n)-T_1)^2}{N-1}}$	(2)	$T_8=\frac{T_5}{T_4}$	(8)
$T_3=\left(\frac{\sum_{n=1}^{N}\sqrt{\lvert x(n)\rvert}}{N}\right)^2$	(3)	$T_9=\frac{T_5}{T_3}$	(9)
$T_4=\sqrt{\frac{\sum_{n=1}^{N}(x(n))^2}{N}}$	(4)	$T_{10}=\frac{T_4}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$	(10)
$T_5=max\lvert x(n)\rvert$	(5)	$T_{11}=\frac{T_5}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$	(11)
$T_6=\frac{\sum_{n=1}^{N}\left(x(n)-T_1\right)^3}{(N-1)T_2^3}$	(6)		
$T_{12}=\int_a^b ds\approx\sum_{i=1}^{N}\vec{r}(t_i+T_s)-\vec{r}(t_i)=\sum_{i=1}^{N}\sqrt{\left(x(t_i+T_s)-x(t_i)\right)^2+T_s^2}\approx\sum_{i=1}^{N}\lvert x(t_i+T_s)-x(t_i)\rvert$			(12)

Where: x(n) for the time-domain feature is a signal series for n=1,2,….,N, N is the number of data points. Especially for the line integral N is the number of sample points (equal to 500) in the non-overlapping windows used to calculate Kurtosis (T_7), the other features and the line integral feature, T_s is the sampling period.

Tab. 2. – Frequency-domain feature parameters

Frequency -domain feature parameters			
$F_1=\frac{\sum_{k=1}^{K}s(k)}{K}$	(13)	$F_7=\sqrt{\frac{\sum_{k=1}^{K}f_k^{\,2}s(k)}{\sum_{k=1}^{K}s(k)}}$	(19)
$F_2=\frac{\sum_{k=1}^{K}\left(s(k)-F_1\right)^2}{K-1}$	(14)	$F_8=\sqrt{\frac{\sum_{k=1}^{K}f_k^{\,4}s(k)}{\sum_{k=1}^{K}f_k^{\,2}s(k)}}$	(20)
$F_3=\frac{\sum_{k=1}^{K}\left(s(k)-F_1\right)^3}{K\left(\sqrt{F_2}\right)^2}$	(15)	$F_9=\frac{\sum_{k=1}^{K}f_k^2 s(k)}{\sqrt{\sum_{k=1}^{K}\sum_{k=1}^{K}f_k^4 s(k)}}$	(21)
$F_4=\frac{\sum_{k=1}^{K}\left(s(k)-F_1\right)^4}{KF_2^2}$	(16)	$F_{10}=\frac{F_6}{F_5}$	(22)
$F_5=\frac{\sum_{k=1}^{K}f_k s(k)}{\sum_{k=1}^{K}s(k)}$	(17)	$F_{11}=\frac{\sum_{k=1}^{K}\left(f_k-F_5\right)^3 s(k)}{KF_6^3}$	(23)
$F_6=\sqrt{\frac{\sum_{k=1}^{K}\left(f_k-F_5\right)^2 s(k)}{K}}$	(18)	$F_{12}=\frac{\sum_{k=1}^{K}\left(f_k-F_5\right)^4 s(k)}{KF_6^4}$	(24)

Where: (k) is a spectrum for k=1,2,…,K, K is the number of spectrum lines, f_k is the frequency value of the k^{th} spectrum line.

Frequency-domain features

Frequency-domain is another description of a signal. This type of description includes some information that cannot be found in time-domain. In this study another twelve features (LEI ET AL., 2008) were used in order to feed the MLP-ARD with additional information with respect to the time domain features. These twelve features were based on the Fourier transform of the vibration signals. Feature F_1 may indicate the vibration energy in the frequency-domain. Features F_2-F_4, F_6 and F_{10}-F_{12} may describe the convergence of the spectrum power. Finally, F_5 and F_7-F_9 give information about the position change of main frequencies. These features are presented in Tab. 2.

Structure of the system

In this paragraph the structure of the system is analyzed. The diagnosis system was based on three Multilayer Perceptron with Bayesian Automatic Relevance (MLP-ARD) with a 10 neurons hidden layer each. The number of neurons at the input level was equal to the number of selected features.

