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Comparison of Neural Networks and Logistic Regression in Assessing the Occurrence of Failures in Steel Structures of Transmission Lines

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Abstract: In this work, we evaluate the probability of falling metal structures from transmission lines. It is our objective to extract knowledge about which variables influence the mechanical behavior of the operating lines and can be used to diagnose potential falling towers. Those pieces of information can become a basis for directing the investments of reinforcement structures, avoiding the occurrence of long turn offs and high costs as a consequence of damage to towers of transmission lines. The results are obtained using the history of 181 metal structures currently in operation in the state of Paraná/Brazil. For the classification of transmission lines susceptible to failures it is proposed to identify the most likely lines considering the following parameters: operating voltage, wind and relief of the region, air masses, temperature, land type, mechanical capacity, function and foundation structure. The classic technique of classifying binary events used in this type of problem is the logistic regression (LR). The more recent technique for classification, using Artificial Neural Networks (ANN) can also be applied. The results are compared through the area under receiver operating characteristics (ROC) curves.

Keywords: Artificial Neural Networks, Fall of Metal Structures, Logistic Regression, ROC Curves, Transmission Lines.

1. INTRODUCTION

Aerial transmission lines are exposed to various risks associated with the environment, to changes in building characteristics and climatic variations. Often, these risks can lead to serious damage, incurring structure falls. The fall of a structure can interrupt the power supply of a location for a long period as well as generate costs in the reconstruction of tracks of the electrical system, the profit loss for the concessionaire and costs in compensations related to damages originated from lack of energy. Due to the importance of aerial lines, a quantitative analysis of their characteristics in order to identify and mitigate them has much to contribute to the planning, operation and maintenance of lines.

It is intended here to extract knowledge about the parameters and variables that influence the mechanical behavior of the operating lines and can be used to diagnose potential falling towers. This information can become a basis for directing the investments of reinforcement structures, avoiding the occurrence of long turn off and high costs as a consequence of damage to towers of transmission lines. Few studies of classification of failures in transmission lines are found in the literature and generally explore constructive aspects of lines, reliability and construction. Wazen *et al.* [1] evaluated the susceptibility of metal structures of a transmission line using logistic regression and approximate joint failures. This paper's findings were obtained by exploring a real case from historical data of 181 metal structures currently in operation in the state of Paraná/Brazil. The dataset analyzed presents ten explanatory variables (voltage, wind, relief, cold air masses, hot air masses, temperature, land, capacity, function, foundation) and a binary response variable of type that considers the fall (or not) of the metal structure. Classification models using LR and ANN

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methodologies were applied to the data and compared through the area under the receiver operating characteristic curve (AUC).

The paper is organized as follows. Section 1 introduced the context of the analyzed problem. Section 2 presents a review of papers reporting the use and comparison of artificial neural networks and logistic regression in different domains. Section 3 presents the case under study highlighting the main aspects of transmission lines and the relevant variables in determining structural failure. Section 4 shows the classic technique of binary logistic regression and classification results for the historical dataset. Section 5 presents the classification methodology and results based on the use of ANNs. A comparative analysis between the proposed ANN and classical LR methods is also performed through the area under the ROC curves. The main results and conclusions are discussed in section 6.

2. REVIEW OF ANN AND LOGISTIC REGRESSION FOR CLASSIFICATION PROBLEMS

Classification is one of the most frequently encountered decision making tasks of human activity. A classification problem occurs when an object needs to be assigned into a predefined group or class based on a number of observed attributes related to that object. Traditionally, statistical classification procedures deal with these kind of problems but one major limitation is that they work well only when the underlying assumptions of the model are satisfied. Thus, due to characteristics aforementioned, ANNs have emerged as an important alternative tool for classification [2].

Over the years, there have been an increasing number of papers exploring the use of ANNs as a promising alternative methodology in comparison to the most consecrated methodology of LR. The characteristics of each of the reviewed works are presented in Table **1**. The first column demonstrates what work is being analyzed. The second shows the nature of the papers, that is, if the authors prioritized a conceptual, a review or an application approach. The third presents their objectives and the fourth exposes which of the two methodologies has had a better performance.

Table 1. Characteristics of previous works.

Paper	Nature	Objective	Performance (ANN x LR)
Tu, 1996 [3]	Conceptual	Predict medical outcomes	Not conclusive
Schumacher *et al.*, 1996 [4]	Application	General comparison of both methods	Not conclusive
Vach *et al.*, 1996 [5]	Conceptual	General comparison of both methods	Not conclusive
Freeman *et al.*, 2000 [6]	Application	Predict in-hospital death after angioplasty	Similar
Leung & Tran, 2000 [7]	Application	Predict shrimp disease outbreaks	ANN
Borque *et al.*, 2001 [8]	Application	Predict pathological stage	Similar
Chun *et al.*, 2007 [9]	Application	Predict the probability of prostate cancer	LR
Kawakami *et al.*, 2008 [10]	Application	Predict the probability of prostate cancer	LR
Ottenbacher *et al.*, 2001 [11]	Application	Predict rehospitalization for patients with stroke	Similar
Nguyen *et al.*, 2002 [12]	Application	Predict death or limb amputation in meningococcal disease	Similar
DiRusso *et al.*, 2002 [13]	Application	Analyze survival in pediatric trauma patients	ANN
Dreiseitl & Ohno-Machado, 2002 [14]	Review	General comparison of both methods	ANN
Hajmeer & Basheer, 2003 [15]	Application	Classify bacterial growth	ANN
Ottenbacher *et al.*, 2004 [16]	Application	Address prediction questions epidemiological research	Similar
Lin *et al.*, 2010 [17]	Application	Predict living setting following hip fracture	ANN
Ergün *et al.*, 2004 [18]	Application	Classify carotid artery stenosis of patients with diabetes	ANN
Yesilnacar & Topal, 2005 [19]	Application	Analyze landslide susceptibility	ANN
Yilmaz, 2009 [20]	Application	Analyze landslide susceptibility	ANN
Pradhan & Lee, 2010 [21]	Application	Analyze landslide susceptibility	ANN
Choi *et al.,*2012 [22]	Application	Analyze landslide susceptibility	LR
Song *et al.*, 2005 [23]	Application	Differentiate between malignant and benign breast masses	Similar
McLaren *et al.*, 2009 [24]	Application	Detection and diagnosis of breast lesions	Similar
Green *et al.*, 2006 [25]	Application	Predict acute coronary syndrome	ANN
Chiang *et al.*, 2006 [26]	Application	Differentiate between web and traditional stores	ANN
Liew *et al.*, 2007 [27]	Application	Predict illness on patients undergoing bariatric surgery	ANN
Gutiérrez *et al.*, 2008 [28]	Application	Map Ridolfia Segetum (a persistent weed) infestation	Not conclusive
Kurt *et al.*, 2008 [29]	Application	Predict coronary heart disease	ANN
Al Housseini *et al.*, 2009 [30]	Application	Predict the risk of cesarean delivery in nulliparas	ANN

