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Proposed model of analysis of the perception of the relative importance of Critical Success Factors (CSF) in the civil construction industry (CCI) using Artificial Neural Networks (ANNs): application in the academic universe

Redes neurais artificiais para análise dos Fatores Críticos de Sucesso (FCS) na Indústria da Construção Civil (ICC): aplicação no universo acadêmico

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Abstract: Critical Success Factors (CSF) identify key areas for a company to succeed. This study creates a model to analyze CSF in civil construction project management, using Artificial Neural Networks (ANNs). For that, a literature review was performed to identify CSF emphasizing project management. Once the CSF were identified, a questionnaire was sent to educational institutions to evaluate the effect of each factor. Response analysis was made by the Relative Importance Index, using ANN coupled with the resilient propagation algorithm to evaluate the CSF. A total of 37,822 articles were found in 2,328 journals. Of 874 e-mails sent, 191 were answered. The respondents were distributed in 26 Brazilian states, with 70% of them being professors/researchers, 26% coordinators, 2% Rector, and 1% Director/Manager. Weights were determined using the Garson algorithm. The most critical factor in project management was ‘Unrealistic inspection and test methods in the contract’. Artificial Neural Networks produce subsidies to know the relevance of the input variables adopted and constitute an effective means for modeling nonlinear variables.

Keywords: Civil construction; Project management; Artificial Neural Networks; Critical Success Factors.

Resumo: Os Fatores Críticos de Sucesso (FCS) identificam o conjunto de áreas chave que se mostram essenciais para a empresa alcance êxito em sua missão. O objetivo do presente artigo é criar um modelo para analisar os FCS que afetam o gerenciamento de projetos na indústria da construção civil (ICC), utilizando Redes Neurais Artificiais (RNAs). Para tal, parte-se de uma

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revisão de literatura sobre identificaçao de FCS com enfase no gerenciamento de projetos, abrangendo 37.822 artigos em 2.328 revistas. Após a identificação dos FCS, busca-se a avaliação de professores e pesquisadores voltados à ICC, sobre efeito de cada fator, utilizando-se um questionário encaminhado às instituições de ensino superior com cursos de Engenharia Civil e Arquitetura. De 874 e-mails enviados, onde 191 respondidos distribuídos em 26 estados, onde 70% ocupa o cargo de professor/pesquisador, 26% coordenadores, 2% Reitor e 1% de Direção/Gerência. A análise das resposta é feita pelo Índice de Importância Relativa, utilizando-se a RNA para avaliar os FCS com o uso do algoritmo *Resilient propagation*. Os pesos são determinados com uso do algoritmo de Garson. Os fatores: Inspeção irrealista e os métodos de ensaio propostos no contrato mostram-se os mais crítico no gerenciamento de projetos segundo as respostas ao questionário. As RNAs produzem subsídios para se conhecer a relevância das variáveis de entrada adotadas e constituem um meio preciso para modelagem de variáveis não lineares.

Palavras-chave: Construção civil; Gerenciamento de projetos; Redes Neurais Artificiais; Fatores Críticos de Sucesso.

1 Introduction

The construction industry is dynamic in nature due to growing uncertainties in technology, budgets, and development processes. The study of success in determining its Critical Factors (CF) can be used as a means to improve project management.

Colauto et al. (2004) state that the identification of CSF provides strategic information and can assist in managerial decision making. It enables addressing problems in current projects and triggering corrective measures towards them (Saqib et al., 2008).

Artificial Neural Networks (ANNs) are computational techniques with a nonlinear approach. They stem from mathematical models that use artificial intelligence and that, like other models, aim to represent or approximate systems (Haykin, 2001; Silva et al., 2004). In many cases, these models are based on real observations and experiments. However, they can also be used as metamodels, in this case stemming from other models such as computer simulation (Blanning, 1975; Meisel & Collins, 1973).

The application of artificial neural networks in civil construction was initially proposed by Moselhi et al. (1991). These authors presented the advantages and the applicability of artificial neural networks in civil construction and mentioned that the productivity index forecast could be modeled with artificial neural networks. Notwithstanding, the authors showed no application for modeling project management.