The first stage includes the data acquisition. At the second stage, from the recording signal the system export two new time signals 1s and 10s. Then, these signals segregate to smaller sections containing 500 values each. For each subdivision (500 values) of the 1s or 10s signal exported 12 features in the time domain and the 12 features in the frequency domain. These 24 features feed the first MLP-ARD (1^{st} level) which have three outputs (healthy condition (no fault) – fault at the front side of the gearbox (No.1 or No.2) – fault at the rear side of the gearbox (No. 3 or No. 4). After this the system was trained in all situations (healthy condition and bearing faults) and for 5Nm load at the output gearbox shaft, in two different gearbox speeds (1st and 5th speed) and in three different rpm (730-1370-2700rpm) at the input gearbox shaft.

After, follows the 2^{nd} level. This level consists of two MLP-ARD which have two outputs each. (1^{st} MLP-ARD – Fault to bearing No. 1 or No.2 and 2^{nd} MLP-ARD – Fault to bearing No. 3 or No.4).

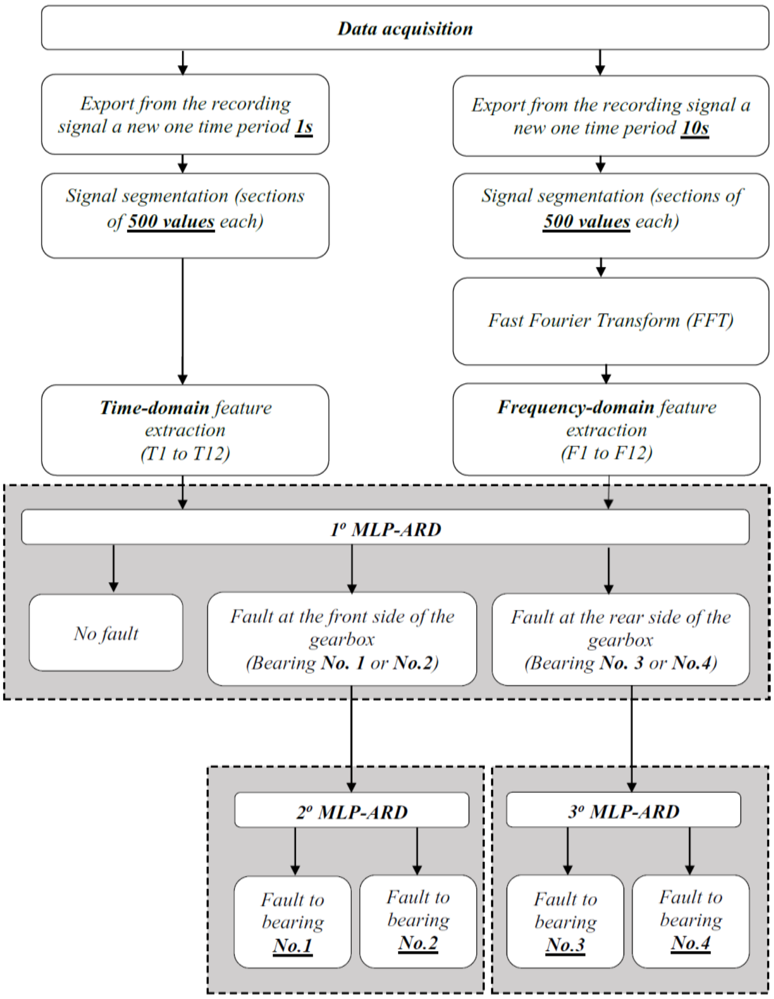

Fig. 7. – Expert system flow chart

After fault bearing assembly at the gearbox, a new vibration signature was carried out in two different gearbox speeds (1st and 5th speed), three different loads (0, 5, 10Nm) at the output gearbox shaft and three different rpm (730-1370-2700rpm) at the input gearbox shaft. The recorded vibration signals were used for feature extraction. These features are descriptive or high-order statistical data, which were extracted from the vibration signals in time and frequency domain.

The combination of results from both levels gives the exact defective bearing. The code of the expert system was written in Matlab. In the next Fig. (Fig. 7) the expert system flow chart is presented.

