ANN based approach to the structural health monitoring of a traction equipment

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Abstract: - The concept of predictive maintenance, whose application became every day more and more diffused was born some years ago. The fundamental idea on which the predictive maintenance is based on is the monitoring of specific parameters that can supply useful information on the system state of health. In the presented application, vibrational levels represent one of these parameters and relative continuous monitoring is proposed. As a drawback of this approach, the availability of monitoring devices and their correct installation is needed, even if many times not availablr for cost or installation reasons. To avoid such limitations, the present work present an Artificial Neaural Network based approach for the management of "virtual" sensors whose data are derived from a limited set of sub-data. The presented application will show interesting results obtained with reference to a traction converter system as an example of the proposed technique.

Key-Words: - Structural health monitoring, Artificial Neural Network, Finite Element Method

1 Introduction

The task of this work is to investigate the reliability of a structural health monitoring system for a train under-floor electric-mechanic component. In the public transportation, the maintenance and safety represent two very important aspects. This two aspects are not easy to accord each other. A good maintenance level is necessary to guarantee the safety on board but is also expensive. In transportation history (airplanes, trains, ships, cars, trucks, buses) there are many accidents due to maintenance lack. The real problem in the maintenance field in that, sometimes, some critical components are not easy to check. During the last decade the predictive maintenance has acquired an important role in all engineering fields. In the proceeding of the paper the predictive maintenance will be explained and an analytical model, based on the neural network approach, will be presented. The final task is to predict the behavior of the mechanical component without any human action.

2 Introduction to maintenance

The task of the maintenance is to preserve the mechanical properties of the system. The maintenance is a mixture of ideas and knowledge of different fields like engineering, physic and management. An important aspect of the maintenance is the approach to the upgrading or optimization in the life-cycle of the product. The maintenance is a complex process based on two aspects

- Reliability: is the probability the component failure during his life;
- Availability: is the percentage of time the component work on the total life time;

The ideal machine have an infinite availability (all life time) and a very high reliability, the common practice is two find a good compromise between the availability – reliability aspect and economic one. To do so is useful to operate in the strict neighborhood to the minimum cost point on the curve of Fig. 1.

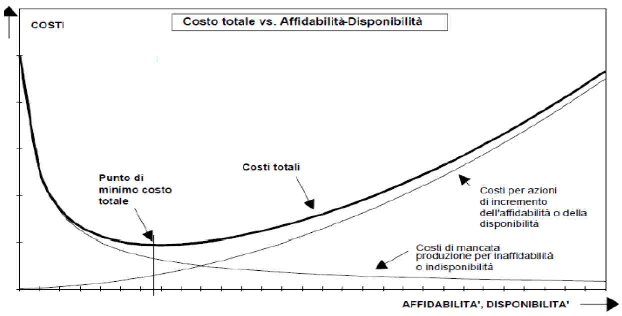

Fig. 1: availability – reliability Vs cost curve

2.1 Maintenance types

The maintenance is a very complex field in which the choice of the maintenance operation increment can be dangerous and make the machine less efficient and productive with an increasing of costs. The right choice is to schedule a complete series of maintenance operation studied to maximize the efficiency and the productivity of the component. In

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a preliminary way we can identify three different maintenance approach

- Corrective maintenance;
- Preventive maintenance;
- Predictive maintenance;

2.1.1 Corrective maintenance

It is applied when an unexpected damage occur in the machine preventing the correct function the machine itself. This type of maintenance is expensive and impossible to prevent and can be applied only for very simple and cheap mechanical components. This type of maintenance is applied to non-critical components.

2.1.2 Preventive maintenance

In this case, the maintenance is performed after a specific time interval without damage also. The task is to minimize the damage possibilities between two maintenance inspections. The great advantage of this approach is the opportunity to choice the period for maintenance, usually, this period is chosen according the age, the fatigue of the components, the period of the year in which the components is not required to be used.

To be clearer the period between two maintenance inspections can be:

- Static, the period is fixed by the manufacturer and is valid for all the component life cycle;
- Dynamic, is fixed by the customer according his knowledge of the component and the preceding experience on similar components;
- On condition, the maintenance is done after a visual inspection if necessary. The risk is to do maintenance operation when not necessary, or the contrary, not do maintenance when it is necessary;

2.1.3 Predictive maintenance

The concept of predictive maintenance was born some years ago. The fundamental idea on which the predictive maintenance is based on is to follow the behavior of the component monitoring some particular parameters from that parameters the health status of all components can be investigated. The monitoring of these parameters is done using some sensors (accelerometers, temperature probe, flowmeter, etc.) in real time. In this case, it is the component itself to check is status giving a warning when one or more investigated parameters are out of the normal range. This is the alert that something inside the system is damaged and a maintenance operation is required. The maintenance is done when and if necessary reducing costs.

