

# Decision and Fusion for Diagnostics of Mechanical Components

Renata Klein<sup>1</sup>, Eduard Rudyk<sup>2</sup>, and Eyal Masad<sup>3</sup>

<sup>1,2,3</sup>*R.K. Diagnostics, P.O.B. 66, Misgav Industrial Park, 20179, Israel*

*Renata.Klein@rkdiagnostics.co.il*

*Eddie.Rudyk@rkdiagnostics.co.il*

*Eyal.Masad@rkdiagnostics.co.il*

## ABSTRACT

Detection of damaged mechanical components in their early stages is crucial in many applications. The diagnostics of mechanical components is achieved most effectively using vibration and/or acoustical measurements, sometimes accompanied by oil debris indications. The paper describes a concept for fusion and decision for mechanical components, based on vibro-acoustic signatures. Typically in diagnostics of complex machinery, there are numerous records from normally operating machines and few recordings with damaged components. Diagnostics of each mechanical component requires consideration of a large number of features. Learning classification algorithms cannot be applied due to insufficient examples of damaged components. The proposed system presents a solution by introducing a hierarchical decision scheme. The proposed architecture is designed in layers imitating expert's decision reasoning. The architecture and tools used allow incorporation of expert's knowledge along with the ability to learn from examples. The system was implemented and tested on simulated data and real-world data from seeded tests. The paper describes the proposed architecture, the algorithms used to implement it and some examples.

## 1. INTRODUCTION

In diagnostics and prognostics, the decision is the process that determines the probability that a certain component, module or system is in a healthy state. In order to reach the decision, health indicators from a variety of sources related to a component are combined. In the implementation described herein a multi-layer approach is used. At each layer the features of a similar nature are combined.

Two levels of decision can be identified: component-level and system-level decision.

Component-level decision generates a single decision for each component. This is a complex decision as there are many different sources of information, sometimes

contradicting, that should be taken into account.

During the system-level decision, the health of each component is translated into recommendations for maintenance operations. This level of decision should incorporate root-cause analysis (RCA) type of logic. For example, let's assume that an abnormal behavior was observed in components C1 (a massive gearwheel) and C2 (an anomaly virtual component). During system-level decision, and knowing the system dynamics, it can be concluded that the actual component that requires maintenance operation is C3 (a pinion gear), which is connected to both the big gearwheel C1 and to the indication on the anomaly C2. It can also be concluded that the pinion gear C3 and the gearwheel C1 are, for example, part of module B1 and the most efficient maintenance operation is full replacement of module B1 and not only the faulty component.

In this paper our focus is on component-level decision making. Information on the health of a single component is collected from several sources and should be integrated into a single decision. The component can be monitored by multiple sensors in several operating conditions. For each sensor and operating condition multiple health indicators can be calculated.

## 2. VIBRATION ANALYSIS

Analysis of vibration signals is performed in several stages. The following processing stages are implemented according to the OSA/CBM layers (MIMOSA) (see Figure 1).

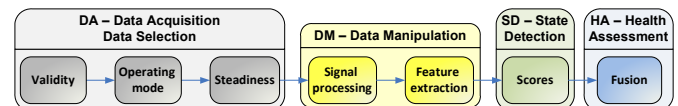


Figure 1. Vibration analysis processing stages

### 2.1 Data Selection

After data sampling the first step of processing is examination of the acquired data and selection of data appropriate for analysis. The data is screened in several

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stages (see grey blocks in Figure 1): validity, operating conditions and steadiness check. Data selection is a part of the OSA/CBM data acquisition layer (DA).

The goal of the validity stage is to filter out invalid or corrupted sections of data such as sensor disconnection, saturation, spikes and others.

The next stage of data selection is recognition of predefined operating modes. Operating modes are frequently repeating conditions during system regular operation that enhance the manifestation of the damaged components (for instance when the components are loaded) and satisfy specific requirements for data analysis.

The last stage of data selection contains stationarity checks of the analyzed signals.

### 2.2 Data Manipulation

The OSA/CBM data manipulation (DM) layer in the current architecture is covered by signal processing and feature extraction.

In the case of vibro-acoustic data, signal processing is the most complex and computationally intensive task implicating sophisticated flows of algorithms including many transformations from one domain of analysis to another (Klein, Rudyk, Masad, Issacharoff, 2009b, Antoni & Randall, 2002, and Klein, Rudyk, Masad, 2011). During signal processing the data is transformed into different signatures (instances of a domain) that enhance manifestation of damaged components while filtering out the excitations from other components. Signal processing is done on sections of raw data selected in the data acquisition stage.

Feature extraction is a process in which the signatures are compared with signatures representing the population of 'healthy' systems. Results of the feature extraction are condition indicators (features) of the 'health' status of specific failure modes of a mechanical component. These indicators organized as a function of time are called trends.

The feature extraction process typically calculates and collects a large number of health indicators for different components of the system under test. The failure modes of a type of component are manifested in the relevant signatures according to a characteristic pattern.