Since then, some international researchers have dedicated themselves to testing the applicability of these networks. For example, Karshenas & Feng (1992) analyzed the productivity of earthmoving equipment; and Holohan (1992) showed that the determination of CSF is the best method for developing a monitoring system.

Abourizk & Wales (1993) used ANN as a means of applying the effects of local environmental conditions to the productivity index. Chao & Skibniewski (1994) performed a case study in which ANN was used to predict the productivity of an excavator. Portas & Abourizk (1997) developed an ANN-based model to predict productivity indexes for formwork for foundation walls. Knowles (1997) developed ANNs to predict relative productivity indexes for industrial piping systems and formwork for concrete walls and slabs. Sonmez & Rowings (1998) [[Q7: Q7]] dedicated themselves to the study of the quantitative evaluation of multiple factors in the productivity of formwork, casting, and finishing of concrete. Abourizk et al. (2001) presented an ANN model to predict the productivity of pipe installation work. Tam et al.

(2002) developed a quantitative model for predicting excavator productivity, which was compared to a multiple regression model. Biondi et al. (2004) proposed the use of ANNs to determine the unknown cost/m^2 values of real estate typologies. Costantino et al. (2015) developed an ANN-based decision support system to predict project performance for any set of CSF, classifying projects as successful or unsuccessful according to the level of risk.. Lorenzi et al. (2017) used artificial neural networks to predict steel-concrete adhesion in pull-out tests. Ribeiro et al. (2018) used geoprocessing and ANN as modeling techniques to generate N-CBR and I-CBR estimates. Addressing problems through ANNs is particularly appropriate for very complex applications.

In this context, using the critical success factors method integrates the competitive intelligence system into the formulation of strategic planning. Thus, in parallel with the needs of theoretical and empirical research on the critical success factors in competitive intelligence systems, the present study analyzes the main Success Critical Factors in in civil construction project management. This analysis is made from ANN modeling and considers the perception of professionals in a specific professional space (in this case, the academic space).

2 **Theoretical framework**

The project management knowledge area has been consolidating over the past few decades, thus arousing the interest of researchers, professionals, and companies. According to Casarotto et al. (2009) [[Q9: Q9]], the benefits of project management are numerous and directly related to meeting technical requirements, delivery times, expected costs, and customer and company satisfaction. The purpose of Project Planning is to establish and maintain plans that define project activities, resources, and responsibilities, as well as to provide information on project status, allowing corrections to be made when there are significant deviations in its performance.

New project management approaches have emerged and the themes addressed have diversified beyond the traditional schedule, budget, and scope. Returning to the theme of project-based companies, and considering that these projects must clearly identify the essential elements for their success (CSF), a sector emerges where projects are part of the daily routine. The identification of CSF is crucial for project success and, consequently, for the management of many resources, including human resources. Critical factors of project success can serve as fundamental criteria to avoid possible failures. This can be ensured with an effective project selection process, considering the company's strategic objectives, the project manager's experience, and the competitive environment.

The need to remain competitive generated the search for increased efficiency. Therefore, it is considered a motivator in Project Management, related to the incorporation of new capabilities that allow greater assertiveness to the project manager. Widespread statistical methods, such as multivariate linear regression (MLR), are limited in describing the correlation between nonlinear input and output data (Foucquier et al., 2013; Jiménez et al., 2013; Kalogirou, 2001; Melo, 2012).

There are several techniques for data modeling and information production that seek to simulate human intelligence, being a fundamental strategy for solving complex problems. These techniques include: Hypothesis Tests, Fuzzy Logic, Expert Systems, Artificial Neural Networks, among others. One of the most promising AI techniques is the Artificial Neural Networks, proposed to solve complex problems from the construction of a computational model composed of circuits that simulate the functioning of the human brain.

Artificial Neural Networks (ANN) can be briefly defined as a multivariate data analysis technique that uses parallel processing to simulate the behavior of a biological neural network.