(Table 1) contd.....

Paper	Nature	Objective	Performance (ANN x LR)
Caocci *et al.*, 2010 [31]	Application	Predict the occurrence of acute graft-*vs*-host disease	ANN
Pavlekovic *et al.*, 2010 [32]	Application	Recognize mathematically gifted children	Similar
Trtica-Majnaric *et al.*, 2010 [33]	Application	Predict influenza vaccination outcome	ANN
Chen *et al.*, 2012 [34]	Application	Differentiate between malignant and benign lung nodules	ANN
Larasati *et al.*, 2012 [35]	Application	Psychological research	ANN
Pourshahriar, 2012 [36]	Application	Psychological research	Similar
Swiderski *et al.*, 2012 [37]	Application	Assess the financial condition of a company	Not conclusive
Askin & Gokalp, 2013 [38]	Application	Assess students' mathematics achievement	Similar
Morteza *et al.*, 2013 [39]	Application	Predict the level of albuminuria in type 2 diabetes	Not conclusive
Vallejos & McKinnon, 2013 [40]	Application	Classify seismic records	Similar

Fig. (**1**) summarizes the characteristics observed, reporting the percentage of works in which ANNs outperformed LR and *vice versa*. Not conclusive or similar performances are also presented.

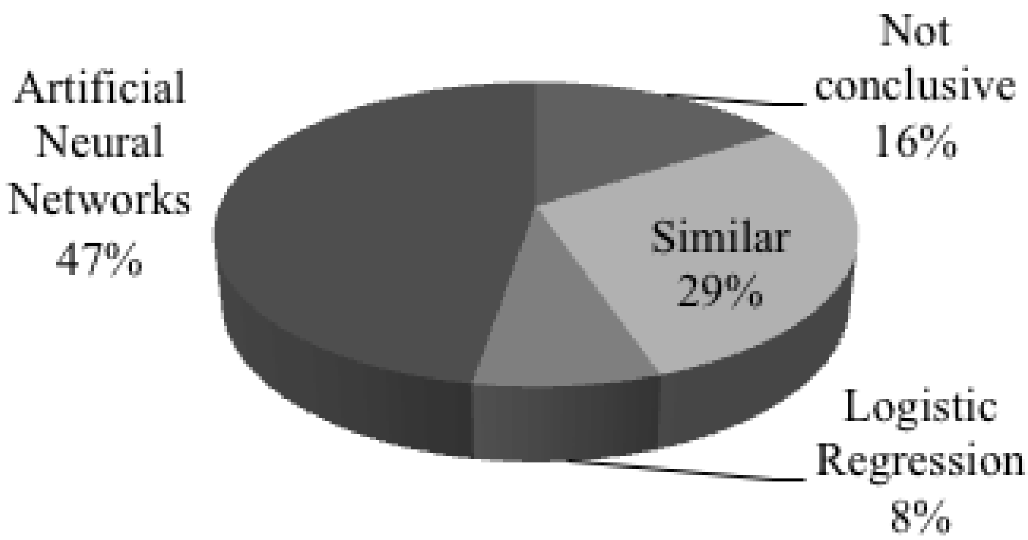


Fig. (1). Percentage of works in which each methodology was better than the other.

3. TRANSMISSION LINES

Transmission lines are circuits that interconnect substations, power plants or energy distributors. These circuits are composed of self-supporting towers or poles, as well as the flow of metal for power wires. Its main function is to transport large volumes of electricity with the least possible loss of energy. Transmission systems can happen in alternating or direct cables. Among the systems, the most used in Brazil is alternating and its application occurs in three-phase circuit chains with just one high voltage transmission line in direct current. These are compositions for interconnection of energy in the country, with different consumer centers as well as to supply large industrial facilities. Brazilian system transmits voltage of 69 kV, 88 kV, 138 kV, 230 kV, 345 kV, 525 kV and 750 kV.

According to Wazen *et al.* [1], in order to conveniently analyze the reasons for the discontinuation of energy transmission due to contingencies in transmission lines caused by external factors, it is necessary to describe the types and configurations of structures, cables and foundations.

- *Structures*: The dimensions and shapes of the structures depend on the required disposition of the conductors, the distance between them, the size and kind of isolation, arrows projected for the conductors, minimum safety height and the number of circuits involved. The design of a transmission line structure depends on both the charge to be transported (directly linked to the capacity and performance of the wire) as well as the size of the structure to be used. These values are calculated considering the security and performance compared to the values of voltage and efforts that structures will be submitted. Structures can be classified on some criteria, described on Table **2**.

Table 2. Types of structure.