The typical failure modes of a bearing are damages to inner and outer races, rotating elements, or cage. The pattern of each failure mode of a bearing can be described by several harmonics of characteristic frequencies (also known as bearing tones or pointers) with sidebands representing the amplitude modulation. More details can be found in Klein, et al. (2009a), Klein et al. (2011), Bhavaraju, Kankar, Sharma, Harsha, 2010, Li, Sopon, He, 2009, and Hariharan, Srinivasan, 2009.

### 2.3 Decision

The stages after feature extraction are part of the state and health assessment (SA and HA) OSA-CBM layers. A decision regarding the health status of a component is taken per run or flight of the machine.

The inputs to the decision process are normalized features. During the normalization process the distance of a feature from the distribution of the same feature in normally operating machines is calculated. Practically during normalization the Mahalanobis distance is calculated.

The decision at each stage is generated as a probability to be in one of pre-defined states, for instance three states representing component health status: 'Normal', 'Low', and 'High' indicating respectively a normally operating component, a component with a small deviation from normal, and a component with a large deviation from normal. An additional state should be considered to represent missing or incomplete information when the decision cannot be taken. In the presented application this state is named 'Unknown'. A set of the 4 probabilities corresponding to the different states is called decision vector. The decision vector generated per run is stored in a trend of decisions.

### 3. ARCHITECTURE OF THE DECISION AND FUSION

A single feature or health indicator is a function of component type, sensor, operating mode, processing domain, pointers (harmonics and sidebands), and type of indicator. For example, processing domain can be orders, location – first harmonic of the shaft, and indicator – energy. To obtain the decision for a component it is therefore required to undergo the following stages: combination of indicators, pointers, processing domains, operating modes, and sensors.

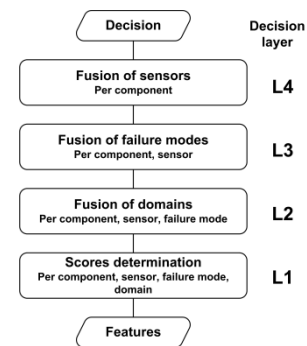


Figure 2. Layers of decision

At the first decision stage features coming from different operating modes and pointers are merged. This process is called scoring and will be denoted L1. The second decision stage (L2) merges processing domains. During the third stage (L3) of decision all the failure modes are merged. At the next and final decision stage the information from all the

sensors is joined (L4). Figure 2 shows a schematic representation of decision layers.

The architecture of the process (layers hierarchy) imitates the way an expert makes a decision. At the first stage (L1) the expert inspects a single spectrogram such as time-orders spectrogram. The expert checks the behavior of the several pointers corresponding to a failure mode as a function of the operating conditions. Depending on the component and failure mode under observation, processing domain and sensor the expert can decide whether the energy levels indicate damage.

On the next stage (L2) an expert seeks additional evidences for presence of the specific failure mode based on other processing domains such as envelope (usually by inspecting the time-orders spectrogram of the envelope). Evidences from several processing domains can strengthen or weaken the indications based on the component and failure mode under observation.

After examination of different domains all the failure modes of the component will be considered. Evidences from all the failure modes are inspected and again can weaken or strengthen the final decision. As the damage progress other failure modes may also rise due to suboptimal component operation. For example, a damage of the bearing outer race might cause a damage of the bearing roller elements.

When several sensors are used to perform the diagnostics of the component the final stage integrates their decisions. Based on relative location between the component and sensors some logic can be implemented to dismiss false positives. An example of such logic can be to take weighted voting between the sensors where the weight is proportional to the distance between the component under observation and the sensor. Such that more proximate sensors have a higher weight, but indications from several distant sensors will also be considered as indications of damage.

The scoring layer (L1) is different from the other decision layers (L2-L4). The inputs for this layer are normalized features and the output is a decision vector. In all other layers the inputs and the outputs of a decision layer are decision vectors.

#### 4. SCORING LAYER (L1)

The first stage of the decision process is the scoring. In this stage the various features that were extracted for a certain failure mode (energy, confidence<sup>1</sup>, pointer-location etc.) are

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<sup>1</sup> Confidence is a feature which represents a distance of a pattern (harmonics of the carrier and corresponding sidebands) from the population of healthy machine signatures – ‘score P’ in Klein et al., 2011.

combined into a single number which may be regarded as the probability for a failure.

Features associated with the same failure mode (e.g. an outer-race pattern with sidebands and without sidebands) are joined together, and results from different operating modes are analyzed together and joined into a single result.

#### 4.1 Scoring algorithm guidelines

The main guidelines for the development of the scores algorithm are presented below. The feature extraction process and the definition of the specific features for bearings are described in Klein et al. (2011). Note that confidence levels and pointer locations<sup>2</sup> are relevant only to bearings scores.

