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Probabilistic Vibration Models in the Diagnosis of Power Transformers

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1. Introduction

Power transformers are some of the most important equipment for the transmission and distribution of electric power. A single failure in a transformer causes disturbances in the electric network and may cause severe conflicts in hospitals, banks, industrial installations or urban areas in general.

In Mexico, the transmission network is composed by 350 power substations and 2,580 power transformers. The capacities of these transformers are typically 375, 225 and 100 MegaVoltAmpere (MVAS), with a nominal tension of 400 kV, 230 kV and lower. Approximately 27% of these transformers have more than 30 years in operation. For this reason, it is important to observe and register the amount and type of failures that have presented the transformers in the country.

Table 1 shows the type of transformer failures from 1997 to 2007 (CFE, 2010).

Failure	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total
winding insulation	11	6	5	10	5	2	9	4	6	5	6	69
core	0	0	0	0	0	0	0	0	0	0	2	2
bushing	3	2	5	3	1	3	1	1	5	7	5	36
on load tap changer	2	0	2	2	2	2	1	1	2	3	1	18
explosion with fire	1	3	0	0	2	0	2	0	3	0	0	11
other failures	1	0	1	0	2	4	1	2	0	0	0	11
TOTAL	18	11	13	15	12	11	14	8	16	15	14	147

Table 1. Type of failures in transformers since 1997.

Notice that the highest percentage of failures corresponds to isolation in the windings. Problems with insulation represent 80% of the failures for contamination, aging and core insulation. Other causes can be overvoltage or short circuits. The insulation failures can be slow degradation, while overvoltage and short circuits represent instantaneous failures. The Mexican case is not unique. Failures in transformers in United States and Russia show similar results.

All these common failures can be considered as mechanical failures, in contrast to other chemical based failures. Consequently, mechanical failures cause vibration.

Literature reports different methods for the diagnosis of power transformers. Among the most important are the following:

- dissolved gas analysis: analyzes the chemical composition of the isolating oil. Percentages of different gases are found and tables provide a relation between these percentages and the status of the transformer. It is widely used to detect all the faults related with oil.
- frequency response analysis: analyzes the transformer response given a voltage or current excitation. The response is analyzed in the domain of frequency in magnitude and phase. Later, this response is compared with known reference responses and then, a difference from the correct operation can be detected. Also, a signature of certain faults can be obtained and compared.
- partial discharge: utilizes acoustic sensors to detect the location of partial discharges occurrence inside the transformer. A partial discharge is a transient electric discharge that bridges the isolation gap between two conductors. It is then possible to detect deficiencies in the transformer isolation.

An alternative method for detecting failures in transformers is the analysis of the vibration produced inside the transformer due to its operation. Normally, the transformer produces vibrations in the windings and the core, and these vibrations vary according to certain operative conditions. Also, in the presence of mechanical failures, the vibration pattern is different than in normal conditions. One advantage of this alternative method for detecting failures, with respect to the mentioned methods is that it is possible to design an on-line diagnosis system. This implies that the detection of the incipient failures can be achieved at all times, while the transformer is working.

This chapter presents the development of a probabilistic model of the vibrations in a transformer given all the possible combinations of operating conditions. The probabilistic models are Bayesian networks (BN). The BN are directed acyclic graphs that represent the probabilistic relation between the variables in a domain. In this case, we obtain a Bayesian network that codifies the relation between the vibration signals with all the variables that conform the operative conditions. The model is obtained using automatic learning algorithms applied to historical data of the transformer working at different conditions. The BN is used to calculate the probability of a failure, given the evidence from the operative conditions.

The next section establishes the central problem in this project, namely the vibrations in a power transformer. Also, section 2 reviews reviews some of the related work reported in the literature.

2. Power transformers

The transformer is an electrical device without moving parts, that is used to transfer energy from one circuit to another through a common magnetic field, with no direct electrical connection between the two circuits, (Harlow, 2007).

Basically consists of two or more windings (coils) and a common core of steel. When a voltage is applied in the exciting coil, the coils exchange energy via magnetic induction that occurs when an electric current variation in time is passed in one of them.

Figure 1 shows the idealized model of a two windings transformer with steel core. When applied an alternating voltage ($V1$) to the exciting winding, a current ($I1$) flows and generates a magnetic flux (ϕ). The flux circulates in the steel core so that the voltage ($V2$) is induced in the second winding. The ratio of applied voltage and induced voltage ideally depends on the number of turns of each coil. For example, if the number of turns in the primary winding is twice that of the secondary winding, then the voltage $V2$ induced in the secondary is half of $V1$. This considering that almost 100% of the flow is driven by the core. In power transformers is commonly used steel laminated core for high capacity that has to drive the magnetic flux (steel core laminated from very thin sheets, such as .23 mm for reduced *eddy* and *hysteresis* losses). The ability of a material to conduct magnetic flux is called permeability. Currently, there are electrical steels for power applications with permeability in the order of 1,500 compared with 1.0 for air.

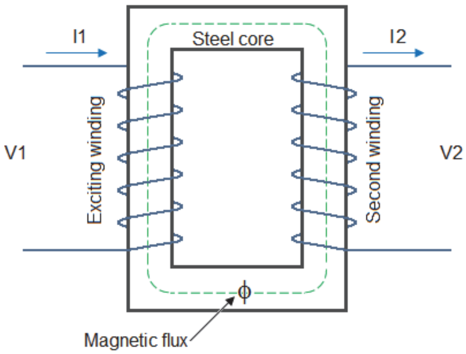

Fig. 1. Ideal transformer: two coils applied on steel core.

Transformers can be classified according to their application, construction or power capabilities. In the electricity transmission process, the utilized power transformers are characterized by the high levels of voltage and current that they handle. Power transmission requires power transformers to transmit energy from voltage production centers over long distances to consumption areas. Here, power transformers decrement the voltage down again for distribution to consumers. The distribution process requires transformers with less voltage and current. They are called distribution transformers.
For the design and construction of power transformers, regardless of size and power, various materials are used such as:

- Thin magnetic steel plates in the core.
- Copper or aluminum as conductor material in the coils (see Fig. 2).
- Cellulose products like high density paper and pressboard as solid insulation material.
- Mineral oil as liquid insulating material, which also functions as a coolant.
- Steel for the tank.