Type of Structure	Description	Classification	Classification Description
About its function	The function of a structure in a transmission line is associated with the efforts to which each structure must be submitted.	Suspension	Structures subjected to efforts of vertical and horizontal transverse components
		Anchoring	Structures subjected to vertical, horizontal transverse and longitudinal forces
About its resistance	How the structures transfer the sustained efforts to the materials and the region they were applied	Self-supporting	The fittings are capable to support all the efforts applied on the same
		Cable-stayed	It uses cables to connect the structure and the soil
About its composition	There are many ways to transmit power using structures of several materials	Metal	Usually made of carbon steel, normal or high strength profiled or tubular
		Concrete	Due to the material used, it must be made with the whole body, hindering its transport and assembly
		Wood	Despite being made of easy extraction equipment and low cost, the wooden pole does not have great mechanical strength

The types and configurations of structures in use are varied. The framework projects are not limited to the models already applied. But to define a new model, a large amount of information is required to find an efficient configuration and is not applied exclusively to a structure of a series of projected lines. The application of appropriate materials as well as voltage levels eventually turns even more difficult to define standardized structures.

- *Cables*: The cables can be differentiated according to the various functions that a transmission line can have, which can be power conductors, protectors against outbreaks atmospheric and overcurrent, or even energy dissipation. The conductor cable can be called as an active part of a transmission line because it serves as a guide to the electric and magnetic fields. In power cables, the great majority is made of aluminium having core galvanized steel (steel core).
- *Foundations*: The foundations are designed to balance the action of the forces acting on the top of the structure and its equipment, and it must take into account the type of soil where it will be located. With this, it is necessary to perform a reconciliation of these factors so that foundations can be better implemented without generating excess material or settling the forces to which it will be exposed.
- *Concrete Foundations:* Some concessionaries use concrete in some of its foundations, and its use depends on the preparation of concrete. For this preparation the concrete should be mixed mechanically according to the amounts stipulated by the structure design. The amount of concrete prepared in each operation is strictly necessary for immediate use. Fresh concrete should suffer the least possible distance of transportation and be released immediately after mixing and kneading. In cases of use of waterproofing for concreting with the presence of water, this time interval for release should be extremely short, so that the mass is practically uniform. Considering these basic situations for applying concrete, follow the types of foundation applied to transmission lines. Among the types of foundation, we highlight the caisson foundation, which is a kind of deeper foundation, excavated with shovel, pick, or auger. Once you put the armor for concrete, concreting is performed. Generally, you use shackles of reinforced concrete, to make the bracing of the trunk (top layer of concrete) and the reinforced concrete shoe, which is a shorter concrete foundation in relation to the dimensions of the base. They are typically a square base and inclined or vertical shaft.
- *Metallic Foundation:* Metallic foundations are used in regions where the ground has good cohesion. The foundations that implemented purely metallic structures of transmission lines have pyramidal shape, so that the connection to the structure is made from the top of the pyramid and all of its internal area is hollow and filled with soil. This format turns the soil itself in a mechanical barrier that prevents the base of the foundation (base of pyramid) to rise or move laterally. Variations on this type of foundation occur as the size height, dimensions of the stringers and sheet metal to be applied. As an example of variations, there is the metal grid, which is classified as a shallow foundation, connected to the foot (amount) of the tower at ground level. The foundation base (grid itself) consists of platters (U profile) and angles. They are shallow foundations with 2-4 feet deep, recommended for clay, sandy soil, but dry and with increasing strength with depth and with the possibility of being excavated in the open air.

Now that the structures, cables and foundations were described, it is important to stress that every type of equipment can suffer great efforts. A functional failure, which can even be a fall of structures, could happen. Fallen towers represent a critical issue and their causes must be examined. Table **3** presents part of the data set which comprehends 181 metal structures of transmission lines currently in operation in the state of Paraná/Brazil.

Table 3. Part of the data set of 181 steel structures of transmission lines.

Case	Voltage	Wind	Relief	Cold Air Masses	Hot Air Masses	Temperature	Land	Capacity	Function	Foundation	Result
1	69	14	plateau	parallel	perpendicular	17	C	high	anchorage	grid	none
2	69	14	plateau	parallel	perpendicular	17	C	high	suspension	grid	none
3	69	14	plateau	parallel	perpendicular	17	C	low	anchorage	grid	none
4	69	14	plateau	parallel	perpendicular	17	C	low	anchorage	stub	none
5	69	14	plateau	parallel	perpendicular	17	C	low	suspension	grid	none
6	69	15	plateau	perpendicular	transversal	18	D	high	anchorage	grid	none
7	69	15	plateau	perpendicular	transversal	18	D	high	suspension	grid	none
8	69	19	plain	perpendicular	transversal	21	B	low	suspension	grid	fall
9	69	20	plateau	parallel	perpendicular	17	B	low	suspension	grid	fall
10	69	20	plateau	parallel	transversal	19	A	low	suspension	grid	fall
11	69	20	plateau	transversal	perpendicular	17	A	low	suspension	grid	fall
12	69	23	plain	transversal	parallel	20	A	low	suspension	grid	fall
13	88	20	plateau	parallel	transversal	22	A	low	suspension	grid	fall
14	88	20	plain	parallel	transversal	22	B	low	suspension	grid	fall
15	138	14	ridge	parallel	transversal	16	B	low	anchorage	grid	none
16	138	14	ridge	parallel	transversal	16	B	low	suspension	grid	none
…	…	…	…	…	…	…	…	…	…	…	…
179	230	26	plateau	parallel	transversal	17	D	high	suspension	stub	none
180	230	26	plateau	parallel	transversal	17	D	low	suspension	stub	none
181	525	17	plain	perpendicular	transversal	20	B	low	suspension	grid	fall

The attributes selected for this article were: operating voltage, wind and relief of the region, air masses, temperatures in the region, land type, mechanical capacity of the structure, function and type of foundation structure.

The response of interest is dichotomous, *i.e.* if there was a structure falling or not. Among all selected explanatory variables or attributes in the data set, only three variables are quantitative and the others are qualitative. Quantitative variables vary within a certain range, according to its characteristic, and qualitative variables have different classifications according to their nature. Explanatory variables are described below.