3 Traction converter

The motion of the train is guaranteed by the traction converter unit, composed of three inverters, a Traction Unit Control (TCU in the following) and a breaking chopper. The system is powered by a continue current (the electrical line) and is governed by a control signal from the cab hood to the TCU. The combined effect of electrical power and manual control of driver make the inverters generating the wave form for the motion and breaking of the asynchronous (electrical) engines. During the breaking phase the kinetic energy is recovered and turned in electrical energy for the line.

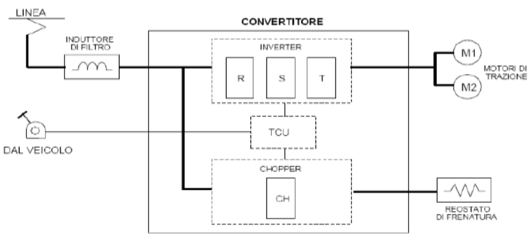

Fig. 2: Power unit logical scheme

The traction converter is installed under the train floor and fixed by bolts. The whole component is composed of three power unit modules (each module is the inverters, TCU) and a control panel. Each module can work independently from others and is the same for engine and chopper. The control panel is centered in the traction converter. It contains the control units, the electro-mechanic system, voltage and current transducer, high voltage and low voltage connectors to the train. The whole system in encapsulated to prevent the contact with water and dust. The hot flow generated by the inverters is dissipated by a static fan and the air flow is guaranteed by the train movement. No rotating fan are mounted on board.

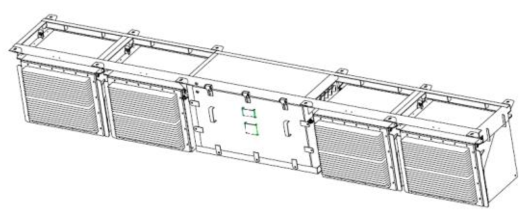

Fig. 3: Traction converter

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3.1 The control panel

The control panel is the real object under investigation. It is centered in the traction converter and contains a certain number of components that can be subject to damaging in case of vibration or shocks. The component inside the control panel are:

- TCU module;
- 1 line tension transducer (TVL);
- 1 filter tension tranducer (TVF);
- 1 line current transducer (TAL);
- 1 principal filter counter (CPF);
- 1 filter charge counter (CCF);
- 4 charge filter resistant (RCF);
- 1 charge filter fusible (RCF);
- 1 filter transducer fusible (FTV);

Fig. 4: Control panel

4 CAD model

The CAD process has been done using CATIA V5 software. The starting point have been the constitutive drawing of the object (see fig. 5). In the CAD model some details have been deleted to simplify the geometry and reduce the computational cost. The neglected details are not relevant for the final results so the computer model is really equivalent to the real object. From Fig. 5 are evident the iron beam structure (thickness 2mm) and the closing plate in the back side and lateral one. The plates are done of iron and have a thickness of 2mm also. The front side have two inspection doors not shown in Fig. 5. They have been neglected because they give no contribution to the structure stiffness. The real effect of both inspection doors is the change in mass distribution but it can be neglected considering the door's mass relatively small when compared to the traction converter's mass.

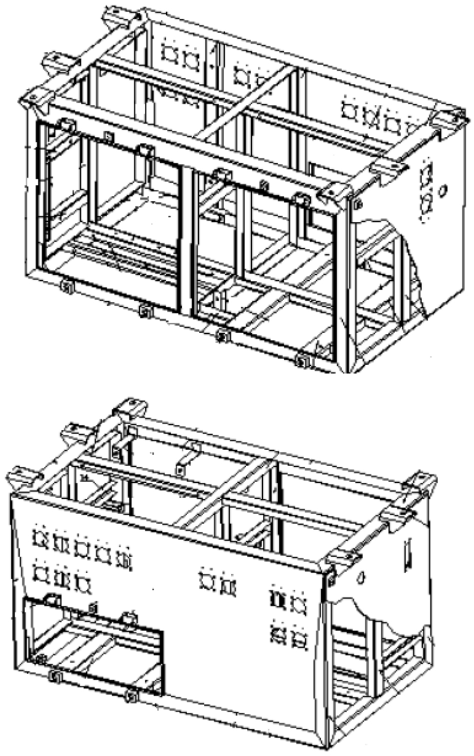
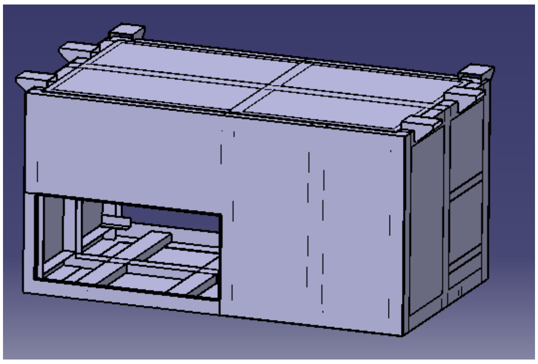