Additionally, the transformer has several external accessories such as (see Fig. 3):

- Radiators, fans and oil circulating pumps for the cooling function.
- Bushings as an insulating structure, for connection of windings to the outside.
- Oil temperature indicators.
- Oil Level Indicator

Fig. 2. Inner part of the transformer. The core and coils assembly is shown at the manufacturing stage. (Courtesy of Prolec GE).

- Pressure relief devices.
- Winding temperature indicator.
- Sudden pressure relay.
- Desiccant breathers.
- Liquid preservation systems.

2.1 Vibration in transformers

Transformers always vibrate while operating. Vibration can be detected at different frequencies, in different places of the transformer and caused by different sources. According to the literature, vibration below 100 Hz. is caused by cooling fans and oil pumps. Vibrations above 1000 Hz. are caused by small elements not related to the state of the core or winding (Golubev et al., 1999). Thus, the vibration frequency range of interest in transformer diagnosis is between the power frequency of 60 Hz (50 in Europe) and multiples of this up to 960 Hz.

In normal operating conditions, the main sources of vibration are the core and the winding of the power transformers. This vibration is transmitted to the transformer tank through the

Fig. 3. Power transformer at the electrical substation. (Courtesy of Prolec GE).

cooling oil and through the solid structure. Different levels of vibration can be measured at different locations of the transformer.

Vibration in the winding is caused by Lorenz forces that depend on the current density and the leakage flux density. Since the leakage flux and the current density have different directions, the winding force density has components in the radial and axial directions. Also, both components are a function of loading current, so the total Lorenz forces are quadratic functions of the current. It is worth to mention that the vibration caused by the winding is not too significant under normal operating conditions, but it is significant under several kinds of failures.

Vibrations at the core are caused by the magnetostriction process. It consists of changes of the dimension of core laminations, made by ferromagnetic materials, due to changes of orientation of the material crystals for magnetic fields. Thus, magnetostrictive effects are function of the magnitude of the applied field. Also, it is known that these magnetostrictive forces have a fundamental frequency of 120 Hz. i.e., twice the exciting frequency. Other source of core vibration is the air gap produced by the magnetic repulsion among laminations. This repulsion forces are mostly present at the corner joints of the core legs with the jokes, and it has also a fundamental frequency of 120 Hz (Lavalle, 1986).

In case of a failure like a short circuit, the mechanical integrity of the transformer can be altered. Certain changes, such as loss of winding clamping pressure, will lead to insulation

deterioration, and therefore, the vibrational response will be altered. In general, most of the failures occurring in the transformer, produce mechanical deformations in the winding, and hence, a change in the vibrational signature of the transformer. Typical failures occurring at the transformer core are caused by short circuits between core laminations or between the core and the tank. Since the tank is grounded, if several contact points between core and tank exist, a current will flow and temperature will rise. Also with laminations short circuits, the temperature increases. In general, temperature changes will produce changes in the insulation system that will produce mechanical changes that provoke changes in the vibrational signature of the transformer.
Summarizing, most of the failures in the winding and core of the transformer, will produce mechanical changes and will turn out in changes in the vibration pattern of the transformers.

2.2 Related work in transformers diagnosis by vibrations

Several technical groups have worked in the study of vibrations for identifying and diagnosing mechanical faults. The basic approach followed by all the research groups is the development of a model that represents the behavior of the transformer under different conditions. Later, when new readings are obtained, the model estimates or predicts the behavior of the transformer and a comparison with the current behavior can identify abnormal events. The key question here is *how can this model be defined?*. This question has been answered differently by some research groups.
The Electrical Engineering and Computer Science Department at the Massachusetts Institute of Technology (MIT) elaborated a series of Master of Science thesis devoted to the development of vibration models for faults identification in transformers (Crowley, 1990; Lavalle, 1986; McCarthy, 1987). First, they utilized an analytical model that relates the harmonic content of one input (square of the current) to one output (the vibration in the winding). The basic model has the form $y = Cu$ where y is a vector whose components are the amplitude of the vibrations discomposed at frequencies multiple of 120Hz. u is the current squared vector at the some frequencies and C is the matrix with parameters that relate them. The elements c_{ij} of C are estimated in a set of experiments made to a transformer free of faults at different conditions of load. For a given load condition, and for each frequency, several measurements were averaged and related with a Least-Squares algorithm to define the c_{ij} parameters. Other experiments were made to relate effects of the temperature in the same structure of measures. A third set of experiments was carried out in presence of a fault: a loosened up the windings. Other experiments consider the effects of the core vibrations in the winding vibrations. When both the winding and the core are excited simultaneously, the sources of vibration may have phase differences. They proposed a model that includes linear compensation for winding temperature, weighted by the harmonic amplitudes of the loading current squared, and linear compensation terms for core temperature and excitation voltage. Summarizing, the MIT theses propose a model that requires the acquisition of certain parameters from experiments implemented off-line. Later, these parameters are compared with the on-line parameters to detect changes in the normal behavior of the transformer.
Spanish Unión Fenosa proposes a model that is also based on vibrations (García et al., 2006a;b). They measure vibrations at the tank of the transformer, claiming that the vibrations are transmitted to the tank from two sources: the winding and the core. Thus, the vibration at the tank results from the vibration of the windings plus the vibration of the core, multiplied by a coefficient of transmission. The winding vibration is proportional to the square of the

current, and the vibration at the core is proportional to the square of the voltage. They also consider the temperature of the transformer as an important parameter in their model, so they complemented their analytical model with complex variables that represent the real and imaginary part of the amplitude of the vibration, the current and the voltage respectively, at the main frequency component. Other parameters are the oil temperature, and the geography of the transformer. These parameters must be defined through measurements taken off-line for each kind of transformer. Their diagnosis method consists of the estimation of the tank vibration and its comparison with the real measure. If the difference is greater that certain threshold, then a fault is detected.