- *Operating Voltage*: The electrical system of the state of Paraná has transmission lines in the following voltages: {69, 138, 230, 525} where each value is given in kV.
- *Wind of the Region*: Wind is an important feature that increases the susceptibility of occurrence of falling structure. It varies according to the region where the structure is located. The wind attribute has the following ranges {16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26} where each value is measured in km/h.
- *Relief*: The land in which the structures are set shows formations that help in the visualization of the points where the structure has a greater chance of falling. This attribute is ranked {plain, plateau, ridge, valley}.
- *Air Masses*: As air masses are different they have different senses of displacement, interference is studied independently. Each of the masses generates lateral forces to the cables may be of greater or lesser impact, causing a strain on the structures that support the cables. When the air mass is acting on perpendicularly to the wires there is a greatest possible force applied to the wires. When the incidence is closest to the direction parallel to the wires, the smaller the force applied by wind pressure on the wires. Therefore, the greatest force is generated on the wires with the mass of air in the direction perpendicular to the lower and occurs in the direction parallel to the wires. Thus, objects that represent the groups of air mass are classified as cold air masses which can be {parallel, perpendicular and transversal} and hot air masses, which are {parallel, perpendicular and transversal}.
- *Temperature*: The southern region is where the greatest variations in temperature throughout the day are registered, due to its distance from the tropics and the fact that it is in the region of strong influence of masses of cold and warm air. This attribute has the bands measured in degrees Celsius {16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27}.

- *Land*: The wind regime is influenced by factors such as topography and roughness of the land. This means that although the average values used, in some points these values can be smaller or larger. Ground can be differentiated into four categories, according to the coefficients of roughness that is: A) Vast expanses of water, shore plains and deserts plans; B) Ground open with few obstacles; C) Land with numerous small obstacles; D) lands and urbanized areas with many tall trees. The tracks which form the group of the attribute are {A, B, C, D}.
- *Mechanical Capacity*: To select a particular type of structure the efforts that it will be applied will be considered and this definition deliberates in the deployment project. Therefore, for this attribute is considered as a {high, low} mechanical capacity.
- *Function Structure*: Concerning this attribute, the structure can be applied as: {suspension or anchorage}, without considering intermediate possibilities. This item refers to the efforts that the tower is subjected, emphasizing that the anchorage compositions of the fittings are more enhanced than the suspension.
- *Foundation Structure*: It can be considered that there are two types of foundation concrete and metal foundation. The concrete can be in various formats, but always with a metal frame that makes its mooring and connection to the tower body. As the vast majority of concrete foundations applied are stub type, this term is used in this work comprehensively, referring to all varieties of concrete. Metal foundations also have different designs, but as to its shape, we can say that all are pyramidal. Among the pyramidal shape, the application is a larger metal grid type. The objects that form the group are classified into this attribute {stub, grid}.

For the classification of transmission lines in their susceptibility to failures we propose applying two different models. First, a logistic regression model will be applied and discussed. Then the automated neural network model will be developed. The comparison of the results obtained will be made *via* the area under the receiver operating characteristics curve known as the area under the curve (AUC). Fawcett [41] affirms that the ROC curve is a two dimensional depiction of a classifier performance. To compare classifiers we may want to reduce ROC performance to a single scalar value, the AUC, which has an important statistical property: the AUC of a classifier is equivalent to the probability that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance.

4. BINARY LOGISTIC REGRESSION MODELING

Regression modeling is one of several statistical techniques that enable an analyst to predict a response based upon a set of inputs. Linear regression models are commonly used when the range of the response is continuous, and can theoretically take any value. This model will be used to estimate the probability that a steel structure of transmission lines will fall due to certain conditions. As the output is restricted to the interval (0, 1), the assumption of an infinite range fails. An alternative is instead to use a logistic regression model [42]. The common form for a logistic model is,

$$P[c \mid \mathbf{X}_t] = \mathrm{G}(\hat{\beta}_0 + x_{1t}\hat{\beta}_1 + x_{2t}\hat{\beta}_2 + \ldots + x_{nt}\hat{\beta}_n) \quad \textbf{(1)}$$

where $P\ [c \mid \mathrm{X}_t]$ is the conditional probability that the observation described by the input vector X_t is a member of class *c*. What makes the logistic equation appropriate for probability modelling is the use of the sigmoid or "s" function.

$$\mathrm{G}(t) = \frac{1}{1+e^{-t}} \quad \textbf{(2)}$$

The sigmoid function in equation (2) is a continuous mapping of the real line on to the interval [0, 1]. While this interval is open with regards to the closed probability interval, it does create a method of modelling percentages and probabilities.

In order to compare more easily the logistic regression model to the feedforward Neural Network model, the logistic model can be described in a matrix form:

$$P[c \mid \mathbf{X}_t] = \mathrm{G}(\hat{\beta}_0 + \mathbf{X}_t^T \hat{\mathbf{B}}) \quad \textbf{(3)}$$

In this matrix form, X_t^T is the transpose of the vector of inputs, $\hat{\mathbf{B}}$ is the vector of estimated parameters, $\hat{\beta}_0$ is the estimated intercept term, and as before, G(o) represents the sigmoid function.

Although the purpose of this model is to predict the expected probability of steel structure rupture, the logistic regression model provides an additional benefit. This second use is its ability to provide insight into the model inputs or explanatory variables. The increase in the probability, in terms of the odds ratio, of a rupture when the variable is present is easily calculated rom the estimated parameters. If input variable *i* has an estimated parameter β_i, the odds ratio can be calculated using equation (4).

Table 4. Response information, factor information, and logistic regression table given by Minitab.

Response Information:

Link Function: Logit

Variable	Value	Count	
Result	none	137	(Event)
	fall	44	
	Total	181	

The Logit function (similar to Eq 1.) was here selected among concurrent functions (Probit and Gompit). The number of observations for the two response categories ("fall" and "none") reveals an unbalanced dataset. The response value that has been designated as the reference event is "none". Statistical effects of factors are calculated having "none" as reference.

