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Artificial Neural Network and a Nonlinear Regression Model for Predicting Electrical Pole Crash

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Abstract

This paper presents the investigation about a problem situation that Electric Distributor Companies are facing in Chile resulting from transit accidents. The number of vehicle crashes to power distribution poles and street lighting has grown. This situation causes discomfort to citizen and mainly to the neighbors due to power cuts and even on occasion , losses of human lives because of the accident that have occurred. Based on previous research, the accidents are not random nor chance dependent, but the majority of transit accident follow parameters or variables from the scenery where it occurs. In order to analyze the variables and the degree this variables affect the accidents, a model of Perceptron and Multipercetron Artificial Neural Networks and a Multiple Nonlinear Regression model are proposed. An empirical study was made; collecting data from a distributor company and from Chilean National Traffic Safety Commission, where the more frequent variables involved in accidents were determined to develop the mentioned models. These variables were investigated and also their influence on the occurrence of vehicle crashes to power distribution poles could be confirmed. With this data, the prediction of post crashes was developed, where through the application of the neural network and multiple nonlinear regression, revealed 95.7% of acceptable predictions. This study will bring benefits to power distribution companies considering a risk index in the streets, based on the number of crashes of poles per street; this will allow optimal decisions in future electrical distribution projects avoiding critical areas.

Keywords: artificial neural networks (ANN), prediction, nonlinear regression.

1 Introduction

Currently, there is an interest in investigating the reason for the existence of traffic accidents of crash to street lighting poles, which causes discomfort to neighbors due to power cuts, losses of human life and others. In addition, the energy distribution companies incur in not sold energy costs. One of the electricity distribution company in Chile, records within a database those crashes, mainly, the types of unfortunate events that occurred in the distribution network; such as crashed posts, crashed post tensioners, general failures. A large number of events or events that are constantly being evaluated to improve their prediction and thus prevent them from being repetitive.

From the records, it has been observed that traffic accidents of the crash to street lighting poles are in first place in the ranking for most common failures in [4] with 10.347% after failures due to new works or engineering modifications.

Therefore, the priority of the designers in electrical distribution is to address the problem effectively. In addition, the benefit takes a turn towards the community, helping the designer to discern the best layout and location of the posts in national goods of public use since sometimes the design guidelines of the roads where posts are installed lack security measures [**?**].

On the other hand, according to car accident specialists, they say that these are not fortuitous events [9], inevitable, unpredictable, depending on luck, but instead, the vast majority of cases follow characteristic parameters of the scenario where it happens; that is, the accident as a whole is always a consequence of some avoidable failure and to some extent predictable system. So to combat the problem, the main thing will be to understand how the environment reflects the reaction to a car driving problem, environment that will be studied in this work.

Given the above, the objective of this work is to predict the crashes to street lighting post in points of interest in a region in Chile through a classic mathematical model and another based on neural networks, to reduce the consequences on the community. On the other hand, the variables that affect crashes accidents to post are studied, which in this case are, among others, road material, number of crossings in the study section, number of tracks.

2 State of the art

During the last 13 years, several investigations related to traffic accidents have been carried out in different cities of the World using Computational Intelligence (CI) techniques. Since about 30 years ago studies were carried out with mathematical models, which currently allows us to visualize variables and significant patterns that help to better identify the conditions in which traffic accidents occur, considering that each incident involves the conjugation of a large number of variables, which determine the number of accidents [3].

One of these CI techniques is Artificial Neural Networks (ANN), which consists of an algorithm that emulates the behavior of the animal nervous system. Technique studies have shown good results in both prediction and classification of data series. This will fulfill the main work for the development of the model to be used in this study [16].

ANN have been utilized in many fields, such as in the prediction of air pollution [14], robot control systems to avoid obstacles [6], training of robots [7], control of parallel robots [11], real power systems data applied for short-term daily load forecasting [5], information processing and pattern recognition [19], pattern recognition in statistical process control [18].

In the case of transport, ANN have been used in many applications such as accident-mapping [8] and understanding gender characteristics of older driver accidents in West Midlands of United Kingdoms [2]. They has also been used in traffic forecasting like the case of Morocco [17] and traffic accident casualty like the case of Sudan [1].

Regarding studies related to this problem such as those mentioned above, in addition to [9] and [10], we studied the best alternatives of factors or variables that describe traffic accidents, which are the best training strategies and that Software are the busiest for the development of these models, and thus expedite the development of the prediction.

A classic mathematical prediction model analyzed in [9] that was able to make predictions of the risk of automobile collisions with a Linear Regression model, the prediction unit used was number of post crashes per kilometer of annual street, and its variables were, density of posts, slope of the street, average lateral length and vehicular flow. Although the simplicity of the model contributed to poor predictions, the choice and lack of variables guided a future study of the measures to be taken to refine the prediction.