Fig. 5: Traction converter drawing

In the upper side of the traction converter are collocated the attachment points between the traction converter and the train. The connection is realized by bolts and no anti-vibration system are mounted on board. Inside the control panel are surely presents some components to attach the electrical boards to the structures. These components are not shown in Fig. 5 but they will be considered in the CAD model because they are the point for which the vibration path from the train to the boards. The final dimensions are 1.2x0.68x0.65 meters for a whole mass of 89 kg. The output file is step (.stp) extension file for the FEM model import.



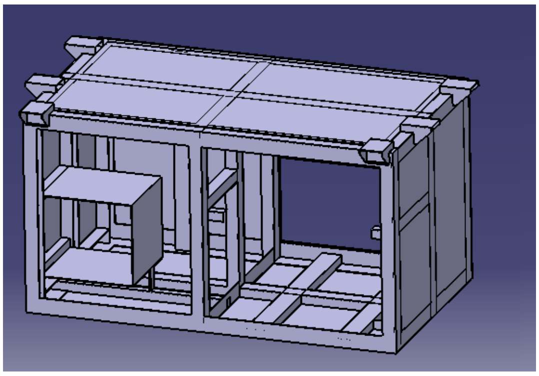


Fig. 6: Control panel CAD model

5 FEM model

5.1 Construction of the model

The geometry, as described in chapter 4, has later been used for the FEM model. The FEM analysis has been done using the Patran (pre and post processor) and Nastran NX (solutor) combination. The preprocessor Patran software has a proprietary geometry module. In this case the module has been used to import the geometry of chapter 4 (see next Fig 7).

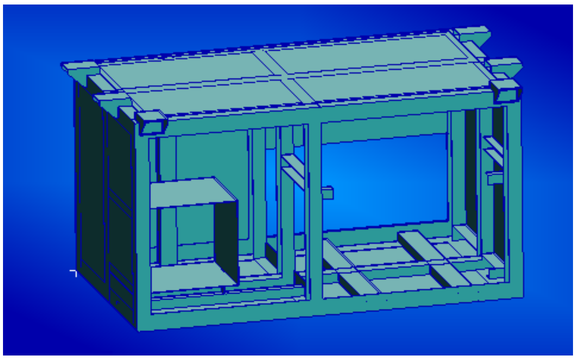


Fig. 7: Geometry imported in Patran

The geometry has then been treated like a single object so the solid mesh is the only possible. The mesh has been composed by thetrahedrical elements (TET4).

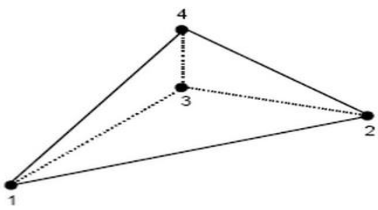


Fig. 8: TET4 element

The TET4 element is in-fact, flexible and can accord a large number of different geometry. The mesh has a maximum dimension of 0.016 meters with a number of about 150000 elements.

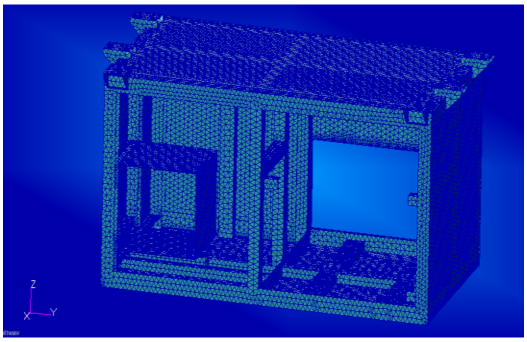


Fig. 9: mesh of model

The structure's material is steel s235jr. The material is isotropic and the value of properties are shown in Table 1.

Young modulus (GPa)	198
Poisson modulus	0.33
Density (kg/m3)	7850

Table 1: Material properties

In the control panel are presented some components not draw in the CAD model. To simulate the presence of this component single lumped masses have been used. This points have been linked to the structure with RBE3 elements. The points (six in total) are shown in Fig. 10 and the respective masses are listed in Table 2.