RESULTS AND DISCUSSION

In order to confirm the systems efficiency, it was trained under the following operation conditions, load 5 Nm at the outlet gearbox shaft, 1st and 5th gearbox speed and 1370rpm at the inlet gearbox shaft. After the training the system tested under different operation conditions - case scenarios (three different loads 0, 5 and 10 Nm at the outlet gearbox shaft, two gearbox speeds (1st and 5th) and three different rpm (730 – 1370 – 2700rpm) at the inlet gearbox shaft). The aim of these case scenarios is to investigate system efficiency in different operational conditions.

Specifically, as shown in Tab. 3, in the case scenario with a small rpm (760rpm) at the gearbox input shaft the system has very good efficiency with little to no fault in the gearbox (98.7-100%) and a fault at the rear part of it (83.2-100%). But when there was a fault at the front part of the gearbox, the system efficiency was significantly reduced (3.1-46.6%). In the second level, in order to diagnose if the fault is at the upper or at the lower bearing the 2nd and the 3rd MLP-ARD were executed. In this situation the diagnostic levels are particularly high (91.8-100%).

Tab. 3. – Evaluation of the efficiency of diagnostic system with training in 5 Nm load at the output gearbox shaft, 1st gearbox speed and 730rpm at the input gearbox shaft

<table>
<tr><td></td><td colspan="5">(Training) 1st speed at the gearbox
1370rpm input shaft - 187rpm output shaft
(Time period 1sec- 131 values)</td><td colspan="5">(Training) 1st speed at the gearbox
1370rpm input shaft - 187rpm output shaft
(Time period 10sec- 1310 values)</td></tr>
<tr><td colspan="11">(Scenario) 1st speed at the gearbox 730rpm input shaft - 99rpm outputshaft</td></tr>
<tr><td></td><td colspan="5">1st MLP-ARD execution</td><td colspan="5">1st MLP-ARD execution</td></tr>
<tr><td>(Nm)</td><td>Bearing without fault (%)</td><td colspan="2">Damage at the front side of the gearbox (%)</td><td colspan="2">Damage at the rear side of the gearbox (%)</td><td>Bearing without fault (%)</td><td colspan="2">Damage at the front side of the gearbox (%)</td><td colspan="2">Damage at the rear side of the gearbox (%)</td></tr>
<tr><td>0</td><td>100</td><td colspan="2">3.1</td><td colspan="2">83.2</td><td>98.7</td><td colspan="2">20.6</td><td colspan="2">100</td></tr>
<tr><td>5</td><td>100</td><td colspan="2">17.6</td><td colspan="2">100</td><td>100</td><td colspan="2">46.6</td><td colspan="2">100</td></tr>
<tr><td>10</td><td>100</td><td colspan="2">17.6</td><td colspan="2">100</td><td>99.9</td><td colspan="2">42.7</td><td colspan="2">99.7</td></tr>
<tr><td></td><td></td><td colspan="2">2nd MLP-ARD execution</td><td colspan="2">3rdMLP-ARD execution</td><td></td><td colspan="2">2nd MLP-ARD execution</td><td colspan="2">3rd MLP-ARD execution</td></tr>
<tr><td></td><td></td><td>Fault to bearing No.1</td><td>Fault to bearing No.2</td><td>Fault to bearing No.3</td><td>Fault to bearing No.4</td><td></td><td>Fault to bearing No.1</td><td>Fault to bearing No.2</td><td>Fault to bearing No.3</td><td>Fault to bear-ing No.4</td></tr>
<tr><td></td><td></td><td>100</td><td>98.5</td><td>100</td><td>100</td><td></td><td>100</td><td>91.8</td><td>100</td><td>100</td></tr>
<tr><td></td><td></td><td>100</td><td>100</td><td>100</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
<tr><td></td><td></td><td>100</td><td>100</td><td>100</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
</table>

In the case study of 1370rpm at the gearbox input shaft the results are very high (>85.6%) for all the cases. This happens, because the system has been trained in these operation conditions. But in the case study of 2700rpm the efficiency is low only when there is a fault at the at the rear part of the gearbox and for 1s signal (38.9-52.7%). This confirms previous suspicions about lack of reliability using small signals (1s) as input to the expert system.

