Intelligent system to control electric power distribution networks

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KEYWORD

Transmission Towers; Agents; Electric Power Distribution; CBR; ANN

ABSTRACT

The use of high voltage power lines transport involves some risks that may be avoided with periodic reviews as imposed by law in most countries. The objective of this work is to reduce the number of these periodic reviews so that the maintenance cost of power lines is also reduced. To reduce the number of transmission towers (TT) to be reviewed, a virtual organization (VO) based system of agents is proposed in conjunction with different artificial intelligence methods and algorithms. This system is able to propose a sample of TT from a selected set to be reviewed and to ensure that the whole set will have similar values without needing to review all the TT. As a result, the system provides a software solution to manage all the review processes and all the TT of Spain, allowing the review companies to use the application either when they initiate a new review process for a whole line or area of TT, or when they want to place an entirely new set of TT, in which case the system would recommend the best place and the best type of structure to use.

1. Introduction

Power line maintenance is a problem that has generated a variety of research lines (Eltawil *et al.*, 2010; Gonçalves *et al.*, 2013; Singht *et al.*, 2013). TT that support the power lines must be reviewed on a regular basis depending on their characteristics. In these reviews it is necessary to determine the ground resistance, as well as the step and touch potentials. These reviews involve a significantly high cost. However, many of the reviews could be predicted, as most of the TT share the same features and are located on similar terrain. Therefore, the possibility of reducing the costs associated to this kind of maintenance is not only attractive, but quite reasonable.

As technology has continued to advance, there have been different approaches that attempt to apply innovations both in the review and the maintenance processes, resulting in a common need to reduce costs. Indeed, this is precisely the reason for having created the proposed predictive maintenance system.

There are 4 common maintenance types for TT: i) corrective, to solve existing problems; ii) preventive, to prevent the system from failures; iii) predictive, to predict possible irregularities; iv) proactive, which is a combination of preventive and predictive maintenances. The present work is focused on the predictive maintenance, where different techniques are already being used. Some authors have used artificial neural networks to model the environment, including (Taher *et al.*, 2010), while other authors use neural networks to set failure times of the devices (Weibull 1951). In addition, data mining or machine learning techniques are used to model different systems.

This study proposes a VO of software agents capable of carrying out a predictive maintenance of TT by selecting only a sample for review. This selection is completely autonomous and is based on different TT parameters that make it possible to determine the status of the analyzed lines of the TT. The system has built-in statistical sampling techniques combined with neural networks to estimate the ground resistance, as well as the step and touch potentials. In addition, the system provides different geopositioning tools to facilitate the search and selection of the TT and lines to be sampled.

The paper is organized as follows: section 2 includes a revision of related work, Section 3 describes the technical proposal, and finally section 4 provides the preliminary results and conclusions obtained.

2. Background

As mentioned before, there are different kinds of maintenance types (De Faria *et al.*, 2015): corrective, preventive, predictive and proactive. Predictive maintenance refers to the capacity of generating assumptions or estimations about the status of a component. When predicting well-known processes, especially in Control Theory (Smith *et al.*, 1991), it is possible to generate a mathematical model which represents reality in a reliable way (Na, 2001). However, in other processes experimental techniques are needed, for example classification algorithms (Krishnanand *et al.*, 2015) or artificial neural networks (Taher *et al.*, 2010). This approach tries to extract and model the system features from historical data.

Support vector machines are used in (Zarnani *et al.*, 2012) to predict the amount of ice that will be accumulated in aerial power lines. This is a serious problem that can interrupt the electrical service for a significant time, and the solution could be really expensive. Because of that proposed work, it is possible to estimate the level of ice (with a minimum error) by using historical meteorological data. More recently, (Ji *et al.*, 2015) proposes an ice-shedding model for overhead power line conductors while considering adhesive/cohesive forces.

Another point to take into account is the machine performance (generators and current transformers). Due to the natural deterioration or machines over time, reviews are required over their useful lifespan. Periodic maintenance can be carried out, so machine performance is evaluated regularly, regardless of their status. This solution is not optimal when the review period is short and the machines are in perfect working condition. An alternative is based on monitoring the status of the equipment and evaluating some of their parameters. From the combination of these two options, a new model is presented in (Zhou *et al.*, 2014), where performance loss is predicted by the using failure rate and the performance degradation in conjunction with their derivatives and a Weibull distribution (Weibull, 1951).