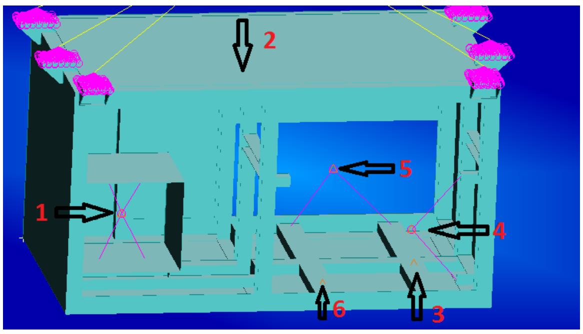


Fig. 10: condensate masses position

Component	Mass (kg)	Component	Mass (kg)
1	4.5	4	3.0
2	1.5	5	5.0
3	2.0	6	1.0

Table 2: Masses list

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5.2 Static analysis

As a first step, a static analysis (SOL103) has been performed, once typical loads have been applied:

- Load Case 1: 3g acceleration in the vertical direction to simulate the gravity;
- Load Case 2: 5g acceleration in the long. direction to simulate a hard braking;

During this step, rigid connection have been considered at the bolt fixing point.
The calculated displacement for the two cases of 5.4.2 are shown in Fig. 11 and Fig. 12.

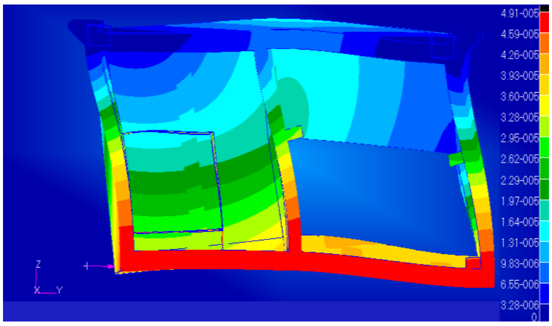

Fig. 11: Displacements of Load Case 1

5.3 Modal analysis

The main target of modal analysis and of later performed forced response has been the determination of the system's normal and forced response under different boundary condition.
This study was, in fact, oriented to identify and quantify the system modification as a function of the boundary bolts clamping force.
For this purpose, a new node has been created 5mm above the supporting plates. This node is used to create a star of Multi Constrain Point of RBE3 with the nodes on the contact plates (slave nodes). The six master nodes are connected with the same RBE3 element to a single node for the load application.
Table 3 and following figure 12 and 13 reports main results of the modal analysis in "full clamped" conditions.

Modal number	Frequency (Hz)	Modal number	Frequency (Hz)
1	205.25	7	387.84
2	230.03	8	412.63
3	277.63	9	429.56
4	302.13	10	461.91
5	327.40	11	474.92
6	345.48	12	533.97

Table 3: Frequencies list

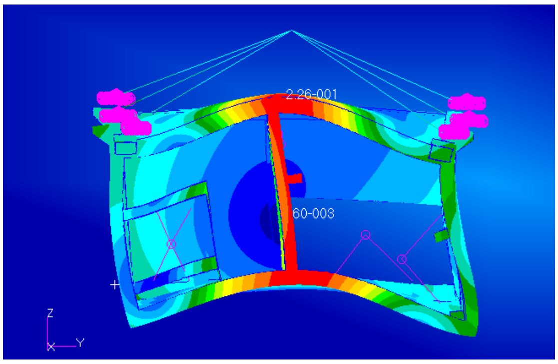

Fig. 12: Mode 1

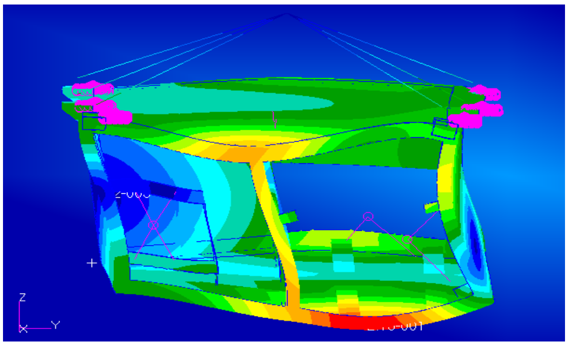

Fig. 13: Mode 2

5.4 Forced response

The main target of the dynamic response calculation both at structure lever than at the component connection point is the determination of the spectral response to an external dynamic load (the vibration induced through the connection point to the train structure).
These induced vibration may in-fact be causes of component fault if not limited within the design limits.
As a general consideration it can be assumed that the vibration levels and spectra mainly depend by the external load but also may be influenced by the boundary conditions (i.e. the connection bolt clamping torque).
Following these consideration, a forced response analysis has been performed under these hypothesis:

- The frequency range of interest has been fixed within 200 Hz and 500 Hz because this interval is characteristic of the operative forcing vibrations and because the principal normal modes are excited within this interval
- The force, simulating a constant force of 10 N to all frequencies under investigation is introduced into the system at the 6 connection point (bolts). The force is applied in the central point simulating

the effect of the train on the structure and transferred through RBE3 elements to the structure itself .