Artificial neural networks were founded in the 1950s and gained significant attention in the last decade due to both the development of more powerful hardware and the creation of algorithms for tracing neurons (Apanavičienė & Juodis, 2003). Its use emerges as an advantageous alternative based on statistical concepts since no previous hypothesis about the distribution of the data to be classified is required and the input data can have different scales (real, integer, logarithmic, etc.).

These networks have been studied and explored by many researchers. Its application and manipulation took place in almost all fields of human knowledge (Identification System Modeling, Pattern Control and Recognition, Pronunciation, System Classification, Medical Diagnosis, Forecasting, Computer Vision, Engineering, and Management).

In civil engineering, most applications concentrate on the use of the most popular neural network class, which is the backpropagation neural network. When studying neural networks to determine the success of civil construction projects, Chua et al. (1997) found ANN models developed from field data that include potential determinants of construction project success. In total, the authors have identified eight main project management factors: (1) number of organizational levels between the project manager and craft workers; (2) amount of detailed design completed at the start of construction; (3) number of control meetings during the construction phase; (4) number of budget updates; (5) implementation of a constructability program; (6) team turnover; (7) amount of money expended on controlling the project; (8) project manager's technical experience. After sufficient training, the final model can also be used to predict the budget performance of a construction project.

Chua et al. (1999) also used ANNs as a method of analysis, identifying eight factors critical to budget performance, namely: number of organizational levels of the project, amount of detailed design completed at the start of construction, number of control meetings during the construction phase, number of budget updates, implementation of constructability programs, team turnover, amount of money expended on controlling the project, and project manager's technical experience.

Kog & Loh (2012) identified five key determinants for construction schedule performance using the neural network approach. These five key determinants are (in decreasing order of importance): amount of project time (time spent by project managers), frequency of managerial meetings, monetary incentive for the designer, implementation of a constructability program, and project manager's technical experience.

Mori (2008) used artificial neural networks to develop a management information system for predicting the levels of productivity in the face of predetermined environmental conditions. In that study, the authors considered the set of factors most influential in the work productivity of elevation masonry.

When studying CSF modeling with the use of ANNs at project level, Elwakil et al. (2009) determined that the model generated can be used to predict the performance of a construction organization based on the value of its critical success factors.

Zayed et al. (2012) used ANNs to determine the most important CSF in assessing the performance of organizations in the civil construction industry (CCI). The authors determined two models of performance prediction developed from regression analysis and ANNs, which show robust results when verified and tested. The analysis showed that the models developed are sensitive to the identified CSF.

When using neural networks to model the effectiveness of project management in construction, Apanavičienė & Daugeliene (2011) identified twelve key factors of construction management (in areas related to project manager, project team, project planning, organization, and control). The established neural network model can be used during the bidding process to assess the construction risk and to predict variation in construction costs. The model allows construction project managers to focus on critical success factors, thereby reducing construction risk.

Costantino et al. (2015) developed an ANN-based decision support system to predict project performance for any set of CSF, classifying projects as successful or unsuccessful according to the level of risk.

França (2016) applied ANNs through the adaptive neuro-fuzzy inference system (ANFIS) to analyze project risks in the construction industry. The authors concluded that risk management can be carried out by modeling human judgments and without the presence of specialists, as long as it is mathematically structured. Using artificial neural networks (ANNs) to determine CSF in civil construction project management is still a little explored area due to the lack of an approach to the certification of such systems.

3 **Methods**

From the methodology presented by Yi & Chan (2013) and Freitag (2015), studies were found with definitions of project management and critical success factors. This search becomes important for developing the questionnaire with the identification of factors already studied in the bibliography.

According to Cervo & Bervian (1983), bibliographic research seeks to explain a problem from theoretical references already published. It can be used independently or as part of a descriptive or experimental research. Its purpose is to understand and analyze cultural or scientific contributions on a given subject or problem. The present study included a search for qualitative data in the scientific bases Scopus and SciELO. All works were related to project management, CSF, and ANN in civil construction. After identifying potential success factors that may affect project management, a questionnaire was prepared as a research tool for data collection to assess and validate the effect of each factor. This questionnaire consists of two parts. The first refers to both the time of experience in civil construction and the research time spent in project management. In the second part of the questionnaire, respondents are asked to evaluate a series of practice-related factors regarding the extent to which they impact on project management in the civil construction industry.