Neural Networks take an important role, as an innovative tool, to give a prediction of events and statistical analysis. This was concluded in [16], where the authors developed the analogy between the functions of an artificial and biological neuron, demonstrating how an artificial neural network can learn through experiences, training strategies, learning functions and what configurations of neural networks are the most appropriate to address this problem in self-interest scenarios.

Resistant Retro-Propagation (RP) [21] is a faster algorithm, than the previous one, in pattern recognition problems. However, it does not work well in function approximation problems. The Conjugated Gradient Scaling (CGS) [21] is an algorithm, which seems to work well in a wide variety of problems, particularly for networks with a large number of weights. Because there is no pattern of configurations established by problems, it was decided to vary ANN in the hidden layer and the number of hidden layers.

Given the above in Olden, [13] a sensitivity analysis of the input variables is carried out, which in this case disease is predicted, the patient's age, body mass and others are used. This sensitivity analysis was used in this work for the input variables involved. In Montt et al. [12] neural networks were used, using the Levenberg Marquardt algorithm, to predict traffic accidents with serious and less serious injuries, for the people involved in them.

3 Methodology

From [4] and [20] all the failures in the distribution network and the consequences of these failures were obtained, as well as the most frequent causes that cause post failures during the last 3 years. In the second place, there are the posts crashes which concentrate 10.34% of the total number of failures registered in the last 3 years. It should be specified that the crashes to braces of post with 2.74%, usually end up knocking down the post itself, so for this study the clashes to the post braces are added to the post crashes since the cause is the crash of a vehicle against the distribution network. Therefore, the percentage is added leaving 13.08% of the total events in the distribution network.

To develop the prediction model, in order to describe the streets involved in the area where post-crashes could occur, it is necessary to have a set of variables.

To develop the prediction model, you must have a set of variables, in order to de-scribe the streets analyzed, of the sectors where a post crashes occurs or not.

Due to this need, it was studied both in [15] and in [9] the parameters involved to use the models, these are:

–number of curves (A);
–zone (B);
–number of posts (C);
–road material [friction coefficient] (D);
–number of crosses (E);
–maximum inclination (degree) (F);
–average inclination (degree) (G);
–length [km] (H);
–number of schools (I).

Because the number of descriptive variables of the problem was similar to those used in studies with low prediction quality [9], it was decided to make an analysis of other variables. Additional variables were obtained through tools such as Google Earth, Ito Map and Waze, mainly street descriptions, with which the following were obtained: Number of Curves; Number of Crosses; Maximum inclination (degree), Average inclination (degree). Longitude [Km] Number of Schools. For the years 2016, 2017 and 2018, 230 streets were described, with the variables mentioned above. Subsequently, the streets were randomly ordered, where 90% of the totality was used to train the network, called Group A and 10% respectively to evaluate the learning of the model, called Group B. This strategy was covered both in the model of multiple nonlinear regression and developed through artificial neural networks.

3.1 Prediction using neural network

The learning of an Artificial Neural Network, corresponds to the part of a set of random synaptic weights, in order to look for a set of weights that allow the network to correctly develop a particular task. This is done through iterative processes where it evaluates the experiences provided (streets of the commune of Valparaíso) and they are compared with the desired exits (number of crashes registered in the streets) described by input variables). After this it is performed an optimization of the iteration error and this is propagated back towards the weights of the network by readjusting them so that though the next iteration the error decreases, this concludes with a progressive learning.

The configurations of artificial neural networks used, that is, the type of neural network used was that of Perceptron and Multipercetron; these are characterized by having layers of neurons (columns of neurons) generating connections between neurons in a single direction towards all the neurons of the next layer as can be seen in the following Figure 1:

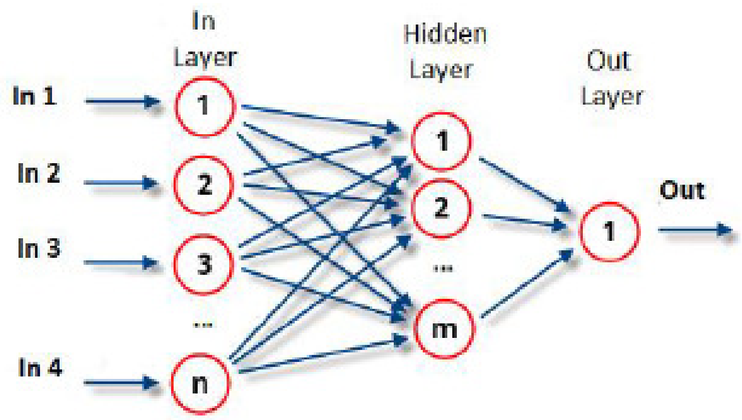

Figure 1: Artificial neural network architecture

From the three configurations used, the best predictions were retro propagation. As for this, the relation (1) corresponds to the output of each artificial neuron, which explains how the inputs and each neuron are multiplied by a specific weighting (synaptic weight) and then added and then sent to the next neurons.