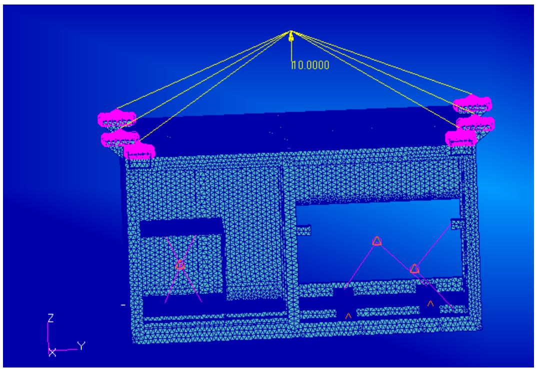

Fig. 144: Applied force for forced response

These RBE3 elements, also simulate the bolt element that guarantees the connection of the structure to the train and has been simulated as a spring element, whose stiffness has been changed from 10e9 N/m for the case of all bolts correctly closed to 10e3 N/m for the case of failed bolt .
As defined, we have two possible conditions for the bolts: right or failed. Considering the six bolts we have a certain number of combinations for bolts. Ten possible configuration have so been studied as reported in next table 4 and better identified in Figure 15.

Case number	Failed bolts
1	1
2	2
3	3
4	4
5	5
6	6
7	1 – 3
8	1 – 2
9	4 – 5
10	5 – 6

Table 4: Case number and failed bolts

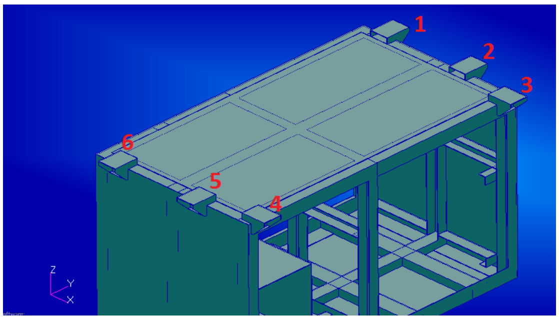

Fig. 155: Bolts number

5.4.1 Results
Different simulation have so been computed and the response at component level has been measured as a function of the “fault£ scenario.
Next pictures show some of the forced response; it appear evident that resonance frequencies are excited presenting the maximum level peaks.
In the following figures, the forced response for some components (see Fig. 10 and Table 2) for case number 1 (see Table 4). The results shown from Fig. 18 to Fig. 23 are the same for all nodes of the structures. Of course the resonance frequencies are different for different nodes and the peak are shifted in frequencies and amplitude but the shape is essentially the same. The results of the forced response will be used in the next phase for the vibration recognition.

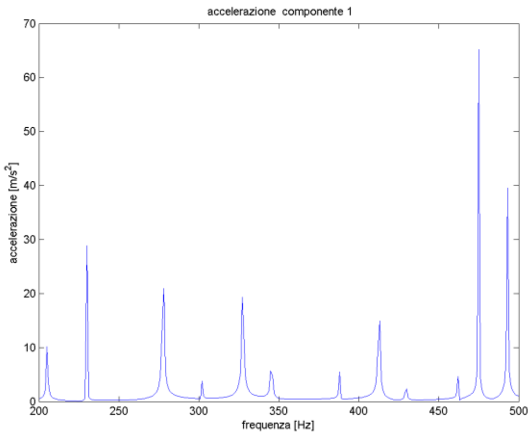

Fig.16: Forced response for component 1

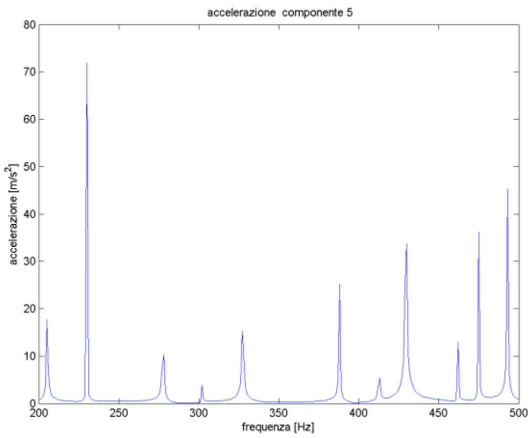

Fig. 17: Forced response for component 5

It has been experienced that the change in the boundary condition generally change the forced response also at component level; this circumstance

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could create excessive vibration to the component, unespected in standard conditions.
For this reason, a preventive maintenance approach should take into account the monitoring of vibration at component level to identify response spectra change and define the limits for tolerance.
Because this is not always possible because of the accessibility of some area of the TCU system, the concept of “virtual accelerometer” would be introduced.
The main concept is the possibility to extrapolate the acceleration in one or more “virtual” accelerometer measuring the “real” vibration somewhere else into the structure.
From a theoretical point of view, this circumstance would be possible. Anyway, the practical implementation require the adoption of advance numerical tools for pattern recognition.