This evaluation used a 5-point Likert scale (Likert, 1932) with the following possible answers: Very Low impact; Low impact; Medium impact; High impact; Very high impact.

This scale is recommended because it is the most used when measuring attitudes. Appolinário (2007) defines the Likert scale as a “type of attitude scale in which the respondent indicates his/her degree of agreement or disagreement with a given object”.

The number of items on the scale is validated by Dalmoro & Vieira (2013). These authors assessed the influence of the number of items on the Likert scale and found that the 3-point scale is less reliable and has less ability to accurately demonstrate the interviewee’s opinion; however, it was considered the easiest and fastest scale. The 5-point scale had, on average, the same precision and proved to be easier and faster than the 7-point scale. Therefore, for this study, the most appropriate scale that was the 5-point scale.

The search for potential respondents to provide the necessary data for this study was shaped by the characteristics of the population. Initially, the search included all Civil Engineering undergraduate and graduate courses in the Teaching Institutions registered with the Ministry of Education (MEC). Sample characterization was based on the randomness and heterogeneity of the return of the questionnaires, whose application was intended to reach the entire population described. Data collection was carried out exclusively by electronic means (google forms). For that, a link was sent to these subjects by email and/or cell phone using the WhatsApp application. The subjects should fill out a virtual form between May and June 2018. There was no possibility of interference by the author in this return, characterizing the impartiality and randomness of the sample collected.

3.1 Data treatment

Response analysis was made by the Relative Importance Index (RII). This index is calculated for each specific factor for each year of experience of the participants, using Equation 1 (Enshassi et al., 2007; Jarkas & Bitar, 2012; El-Gohary & Aziz, 2014):

$$\left(RII\%\right)_k = \frac{5\left(n5\right)+4\left(n4\right)+3\left(n3\right)+2\left(n2\right)+n1}{5\left(n1+n2+n3+n4+n5\right)} \times 100 \quad (1)$$

Where: RII (%) k is the annual percentage of the relative importance index of each factor, which is calculated separately for the corresponding year of experience (k) of the categorized respondents; k is the number that represents the years of experience of the categorized respondents (from the first year of experience, k = 1, to the last year of experience, k = K); and n1, n2, n3, n4, n5, and n6 are the numbers of respondents who chose: “1”, for very low impact; “2”, for low impact; “3”, for medium impact; “4”, for high impact; and “5”, for very high impact.

The overall Relative Importance Index (RII) for each factor of all respondents, considering all years of experience of respondents together, is calculated as a weighted average of RIIk (Equation 2):

$$Overall\ RII\left(\%\right) = \frac{\sum_{k=1}^{k=K}\left(k \times RII_k\right)}{\sum_{k=1}^{k=K} k} \quad (2)$$

Where: overall RII (%) is the percentage of the total weighted average of the relative importance index of each factor, which is calculated based on all the years of experience of the interviewees together; k is the number that represents the years of experience of the categorized respondents (from one year of experience, k = 1, to the last year of experience, k = K); and RII_k is the annual percentage experience of the Relative Importance Index for each factor, which is calculated separately for the corresponding year of experience (k) of the categorized interviewees, calculated by the previous equation.

The artificial neural network (ANN) was used to assess the most significant success factors using Neuro4 software (version 4.0.2). This required an output value for these variables, which was achieved by the weighted average according to Equation 3:

$$V_s = \frac{\sum_{i=1}^{n}\left(x_{ij} \times GII_j\right)}{\sum_{j=1}^{n} GII_j} \tag{3}$$

Where: x_{ij} = value of each factor per respondent; GII_j = importance index for each factor.

3.1.1 Training of artificial neural networks

Propagation algorithms were used for training artificial neural networks that fit the supervised learning paradigm, that is, the training algorithm receives a pair of inputs with their respective desired outputs. The propagation algorithm goes through a series of iterations to minimize estimation error.