Factor Information:

Factor	Levels	Values
Voltage	2	138; other
Relief	3	plain; plateau; ridge_valley
ColdAirMass	3	parallel; perpendicular; transversal
HotAirMass	3	parallel; perpendicular; transversal
Land	4	A; B; C; D
Capacity	2	high; low
Function	2	anchorage; suspension
Foundation	2	grid; Stub

Six factors (with different levels) are considered in the model. The factor level that has been designated as the reference level is first entry under values.

Logistic Regression Table:

Predictor	Coef	SE Coef	Z	P	Odds Ratio	Lower	Upper
Constant	59,3711	14,6063	4,06	0,000			
Voltage							
other	-8,05377	2,29698	-3,51	0,000	0,00	0,00	0,03
Wind	-0,282987	0,202494	-1,40	0,162	0,75	0,51	1,12
Relief							
plateau	-5,14588	1,80962	-2,84	0,004	0,01	0,00	0,20
ridge_valley	-7,70186	2,34577	-3,28	0,001	0,00	0,00	0,04
ColdAirMass							
perpendicular	-0,403916	1,05317	-0,38	0,701	0,67	0,08	5,26
transversal	-5,48150	1,82560	-3,00	0,003	0,00	0,00	0,15
HotAirMass							
perpendicular	-3,08682	1,39565	-2,21	0,027	0,05	0,00	0,70
transversal	-3,01681	1,49606	-2,02	0,044	0,05	0,00	0,92
Temperature	-2,21225	0,547453	-4,04	0,000	0,11	0,04	0,32
Land							
B	1,30160	0,906144	1,44	0,151	3,68	0,62	21,71
C	6,32315	2,10111	3,01	0,003	557,32	9,07	34243,69
D	4,80950	1,80180	2,67	0,008	122,67	3,59	4192,17
Capacity							
low	-4,16272	1,15683	-3,60	0,000	0,02	0,00	0,15
Function							
suspension	-2,54554	1,32737	-1,92	0,055	0,08	0,01	1,06
Foundation							
Stub	4,39213	2,19840	2,00	0,046	80,81	1,09	6008,38

The estimated coefficients, standard error of the coefficients, Z-values, and p-values are represented in this table. Using the logit link function, the odds ratio and a 95% confidence interval for the odds ratio is computed. From the output, one can also see that the estimated coefficients for several inputs have P-values less than 0.05, indicating that there is sufficient evidence that the coefficients are not zero. This means that several factors are influential on the regression model. The greater the linear predictor, the greater the likelihood of the model in recognizing "fall" and "none". The order and importance of significant variables for the occurrence of "fall" against "none" is given by the absolute value of the estimated coefficient.

$$\psi_i = e^{\beta_i} \tag{4}$$

Whether a linear regression model or a feedforward neural network is chosen for the model, the response data are dichotomous. It is because of this ability to model dichotomous outputs that the logistic model is a common tool in many fields.

The main findings for the regression model for the steel structure (Table **1**) are described in the following tables and graphs. Minitab software was used to run the analysis and comments are also included. Table **4** describes the response information, factor information and logistic regression table given by the Minitab results. Table **5** shows the Mintabresults for the G Statistic, Goodnesss-of-fit Tests, table of frequencies and Measures of association. Fig. (**2**) presents the Delta chi-square plots and their respective interpretation.

Table 5. G Statistic, Goodnesss-of-Fit Tests, table of frequencies and measures of association.

Log-Likelihood test:

Log-Likelihood = -25,719
Test that all slopes are zero: G = 149,335, DF = 15, P-Value = 0,000

The G statistic tests the null hypothesis that all the coefficients associated with predictors equal zero versus these coefficients not all being equal to zero. P-value =0 reject the null hypotheses.

Goodness-of-Fit Tests:

Method	Chi-Square	DF	P
Pearson	122,544	161	0,989
Deviance	51,438	161	1,000
Hosmer-Lemeshow	1,915	8	0,984

The P- values of all three fit tests are well above 0,05, then we cannot reject the hypothesis that the model is suitable.

Table of Observed and Expected Frequencies:

Value	1	2	3	4	5	6	7	8	9	10	Total
none											
Obs	0	2	10	17	17	18	18	18	18	19	137
Exp	0,0	2,1	10,3	16,0	17,6	17,9	18,0	18,0	18,0	19,0	
fall											
Obs	18	16	8	1	1	0	0	0	0	0	44
Exp	18,0	15,9	7,7	2,0	0,4	0,1	0,0	0,0	0,0	0,0	
Total	18	18	18	18	18	18	18	18	18	19	181

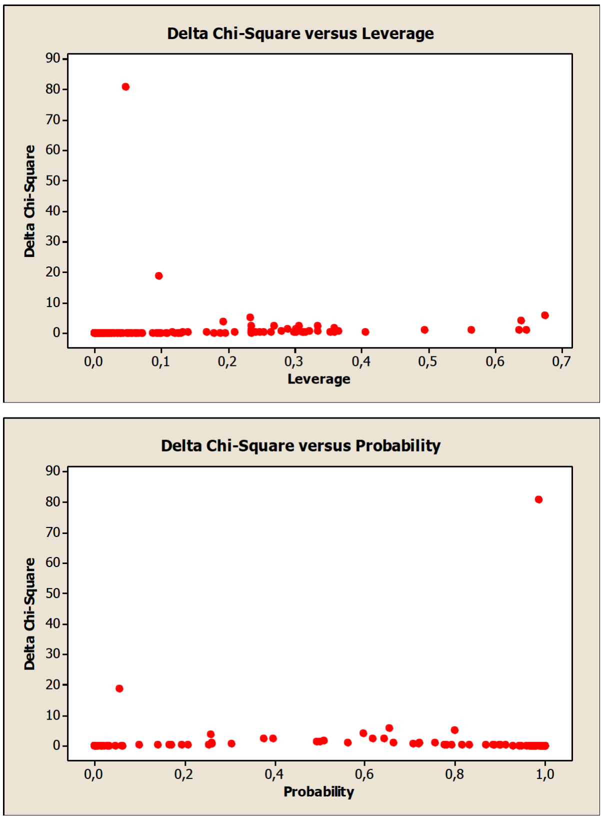
This table allows one to see how well the model fits the data by comparing the observed and expected frequencies. There is insufficient evidence that the model does not fit the data well, as the observed and expected frequencies are similar. This supports the conclusions made by the Goodness of Fit Tests.