The Russian experiments (Golubev et al., 1999) install accelerometers in both sides of the transformer in order to acquire vibration measurements while the transformer is working properly. They executed two sets of experiments. In the first experiments, no load is included in order to detect the vibration pattern due to the core. In the second set of experiments, load is included for detecting vibration from both, core and winding. Thus, they subtract the effect of both minus the effect of the core to deduce the effects of the winding. With this information, they calculate four coefficients that reflect the clamping pressures. If these coefficients exceed 90%, then the clamping pressure is in a good state. Between 80% and 90%, the pressure is in a fair state but the transformer can continue operating. Below 80%, the pressure is critical and requires immediate attention. This approach has been tested in more than 200 transformers 110-500 kV to 50 MVA in Russia with a rate of more than 80% confirmed diagnosis. Also, Manitoba Hydro power plants in Canada tested their large power transformers with this methodology with good results.

The approaches commented above, and our approach have similar basis. All utilize vibration measures in the tank of the transformer. All transform the vibration signals to the frequency domain in order to process the vibration components at the different frequencies. All propose a model that is utilized to estimate vibration amplitude values, and then compare with real measurements in order to detect changes in the behavior. In the revised work, models are deduced with analytical equations to define certain parameters that have to be acquired off-line over a testing transformer. Experiments are required over different operating conditions and also, in presence or absence of different faults. All these approaches deduce a general model for all kind of transformers where the experiments define the specific parameter for each kind of transformer.

The approach proposed in this chapter also utilizes a model. However, this model represents the probabilistic relations between condition operational variables and vibration measurements. This implies some special advantages:

- several automatic learning algorithms are available for model construction,
- empirical human expertise can be included in the models,
- the models can be adapted constantly for each kind of transformer in its real operational condition. This means that the diagnosis may still work even if the transformer is old and vibrates more that when new, but still working properly.
- other sources of information can be included, for example, structural characteristics of a transformer.

The next section describes basis for the proposed model.

3. Probabilistic modeling

The basic idea in this work is the representation of the vibration behavior of the transformer under different operational conditions. This allows detecting deviations of the normal behavior of the transformer. Therefore, the idea is to calculate the probability of an abnormal behavior, given the operational conditions and the vibration measured. The representation of the behavior is built using probabilistic models and specifically Bayesian networks.

The basic idea is the following. Calculating the probability of an abnormal behavior (hypothesis H) can be made using the evidence recollected (E) and the Bayes theorem as follows:

$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E)} \tag{1}$$

For example, if we want to calculate the probability of a windings loosened up hypothesis ($P(H \mid E)$) given that we observe high vibration as evidence, we could easily calculate by counting the times that we observe high vibration given that we knew that the transformer has loosened up windings ($P(E \mid H)$). However, if multiple hypotheses exist, and multiple evidence can be obtained, then the Bayes theorem in this form is not practical. What is needed is a practical representation of the dependencies and independences between the variables in an application. This representation is formed by the Bayesian networks (BN).

Formally, a Bayesian network is defined as a directed acyclic graph, whose nodes represent the variables in the application, and the arcs represent the probabilistic dependency of the connected nodes (Pearl, 1988). The Bayesian network represents the joint probability distribution of all variables in the domain. The topology of the network gives direct information about the dependency relationship between the variables involved.

As an example, assume that some application deals with the following variables: temperature (*temp*), excitation with voltage (*voltage*), load (*load*), amplitude of the acceleration (*amplitude*) and frequency (*freq*). Suppose for this example that voltage excitation of the transformer produces an increase of the temperature and a variation on the load fed. Also, the load produces an increment on the acceleration and variations of the frequency of this acceleration. This knowledge can be represented in a Bayesian network as shown in Fig.4. In this case, the arcs represent a relation of causality between the source and the destination of the arcs, according to the text above. Variables *load* and *temperature* are probabilistically dependent of variable *voltage*. Also, variables *frequency* and *amplitude* are dependent on *load*. Notice that besides the representation of the dependencies, the representation of the independences is an important concept in BN. In this example, *frequency* is probabilistically independent of *voltage* given *load*. Also, *amplitude* is independent of *temperature*.

Using the dependency information represented in the network, and applying the chain rule, the joint probability function of the set of variables in the application is given by:

$$P(t,l,v,f,a) = P(freq \mid load)P(amplitude \mid load)P(load \mid voltage)P(temp \mid voltage)P(voltage)$$

This corresponds to the product of $P(node_i \mid parents(node_i))$.

Besides the knowledge represented in the structure, i.e., dependencies and independencies, some quantitative knowledge is required. This knowledge corresponds to the conditional probability tables (CPT) of each node given its parent (corresponding to the term $P(E \mid H)$ in the Bayes theorem) and a-priori probability for the root nodes (corresponding to the term $P(H)$ in the Bayes theorem).

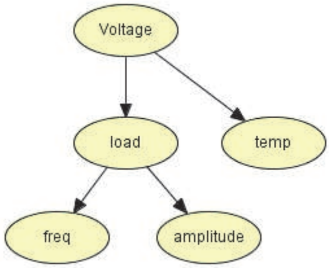

Fig. 4. Example of a Bayesian network with 5 variables.