6 Neural Network

Neural Network are a powerful tool used in many engineering fields, used for different applications from text recognition to statistical data analysis. The really notable property of neural network is that they can learn from a training set defined by the user. This learning ability is based on what happen in the brain. The idea on which the neural network is based is inspired to the human brain and its capacity to learn and memorize information in the first phase and then use the information when necessary to solve similar problems. The advantage given by the learning capacity is also the lack point of this approach; if the training set is wrong the neural network will base the response on wrong information giving a wrong response. In the last few years many models of neural network has been developed; the most famous are the multilayer perceptron and the radial basic function. Both neural network are feed forward model, the information goes in one direction and no iterative optimization is present.

6.1 Biological neural network

In the brain (human and not) are present millions of neurons. Every neurons is maiden up of a cellular body and an extension called dendrites. The dendrites are used by neurons to exchange electrical impulse each other’s. Every neurons has a long (from 1cm to 1m) extension called axon also. At the end of the axon are situated the synapses. The synapses have the function to exchange information (electrical impulse) with different cellules (not neurons). The synapses contain a certain quantity of chemical substance for electrical conduction, this substance is called neurotransmitter. The neurons send an electrical impulse along the axon when a difference in electrical potential is present between the inside and outside of the cellule. Every neurons has an elaboration time in the order of milliseconds (not really elevated if compared to the modern computers) but the combination of millions of neurons make the human brain the best performed computer of ever since now (according to the Moore law the calculation power of computers double every 18 months, in the future the computers will be more potent of human brain).

6.2 Artificial neural network

The artificial neural network (neural network also in the following) has the task to reproduce the human brain. To do this a new mathematical entities has been introduced, the artificial neurons. This entity has multiple input and a single output. Every input is weighted. The neurons is activated for a certain combination of weight. The neural network is trained with a certain set with known input and output. The neural network response is compared to the real one. The difference is the error of the neural network. The weight on the inputs are changed with an iterative optimization process to minimize the error. The optimization process ends when the error is smaller than a certain quantity.

6.3 Artificial neurons

In Fig. 18 the logical scheme for an artificial neuron is shown. The neuron (sum symbol) has a multiple input $x_1, x_2, \dots, x_m$. Every input channel is weighted by the coefficients $w_{k1}, w_{k2}, \dots, w_{km}$.

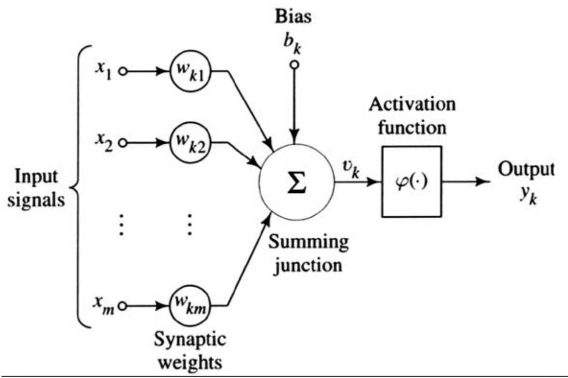

Fig. 16: Artificial neurons scheme

If the weight value is positive the channel is called active, inhibitory in the opposite case. The absolute value of the weight coefficient is a measure of the channel power. The response of the neurons (the output) is

$Y = f(a) = f(\sum_{i=1}^{m} w_i x_i)$

This contribution is the bias. To keep in account the bias effect on the global response the up wrote equation can be modified as

$Y = f(a) = f(\sum_{i=0}^{m} w_i x_i)$

Where the $x_0 = 1$ contribution is due to the bias.

6.4 Activation function

In Fig. 25 is present another element: the activation function (φ). It gives the response of the neuron to a known input. In the following pictures some remarkable activation function are shown.