Measures of Association (Between the Response Variable and Predicted Probabilities):

Pairs	Number	Percent	Summary Measures	
Concordant	5924	98,3	Somers' D	0,97
Discordant	102	1,7	Goodman-Kruskal Gamma	0,97
Ties	2	0,0	Kendall's Tau-a	0,36
Total	6028	100,0		

These statistics displays the number and percentage of concordant, discordant, and tied pairs, as well as common rank correlation statistics. These values measure the association between the observed responses and the predicted probabilities. The table of concordant and discordant pairs and tied pairs is calculated by pairing the observations with different response values. A pair is concordant if the pair of observations are in the same direction. A pair is discordant if the pair of observations are in opposite directions. Here, you have 137 structures with a value of "none" and 44 with a value of "fall", resulting in 137 * 44 = 6028 pairs with different response values. Based on the model, a pair is concordant if the structure with a "none" value has a higher probability of having "fall" value, discordant if the opposite is true, and tied if the probabilities are equal. Here, 98,3% of pairs are concordant (the same of the AUC) and 1,7% are discordant. Somers' D, Goodman-Kruskal Gamma, and Kendall's Tau-a are summaries of the table of concordant and discordant pairs. These measures most likely lie between 0 and 1 where larger values indicate that the model has a better predictive ability. In this example, the measure range from 0.36 to 0.97 which implies desirable predictive ability.

With the probabilities of occurrence of failures given by the LR, the ROC curve demonstrated in Fig. (**3**) can be plotted. The calculated result for the AUC was of 0,983, which indicates an excelent perfomance for the classifier.



The two graphs indicate that some observations are not well fit by the model (high delta χ^2). A high delta χ^2 can be caused by a high leverage and/or a high Pearson residual. Hosmer and Lemeshow indicate that delta χ^2 or delta deviance greater than 3.84 is large. Detection of influential information in the diagnostic analysis is an important topic, because these observations are points that exert a disproportionate weight in the estimates of the model parameters. Deleting points is best known for evaluating the impact of the withdrawal of a particular observation in the estimates of the regression technique. In this way Logistic Regression is limited when such influential points are present.

Fig. (2). Delta Chi-Square plots and interpretation.

5. ARTIFICIAL NEURAL NETWORKS MODELING

Artificial neural networks (ANNs) have been used increasingly as a promising modeling tool in almost all areas of human activities where quantitative approaches can be used to help decision making. They have already been treated as a standard nonlinear alternative to traditional models for pattern classification, time series analysis, and regression problems [43].

ANNs were first used in the fields of cognitive science and engineering, are universal and highly flexible function approximators [44]. As cited by Tsay [45], ANNs are general and flexible tools for forecasting applications:

A popular topic in modern data analysis is ANN, which can be classified as a semiparametric method. As opposed to the model-based nonlinear methods, ANNs are data-driven approaches which can capture nonlinear data structures without prior assumption about the underlying relationship in a particular problem.

Fig. (**4**) shows the ANN structure employed in the present study: A multilayer feedforward network trained with Backpropagation. The ANN has three types of layers, namely, the input layer, the output layer and the hidden layer, which is intermediate between the input and output layers. The number of hidden layers is usually one or two. Each layer consists of neurons, and the neurons in two adjacent layers are fully connected with respective weights, while the neurons within the same layer are not connected. In this paper, the output layer has just a single neuron, which represents the one-step forecasting based on previous points.

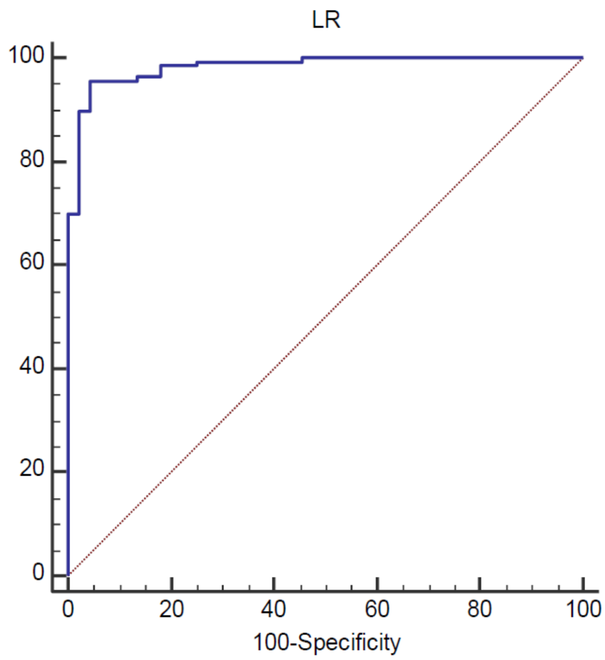


Fig. (3). ROC curve of the LR classifier.

