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A new approach for local detection of failures and global diagnosis of LV switchboards.

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Abstract-

This paper deals with an original diagnosis system for LV switchboards. It is based on a local and global diagnosis approach with local temperature and current measurements. The thermal measurements including ambient and temperatures near electrical joint, are done by wireless thermal sensors. The system is composed of three complementary stages: An internet data collection stage, and two centralized data processing stages for the local detection of failures and the global diagnosis respectively. The analyses done with the diagnosis stage lead to predictive maintenance recommendations in order to avoid LV switchboard breakdown, which although rare could be catastrophic. Each stage of the centralized data processing is presented and discussed. Some results based on experimental data and expertise's information are presented to validate the feasibility of these methods.

I. INTRODUCTION

The role of a LV switchboard is to receive electrical energy and to distribute it ensuring the safety of the users and the plants supplied. An LV switchboard failure involves economic losses according to the size and the process of the plant supplied. These losses are mainly linked to the downtime cost that can be huge according to the plants. To avoid these catastrophic situations, LV switchboard users need to detect and solve the problems before failures appear. Alternatively, even in case of failure, they need to diagnose properly and rapidly the failure's causes in order to eliminate them as soon as possible. An inquiry to Schneider-Electric worldwide experts gives the following failure distribution (Fig.1). This pie chart shows that the first cause of LV switchboards failures is joints fault (bad tightening torque, inappropriate design). Joints fault lead to an overheating on the joint (developed in section II). It should be noticed that the other failure causes such as overloads, harmonics and malfunction of ventilation are also associated with overheating.

Fig 1 LV switchboard failure distribution.

Therefore, there is reason to address the detection and diagnosis problems with a monitoring system based on thermal measurements. Up to now, the trend was to carry out frequent thermographic inspections (Once every 2 years) to determine

the hot points in one shot. Today, with internet technology, and wireless temperature sensors, it is possible to continuously record the thermal data from sensors. This recording process including wireless temperature sensors and internet server is now available at Schneider-Electric. Current measurements could also be available via some communicating equipment. This paper aim to present a monitoring system that uses the data from existing recording process to detect and then diagnose the failures.

Fig 2. Monitoring and diagnosis system based on wireless thermal sensor and current measurements

As can be noticed in fig 2. This system is composed of three stages: • First, the data transmission via internet technology, •Second, the detection stage with alarm generation, •Third, the diagnosis itself in order to analyze the alarms generated from the detection stage to make some preventive or curative maintenance recommendations.

This paper will not go into the data transmission stage. The focus will be on the centralized data processing including detection and diagnosis stages. Section III will be devoted to the detection stage. In this section, two methods for the automatic detection of abnormal heat of electrical joints are presented. The first method is based on a physical model and the second is based on artificial neural networks techniques. In Section IV the diagnosis stage using probabilistic reasoning is presented. This stage is based on Bayesian network techniques. Prior to the detection and the diagnosis, one important step is to understand the failure phenomena and to know the right sensor placement that permits the detection. This will be addressed in the following section.

II. EXPERIMENTS ON ELECTRICAL JOINTS

In this section, two representatives experiments carried out on the following types of electrical joints are presnted. These experiments are about "Joint progressive loosening" and "Joint aging".

Fig 3 Different types of electrical joints.

A. Joint progressive loosening

The goals of this experiment are:

- To analyze the temperature changes generated by a progressive loosening on three common technologies of electrical joints (grippéd joint, bolted joint, on edge joint).
- To find the distance from which it is possible to detect a default caused by loosening.

This test consists in supplying a busbar leading to a joint (grippéd, bolted or on edge) with about the rated current. After the stabilization of the temperature, progressive loosening of $\frac{1}{2}$, $\frac{1}{4}$... of the rated tightening torque (28Nm) is made. The profile of temperature is measured using thermocouples placed along the busbar (fig4).

Fig 4 Progressive loosening test assembly and results for the grippéd joint.