1. In bearing scores, if the confidence is too low the respective energy levels should be disregarded. If the confidence is high the respective energy levels should be more significant.
2. Consistently high energy and/or confidence levels should be more significant than sporadic high energies and confidence, since the latter may be caused by noise.
3. Consistency is particularly important in a feature produced in approximately similar conditions, and (in bearings) ones which have close pointer locations.
4. The final score will be a decision vector.

#### 4.2 Algorithm description

The general scores algorithm can be separated into 5 steps as described below. The 1<sup>st</sup> stage is relevant only to bearing scores.

##### 4.2.1 Confidence filtering (for bearing scores)

In order to accommodate the 1<sup>st</sup> guideline, we multiply the energy of each pattern by a decrease factor which is a function of the respective confidence  $(c, e_1, \dots, e_N) \rightarrow (f(c)e_1, \dots, f(c)e_N)$  where  $f$  is a continuous monotonically ascending function with values in  $[0,1]$ . If  $f$  is properly configured, low confidence will lead to low energy levels.

##### 4.2.2 Energy conversion

The 2<sup>nd</sup> guideline means that the affect of the energy on the score should be subadditive<sup>3</sup>. We therefore convert the energy values into new values using a continuous

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<sup>2</sup> The algorithm selects the location, with the highest corresponding z-score. This selection represents the most probable location of the peaks.

<sup>3</sup> A subadditive function is a function  $\varphi$  that  $\varphi(x+y) < \varphi(x) + \varphi(y)$ .

monotonically ascending function  $\varphi: \mathbb{R} \rightarrow \mathbb{R}$ , which is subadditive and in fact strictly subadditive above a certain threshold  $E_0 > 0$ . Below  $E_0$   $\varphi$  will be zero, so that low energies do not contribute to the score. Choosing the right function is a matter of assessing the distribution of energy values. For example a simple logarithmic function may be used.

For  $e < E_0$   $\varphi(e)$  may be some small negative constant (instead of zero).  $\varphi$  may also be smoothed around  $E_0$  to prevent edge effects. After all we need  $\varphi$  to be subadditive only for large values.

$$(u_1, \dots, u_N) = \varphi(f(c)e_1, \dots, f(c)e_N) \quad (1)$$

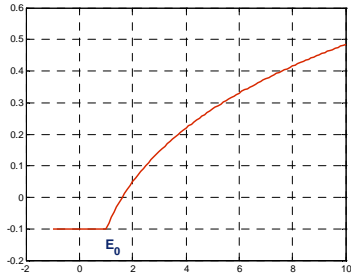


Figure 3. An example of a monotonically ascending function  $\varphi$  which is strictly subadditive above  $E_0=1$

#### 4.2.3 Interaction between record fragments

In the data-selection stage the recording was fragmented into intervals with similar operation modes. In each fragment the vibrations were assumed to be stationary. Each fragment was processed separately. Now we wish to compare the features extracted from various fragments and look for consistency. According to guideline 3, we need to measure proximity of conditions and pointer locations (pointer locations are only relevant to bearings, since other components have fixed pointer locations which may be determined from their geometry). We construct a metric  $d$  based on measures of RPM, load, and other operation parameters, as well as pointer shifts, which may indicate if energies are related to the same origin. Using this metric we can determine the amount of correlation we may expect between the fragments.

This correlation may then be used to increase or decrease energy levels.

$$v_{kn} = u_{kn} + h(d(k, j), u_{jn}, u_{kn}) \quad n = 1, \dots, N \quad (2)$$

where  $k$  and  $j$  are two distinct fragments.

#### 4.2.4 Initial score estimation

In this step we turn energy levels  $v_{kn}$  into probability. This is done by a configurable fuzzy filter. In accordance with guideline 4, we use several fuzzy filters  $p_{knm}$ .

$$p_{knm} = s_m(v_{kn}) \quad (3)$$

#### 4.2.5 Merging scores of fragments

Now we merge the scores of different record fragments. We regard the different fragments as though they were independent measurements<sup>4</sup>  $P_{nm}$ .

$$P_{nm} = 1 - \prod_{k=1}^K (1 - p_{knm}) \quad (4)$$

#### 4.2.6 Merging pointer scores

Merging pointers is a simple matter of applying a statistical function  $g$  (such as mean, percentile etc.) on the scores produced in the previous step.

$$score_m = g(P_{1m}, \dots, P_{Nm}) \quad (5)$$

The function  $g$  is applied to the results of all the patterns associated with the current failure mode. Thus, the scores of the various patterns are also merged.

### 4.3 Algorithm illustration

The results of the algorithm on two sets of simulated data are provided below. The first set represents features of bearing with damaged outer race OR (Figure 4), and the second set represents features of a healthy bearing with some abnormal energy levels that may occur due to feature overlap (Figure 5). Both sets of simulated features included outer race energy level for BPFO and its harmonics (ORS1 and ORS2), energies of sidebands around a bearing fault frequency peak (OR1-OR6), and confidence levels for the outer race expected pattern. The labels on y axis of both figures represent different operating conditions (fragments).