In other works, such as (De Faria *et al.*, 2015), current transformer failures are analyzed by Dissolved Gas Analysis (DGA). The currently existing methods are based on monitoring every substance ratio in oil; limit values are then established to determine all the possible failures (Duval *et al.*, 2001). The possibility of applying artificial neural networks and similar techniques to try to predict values is also presented in (De Faria *et al.*, 2015). (Trappey *et al.*, 2015) applies Principal Component Analysis (PCA) and back-propagation artificial neural networks (BP-ANN) to obtain a discrete transformer status (normal, waiting for confirmation, abnormal). The accuracy levels reached are between 92% and 96% largely due to the input data PC treatment. Without this technique, the accuracy varies from 69% to 75%.

3. Technical proposal

The objective of this study is twofold: first, to predict the resistance of existing TT with unknown values, and second, to reduce the number of TT to be reviewed with samples. To carry out these tasks, we propose a multi-agent system (MAS), which follows the structure shown in figure 1. The organization data processing includes agents to process the information. In this organization there are 4 agents to predict the resistance, resistivity, Kp (step potential) and Kc (touch potentials). An additional agent provides a MLP to carry out these predictions. The Kp and Kc are calculated according to the Kr with the MLP and resistance and resistivity are calculated with the algorithm in section 3.1

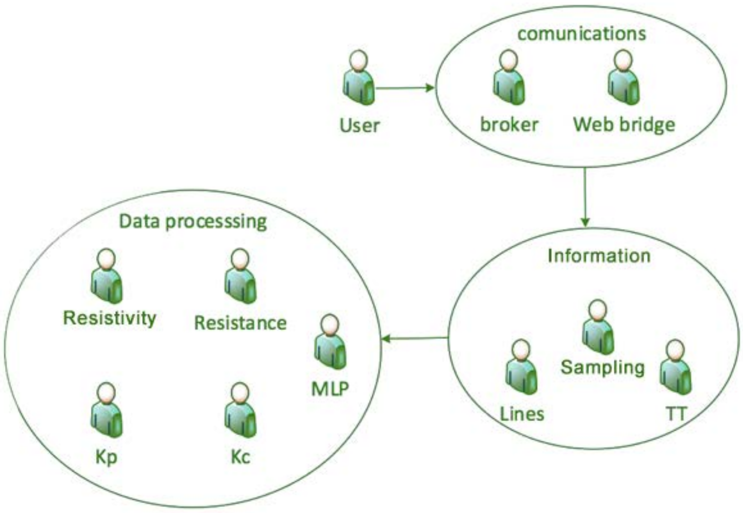

Fig 1. VO of agents

3.1. Resistance and Resistivity

To estimate resistance as related to the different measured parameters, the only parameters used are those that were shown to influence the final value. To determine what the most influent parameters are, the correlation analysis and Kruskal Wallis methods were used. Once these parameters were known, the estimation was carried out by a CBR system, as shown in figure 2. The cases memory is grouped by the TT types as defined by their Kr value. To group them by their Kr value, PAM (Partitioning Around Medoids) is applied; the Henning and Liao (Henning *et al.*, 2013) proposal is then used to determine the number of clusters. More specifically, three clusters are generated. In these three clusters, the cases base is organized whereby every case contains: resistivity, temperature, humidity, Kr and resistance values.

Every cluster has a trained multi-layer perceptron (MLP) where the inputs are resistivity, humidity, temperature and Kr, and the output is the resistance. In the recovery phase, the system recovers the previously trained network associated to the new Kr value. In the adaptation phase the network is used to generate the prediction. Finally, the data and training are updated in the revise phase.

With regards to the proposed algorithm, its input is based either on the known information about a TT that already exists in the system, or a fictitious TT to be placed in a determined location. The only difference for the algorithm is the evaluation of the nearest neighbors.

First, the nearest neighbors have to be found and identified depending on different established parameters such as the maximum distance to be considered a neighbor, or the maximum number of neighbors to use.