Thus, a complete probabilistic model using Bayesian networks is formed by the structure of the network, and the CPT tables corresponding to each arc, and a-priori vectors corresponding to the root nodes (nodes without parent).
One of the advantages of using Bayesian networks is the three forms to acquire the required knowledge. First, with the participation of human experts in the domain, who can explain the dependencies and independencies between the variables and also may suggest the conditional probabilities. Second, with a great variety of automatic learning algorithms that utilize historical data to provide the structure, and the conditional probabilities corresponding to the process where data was obtained (Neapolitan, 2004). Third, with a combination of the previous two, i.e., using an automatic learning algorithm that allows the participation of human experts in the definition of the structure.
Once that the probabilistic model has been constructed, it can be used to calculate the probability of some variables given some other input variables. This consists of assigning a value to the input variables, and propagating their effect through the network to update the probability of the hypotheses variables. The updating of the certainty measures is consistent with probability theory, based on the application of Bayesian calculus and the dependencies represented in the network.
For example, in the network in Fig. 4, if *load* and *temp* are measured and *freq* is unknown, their effect can be propagated to obtain the posterior probability of *freq* given *temp* and *load*.
Several algorithms have been proposed for this probability propagation. For singly connected networks, i.e., networks in what all nodes have at most one parent as in Fig. 4, there is an efficient algorithm for probability propagation (Pearl, 1988). It consists on propagating the effects of the known variables through the links, and combining them in each unknown variable. This can be done by local operations and a message passing mechanism, in a time that is linearly proportional to the diameter of the network. The most complete and expressive Bayesian network representation is multiply connected networks. For these networks, there are alternative techniques for probability propagation, such as clustering, conditioning, and stochastic simulation (Pearl, 1988).
This project obtains historical data from different accelerometers collocated in different parts of the prototype transformer. The transformer is operated at different conditions of load, temperature, and excitation. The data acquired is fed to an automatic learning algorithm that produces a probabilistic model of the vibrations in the transformer working under different conditions. Thus, given new readings in a testing transformer, the model calculates through probabilistic propagation, the probability of certain vibration amplitudes at certain

frequencies. Therefore, a deviation of this behavior can be detected when reading the current values of acceleration and frequency. The next section explains this process detailed.

4. Probabilistic vibration models

Two approaches were considered for the diagnosis of transformers based on vibration signals. The first approach consists of inserting failures in a transformer and measures the vibration pattern according to the operational conditions. The diagnosis becomes a pattern recognition procedure according to the set of failures registered. Some examples of common failures are loosening the core or loosening the windings. These failures are similar to those failures caused by strikes or short circuits. The second approach consists of the measurement of vibration signals of a correct transformer working at different operational conditions. These measures allow the creation of a vibrational pattern of the transformer working properly. Only one model is obtained in this approach. Only measures in a correct transformer are required. As a consequence, this second approach is reported in this chapter, i.e., the construction of a model for the correct transformer.

Additionally, two sets of experiments were conducted. In the first, experiments considered the operational tests performed at the factory in the last steps of the construction of the transformers. These tests increments the number of factory acceptance tests (FAT). The second set of experiments considers the normal operational conditions of the transformer and detects abnormal behavior in site (SAT).

In the next section, we include a description of the experiments conducted, and the construction of the model of correct transformer. Finally, we discuss the difference between FAT and SAT models.

4.1 Experiments

The creation of a model for the correct functioning of the transformer requires correct transformers. The experiments were done at the Prolec-General Electric transformer factory in Monterrey, Mexico. We had access to the production line at the last step of the new transformers tests. We installed 8 sensors around the transformer as shown in Fig. 5: two in each side, one in the lower and the other in the upper part of every side. This array of sensors permits us to identify the specific points of the transformer where the vibrations signals can be detected properly.

Experiments in Prolec GE factory consisted in 19 different types of operational conditions. Table 2 shows the operational conditions and the effect we wanted to study.

	Temperature		
Excitation	Cold	Hot	Condition
Voltage	Effect of voltage in core vibrations	Effect of voltage and temperature in core vibrations	70%, 80%, 90%, 100%, 110%
Current	Effect of current in winding package vibrations	Effect of current and temperature in winding package vibrations	30%, 60%, 100%, 120%

Table 2. Type of experiments in factory.

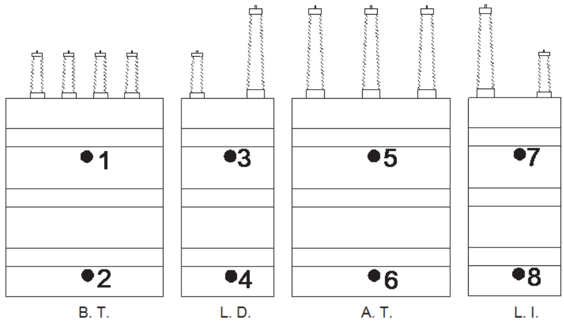

Fig. 5. Location of the sensors in the transformer. Two in the low voltage side (B.T.), the following in the right side (L.D), two in high voltage side (A.T) and the last in the left side (L.I).

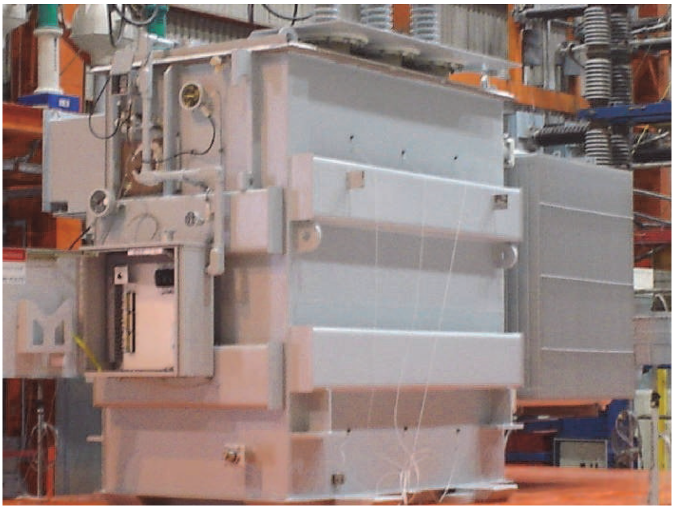

Fig. 6. Transformer in Prolec GE factory with the sensors (Courtesy of Prolec GE).

The experiments combine temperature and excitation. The experiments with cold transformer excited with voltage and no current are used to study the effects of voltage in core vibrations. Cold transformers excited with current and no voltage are used to study the effects of current in winding packages. Hot transformers with voltage study effects of temperature and vibration in the core. Finally, hot transformers and current study the effects of temperature and vibrations in the winding. Additionally, the experiments that study the effects when excited with current and no voltage, included variations between 30%, 60%, 100% and 120% of the nominal current for each transformer. Every transformer report its nominal current and nominal voltage. Similarly, the effects when excited with voltage and no current included variations between 70%, 80%, 90%, 100% and 120% of the nominal voltage. In total, 19 different types of experiments were conducted to all the transformers.