Point 1: Thermocouple placed at 60cm, Point3: Thermocouple placed at 20cm
Point5: Thermocouple placed on the contact, Ambient: approximately 50 cm far from the busbar

The results in fig 4 show that it is necessary to loosen down to less than $\frac{1}{8}$ of the rated torque, to be able to see significant overheating. This shows that the electrical resistance of the grippéd joint does not vary enormously during loosening until 4 Nm (around $\frac{1}{8}$ of the rated torque), from which it increases exponentially. Since the heating results from Joule effect, heating increases with electrical resistance. That is the reason why in the curve representing the rise in temperature when loosening (fig 4), the overheating is visible only at $\frac{1}{4}$ of the rated torque and much more visible from $\frac{1}{8}$ of the rated torque. The overheating attenuation can be calculated as the ratio of overheating on the joint (point 5) to the overheating 200 mm far from the joint (point 3). There is 52% attenuation on average of the overheating on the three types of joints at 200 mm from the joint (point 3). With regard to the other types of joints, this experiment gives similar results. The on edge joint distinguishes itself somewhat by greater joint electrical resistance, more overheating being generated on this type of joint(fig5).

	Grippéd	Bolted	On edge
Rated torque (RT)	28Nm	50Nm	28Nm
Busbar cross-section(mm ²)	80*10	60*10	60*10
Current	1800A	1500A	1500A
Time constant (minutes)	45	40	42
Overheating with 1/4 RT	4°C	3°C	12°C
Attenuation at 20cm	47%	53%	55%

Fig 5 Result of progressive loosening test, on the three types of joints.

In this test, the aging process of the joints is investigated and then analysis of the influence of the current level on this aging is made. The test is made on the grippéd joint tightened beforehand at $\frac{1}{8}$ of its rated torque to accelerate the aging process. The experiment consists of supplying the busbar with cycles of currents. Each cycle consisted of two hours of current supply followed by a cool-off period of about two hours and half. The e-hour duration was chosen to allow the busbar to reach a stable temperature, after which the busbar was allowed to cool down to ambient temperature. For the first 12 cycles, the busbar was supplied with a current of 1800 A, after which it was supplied with a current of 2200A until cycle 32. Fig 6 gives the temperature rise calculated as the difference of temperature between point 5 (on the contact) and point 2 (400 mm far from the contact). This curve shows that the number of cycles affects the joint contact.

Fig 6 Aging test on grippéd joint

The aging is apparent by local heating that increases with the number of cycles. The first part is relatively flat from cycle 1 to cycle 12, without a significant increase in the overheating. In other words, the contact has not aged significantly during these cycles. From cycle 12 to cycle 32 the supplied current was 2200A (about 1.5 time of the rated current). On this part of the curve, a steady increase of the overheating can be noticed. Therefore, the conclusion is that the joint indeed ages with the number of cycles. This aging is accelerated by overloads. In fact overloads contribute to increase the global temperature of the busbars by joule effect, so the local chemical reaction of corona is accelerated according to Arrhenius's law [1]. The aging is also due to the fact that, the busbar expands with the rise in temperature and contracts with cooling. This expansion and contraction phenomena can create small gaps on the joints contact surface, which lead to a rise in the local electrical resistance. Through the two previous experiments, it is apparent that an electrical joint holds onto its failure state once the failure appears, and could get worse under certain conditions. In the following section, different techniques for detection of failures are tested. The idea of testing different techniques is to check their efficiency without excluding their possible complementarities.

III. AUTOMATIC DETECTION OF ABNORMAL HEATING

In this section, it is assumed that sensors are placed in such a manner as to be able to see thermal changes when a default appears. The following step is the failure detection itself. This section deals with two methods for detecting the abnormal heating of a joint. The first method is a comparison with a physical model of the LV switchboard and the second is a mathematical estimator based on artificial neural network (ANN) to estimate the joint state.

A. Detecting abnormal heating by comparison with a healthy model.

In Schneider-Electric, there is an in-house thermal computation software based on a representation of the LV switchboard as a network of nodes connected to each other by thermal conductance (convective, conductive, and irradiative). The principle of modeling is a nodal method and the calculations are done by finite difference. The software takes into account the electric aspect of the problem through the electrical resistance.

Fig 7 Electrical joints' states estimator.

This model is suitable for modeling conduction phenomena, which represents 60 to 70% of heat exchange phenomena in switchboards. This software can be used to have a thermal modeling of the switchboard (Schneider-Electric model library). The inputs of the model are the currents and the ambient temperature of the switchboard. The output of the model is the temperature on some selected electrical joints. It should not be forgotten that most of the time the model result is a bit different from the experimental results. For reducing the disparity between the model and the real system, something important to do after modeling is to make the model be in line with an experimental measurement from a healthy switchboard. This is done by tuning some parameters as joint electrical resistance, thermal resistance and heat exchange coefficient. This tuning has to be done on the operating currents range. Then the fitted model is used as a reference of a healthy switchboard. Over time, the drift of the difference from the temperature measured in comparison with the corresponding temperature from the model is an estimator of the joints state (fig7).