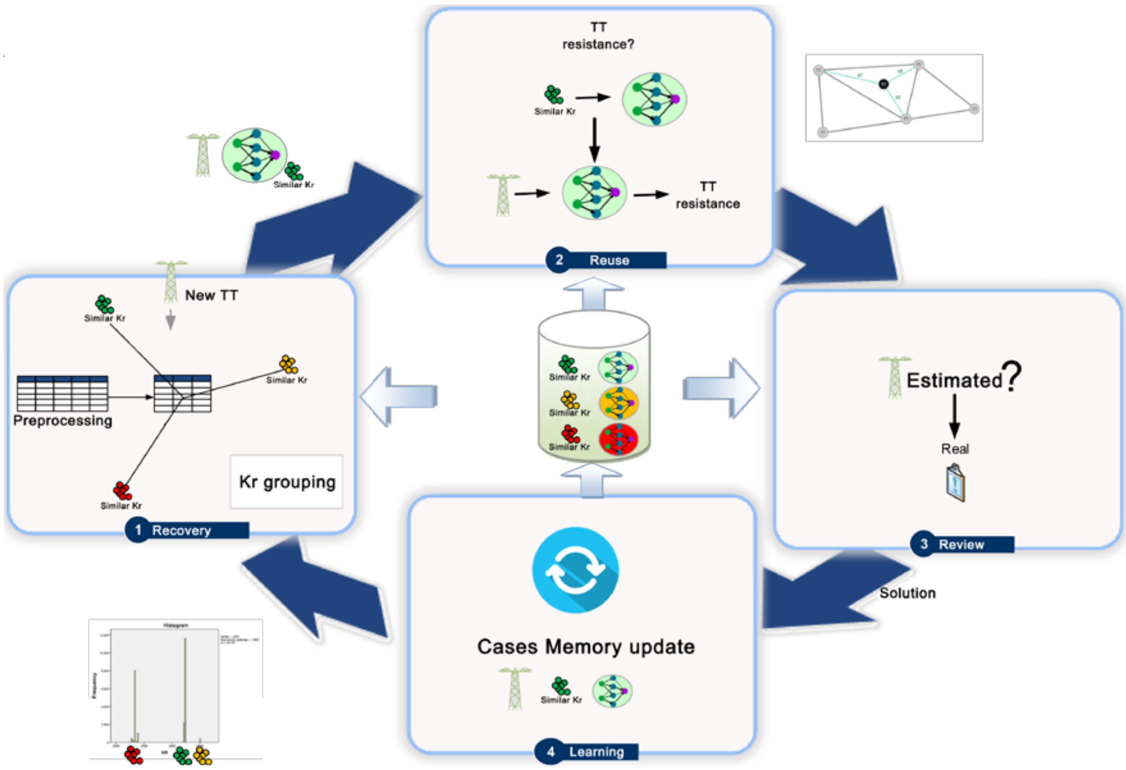

Fig 2. CBR cycle for the resistivity and resistance estimation.

Once determined, if the TT resistivity is unknown, it is estimated by the Inverse Distance Weighting (DW) method by applying this equation:

$$\bar{\rho} = \sum\nolimits_1^n \rho(TT_i) * \frac{D_{max}/d_i}{\sum_1^n D_{max}/d_i}$$

Where: $\rho(TT_i)$ is the resistivity of the ith TT, D_{max} is the largest distance, d_i is the distance of the ith TT.

The equation provides the resistivity value with an estimated deviation of σ^2, where:

$$\sigma = \sqrt{\frac{1}{n}\sum\nolimits_1^n (\rho_i - \bar{\rho})^2 \frac{D_{max}/d_i}{\sum_1^n D_{max}/d_i}}$$

When the resistivity value and range of the TT are obtained, the value of the resistance can be estimated. In order to estimate the resistance, an artificial neural network is used, specifically, an MLP with four inputs: resistivity, Kr value, ground humidity and temperature. The hidden layer consists of 9 neurons and provides a single output with the value of the estimated resistance.

3.2. Sampling

The main objective of this work is to reduce the number of reviews in order to reduce the TT maintenance cost. To attain this objective, a new algorithm was proposed. It uses several TT parameters as inputs, such as the Kr value, which determines the type of the TT, and the TT resistivity value to create stratums which are defined based on both parameters. The proposed algorithm follows these steps:

1. The sample provided as an algorithm input is analyzed to determine how many Kr intervals will be generated. For every interval, a list with the corresponding TT is created, so TT are now grouped by type (Kr value).
2. All lists are sorted in ascending order according to TT resistivity.
3. Once the lists are sorted, the deciles are calculated for each of the lists created according to the resistivity of similar Kr TT groups (step 2). The lowest and highest resistivity values of every list are also stored.
4. For every list of Kr groups (step 2) there are 10 sub-lists (step 3) containing TT with similar structure (associated to the Kr value) and similar resistance. The algorithm will now contain 10 n lists (equal to the number of Kr intervals selected in step 1), which are in turn divided into 10 sub-lists, which are generated after calculating the deciles in the lists found at the first level.

5. Variance is calculated and stored for every sub-list created in step 4.
6. The maximum error e is calculated and stored for every sublist from step 4. This error is considered as the maximum between 0.1 mid-point of two consecutive deciles and 0.1 distance between two consecutive deciles:

$$e = Max[0.1 * \frac{d[i] + d[i+1]}{2}, 0.1 * (d[i+1] - d[i])]$$

7. From the sub-lists generated in 4, the variance calculated in 5, and the maximum error calculated in 6, the number of TT to be reviewed for every sub-list n is defined by the following equation:

$$n = N * z^2 * \sigma^2 / ((N-1) * e^2 + z^2 * \sigma^2))$$

where: N is the size number of TT, n: Number of TT to review for every sub-list, z= 1.9599, σ deviation, e is máximum error allowed

8. The output of the algorithm, n is provided for every sublist.
   If the output number is too high the interval is divided recursively to reduce the elements in the sample.