For each experiment, once that the transformer is prepared to a specific test, our data acquisition system collects vibration data at 5 K samples per second during two seconds for each sensor. Later, we apply the discrete Fourier Transform (DFT) and extracts the frequency content of the data set acquired. This is repeated ten to twelve times for each operational condition.
Repeating this procedure for all operational conditions, for all the sensors, we obtain the graphs as shown in Figures 7 to 10. Notice that the only information that we need to extract with the DFT is the frequency content of the vibration at frequencies multiple of 60Hz. In fact, we find no other components in frequencies different than these multiples.

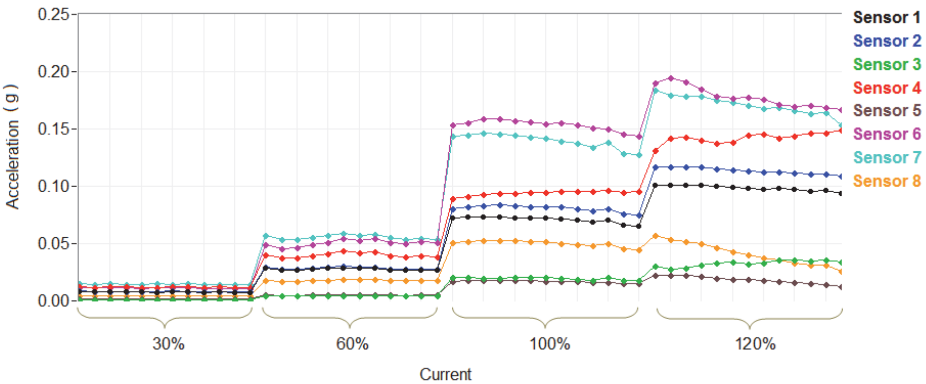

Fig. 7. Vibration signals when excited with current at 120 Hz. in all sensors.

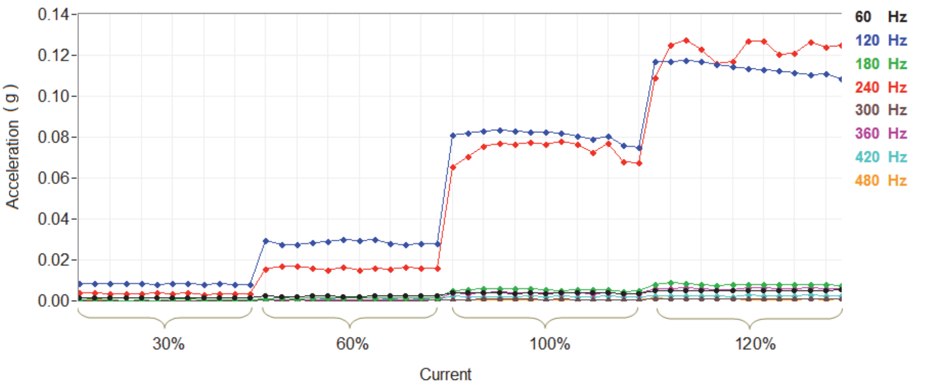

Fig. 8. Vibration signals when excited with current at sensor 2 in all frequencies.

Figures 7 to 10 show some examples of the experiments corresponding to cold transformer excited first with current and no voltage, and then excited with voltage and no current, i.e., windings excited or core excited. The vertical axis represents the magnitude of the vibration measured in terms of acceleration and expressed in g, the gravity. The horizontal

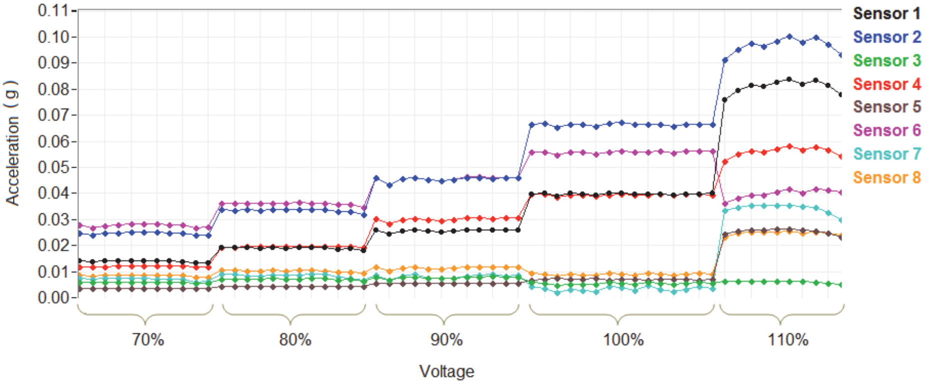

Fig. 9. Vibration signals when excited with voltage at 120 Hz. in all sensors.

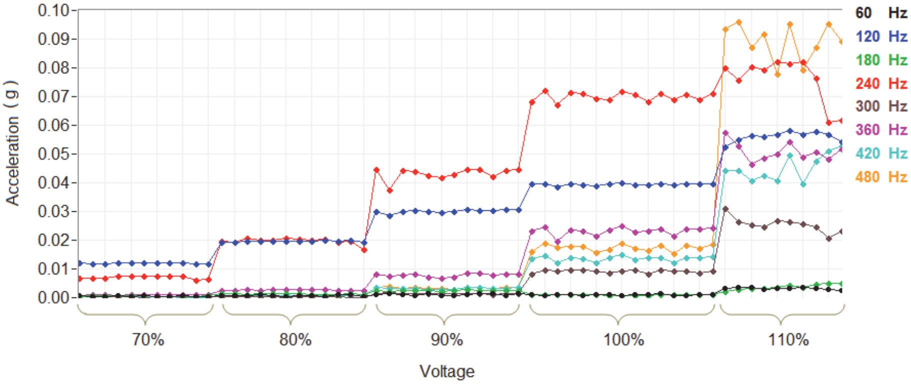

Fig. 10. Vibration signals when excited with voltage at sensor 2 in all frequencies.

axis represents each one of the ten (or twelve) repetitions of each experiment with the same operational condition.