$$a = (X^T W) = x_1 w_1 + x_2 w_2 + ... + x_n w_n = \sum_{i=1}^{n} x_i w_i \tag{1}$$

As for the training methods used were Levenberg-Marquardt LM, RP Retro-Propagation Resistant and Conjugate Gradient SCG Scaling, which are concerned with optimizing learning time.

In this case the input variables of the model are:
–Number of curves;
–Zone (rural, urban);
–Roadway (bidirectional, bidirectional with center tray, unidirectional);
–Road material (concrete, asphalt, cobblestone, mixed, gravel, earth);
–No.of crossings;
–Maximum incline (degree);
–Average inclination (degree);
–Length (km);
–No. of schools;
–No. of crashes.

A frequent complaint about neural network models is that they do not explain their results in a useful way. The problem is not the lack of information, but the abundance of information that is difficult to interpret. When training, neural networks provide a predicted output, for a postponed input, they can provide additional information in the form of connection intensities between elements. However, the latter information is of little use to analysts and managers who wish to interpret the results they have received. Therefore, the study also developed a measure of the relative importance of the various input elements mentioned in the previous paragraph, the hidden layer elements, and this was also used to interpret the contribution of these components to the network results [13]. This is based on the following equation:

$$S_i = \sum_{j=1}^{J} x_{i,j} w_{i,k} \tag{2}$$

Where i : variable to analyze sensitivity (those that were used to train the network, input variables); J : number of neurons in hidden layer; K : number of model outputs; w : weights between input layer and hidden layer; v : weights between hidden layer and output layer.

These results produce a ranking to find the most influential variables in the prediction, once the ANN has been trained. This would facilitate the practice of an excess of descriptive variables in the experiences or choice of variables that are not significant in the prediction.

3.2 Prediction using nonlinear regression

Nonlinear regression generates an equation to describe the nonlinear relationship between a continuous response variable and one or more predictor variables. This equation will be described by functions specific to each input variable, be they polynomials, logarithms, parabolas, etc., depending on the individual analysis of each variable related to the crash to poles and to these multiplied by coefficients. This can be visualized in the equation (3):

$$Y_{x_1,x_2,\ldots,x_n} = w + w_1 f(x_1) + w_2 f(x_2) + \ldots w_n f(x_n) \tag{3}$$

Where $w_i : i \in 0, 1, .., n$ are coefficients that weigh each chosen function and thus propose a better final approximation. The functions $f(x_1), f(x_2), f(x_3), \ldots, f(x_n)$ are those that describe each variable with respect to its crashes post index.

To study the behavior of the variables, the 9 variables under study were analyzed, the same ones used in the neural networks, in order to choose which functions describe the number of post crashes per year per street. To accomplish this, the Excel tool was used, which also graphs the dispersion of data according to each variable, provides a trend line of data dispersion, with its respective equation and correlation coefficient R^2.

The coefficient of determination fulfilled of indicator function the best approximation function. In other words, as long as its value is closer to 1, this function has a better approximation to the recorded data set.

To study the behavior of the variables, the same used in the neural networks, the representative functions of each variable were first obtained, looking for the best combination of these in which the error was minimal, so capital letters were assigned from the "A" To "I" to the functions of inputs and "J" in the output, obtaining the following non-linear regression equation (4):

$$\begin{aligned} Y = {} & 12889.8 + 0.000211727E^3 + 0.00872022E^2 - 0.0168694E - 0.0000615644A^6 + \\ & 0.00219875A^5 - 0.0292012A^4 + 0.177945A^3 - 0.483011A^2 + 0.740802A - \\ & 0.0679519H^4 + 0.187047H^3 - 0.196681H^2 + 22136.8D^2 - 33781.8D + 0.381264I^4 - \\ & 3.34419I^3 + 8.52872I^2 - 5.2624I + 0.262374C^2 - 0.628695C - 0.00000000987981F^6 - \\ & 0.00000086429F^5 + 0.000150924F^4 - 0.00683017F^3 + 0.137551F^2 - 1.27352F \end{aligned} \tag{4}$$

This equation is obtained starting from only one variable, adding the missing ones, and discarding the combinations that cause an increase in the error, the EAHDICF combination is obtained, which discriminates in the zone of location and average inclination as the variables that most deficiency contribute to the prediction.