In both Figure 4 and Figure 5 when comparing graphs (a) and (b) the energies corresponding to the fragments with low confidence were decreased considerably, whereas energies corresponding to high confidence levels remained intact. On the next stage (c) consistently high levels in adjacent fragments were increased (see Figure 4). After the last stage (d) the energies that were well below the threshold yielded low probabilities. Comparing raw features (a) and the final scores (d) it can be observed that in the simulated damage (Figure 4) the scores are high whereas in the simulation of healthy bearing (Figure 5) the scores are small thus illustrating the capability of the algorithm to reduce false alarms.

<sup>4</sup> The fragments merged can be considered independent because they represent separated segments of time and usually different operating modes with different load.

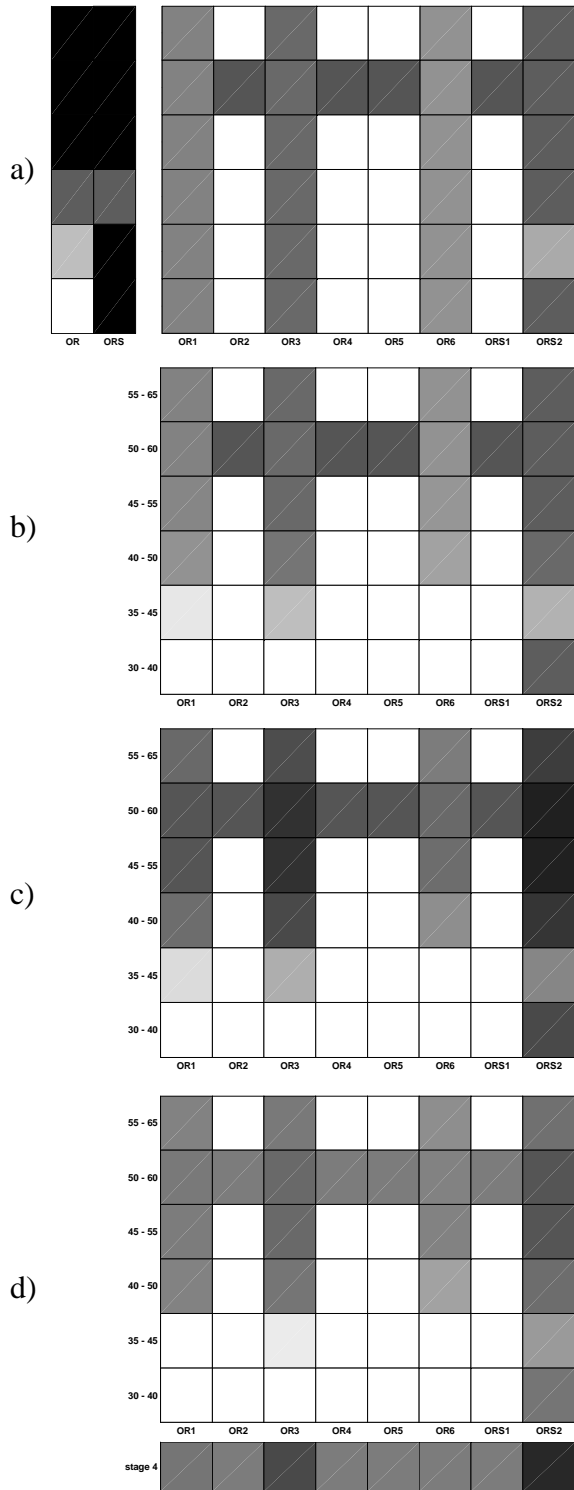


Figure 4. Results of damage in OR: a) raw features, on the left side – confidence and on the right – energy levels in logarithmic scale; b) energy levels after confidence filtering  $\vec{u}$ ; c)  $\vec{u}$  after correlation of fragments  $\vec{v}$ ; d) probability of abnormal behavior, before (upper graph) and after (lower graph) merge of record fragments.