Figure 7 shows the vibration signals when excited with current at 120 Hertz in all sensors. Notice that the steps shown in the figure correspond to excitations of 30% of the nominal current (lower amplitudes) and then 60%, 100% and 120%. Figure 8 shows the vibration signals captured at sensor 2 in all the frequencies of the same experiment. Notice that the amplitude of the vibration increases when current increases. Notice also that the frequencies of 120 and 240 Hertz are the only representatives of the vibrations compared to other multiples of 60 Hertz.

Figures 9 and 10 show the experiments with voltage and no current. Figure 9 shows the vibration signals at 120 Hetrz in all sensors, and Fig. 10 shows the vibration at sensor 2 in all frequencies.

These graphs are examples of the kind of variations that we found in the vibrational pattern, under different operational conditions.

Following the transformation of the vibration signals in their frequency components, a normalization procedure is applied. Normalization in this context means that all variable values lie between 0 and 1. This is because we only need to compare the behavior between all the vibration signals. The normalization is obtained dividing all the vibration signals by the highest measure of each sensor. Figure 11 shows an example of normalized signals. Notice that all signals detected at all sensors behave similar even if their amplitude are different as was shown in Fig. 7.

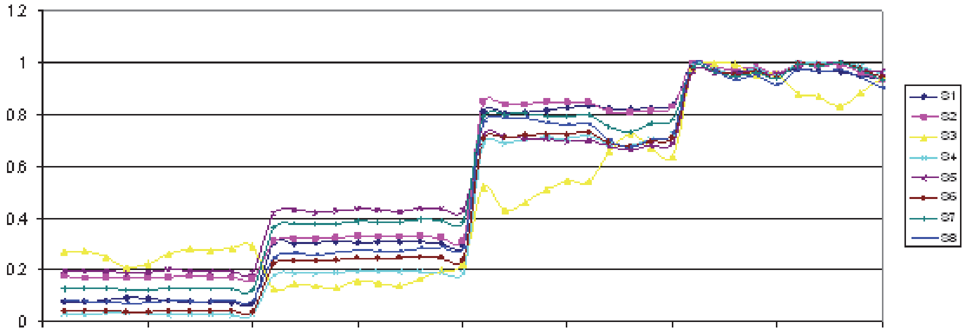

Fig. 11. Comparison between the behavior of all the signals when normalized.

Finally, a discretization is required since the probabilistic model utilizes Bayesian networks with discrete signals. Discretization is the division of the complete range of values in a fixed number of intervals. In our experiments, the vibration signals were discretized in 20 intervals or *states* $S_0, S_1, \ldots, S_{19}$. Since normalized, the states consists in 5% of the normalized signals, i.e., $0 - 0.05$, $0.05 - 0.1$ and so on.
Table 3 resumes the variables utilized in the diagnosis and the values that they can take.

Variable	*Values*
Temperature	Cold, hot
Excitation	Voltage, Current
Nominal Voltage	70%, 80%, 90%, 100%, 110%
Nominal Current	30%, 60%, 100%, 120%
Sensors	A1, A2, ..., A8
Frequencies	60 Hz., 120 Hz., 180 Hz., ..., 900 Hz., 960 Hz.

Table 3. Variables utilized in the diagnosis.

The next section utilized these variables to build the probabilistic models.

4.2 Model of correct transformers

In the first stage of this project, the variables available for constructing the model are sensors, frequencies, temperature and excitation of the transformer (voltage or current). Following the experts' advice, we consider two possible set of models. The first is a model relating operational conditions and frequencies. One model for each sensor. The second possible set of models relates operational conditions and sensors. One model for each frequency. We decided to try a set of models that relates conditions and sensors, i.e, operational conditions and vibrations detected in certain parts of the transformer. Figure 12 shows one instance of the resulting model.

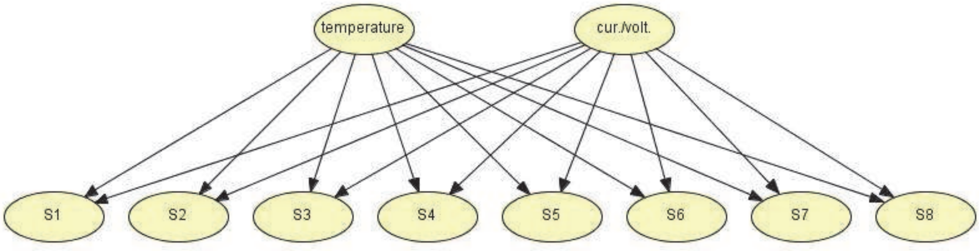

Fig. 12. Model that relates operational conditions with the amplitude measured by each sensor.

Actually, the complete model is formed by two BNs like the one shown in Fig. 12. One corresponding to the 120 Hz component and the second corresponding to 240 Hz. Once defined the structure, the EM (Estimation-Maximization) algorithm (Lauritzen, 1995) is utilized to obtain the conditional probability tables. We used 10 experiments of each type as indicated in Table 2 and applied in 5 transformers. The structure and the parameter learned, complete the models for the diagnosis. Next section describes the diagnosis procedure in the factory floor.

4.3 Diagnosis procedure in FAT

Utilizing the models described above, the algorithm 1 is applied to identify abnormal vibrations in the sensors given certain operational conditions:

Algorithm 1 Detection of abnormal vibrations.

Require: Operational conditions of temperature and excitation.
  assign a value (instantiate) to the *t*emperature and *e*xcitation nodes
  for all sensors (frequencies) in the network **do**
    propagate probabilities and obtain a posterior probability of all sensors (frequencies) nodes
    compare the real value measure and the estimated value
    evaluate if there is an error in the sensor (frequency)
  end for

As an example, Table 4 shows the measures that have been obtained and normalized in the sensors of a cold transformer excited with 100% of nominal current.

Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Sensor 6	Sensor 7	Sensor 8
0.3284	0.3710	0.0895	0.4161	0.0811	0.7084	0.6531	0.2333

Table 4. Example of vibration measured in the sensors.