4. Results and conclusions

As a result, the system offers a web application with a series of tools for companies in charge of reviewing the TT. For example, the user can select a set of lines of an area to be reviewed and the system will show the user a subset of TT to review that would ensure that the system works fine with a confidence level of 95%. This makes it possible to reduce the number of TT to be reviewed, with the added benefit of improving efficiency and reducing costs. Figure 3 shows the process to execute the algorithm and obtain the result. For example, in figure 119, the TT selected close to the region of Murcia (Spain) are selected, as seen in “2. Selected towers are shown on the map”. When the algorithm is run, the system proposes the review of 42 TT from the initial 119 (“4a. Number of towers to review”) and shows exactly which TT have to be reviewed in “4b. Towers to be reviewed”. Finally, the user can see where the proposed TT are on the map or the output, as well as the details of every algorithm step in “5. Algorithm details, steps and outputs can be shown”.

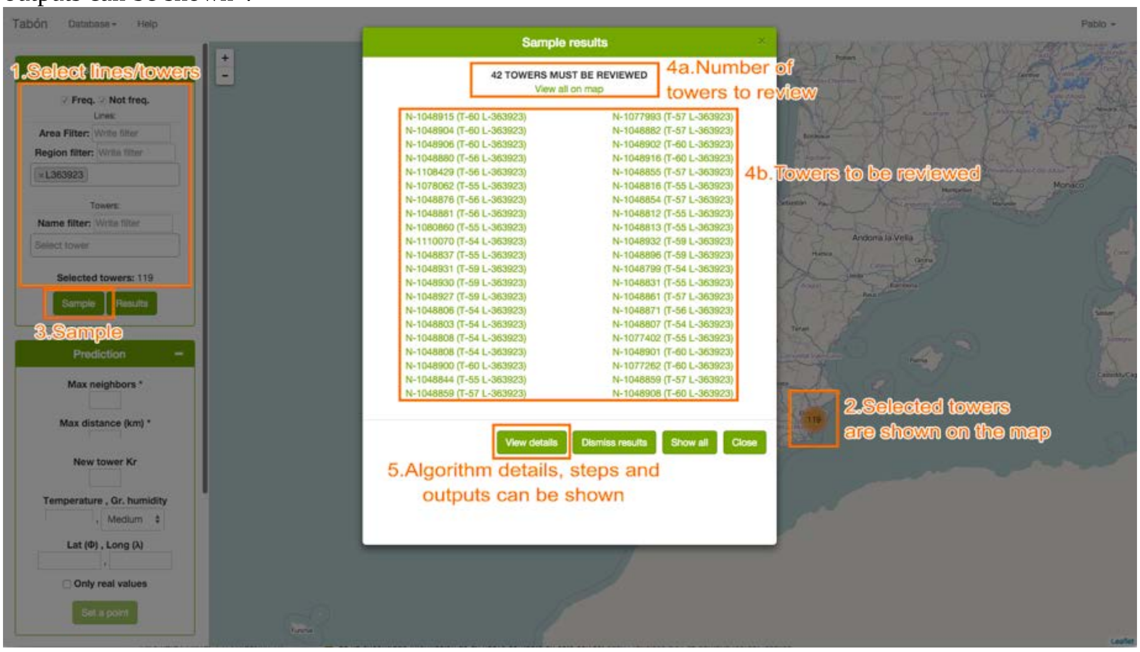

Fig 3. Web application, sampling process

The web application provides an additional tool. Since one part of the required calculations is already included in the previously implemented sample algorithm, it would be worthwhile to include a tool that could determine the best structure to use in each location. In addition, unknown resistivity and resistance values of existing TT can be estimated. This is a very frequent situation because there is no information of most TT throughout Spain.

In general, the efficiency on of the algorithm is evaluated according to the reduction percentage, which can be seen in table 1.

Table 1. Reduction percentage depending on the number of selected TT and the average distance

TT	**Average distance (km)**	**Proposed TT**	**Reduction (%)**
100	~50	27	73
200	~50	35	82.5
500	~50	64	87.2
800	~50	83	89.625
800	~300	154	80.75

The best results are achieved when selecting the more TT and the closer the average distance is. The efficiency and accuracy of the system is expected to increase with future work as the information and the values of existing TT become more complete.

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