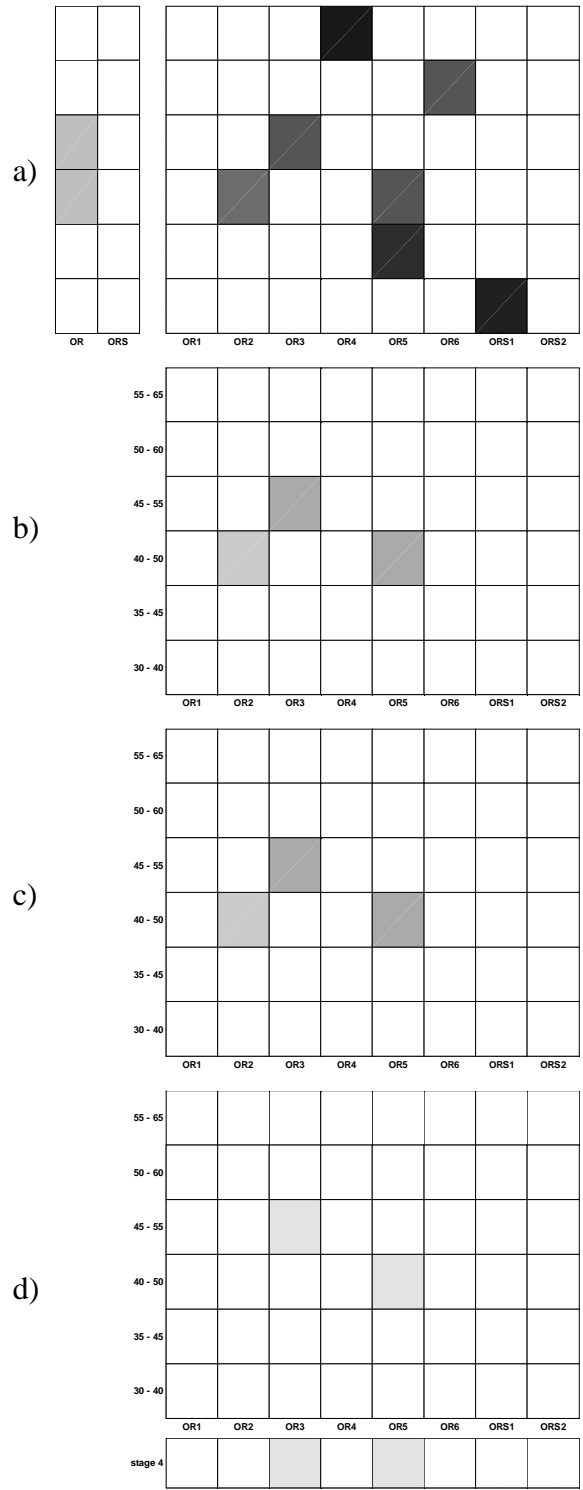


Figure 5. Results of healthy bearing: a) raw features, on the left side – confidence and on the right – energy levels in logarithmic scale; b) energy levels after confidence filtering  $\vec{u}$ ; c)  $\vec{u}$  after correlation of fragments  $\vec{v}$ ; d) probability of abnormal behavior, before (upper graph) and after (lower graph) merge of record fragments.

## 5. FUSION LAYERS (L2-L4)

Each decision layer (L2-L4) can be implemented by a different decision model. All decision models share an identical interface and allow a plug-and-play behavior.

In the current implementation 2 types of models were used: worst-case scenario and Bayesian network (Neapolitan, 2003).

### 5.1 Bayesian network model

The Bayesian network model allows definition networks of arbitrary complexity. The network is initialized with a corresponding conditional probability table (CPT). This table defines the effect of each combination of inputs on the respective output.

The model allows manual assign of CPT or learning of expected behavior using examples.

### 5.2 Worst-case scenario (WCS) model

The WCS model receives several decision vectors as input. The input vector with the highest deviation from the normal is selected as output of the model.

One subject that should be specifically addressed is the case of non-zero ‘Unknown’ probability. It is clear that if one of the inputs contains non-zero probability in an abnormal state (indicating some kind of deviation from normal behavior), the ‘unknown’ state should be ignored. Otherwise if all other inputs indicate completely ‘normal’ behavior 3 options should be considered:

1. To generate a ‘normal’ decision,
2. To generate an ‘unknown’ decision,
3. To generate a combination between ‘normal’ and ‘unknown’ states by assigning non-zero probability to each.

Each option has its own logic and should be considered depending on the application.

### 5.3 Model selection

Selection of the decision model for each decision layer is based on the level of mutual correlation between the merged decisions. If high level of correlation is expected between the merged decisions then it is beneficial to use the Bayesian network model. This model can incorporate complex interconnections between the elements and provide means for more sophisticated decision-making. For example, it is plausible that different processing domains (layer L2) will provide indications of declining health of component. Thus multiple weak indications may intensify the decision that the component’s health is declining. In contrast, if only a single weak indication was received it

may be dismissed as no other supporting factors were detected.

On the other hand, if minor or no correlation is expected between the input elements then a WCS model is more appropriate. It actually states the health of the combination is the same as the health of the weakest (highest probability of damage) element in that combination. For example, in the L4 layer a fusion of sensors is performed. At early stages of fault development only the closer sensors will be able to detect a shift from the normal. Depending on the sensors locations as the fault development progresses more distant sensors may or may not detect some discrepancy also. So in case of insufficient information on correlation between sensors and transmission path (component-sensor) a WCS decision may be selected.

Decision modules used at each layer and corresponding parameters can be defined for each component separately based on available information and component specificity.

In current application the L2 layer (fusion of domains) is implemented by Bayesian network model. Layers L3-L4 are using WCS model.

## 6. ANALYSIS OF REAL DATA

Data used in this section originates from PHM ’09 data challenge (Klein et al., 2009b).

The PHM09 marked data set included 280 recordings of 4 seconds, measured on the gearbox described in Figure 6, using two vibration sensors and a tachometer. All the bearings were similar. Some of the signals were recorded when the gearbox was in ‘spur’ configuration, and others when it was in ‘helical’ configuration. Data were collected at 30, 35, 40, 45 and 50 Hz shaft speed, under high and low loading.