According to the algorithm 1, one sensor vibration is estimated using the rest of the sensor signals and the operational conditions. The probabilistic propagation in the BN produces a posterior probability distribution of the estimated sensor value. The problem is to map the observed value and the estimated value to a binary value: $\{correct, faulty\}$. For example, Fig. 13 left shows an example of a posterior probability distribution, and Fig. 13 right shows a wider distribution. In both cases, the observed value of the estimated sensor is shown by an arrow. Intuitively, the first case can be mapped as correct while the second can be taken as erroneous.

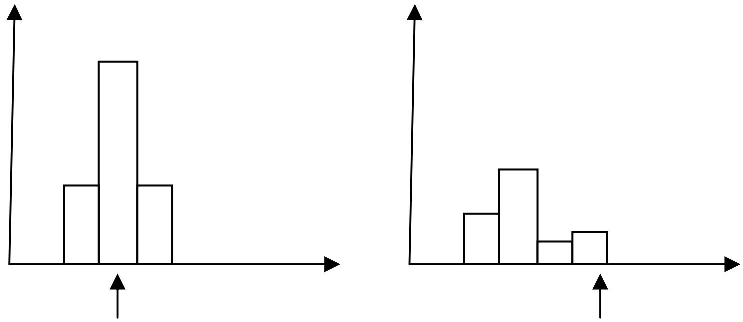

Fig. 13. Example of two posterior probabilistic distributions and the comparison with the value read.

In general, this decision can be made in a number of ways including the following.

1. Calculate the distance of the real value from the average or *mean* of the distribution, and map it to faulty if it is beyond a specified distance and to correct if it is less than a specified distance.
2. Assume that the sensor is working properly and establish a confidence level at which this hypothesis can be rejected, in which case it can be considered faulty.

The first criterion can be implemented by estimating the mean μ and standard deviation σ of the posterior probability of each sensor, i.e., the distribution that results after the propagation. Then, a vibration can be assumed to be correct if it is in the range $\mu \pm n\sigma$, where $n = 1, 2, 3$. This criterion allows working with wider distributions where the standard deviation is high and the real value is far from the mean μ value as shown in Fig. 13 right. However, this technique can have problems when the highest probability is close to one, i.e., the standard deviation is close to zero. In such situations, the real value *must* coincide with that interval.
The second criterion assumes as a *null-hypothesis* that the sensor is working properly. The probability of obtaining the observed value given this null-hypothesis is then calculated. If this value, known as the *p-value* (Cohen, 1995), is less than a specified level, then the hypothesis is rejected and the sensor considered faulty. Both criteria were evaluated experimentally. Here, it is worth mentioning that using the *p-value* with a 0.01 rejection level, works well.

4.4 Experiments for FAT

We designed a computational program that utilize the measurements obtained in the experiments described in Table 2. We run experiments and identify if there is a failure.
An experiment consists in establishing the operational conditions of excitation and temperature. Next, the system obtain the measurements of the sensors, and executes the

algorithm for detection of abnormal vibrations. Since we have 16 indicators of fault (eight sensors in two frequencies), a sensor fusion technique is required. We decided to make a weighted sum of the conclusion of each sensor. If one sensor is sensible and detects deviations easily, then a low weight is assigned. Other less sensible sensors may have higher weights. Given the sum of each frequency, we can configure ranks for declare a transformer as {correct, suspicious, faulty}.

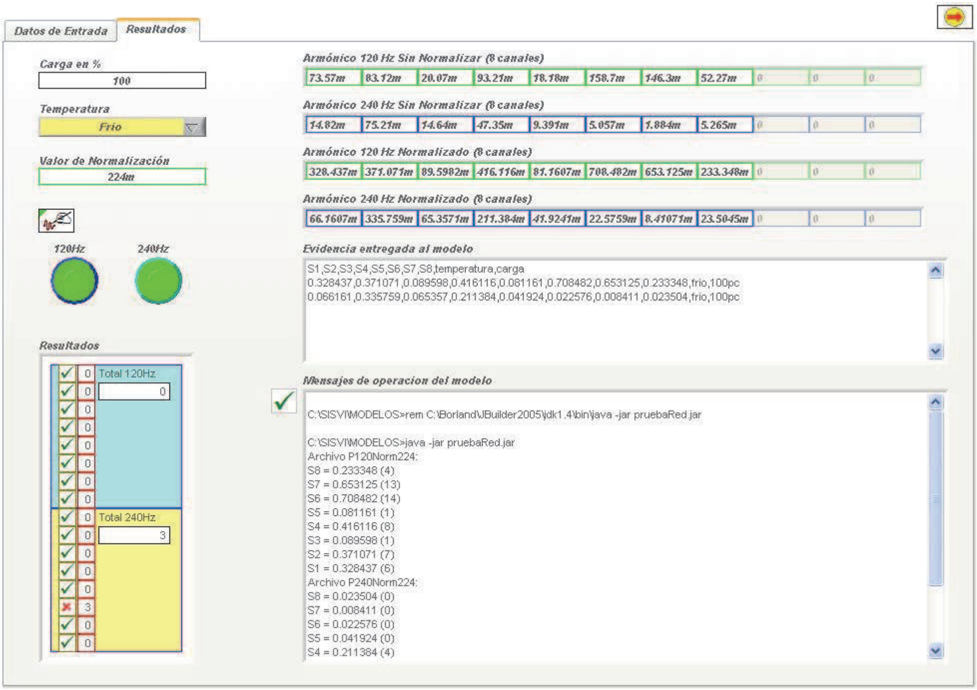

Fig. 14. User interface of the diagnosis software (in Spanish).