Tab. 4. – Evaluation of theefficiency of diagnostic system with training in load 5Nm at the output gearbox shaft, 1st gearbox speed and 1370rpm at the input gearbox shaft

	(Training) 1st speed at the gearbox 1370rpm input shaft - 187rpm output shaft **(Time period 1sec- 131 values)**			(Training) 1st speed at the gearbox 1370rpm input shaft - 187rpm output shaft **(Time period 10sec- 1310 values)**		
	(Scenario) 1st speed at the gearbox 1370rpm input shaft - 187rpm output shaft					
	1st MLP-ARD execution			**1st MLP-ARD execution**		
(Nm)	Bearing without fault (%)	Damage at the front side of the gearbox (%)	Damage at the rear side of the gearbox (%)	Bearing without fault (%)	Damage at the front side of the gearbox (%)	Damage at the rear side of the gearbox (%)
0	100	90.8	100	100	85.6	100
5	100	100	100	100	100	100
10	100	100	100	100	100	100

2nd MLP-ARD execution		**3rd MLP-ARD execution**		**2nd MLP-ARD execution**		**3rd MLP-ARD execution**	
Fault to bearing No.1	Fault to bearing No.2	Fault to bearing No.3	Fault to bearing No.4	Fault to bearing No.1	Fault to bearing No.2	Fault to bearing No.3	Fault to bearing No.4
100	100	100	100	100	100	100	100
100	100	100	100	100	100	100	100
100	100	100	100	100	100	100	100

Tab. 5. – Evaluation of theefficiency of diagnostic system after training with a 5 Nm load at the output gearbox shaft, 1st gearbox speed and 2700rpm at the input gearbox shaft

	(Training) 1st speed at the gearbox 1370rpm input shaft - 187rpm output shaft **(Time period 1sec- 131 values)**			(Training) 1st speed at the gearbox 1370rpm input shaft - 187rpm output shaft **(Time period 10sec- 1310 values)**		
	(Scenario) 1st speed at the gearbox 2700rpm input shaft - 380rpm output shaft					
	1st MLP-ARD execution			**1st MLP-ARD execution**		
(Nm)	Bearing without fault (%)	Damage at the front side of the gearbox (%)	Damage at the rear side of the gearbox (%)	Bearing without fault (%)	Damage at the front side of the gearbox (%)	Damage at the rear side of the gearbox (%)
0	100	100	38.9	97.4	94.1	93.1
5	100	100	48.1	60.2	99.8	83.3
10	100	100	52.7	45.9	95.3	94.1

2nd MLP-ARD execution		**3rd MLP-ARD execution**		**2nd MLP-ARD execution**		**3rd MLP-ARD execution**	
Fault to bearing No.1	Fault to bearing No.2	Fault to bearing No.3	Fault to bearing No.4	Fault to bearing No.1	Fault to bearing No.2	Fault to bearing No.3	Fault to bearing No.4
100	100	100	80.9	100	100	100	100
94.7	100	100	6.1	91.7	100	100	100
97.7	100	100	3.8	97.7	100	100	100

In the case where the 5th gearbox speed was selected the problem that occurs at low speed at the input shaft continues for diagnosis at the front side of the gearbox which means that the systems weakness is not affected by the selected gearbox speed. This hypothesis is confirmed by the recorded results after the other gearbox speeds selection where the phenomenon continues. As shown in Tab. 6, in the scenario with a small rpm (760rpm) at the gearbox input shaft the system has excellent efficiency in all cases, there is no fault in the gearbox (100%) and a fault at the rear part of the gearbox (100%). But when there is a fault at the front part of the gearbox, the system efficiency was significantly reduced (3.8-84.7%). In the second level, in order to diagnose whether the damage is at the upper or at the lower bearing the 2nd and the 3rd MLP-ARD were executed. In this case the diagnostic efficiency is extremely high close to 100%.

Tab. 6. – Evaluation of the efficiency of diagnostic system after training with a 5 Nm load at the output gearbox shaft, 5th gearbox speed and 730rpm at the input gearbox shaft