Each neuron in the input layer is designated to an attribute in the data, and produces an output which is equal to the (scaled) value of the corresponding attribute. For each neuron in the hidden or output layer, the following input-output transformation is employed:

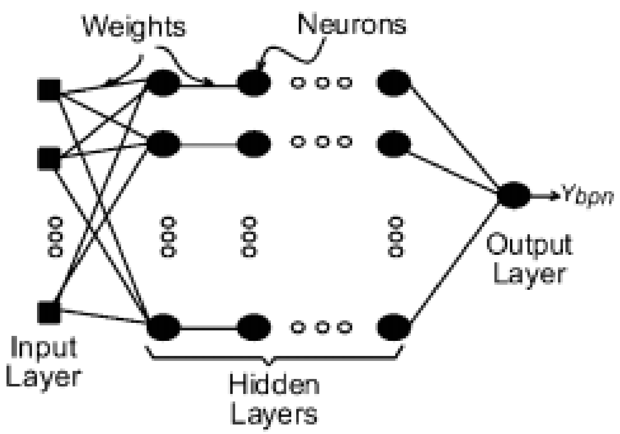


Fig. (4). Multilayer feedforward ANN structure.

$$v = f(\sum_{h=1}^{H} w_h u_h + w_0) \quad (5)$$

where v is the output, H is the total number of neurons in the previous layer, u_h is the output of the h^{th} neuron in the previous layer, w_h is the corresponding connection weight, w is the bias (or intercept). f is the nonlinear transformation function (or activation function) also used in the output layer. The following transformation function, as example, is employed very often:

$$f(z) = 2/(1+e^{-z}) - 1 \quad (6)$$

When the ANN is trained using the Backpropagation algorithm the weights and biases are optimized. The objective function employed for optimization is the sum of the squares of the difference between a desirable output (y_{target}) and an estimated output (y_{bpn}).

Review of ANNs from statistical and econometric perspectives can be found in [46]. Today ANNs are used in a variety of modeling and forecasting problems. Although many models commonly used in real problems are linear, the nature of most real data sets suggests that nonlinear problems are more appropriate for forecasting and accurately describing it. ANN plays an important role for this kind of forecasting.

The literature on ANN is enormous and its applications spread over many scientific areas with varying degrees of success. In the M-Competition [47], M2-Competition [48] and M3-Competition [49] many participants used ANNs. The main reason for this increased popularity of ANNs is that these models have been shown to be able to approximate almost any nonlinear function arbitrarily close.

Several factors have been considered in the literature when training ANNs. Table **6** presents the characteristic of the ANN constructed and details are given next. For the development of the net, the software Statistica (with Automated Neural Network toolbox) was employed (Statsoft, 2008).

Table 6. ANN characteristics.

Net. Name	Training Perf.	Test Perf.	Training Algorithm	Error Function	Hidden Activation	Output Activation
MLP 23-13-2	99,31034	94,44444	BFGS 27	SOS	Logistic	Identity

1. ANN Architecture/Net. name: ANNs are nonlinear modeling algorithms. Examples of ANN for nonlinear time series are Multilayer Perceptrons (MLP), Radial Basis Function (RBF), Support Vector Machine (SVM), among many others. The multilayer perceptron is the most common form of network and the one used here. It requires iterative training, which may be quite slow for large number of hidden units and datasets, but the networks are quite compact, execute quickly once trained, and in most problems yield better results than the other types of networks. Each model has a name depending on its type, *i.e.* MLP (Multilayer Perceptron), number of inputs, number of neurons in the hidden layer, and the number of outputs. For example, the model named as MLP 23-13-2 refers to a multilayer perceptron network with 23 inputs, 13 neurons in each layer, and 2 outputs.

2. Training Performance/Test Performance: These columns indicate the performance of the network on the subsets used. The performance measure depends on the type of network target variable. For nominal variables (classification networks), the performance measure is the proportion of cases correctly classified, which is known as the classification rate.

3. Training Algorithm: This factor is related to the following training algorithm chosen for the MLP such as:

- Gradient Descent. Gradient descent is a first order optimization algorithm that attempts to move incrementally to successively lower points in search space in order to locate a minimum.
- Conjugate Descent. Conjugate descent is a fast training algorithm for multilayer perceptrons that proceeds by a series of line searches through error space. Succeeding search directions are selected to be conjugate (non-interfering). It is a good generic algorithm with generally fast convergence.
- BFGS. BFGS (Broyden-Fletcher-Goldfarb-Shanno, or Quasi-Newton) is a powerful second order training algorithm with very fast convergence but high memory requirements due to storing the Hessian matrix.
- The results present the algorithm used followed by the number of epochs for which the algorithm ran (if an iterative algorithm). For example, the code BFGS 27 indicates that the BFGS algorithm was used and that this network was found on the 27^{th} cycle (the actual number of cycles used to train the model might be more than that).

4. Error Function: It indicates the error function used. It is either sum-of-squares (SOS) or Cross entropy (CE). CE is used for classification tasks only. SOS can be used for both classification and regression tasks.

5. Hidden Activation: This column indicates the activation function used for the hidden layer. Possible activation functions for MLP networks include Identity, Logistic, Tanh, Exponential, Sine.

- Identity. Uses the identity function. With this function, the activation level is passed on directly as the output of the neurons.

- Logistic. Uses the logistic sigmoid function. This is an S-shaped (sigmoid) curve, with output in the range (0,1).
- Tanh. Uses the hyperbolic tangent function (recommended). The hyperbolic tangent function (tanh) is a symmetric S-shaped (sigmoid) function, whose output lies in the range (-1, +1). Often performs better than the logistic sigmoid function because of its symmetry.
- Exp. Uses the negative exponential activation function.
- Sine. Uses the standard sine activation function.

6. Output Activation: Indicates the activation function used for the output layer. Possible activation functions for MLP type of networks include Identity, Logistic, Tanh, Exponential, Sine, and Softmax. Softmax activation functions are used with cross entropy error which be used only for classification tasks.

Fig. (**5**) shows the receiver operating characteristics curve for the MLP 23-13-2. The area under the curve was of 0,994 demonstrating apparent superior performance when compared with the one obtained by the logistic regression (0,979) model.