Figure 14 shows the results of one experiment (in Spanish). In the upper left of the window, the operational conditions are indicated. First, load *(carga en %)* with 100% of current, and cool transformer temperature *(frio)*. In the middle left of the window, there are two lights. One corresponds to a model for 120 Hz. and the other corresponds to 240 Hz. As mentioned above, we are using one model for each frequency. These lights become green if the transformer is correct, yellow if the transformer is suspicious and red if there is definite a failure. Below, in the lower left of the window, there are a little box for each sensor in the transformer. The first 8 corresponding to 120Hz and the last corresponding to 240 Hz. If the posterior probability obtained in a node (sensor) corresponds to the vibrational value currently detected, then an OK mark is described, and a NO-OK mark otherwise. Notice that the sixth sensor detected a deviation in the model of 240 Hz. In the upper right of the window, four rows of data are included. The first two correspond to the current vibration amplitude measured in the 8 sensors in the transformer. The next two rows correspond to the normalized information. They are actually the inputs to the BNs. The lower right part of the window displays other prototype information.

Several transformers have been tested in factory and some faults have been detected. The next section describes the changes made to the model in order to run SAT tests.

4.5 Preliminary experiments for SAT

Experiments in site have certain differences with FAT experiments. The main difference is that transformers always operate at their fixed nominal voltage but variable current. The current value corresponds to the demanded power by the consumers.
In order to utilize the information acquired in FAT experiments, one assumption was necessary: vibration corresponds to the sum of vibration by current (produced at the winding) plus vibration by fixed voltage at 100% of nominal value (produced at the core). This assumption is valid at the transformer operational condition below the saturation condition. Voltage is always fixed at its nominal value (controlled by the grid), and the current is always tried to keep in normal conditions. In reality, we use all the information acquired for FAT experiments, modified with this assumption.
Additionally, we run experiments in power transformers working on site. Of course, we could not modify the working conditions and we took only data in certain loads.
Table 5 shows an example of the experiments carried out at the power transformer in Prolec GE substation. The transformer provides power to the entire plant. Columns indicate the measurement obtained by all every sensor. The first row indicates the real amplitude obtained by the sensor and normalized. Once normalized, the signals are discretized in 20 intervals. The second row indicates the interval number, from 0 to 19. Third row indicates the posterior probability obtained after the propagation in the probabilistic model. This number indicates the probability of being a normal measurement, so the fourth row decides if there is a failure (1 value) or there is no failure (0 value). This decision is based on the assumption that the posterior probability distribution is Gaussian given certain operational conditions. Thus, the real value measured is compared with $\pm\sigma$ from the media.

	S1	S2	S3	S4	S5	S6	S7	S8
Real value measured	0.159	0.121	0.184	0.178	0.083	0.016	0.729	0.141
Corresponding interval	3	2	3	3	1	0	14	2
Posterior probability	0.312	0.312	0.0	0.0	0.687	0.0	0.0	0.375
Decision	0	0	1	0	0	0	1	0

Table 5. Example of one experiment.

For example in Table 5 , sensor 2 measured a normalized value of 0.121 that corresponds to the interval number 2. Propagation indicates 31% of the value that corresponds to no failure. On the contrary, sensor 7 reads a normalized value of 0.729, corresponding to interval 14 and there is no probability of being correct. The decision is 1. Notice however, that sensor 6 has the same 0 probability but the standard deviation may be very wide and the decision marked 0.
The prototype was constructed using the *hugin* platform (Andersen et al., 1989), so the off–line automatic learning and the on–line propagation are carried out with the Java APIs of this package.
Several tests were made in this Prolec GE substation transformer and the model resulted in a correct tool for transformer diagnosis.

5. Conclusions and future work

The main contribution of this work is the construction of a probabilistic vibration model obtained with the vibration signals measured in a power transformer. Thus, if a model of correct behavior can be obtained, then early deviations of this behavior can also be achieved. Our approach utilizes Bayesian networks as the formalism for constructing and utilizing the models. We used 8 sensors situated all around the tank of the transformer. Every measure was transformed to the frequency domain and only amplitude multiples of the 60 Hz were considered. Experiments were carried out at different operational conditions to construct the models. Finally, a diagnosis program receives vibration data from a transformer, inserting it as evidence and probability propagation allows calculating the probability of proper behavior. Bayesian networks have the advantage of generate conclusions even when the evidence is incomplete. This means that even with less sensors or less frequencies, a conclusion can be obtained. Also, BNs include several algorithms that automatically adapt the models, based on vibration in the normal life of the transformer. This means we can detect the normal behavior of old transformers even if they vibrate much more that their vibration when new.

Future work is needed in the determination of additional operation conditions variables, like parameters in the construction of each transformer. We can detect the vibration transmission between different parts of the transformer and identify more clearly if the behavior is normal or not.

Final results will be available after months of tests in new and old transformers, in site and at the factory.

6. Acknowledgments

This research is partially supported by Consorcio Xignux-Conacyt and by the Prolec GE-IIE project 13261-A.

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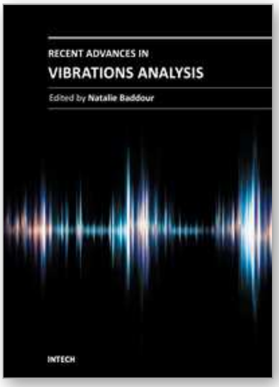

Recent Advances in Vibrations Analysis

Edited by Dr. Natalie Baddour

ISBN 978-953-307-696-6
Hard cover, 236 pages
Publisher InTech
Published online 09, September, 2011
Published in print edition September, 2011

This book covers recent advances in modern vibrations analysis, from analytical methods to applications of vibrations analysis to condition monitoring. Covered topics include stochastic finite element approaches, wave theories for distributed parameter systems, second other shear deformation theory and applications of phase space to the identifications of nonlinearities and transients. Chapters on novel condition monitoring approaches for reducers, transformers and low earth orbit satellites are included. Additionally, the book includes chapters on modelling and analysis of various complex mechanical systems such as eccentric building systems and the structural modelling of large container ships.

How to reference

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Pablo H. Ibargüengoytia, Roberto Liñan, Alberth Pascacio and Enrique Betancourt (2011). Probabilistic Vibration Models in the Diagnosis of Power Transformers, Recent Advances in Vibrations Analysis, Dr. Natalie Baddour (Ed.), ISBN: 978-953-307-696-6, InTech, Available from: http://www.intechopen.com/books/recent-advances-in-vibrations-analysis/probabilistic-vibration-models-in-the-diagnosis-of-power-transformers

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