<table>
<tr><td></td><td colspan="5">(Training) 5th speed at the gearbox
1370rpm input shaft - 1370rpm output shaft
(Time period 1sec- 131 values)</td><td colspan="5">(Training) 5th speed at the gearbox
1370rpm input shaft - 1370rpm output shaft
(Time period 10sec- 1310 values)</td></tr>
<tr><td colspan="11">(Scenario) 5th speed at the gearbox 730rpm input shaft - 730rpm output shaft</td></tr>
<tr><td></td><td colspan="5">1st MLP-ARD execution</td><td colspan="5">1st MLP-ARD execution</td></tr>
<tr><td>(Nm)</td><td>Bearing without fault (%)</td><td colspan="2">Damage at the front side of the gearbox (%)</td><td colspan="2">Damage at the rear side of the gearbox (%)</td><td>Bearing without fault (%)</td><td colspan="2">Damage at the front side of the gearbox (%)</td><td colspan="2">Damage at the rear side of the gearbox (%)</td></tr>
<tr><td>0</td><td>100</td><td colspan="2">3.8</td><td colspan="2">100</td><td>100</td><td colspan="2">84.7</td><td colspan="2">100</td></tr>
<tr><td>5</td><td>100</td><td colspan="2">32.1</td><td colspan="2">100</td><td>100</td><td colspan="2">48.9</td><td colspan="2">100</td></tr>
<tr><td>10</td><td>100</td><td colspan="2">36.7</td><td colspan="2">100</td><td>100</td><td colspan="2">52.7</td><td colspan="2">100</td></tr>
<tr><td></td><td></td><td colspan="2">2nd MLP-ARD execution</td><td colspan="2">3rd MLP-ARD execution</td><td></td><td colspan="2">2nd MLP-ARD execution</td><td colspan="2">3rd MLP-ARD execution</td></tr>
<tr><td></td><td></td><td>Fault to bearing No.1</td><td>Fault to bearing No.2</td><td>Fault to bearing No.3</td><td>Fault to bearing No.4</td><td></td><td>Fault to bearing No.1</td><td>Fault to bearing No.2</td><td>Fault to bearing No.3</td><td>Fault to bearing No.4</td></tr>
<tr><td></td><td></td><td>100</td><td>100</td><td>100</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
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<tr><td></td><td></td><td>100</td><td>100</td><td>100</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
</table>

In the case study of 1370rpm at the gearbox input shaft the results are very high for all the cases (99.2-100%). This occurs, because the system has been trained in these operation conditions. But in the case study of 2700rpm the efficiency is low only when there is a fault at the at the rear part of the gearbox and for 1s signal (60.3-100%). This confirms previous suspicions concerning the low reliability of the use of such a small signal as input to the expert system. In the second level, in order to diagnose whether the damage is at the upper or at the lower bearing the 2th and the 3rd MLP-ARD were executed. In this case the diagnostic efficiency is good (64.1-100%).

Tab. 7. – Evaluation of theefficiency of diagnostic system after training with a 5 Nm load at the output gearbox shaft, 5^{th} gearbox speed and 1370rpm at the input gearbox shaft

<table>
<tr><td colspan="6">(Training) 5^{th} speed at the gearbox
1370rpm input shaft - 1370rpm output shaft
(Time period 1sec- 131 values)</td><td colspan="5">(Training) 5^{th} speed at the gearbox
1370rpm input shaft - 1370rpm output shaft
(Time period 10sec- 1310 values)</td></tr>
<tr><td colspan="11">(Scenario) 5^{th} speed at the gearbox 1370rpm input shaft -1370rpm output shaft</td></tr>
<tr><td colspan="6">1^{st} MLP-ARD execution</td><td colspan="5">1^{st} MLP-ARD execution</td></tr>
<tr><td>(Nm)</td><td>Bearing without fault (%)</td><td colspan="2">Damage at the front side of the gearbox (%)</td><td colspan="2">Damage at the rear side of the gearbox (%)</td><td>Bearing without fault (%)</td><td colspan="2">Damage at the front side of the gearbox (%)</td><td colspan="2">Damage at the rear side of the gearbox (%)</td></tr>
<tr><td>0</td><td>100</td><td colspan="2">100</td><td colspan="2">100</td><td>100</td><td colspan="2">100</td><td colspan="2">100</td></tr>
<tr><td>5</td><td>100</td><td colspan="2">100</td><td colspan="2">100</td><td>100</td><td colspan="2">100</td><td colspan="2">100</td></tr>
<tr><td>10</td><td>100</td><td colspan="2">100</td><td colspan="2">100</td><td>100</td><td colspan="2">100</td><td colspan="2">100</td></tr>
<tr><td colspan="2"></td><td colspan="2">2^{nd} MLP-ARD execution</td><td colspan="2">3^{rd}MLP-ARD execution</td><td></td><td colspan="2">2^{nd} MLP-ARD execution</td><td colspan="2">3^{rd} MLP-ARD execution</td></tr>
<tr><td colspan="2"></td><td>Fault to bearing No.1</td><td>Fault to bearing No.2</td><td>Fault to bearing No.3</td><td>Fault to bearing No.4</td><td></td><td>Fault to bearing No.1</td><td>Fault to bearing No.2</td><td>Fault to bearing No.3</td><td>Fault to bearing No.4</td></tr>
<tr><td colspan="2"></td><td>99.2</td><td>100</td><td>100</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
<tr><td colspan="2"></td><td>100</td><td>100</td><td>100</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
<tr><td colspan="2"></td><td>100</td><td>100</td><td>100</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
</table>