Data are presented to the network at each iteration; with each observation presented, the weight matrix is changed by the steps known as forward and backward. In the forward step, input values are presented to the network and propagated to the output layer that generates a response; the obtained estimates are compared with the observed values, thus obtaining the error. It is noteworthy that network weights are all fixed in this stage. The backward step consists of the propagation of the error from the output layer towards the input layer, that is, backwards through the network, in which weights are adjusted according to an error correction rule so that the output value of the network is the closest to the desired.

The resilient propagation algorithm (Riedmiller & Braun, 1993) was implemented. This algorithm was designed to optimize backpropagation so as to obtain satisfactory ANNs. Resilient backpropagation (Rprop) has two main advantages. The first is that Rprop training is often faster than standard backpropagation training. The second advantage is that Rprop does not require specifications of any free parameter values, unlike standard backpropagation, which requires learning rate values.

The training of a network is completed when a certain stopping criterion is met. This study used three criteria: mean error, number of cycles, and convergence. Considering the k-th training sample, the quadratic error function measures the performance of the values produced by the output neurons (*j*), that is (Equation 4):

$$e(k) = \frac{1}{2}\sum_{j=1}^{n}\left(y_d^j(k) - y_j(k)\right)^2 \tag{4}$$

Where: y_d^j is the desired output value; y_j is the value obtained by the network.

Considering a training set consisting of "*p*" samples (Equation 5), the overall performance of the training algorithm can be measured by the mean square error (e_M), or simply the mean error:

$$e_M = \frac{1}{p}\sum_{k=1}^{p} e(k) \tag{5}$$

A cycle (or season) corresponds to the complete presentation of all elements of the training set accompanied by adjustments to the network weights. Therefore, a stopping criterion based on the number of cycles finishes network training after a certain number of cycles is reached. The criterion called 'convergence' defines the number of cycles after which training is completed if the mean error does not decrease.

The criteria for ANN training must be specified in advance, including maximum and minimum absolute errors and the number of training cycles without significant performance improvement. The data space is divided into two data sets: training and validation. The data set of the training phase is used to train the ANN. In this phase, error is calculated in relation to the training cycles, where the data are used to test the network during development/training, making continuous corrections and adjusting the weights of network connections to reduce error. The validation set is the piece of data that is used to validate the model(s).

With this processing, the statistical values Root Mean Square Error (RMSE), Variance, Residual Square Sum (RSS), and Correlation were obtained by varying the number of neurons in the hidden layer until stability was reached. After obtaining the best configuration for training, the data were entered again in NEURO to obtain the weights for the characterization of the variables. In this phase, NEURO was set to randomly separate 70% of the data (134 respondents) for training, and 30% (57 respondents) for validation. The selection of the networks used for the continuity of processing considered the best performance of the statistical analysis of the values obtained from the aforementioned statistical variables.

To obtain the relative importance of each variable, the Garson (1991) algorithm was used according to the following steps:

1. For each intermediate neuron *i*, the absolute value of the weight of the connection between this neuron and an output neuron is multiplied by the absolute value of the weight of the connection between the same hidden neuron and an input neuron. This calculation must be done for all j-nth neurons in the input layer. Then the product P_{ij} is obtained from Equation 6:

$$P_{ij} = w_{ij} \times w_{i0} \tag{6}$$

2. For each hidden neuron, P_{ij} is divided by the sum of all P_{ij} for each input neuron, obtaining Q_{ij} according to Equation 7, as follows:

$$Q_{ij} = \frac{P_{ij}}{\sum_{j=1}^{n} P_{ij}} \tag{7}$$

3. For each input neuron, Q_{ij} values are added to obtain S_j according to Equation 8:

$$S_j = \sum_{i=1}^{n} Q_{ij} \tag{8}$$

4. Dividing each S_j value by the sum of all S_j values, we obtain the relative importance R for each variable, according to Equation 9:

$$R_j = \left(\frac{S_j}{\sum_{j=1}^{n} S_j} \right) \times 100 \tag{9}$$

The Garson algorithm uses absolute values of the weights of the connections to calculate the contribution of the variable, not allowing an analysis of the direction of the changes that occurred in the output variable when there is a change in the input variables (Valença & Ludemir, 2007). When using the chain rule, each hidden layer receives an estimate of the error of the subsequent layer, so that the greater the number of layers, the more complete the approach of the algorithm, which can be found in Hagan & Menhaj (1994).