Some papers have discussed how to test the statistical significance of the difference between the areas under two dependent ROC curves.The methods discussed in Hanley and McNeil's [50] work and in Delong *et al.* [51] are the most significant in revised papers. We tested the statistical significance of the difference according to both methodologies and the results are presented in Table **7**. As demonstrated by the significance level (p-values > 0,05), there is insufficient evidence that one area is more expressive than the other. In other words, logistic regression and neural networks have both excellent and similar classification performances for the example under investigation. Fig. (**6**) shows both curves plotted on the same graph.

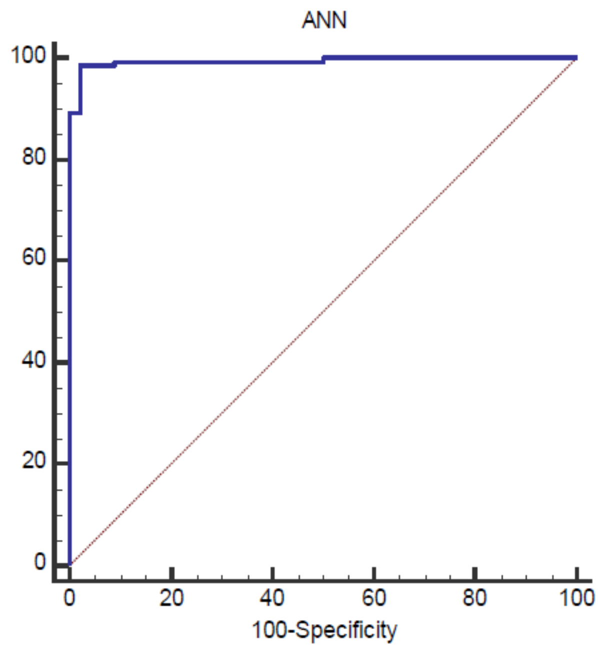


Fig. (5). ROC curve of the ANN classifier.

Table 7. Results of the tests reporting statistical significance of the difference between AUC.

	Hanley and Mcneil's Method	**Delong *et al.* Method**
Difference between areas	0,0108	0,0108
Standard Error	0,00790	0,00815
95% Confidence Interval	-0,00470 to 0,0263	-0,00520 to 0,0268
z statistic	1,365	1,322
Significance level	P = 0,1724	P = 0,1860

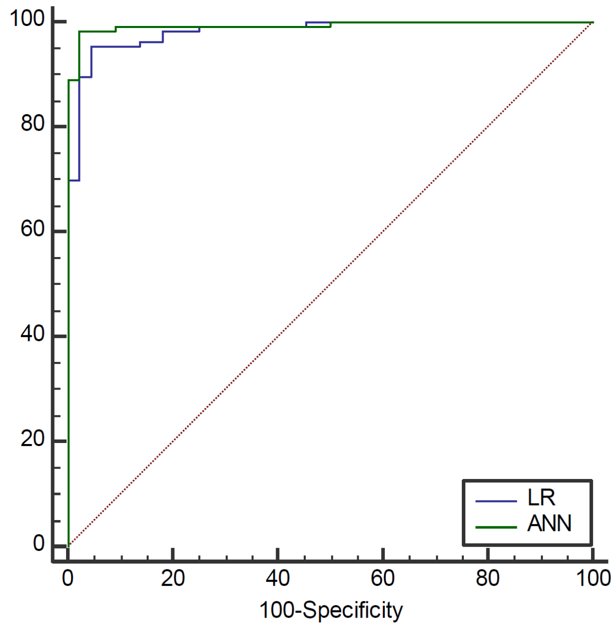


Fig. (6). LR and ANN ROC curves.

6. CONCLUSION

In this paper, we discussed assessing the probability of occurrence of failures in steel structures of transmission lines through two different techniques: logistic regression and artificial neural networks to extract knowledge about which variables influence the mechanical behavior of the operating lines and can be used to diagnose potential falling towers. For the classification of transmission lines susceptible to failures, the following parameters have been considered: operating voltage, wind and relief of the region, air masses, temperature, land type, mechanical capacity, function and foundation structure.

The results of the logistic regression and neural networks modelling show a direction in relation to the structures that are more susceptible to fall. Analyzing the logistic regression results we can infer that variables with p-values inferior to (0,05) are significant and those with high coefficient absolute values influence more the outcome of interest. For example, relief p-values are very low while their coefficients are high, demonstrating that this variable has considerable influence on the outcome under investigation. On the other hand, wind p-value is high which implies irrelevant influence on the outcome. Thus, with these preliminaries evaluation of the structures vulnerable, studies and implementations of improvements and actions can be previously programmed, minimizing the costs of load shedding and avoiding high values of lost profits and damages. The risks and costs involved to a fallen tower for both the energy concession as for the general population are higher than acting preemptively.

Depending on the goals or the characteristics of the data one model can be more adequate than the other. The use of artificial neural networks may be particularly useful when the main goal is outcome classification and important interactions or complex nonlinearities exist in a data set, also it requires less formal statistical training and can be developed using multiple different training algorithms. A limitation of neural network models is that standardized coefficients and odds ratios corresponding to each variable cannot be easily calculated and presented as they are in regression models.

Logistic regression remains the clear choice when the primary goal of model development is to look for possible causal relationships between independent and dependent variables, and a modeler wishes to easily understand the effect of predictor variables on the outcome given that the model equation is also provided.

Numerically the performance of artificial neural networks was higher than logistic regression model. However, there was no statistical difference between them and both classifiers have excellent performances. In other words, it can be inferred that the performance of models selected by ANN and LR was quite similar, and the analytic methods were found to be roughly equivalent in terms of their classification ability as demonstrated by equivalent AUC graphs. The ANN methodology is more robust (*i.e.*, it does not require a high level of operator judgment), and it uses a sophisticated nonlinear model to achieve high classification performance. On the other hand, logistic regression may generate many sets of models that yield similar performances, and the operator will need to make intellectual judgments to select the best models.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

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