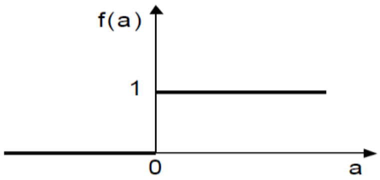

Fig. 17: Step activation function example

In this case the output is

$$Y = \begin{cases} 0, for\ a < 0 \\ 1, for\ a > 0 \end{cases}$$

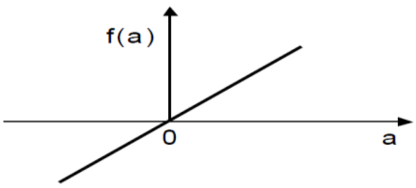

Fig. 18: Ramp activation function example

That gives $Y = a$

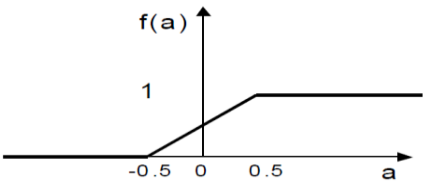

Fig. 197: Piecewise activation function example

And the output is

$$Y = \begin{cases} 0, for\ a < -0.5 \\ a + 0.5, for - 0.5 < a < 0.5 \\ 1, for\ a > 0.5 \end{cases}$$

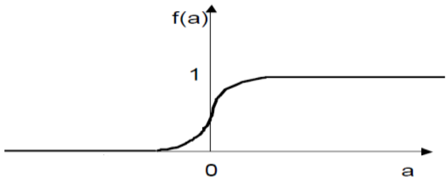

Fig. 20: Sigmoid activation function example

For an output in the form

$Y = \frac{1}{1+e^{-a}}$

7 Neural network architecture

There are, substantially, two different architecture types

- Fully connected networks;
- Layered networks;

In the fully connected network every neuron is connected with all neurons in the network. For every connection is defined a weight to identify the influence of connection on the network. To the network is associated e square matrix with dimension n with n number of neurons.

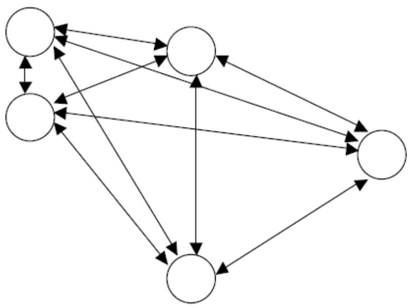

Fig. 21: Fully connected network

For layered networks there are more level connected each other. Every neuron in level is connected with all neurons of near levels but not whit neurons of the same level. The network is maiden up of a first layer in which the neurons receive the external input and a last layer in which the neurons give the output. Between the first and last layer there are one or more hidden layers. In these layers are created the connections and the mathematical operation to calculate the output from the input (see Fig. 29).

7.1 Network's training

After the network set up the more important phase to guarantee the right application of the network is the training phase. It is divided in two sub-phases: the training phase and the testing phase. In the training phase a known couple of input/output is used to modify the weight inside the network. This phase is an iterative phase and is stopped when the error between the known output and the calculated one is less than a specific value. In the testing phase only an input set is used. The output set is known to the user but unknown to the network. In this phase the network is tested for different types of inputs to be sure of its capability of reconstruction.

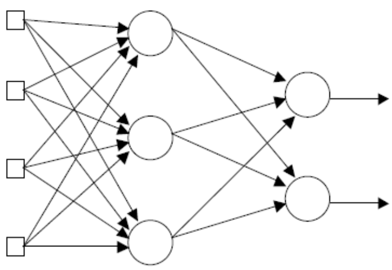

Fig. 22: Layered networks

7.1.1 The delta rule

The weight optimization is done, commonly, using the delta rule called Widrow – Hoff rule also. In this case $x = (x_1, x_2, \dots, x_i)$ is the input to the network, y is the real output and t the calculated one. The error, in this case, is the difference between real and calculated output

$\delta = t - y$

Now, the question is: How, known the error (δ), I can change the weight to optimize the results? The answer is the delta rule. According to the delta rule the weight change (Δw_i) is equal to

$\Delta w_i = \eta \delta x_i$

with η the learning rate of the neuro and is included in the 0 – 1 interval. The delta rule has the capacity to modify only the weight for neurons that have given a contribute to the error ($x_i \neq 0$).

8 Neural network application

The neural network application has the task, as said before, to reconstruct the acceleration on all component listed in Table 2 starting from a reduced number of sensors (in this case accelerometers). To know the acceleration on the components is necessary to use six accelerometers mounted on the component itself. In the real case is very difficult the combined use of six accelerometers and the small size of components make the accelerometer installation very difficult. The problem can be solved if, from a less number of accelerometers installed in some structure points and not necessary on the components, the accelerations can be calculated analytically. This is possible training and using the neural network described in chapter 6 and 7.

8.1 Training phase

In this phase (see 7.1) the weight of the neural network are settled to guarantee the convergence of the results. To train the network have been created two matrix; the first is a matrix Ti having 6x300 elements. The j-th row (with 1<j<6) of the matrix Ti is the acceleration on the j-th component (see Table 2) in the i-th case study (see Table 4). The second matrix, Xi, is an nx300 elements matrix where n is the number of accelerometers mounted on board. To simplify the calculation and reduce the cost n must be small. In this case have been tested three different accelerometer combinations (see Fig. 31).