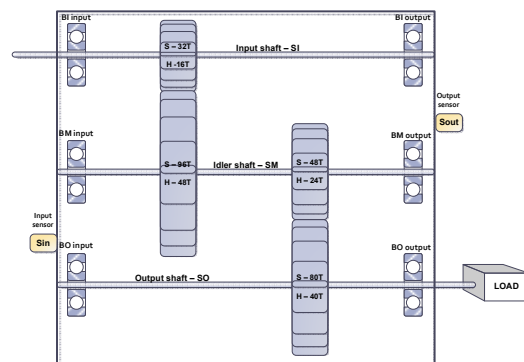


Figure 6. Challenge apparatus: spur (S) and helical (H) configurations.

The records used in the following analysis are listed in Table 1.

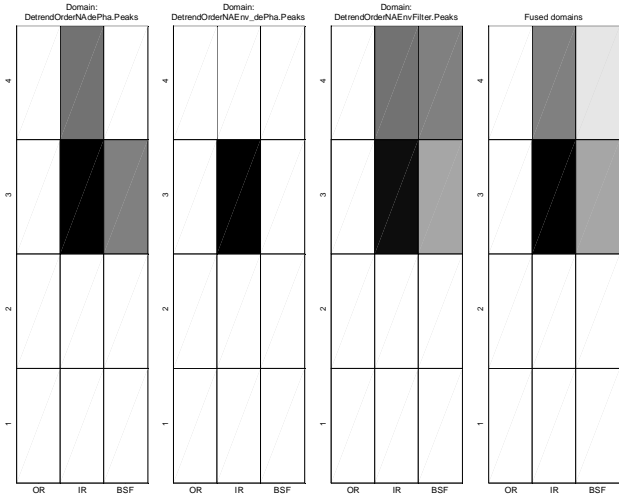


Figure 7. bA1, sensor Sin (L2)

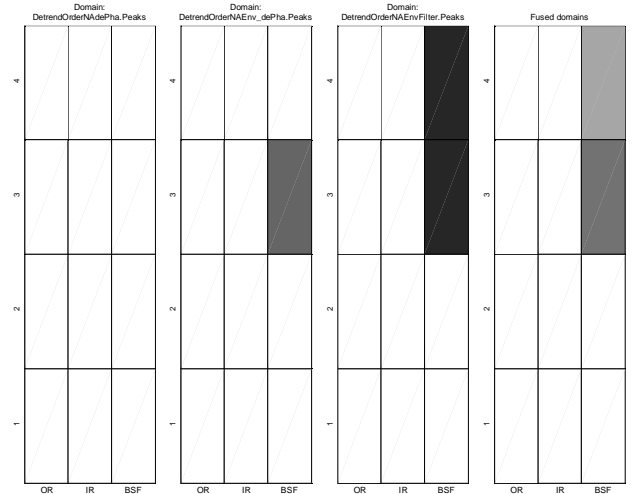


Figure 10. bB1, sensor Sin (L2)

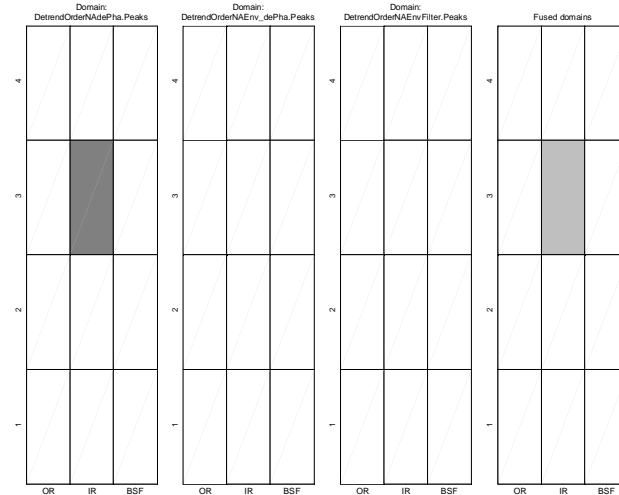


Figure 8. bA1, sensor Sout (L2)

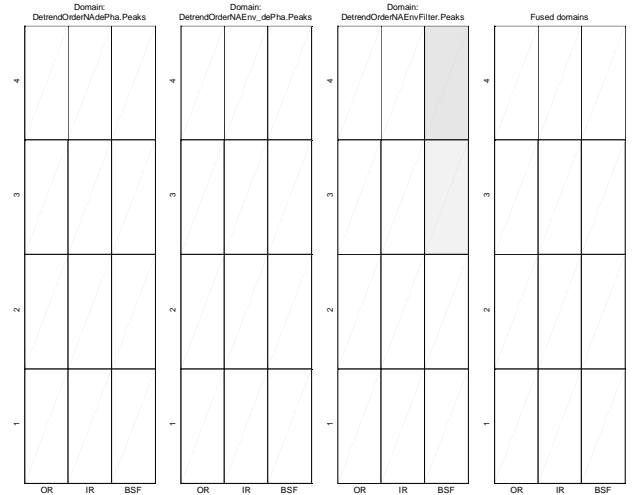


Figure 11. bB1, sensor Sout (L2)