Tab. 8. – Evaluation of theefficiency of diagnostic system after training with a 5 Nm load at the output gearbox shaft, 5^{th} gearbox speed and 2700rpm at the input gearbox shaft

<table>
<tr><td colspan="6">(Training) 5^{th} speed at the gearbox
1370rpm input shaft - 1370rpm output shaft
(Time period 1sec- 131 values)</td><td colspan="5">(Training) 5^{th} speed at the gearbox
1370rpm input shaft - 1370rpm output shaft
(Time period 10sec- 1310 values)</td></tr>
<tr><td colspan="11">(Scenario) 5^{th} speed at the gearbox 2700rpm input shaft -2700rpm output shaft</td></tr>
<tr><td colspan="6">1^{st} MLP-ARD execution</td><td colspan="5">1^{st} MLP-ARD execution</td></tr>
<tr><td>(Nm)</td><td>Bearing without fault (%)</td><td colspan="2">Damage at the front side of the gearbox (%)</td><td colspan="2">Damage at the rear side of the gearbox (%)</td><td>Bearing without fault (%)</td><td colspan="2">Damage at the front side of the gearbox (%)</td><td colspan="2">Damage at the rear side of the gearbox (%)</td></tr>
<tr><td>0</td><td>100</td><td colspan="2">100</td><td colspan="2">60.3</td><td>100</td><td colspan="2">100</td><td colspan="2">100</td></tr>
<tr><td>5</td><td>100</td><td colspan="2">100</td><td colspan="2">74.8</td><td>100</td><td colspan="2">100</td><td colspan="2">100</td></tr>
<tr><td>10</td><td>100</td><td colspan="2">100</td><td colspan="2">60.3</td><td>100</td><td colspan="2">100</td><td colspan="2">100</td></tr>
<tr><td colspan="2"></td><td colspan="2">2^{nd} MLP-ARD execution</td><td colspan="2">3^{rd}MLP-ARD execution</td><td></td><td colspan="2">2^{nd} MLP-ARD execution</td><td colspan="2">3^{rd} MLP-ARD execution</td></tr>
<tr><td colspan="2"></td><td>Fault to bearing No.1</td><td>Fault to bearing No.2</td><td>Fault to bearing No.3</td><td>Fault to bearing No.4</td><td></td><td>Fault to bearing No.1</td><td>Fault to bearing No.2</td><td>Fault to bearing No.3</td><td>Fault to bearing No.4</td></tr>
<tr><td colspan="2"></td><td>94.7</td><td>99.7</td><td>99.2</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
<tr><td colspan="2"></td><td>64.1</td><td>100</td><td>100</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
<tr><td colspan="2"></td><td>72.5</td><td>100</td><td>100</td><td>100</td><td></td><td>100</td><td>100</td><td>100</td><td>100</td></tr>
</table>

CONCLUSIONS

It is evident that the neural network MLP-ARD can provide reliable results using as inputs features in time domain and in frequency domain. These features were extracted from vibration signals with different time lengths (1s and 10s). These features (according to their nature) can be used with success for fault diagnosis of rolling and roller bearings. The combination of the futures with the appropriate neural network gives us a powerful tool for bearing condition monitoring and early fault diagnosis in mechanical gearboxes. Furthermore, the features can identify with sufficient precision the point in which the fault occurs. It has been observed that a small signal (1s) provides a smaller diagnostic efficiency compared to a larger one (10s). Also, when the system is verified in training operational conditions then it gives better results relative to all other combinations training - verification. The system has a strong ability to be trained in a specific load at the output gearbox shaft. In future work the expert system effectiveness will be investigated using more data from different types of faults in rolling bearings of the gearbox in order to confirm further the system reliability.

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