4 Results

For Group A, the neural network configuration that obtained the best predictions was the neural network of three hidden layers and 20 neurons, with predictions of 10.8% of average error. The best rated neural network with unknown data (group B) is that of 3 hidden layers and 10 neurons. Primarily, greater importance is given to ANN with better prediction in face of unknown data (group B). This is to prevent learning from becoming more widespread and prevent it from being "of memory". This is checked by analyzing the case of the three-layer neuronal network and 20 neurons.

This network, while obtaining a $10,8\%$ of error in the prediction (the best in group A), learned the behavior of a fixed data sample and when faced with group B, this increased his average error to 52.5%.

In the case of the neural network, 36 different configurations of neural networks were trained, where the best prediction, in streets not used in the training (unknown to ANN), the network was structured. The candidate for a prediction of a known street was as follows:

In the case of the neural network, 36 different configurations of neural networks were trained where the best prediction, in streets not used in their training (unknown to ANN), was structured as follows: candidate for a prediction of a known street was as follows:

–Type of neural network: Perceptron;
–Learning Function: Retro Propagation;
–Error used in learning: mean square error;
–Number of hidden layers: 4;
–Number of Neurons per hidden layers: 50;
–Activation Function: Sigmoid.

The result of the artificial neural network, Pearson's correlation coefficient was used, to quantify the prediction quality, since this can be used to measure the degree of relationship of two variables as long as both are quantitative and continuous. In this case, the quality of ANN prediction is shown, since there was only one street, out of a total of 23 unknown streets, it did not meet as a satisfactory prediction. In other words, we have 95.7% of acceptable predictions. Regarding the correlation coefficient reached, it was 0.64. Using the Nonlinear Regression Model in terms of the acceptable or unacceptable prediction classification, it is governed by the same range described in the previous paragraph (ANN). In this model, predictions were recorded and qualified as no acceptable, having 87% of acceptable predictions, with a correlation coefficient of 0.56.

4.1 Results analysis

The correlation coefficients and the counting of registered predictions with a range of non-acceptance are presented in Table 1, with the prediction model of Artificial Neural Networks and the Non-Linear Regressions model:

Table 1: Effectiveness rates of both models obtained

	Artificial Neural Networks	Nonlinear Regression Model
Correlation coefficient	0.64	0.56
Nro. of acceptance in prediction	1(4.3%)	3(13%)

The predictions of a certain group of streets (23 streets) are obtained, each with its descriptive variables, record of shocks in the period of one year and the predictions made for both models. This allows us to visualize how accurate the predictions are individually, in addition, predictions can be highlighted where the prediction exceeds the actual number of registered shocks by 2 shocks and classified as predictions not satisfactory. Finally, the percentage of streets that did not have a satisfactory prediction is obtained, highlighting the ANNs as the best alternative to anticipate these events.

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4.2 Sensitivity analysis

In this analysis, the impact of each of the input variables on the predictions is determined. For the above, the connection weight approach method was used. This analysis, through the reading of all the weights associated with each input, allows quantifying the final excitation within the neural network of each input variable. Therefore, the greater the excitations or inhibitions (weights between neurons) of an input this will be qualified as "influential" in the prediction. The value of S is the sensitivity value that is obtained for each input. Then a ranking is obtained of the most and less influential variables.

Finally, it was obtained that the 5 variables with the greatest contribution to the prediction were; the road (number of tracks), the number of crossings, the length of the street, number of curves and inclination of the road.

Sensitivity analysis was performed to determine the impact of each of the input variables on the predictions. For the above, the weight-on-connection approach method was used. In this case, Equation (2) was used, where S is the sensitivity value that is obtained for each input, obtaining a ranking of the most influential variables that they are: road (number of tracks), the number of crossings, the length of the street, number of curves and inclination of the road

5 Conclusions

An alternative ANN was used to make predictions of the risk present in the streets. The objective was to propose a mathematical model based on non-linear regressions, so it was developed successfully, obtaining predictions with a low error and a correlation coefficient 0.56, with 87% of acceptances. Even though the index explains a satisfactory prediction, it does not exceed the capacity of the model with ANN, which registered a 0.64 correlation coefficient, or in other words 95.7% acceptable predictions.

With the sensitivity analysis, the effective property of the neural network was verified, considering or canceling variables that contribute or not, to the prediction performance respectively, this due to the function they perform of neuronal biases and the treatment that was carried out with the input variables.

Thanks to the results obtained, the designer can already be certain when discriminating on which street to install or not the pole. Thus the problem can already be treated efficiently, with a 95.7% probability of obtaining an acceptable prediction.

Given the above, the prediction will be studied in the future using variables such as power outages due to the crash, state and place of installation of the pole and its distance from the road.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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