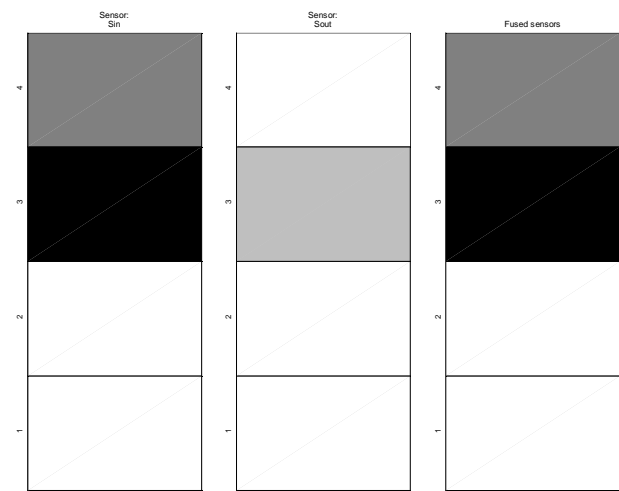


Figure 9. bA1 final decision (L4)

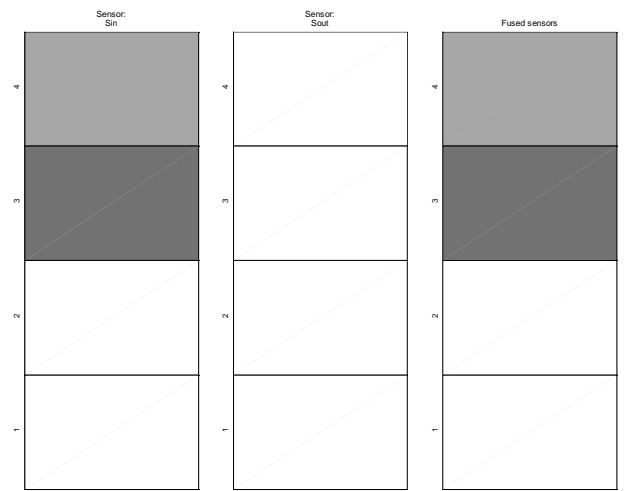


Figure 12. bB1 final decision (L4)

	Name	bA1	bB1	Other damages
1	Spur 1	Good	Good	Good
2	Spur 2	Good	Good	Gear
3	Spur 6	Inner race	Ball	Gear, Shaft
4	Spur 8	Good	Ball	Shaft

Table 1. Analyzed records and corresponding bearing damages (bA1, bB1).

Recordings from 2 sensors (called Sin and Sout) were provided. Both bearings are identical and located closer to sensor Sin. Bearing bA1 was mounted on the input shaft and bearing bB1 on the idler shaft. The corresponding bearing tones overlap since the idler shaft rotates at a third of the rotating speed of the input shaft (see Klein et al., 2009b).

Results of fusion layers are presented in Figure 7-Figure 12. Due to space limitations the score results are not presented herein. All the graphs present probabilities for damage in a gray scale color map (white represents zero probability and black a probability of 1). Conclusions maybe derived on probabilities of damage for components (L4) or failure modes (L2) according to a specific sensor. For practical purposes the decision on component probability of damage (L4) is the most relevant.

Figure 7, Figure 8, Figure 10 and Figure 11 show results of domain fusion (layer L2). Three domains corresponding to the leftmost subplots were fused. The domains that were considered were: order of the dephased signal, order of the envelope of the band-pass filtered signal, and order of the envelope of the dephased signal (see Klein et al., 2009b). The fusion result is displayed on right subplot of each figure. The columns of each subplot correspond to the bearing failure modes (IR – inner race, OR – outer race, BSF – ball), and the rows correspond to the different records as described in Table 1.

In Figure 7 incorrect indications of ball damage can be observed. This is due to the bearing tones overlap mentioned beforehand. The third harmonic of ball spin frequency (BSF) of bB1 coincides with BSF of bA1. In the case of the PHM'09 challenge apparatus the discrimination between these bearings is problematic. In practical cases this situation is rare.

Figure 9 and Figure 12 present results of failure mode and sensor fusion (layers L3 and L4 respectively). On the leftmost subplots results of layer L3 (failure mode fusion) are displayed. Each subplot corresponds to a single sensor. The rightmost subplot represents the result of layer L4 (sensor fusion) which is actually the final decision.

All damages were recognized correctly. All recordings from undamaged bearings were classified correctly as well. Moreover, the probabilities for sensor Sin were significantly higher compared to the probabilities for sensor Sout. This

may be due to the fact that the bearings are located closer to sensor Sin.