B. Estimation of the state of the contact by training with artificial neural networks (ANN).

Another way to estimate the states of the electrical joints is the use of ANN. ANN is an original information processing technique inspired by the operation of biological nervous

systems [2]. This technique leads to an estimating function between a set of inputs and a set of outputs by a training and validation process. More specifically, in our case we use a classic MLP (Multilayer Perceptron Network) with a LM (Levenberg-Marquard) algorithm for the training [3]. To test this method, it is necessary to have a list of inputs and corresponding output.

1) Inputs

Since current is a parameter very correlated with the temperature, current and heating are commonly taken as the main inputs. The heating is calculated as the difference of temperature between the sensor near the joint, and the internal ambient sensor. The results are a bit better; with the complementary inputs, which are the first derivatives of current and heating. This is because these complementary parameters contribute to give more information to the ANN. According to physical considerations, joint resistance for instance corresponds to the time constant of the joint temperature. The higher the joint resistance, the smaller is the time constant. Furthermore, all input data have been normalized.

2) Output

The output of the ANN in our problem is a joint state estimation. It is based on the idea drawn from the previous experiments: for the family of the bolted joints (bolted, on edge, gripped joints) we consider that a tightening torque less than 1/8 of the rated torque is unacceptable. There is another type of joint: the clamped joint used for withdrawable apparatuses in the switchboard. For the clamped joints, there is no notion of rated torque, as it is not bolted, and so its states are directly linked with its electrical resistance. To be able to do a homogenous reasoning on all kind of joints, it is much easier to link the state of the joint to its electrical resistance. So apart from the clamped joints, for the others kinds of joints, it was necessary to model the joint resistance as a function of joint torque in such a manner as to have the joint state directly linked with the joint resistance instead of the joint torque. To achieve this aim, a simplified analytical model has been extracted from [4] and validated with experiments. The joint state is a value on the interval [0 1]. 0 means that the joint is safe, 1 means that the joint is very damaged. This transformation contributes to normalized data for the training algorithm.

3) ANN training process.

The MLP takes each input sample from the database, evaluates one by one their corresponding outputs, and then compares the calculated output with the experimental ones. Then it modifies the internal weighting to estimate the output. The model then reiterates this process until it obtains results sufficiently close with acceptable error (fig8). Before using the resulting MLP, a validation step is necessary. The validation step consists of evaluating the ability of the network to give suitable results for a list of inputs/outputs, which is in general different from the training database. To achieve this, it is necessary to have a large database from experiments. The experiments consist of recording the temperature $T(t)$ and the current $I(t)$ for various tightening torque for the bolted, on

edge and gripped joints. For clamped joints, the experiment consists of recording currents $I(t)$ and temperature $T(t)$ for different number of clamps corresponding to a given joint state. We have implemented this detection method with Matlab ANN toolbox with the set of experimental data at our disposal.

Fig 8 Principle of training

4) Results:

In this example, the experimental database is composed of 8000 vectors of input/output couples. The database is divided into two sets: a training database (TD) and a validation database (VD). The 3 MLP layers used are composed of maximum thirty neurons (quite a small neural network). A classification error can be calculated considering an output with two levels of joint state: bad or good. When the VD contains only a set of cases that are not easily recognized (having a large transient part), the classification error is about 1% (percentage of misclassified vectors) in training and 33% in validation. However, when the experimental database is randomly divided into two sets: one half for the TD containing all the cases not easily recognized and the others for the VD, the classification error gives an optimal value of 10% in training and the same value in validation (which are quite good results). Fig 9 gives some results in which the input temperature, the estimated state and the expected state are shown. It can be noticed that the estimated output is close to the expected one, an encouraging result.