The following cases have been taken in account: only accelerometer 1; accelerometer 1 plus accelerometer 2; accelerometer 1, accelerometer 2 and accelerometer 3 combination. For every case the trend of mean square error of the network is shown in Fig. 32.

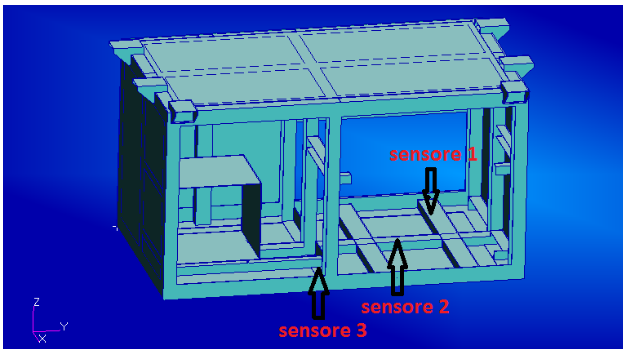

Fig. 23: Accelerometers position on the traction converter

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On the x axes is shown the iteration number (the maximum iteration number to find convergence is 100) and on the y axes the mean square error. The case with 3 accelerometers give an error of 10e-2 so we can be satisfied of the results of the training phase.

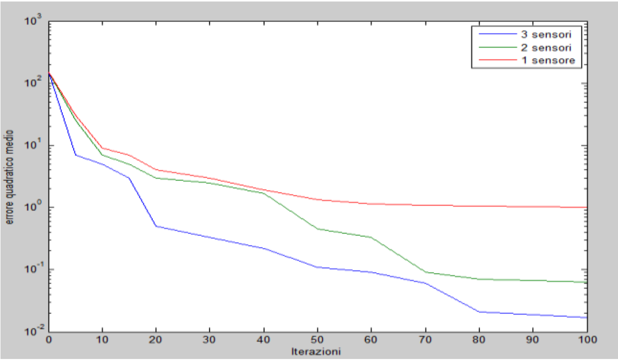

Fig. 24: Mean square error for different accelerometers number

8.2 Testing phase

In this phase a different input set has been created. In particular to simulate a different case we have supposed to fail the bolt 1 (see Fig. 17) with a different value of connection's stiffness (2*10e3 N/m). The FEM model has been used to find the acceleration in the points of three accelerometers (input set of functions) and in the six components (output set). This time the network received as input the input set also. The output is reconstructed using the weight matrix of 8.1. In the following figures is shown a comparison between numerical acceleration and neural network acceleration.

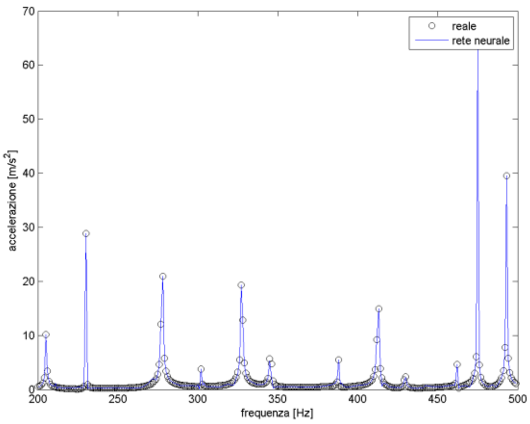

Fig. 25: comparison of acceleration, numerical and neural network for component 1

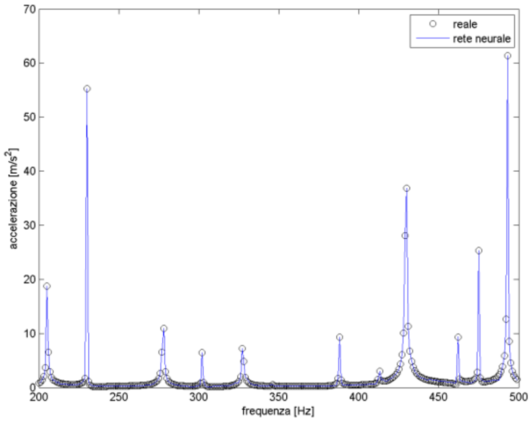

Fig. 26: comparison of acceleration, numerical and neural network for component 3

9 Conclusion

The results of acceleration reconstruction are really close to the numerical one (see Fig. 33 and Fig. 34). This the demonstration that the neural network can efficiently reproduce the logical path between input and output. The most important phase in the neural network utilization is the training phase. To be sure of network reliability it is important to use an appropriate training set as large, in function number, as possible. Another important aspect is the correlation between input and output. For the training set is important to verify that the used data are correct. In the opposite case a wrong weight matrix is founded and the simulation phase will fail.

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