It should be noted that the damages in other components did not affect the decisions for the bearings bA1, bB1.

## 7. CONCLUSIONS

Hierarchical architecture of knowledge based system for decision and fusion was presented. The architecture was implemented using an original scoring algorithm and Bayesian belief networks.

The hierarchy and algorithm design was inspired by vibration expert reasoning. The system allows incorporation of expert knowledge along with ability to learn from examples.

The architecture was tested with both simulated and real data and displayed good discrimination between damaged and healthy mechanical components. Detection of the damage in bearings was not affected by damages in shafts and/or gears.

In the future the system should be checked on more extensive data collections. Implementation of additional decision models such as neural networks and other types of classifiers may be also considered. As well the condition probability tables of the Bayesian networks can be determined automatically based on examples.

## REFERENCES

- Antoni, J., Randall, R. B., (2002, April), Differential Diagnosis of Gear and Bearing Faults, *Journal of Vibration and Acoustics*, Vol. 124 pp. 165-171.
- Bhavaraju, K. M, Kankar, K., Sharma, S. C., Harsha, S. P., (2010). A Comparative Study on Bearings Faults Classification by Artificial Neural Networks and Self-Organizing Maps using Wavelets, *International Journal of Engineering Science and Technology*, Vol. 2(5), 2010, pp. 1001-1008.
- García-Prada, J., C., Castejón, C., Lara, O. J., (2007). Incipient bearing fault diagnosis using DWT for feature extraction, *12th IFToMM World Congress*, Besançon (France), June18-21, 2007.
- Hariharan, V., Srinivasan, PSS. (2009). New Approach of Classification of Rolling Element Bearing Fault using Artificial Neural Network, *Journal of Mechanical Engineering*, Vol. ME 40, No. 2, December 2009, Transaction of the Mech. Eng. Div., The Institution of Engineers, Bangladesh, pp. 119-130.
- Klein, R., Rudyk, E., Masad, E., Issacharoff M., (2009a). Emphasizing bearings' tones for prognostics, *The Sixth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies*, pp. 578-587.
- Klein, R., Rudyk, E., Masad, E., Issacharoff M., (2009b). Model Based Approach for Identification of Gears and



Bearings Failure Modes, *International Journal of Prognostics and Health Management*.

Klein, R., Rudyk, E., Masad, E. (2011). Methods for diagnostics of bearings in non-stationary environment, *CM2011-MFPT2011 Conference Proceedings*. June 20-22, Cardiff, UK.

Li, R., Sopon, P., He, D., (2009). Fault features extraction for bearing prognostics, *Journal of Intelligent Manufacture*, DOI 10.1007/s10845-009-0353-z.

MIMOSA, OSA-CBM V3.1L: Open Systems Architecture for Condition-Based Maintenance, [www.mimosa.org](http://www.mimosa.org)

Neapolitan, R.E., (2003). Learning Bayesian Networks, *Prentice Hall Series in Artificial Intelligence*, Prentice Hall (April 6, 2003), ISBN-13: 978-0130125347.

Ocak, H., Loparo, K. A., (2001). A new bearing fault detection and diagnosis scheme based on hidden Markov modeling of vibration signals, *IEEE International Conference on Acoustics, Speech, and Signal Processing, 2001 Proceedings (ICASSP '01)*. May 07-11, Salt Lake City, UT, USA.

analysis and topological dynamics. In the last 4 years, Eyal is an algorithm developer at "R.K. Diagnostics".

**Renata Klein** received her B.Sc. in Physics and Ph.D. in the field of Signal Processing from the Technion, Israel Institute of Technology. In the first 17 years of her professional career she worked in ADA-Rafael, the Israeli Armament Development Authority, where she managed the Vibration Analysis department. In the decade that followed, she focused on development of vibration based health management systems for machinery. She invented and managed the development of vibration based diagnostics and prognostics systems that are used successfully in combat helicopters of the Israeli Air Force, in UAV's and in jet engines. Renata was a lecturer in the faculty of Aerospace Engineering of the Technion, where she developed and conducted a graduate class in the field of machinery diagnostics. In the last three years, Renata is the CEO and owner of "R.K. Diagnostics", providing R&D services and algorithms to companies who wish to integrate Machinery health management and prognostics capabilities in their products.

**Eduard Rudyk** holds a B.Sc. in Electrical Engineering from Ben-Gurion University, Israel, M.Sc. in Electrical Engineering and MBA from Technion, Israel Institute of Technology. His professional career progressed through a series of professional and managerial positions, leading development of pattern recognition algorithms for medical diagnostics and leading development of health management and prognostics algorithms for airborne platforms, such as UAV's and helicopters. For the last 4 years Eduard is the director of R&D at "R.K. Diagnostics".

**Eyal Masad** received his B.Sc., M.Sc. and Ph.D. degrees from the Faculty of Mathematics in the Technion, Israel Institute of Technology. His research topics were in the fields of Machine learning, Information theory, nonlinear