Fig 9 Results of joint fault estimation with ANN

IV. DIAGNOSIS OF FAILURES BASED ON BAYESIAN NETWORKS.

Once the failure has been detected, the following stage should be the diagnosis itself, that is to know the causes of the failure. In the present methodology, when a failure occurs, the experts go on site to seek some indications guiding them to find the

failure causes. More specifically, knowing the failure, they seek the indications in a probable family of indications, and work by an elimination process to find the most likely cause. Since experts have a probabilistic and inference based reasoning, one of the natural ways to represent and to automate this reasoning is by a Bayesian Networks (BN) approach. BN also allows predictive diagnosis ie knowledge of consequences to LV switchboard working condition, early drift detection. The second reason in support of the BN choice is that, in numerous industrial diagnosis problems BN showed encouraging results [14].

A. Bayesian Network.

It is to Bayes rule that we owe the term "Bayesian". BN is the research results of J.Pearl and a Danish team of Aalborg University [5]. BN is a causal graph making it possible to bind a set of effects to their causes. BN combines tables of conditional probabilities with the causal graph that enables a probabilistic reasoning on the graph to be accomplished. With BN it is possible to make reasoning in the two directions: the calculations of the probability of causes knowing the effects but also the probabilities of the effect knowing the causes. The implementation of a BN is done in two stages:

- Knowledge acquisition and graph creation.
- Conditional probabilities table (CTP) filling.

Several internal documents in Schneider-Electric deal with LV switchboard failure causes. The reading of these documents [6]-[7]-[8]-[9] enables us to get some ideas of the parameters acting on the operation of LV switchboard and which could be useful for its diagnosis. This information has been completed with various discussions with experts. Indeed six experts were questioned on the possible causes of degradations of LV switchboards and three among these experts intervened in the construction and the final validation of the BN. With regard to BN implementation, we use MATLAB Toolbox, FullBNT-1.0.2 developed by Kervin Murphy at Berkeley [10].

B. Case of application: Example extracted from the whole graph.

In this section a concrete example of BN is given. This example is drawn from a complete BN of the LV switchboard. The choice of this part of the graph was guided by a preoccupation with simplification. Thus, a part of the graph with variables that have a reduced number of states was taken. These variables have been considered as binary. By considering binary variables, we place ourselves on a level of diagnosis, which can be interpreted as a "roughing" step in diagnosis.

1) Information coming from the experts:

- An increase in the external temperature (ET) automatically involves an increase in the LV switchboard ambient temperature.
- A ventilation obstruction (VO) makes the circulation of fresh air difficult. Hence, with a VO additional heating of the internal air of the switchboard is observed.
- The rated current is distributed in the different circuits of the LV switchboard by taking into account a multiplying factor called the diversity factor (DF), given by the manufacturer.

The failure to respect this requirement leads to a rise in the internal temperature of the table.

- Abnormal heating (AH) is a local phenomenon, which does not contribute very much to the heating of the ambient temperature of the switchboard, but rather contributes to the degradation of the insulators (ID) that are close to the hot point.

- A high internal temperature (IT) has two consequences, which are the tripping of thermal release (TTR) of circuit breakers or the degradation of insulators that are under additional thermal stresses.

2) Graph construction and CPT filling.

All this information enables us to identify the variables and build the causality graph (Fig10). The experts set the direction of the arrows of causality, and some weights corresponding to some extent to the force of the causality.

Therefore, these weights transformed into probabilities are useful to compute the probabilities of the nodes IT, ID and TTR on Noisy Or variable assumption.

Fig 10 Causal graph deduced from experts information with corresponding arc strength meaning.

In fact the estimation of all the combinations by an expert would be very tiresome. For example for a binary node, Y with four parents X, it should be necessary for the experts to estimate $2^4 = 16$ probabilities. That becomes unrealistic on the scale of a complex graph. As suggested by Finn V Jensen in his book Bayesian Networks and Decision Graphs [11], in such a case it is possible to make the assumption of the variable Noisy-Or. The Noisy-Or variable aims to simplifying the calculation of all the combinations. For binary variables and on the assumption that event “Xi causes Y” either independent of the events “Xj causes Y” for i different from j, The Noisy -Or assumption gives:
$$p(Y / X) = 1 - \prod_{i / X_i \in X_p} (1 - p_i) \quad (1)$$

Thus for a node Y with N parents X, N probabilities will be specified instead of 2^N probabilities. In addition to this calculation, the following assumption is made: When all the parents X are false, the probability of having the result "false" is 0.9 instead of 1, because we are not sure that all cases have been considered. The literature in this case, proposes to add a leaky node that is always activated on “true”. This method is not followed because it contributes to increase CPT length. The use of Noisy-Or assumption for IT and ID nodes is not really necessary, because the dimension of the CPT for these two variables are not high. However, the resultant CPT for these two variables, by making this assumption was close to those expected by the experts.

C. Results:

1) Diagnosis analysis.

Let us consider the case where the client observes that his switchboard is failing but still operating. For instance, he observes a tripping of thermal release (TTR=true) and an insulation degradation (ID=true). Therefore, he wants to know the failures cause. The Bayesian network is then questioned about effects toward causes. This leads to the results in fig 11.

Fig 11 Inference to diagnose a failure

Although the results say that an abnormal heating (AH) is the most probable cause, an increase of the exterior temperature (ET) is also a probable cause since the two probabilities do not differ so much. In this case, we want to know the true cause. Therefore, the variable which is the most cost effective to be checked, should be investigated. In this case, AH could not be checked without stopping the process supplied by the LV switchboard, leading to high cost.

Fig 12 help for diagnosing principle scheme.

In this case it is more cost effective to check if the exterior temperature is high for instance by the weather report. Afterward, an effective maintenance strategy can be implemented according to result of the weather report. As can be noticed, Bayesian Network is a tool for focusing our attention on the main causes to check.

2) Risks analysis purpose:

In the case where the client does not notice any failure of the system, but wants to know the risks of defaults taking into account the environment of the system and its operating condition, BN can be used to achieve this aim.

Fig 13 Risk analysis principle scheme

The graph is then questioned causes towards the effects. For instance, the client knows that the ventilation does not work well, the question it can ask himself is: Is it risky for the plant? The implemented BN can answer this question. Fig 14 shows that, there is about 70 % of chance that an insulation degradation (ID) appears. That can be risky for the client to let its LV switchboard without doing anything.

Therefore, it should be decided to repair as soon as possible the ventilation.

Fig 14 Inference for risk analysis.

D. The use of BN with learning process.

When constructing a Bayesian network, it is not always possible to be certain of the correctness of the chosen conditional probabilities tables. It is often the case that experts in design tend to overestimate the reliability of the equipment that they design. Therefore, we want to build a system that automatically adapts the probabilities tables (Fig15).

Fig 15 Automatically update of CPT.

A learning process could accomplish this using a database. Learning conditional probabilities from database is a well-known concept. This is well explained in [12]. In the case that all the variables are observed, one of the simple ways for learning probabilities is statistical learning [13]. For instance, according to statistical learning, the calculation of the conditional probability from a database $p(ID=1/AH=1,IT=1)$

$$\text{is given by: } \frac{N_{ID=1,AH=1,IT=1}}{N_{ID=1,AH=1,IT=1} + N_{ID=0,AH=1,IT=1}} \quad (2)$$

where $N_{ID=1,AH=1,IT=1}$ is the amount of time the combination $ID=1, AH=1, IT=1$ occurs, and $N_{ID=0,AH=1,IT=1}$, the amount of time the combination $ID=0, AH=1, IT=1$ occurs. Most of the time, in practical problems, there are some unobserved variables. The databases are then incomplete. In this case, there are some methods for learning, based on the estimates of the missing parameters. The most used method is the Expectation-Maximization (EM) algorithm [13]. The centralized database will contain all the encountered cases that the experts will have validated the coherence and logic before registering them into the database. This allows a diagnosis of a switchboard by using the cases encountered in other switchboards. The database could be initialized with some samples whose distribution reflects the probabilities given by the experts. The higher the

initial samples size, the higher the probabilities will be resistant to changes.

V. CONCLUSION

The paper proposes a combined local and global approach for LV switchboard diagnosis. Through some experiments, it is shown that with proper placement of sensors it is possible to detect electrical joint failures. Different stages leading to the diagnosis have been presented. Two methods to raise alarms with electrical joint failure have been presented. Whatever the way to build the alarms, a Bayesian network that is a suitable technique to automate the probabilistic way of thinking of the experts, is used to make a global diagnosis of the switchboards. How the Bayesian Network relative to the LV switchboard may be built, is shown concretely. A complete implementation of a part of the whole switchboard Bayesian network shows that this method can be a useful tool for the diagnosis and besides this; it could be used for risk analysis. The benefit of using Bayesian Network is that it allows taking into account the experience feedback for updating the conditional probabilities with learning process (fig 15). Above all, this paper shows the feasibility of a diagnosis system for LV switchboard based on thermal and current measurements.

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