A total of 37,882 articles were found, divided into 2,348 journals in the search period between the years 2014 and 2018. Of these, 997 articles in 78 journals contained the terms critical factors and project management; 200 articles in 10 journals mentioned critical factors and ANNs; 125 articles in 3 journals cited project management and ANNs; and lastly, 4 articles cited project management, critical factors, and ANNs. Subsequently, a search was carried out using success in civil construction as a reference, where 1913 articles were found. For Critical Success Factors in construction, 157 articles were listed. After analyzing the selected files as to which contained contributions to the theme, the elaboration of the questionnaire also considered the factors listed by Cooke-Davies (2002), Fortune & White (2006), Lopes (2009), Doloi (2012), Morioka & Carvalho (2014), and Tsiga et al. (2016). Furthermore, a parallel was drawn with the knowledge areas of the PMBOK guide (Table 1).

Table 1. List of selected Project Success Factors.

Cod	Critical Factor	Cod	Critical Factor
F1	Increased scope of work	F11	Conflict between owners and other parties
F2	Ambiguity in specifications and/or conflicting interpretation	F12	Obtaining authorization from local authorities
F3	Rework due to project change	F13	Changes in government regulations and laws
F4	Unrealistic schedule in the contract	F14	Simplicity and clarity in project specifications
F5	Rework due to an execution error	F15	Poor coordination between project parties
F6	Inaccurate specification of site condition	F16	Lack of feedback on project progress
F7	Difficulty in accessing information, materials, and equipment in the project office	F17	Lack of knowledge of quality requirements
F8	Poor coordination among stakeholders	F18	Clear definition of the project scope
F9	Lack of registration of companies for subcontracts	F19	Lack of experience of the project team
F10	Reluctance of the engineer or architect to changes	F20	Unrealistic inspection and test methods in the contract

A total of 874 e-mails were sent to all educational institutions registered in the e-MEC system available on the website of the Ministry of Education, with a total of 191 questionnaires answered. The sample size for the intended purpose is validated by the authors Hair et al. (1998), who recommend that the sample be at least five times the number of variables studied, although considering the ratio of ten to one as the most acceptable. In addition, Malhotra (2001) recommends that the sample has at least four to five times more observations than variables. Crocker & Algina (1986) indicate the general rule of using 10 subjects per variable, with a minimum of 100 subjects in the total sample. Gorsuch (1983) states that in the factorial analysis, the sample must have at least 5 participants per variable, and the total sample should include at least 200 subjects.

The 191 questionnaires obtained and the 20 CSF addressed in the field research led to a questionnaire/variable ratio of 9.55, which is greater than the upper limit suggested by Malhotra (2001) and corroborates Hair et al. (1998). This ratio is still reinforced by Guadagnoli & Velicer (1988) *apud* Laros (2012), who, in defying Gorsuch's criterion, argued that there is no theoretical or empirical basis for recommendations on the ratio between the number of participants and the number of variables.

The answer to the questionnaire clearly demonstrated the randomness of the collection, with respondents from several Brazilian states, including: Rio Grande do Sul (26 teachers and 10 coordinators); São Paulo (21 teachers and 8 coordinators); Paraná (12 teachers and 9 coordinators); Minas Gerais (11 teachers and 7 coordinators); Goiás (9 teachers and 3 coordinators); Tocantins (7 teachers and 4 coordinators). None of the participants from Espirito Santo State answered the questionnaire. As for the profile of respondents regarding research time, 70% had 1 to 10 years of research experience, 22% between 10 and 20 years, 6% between 20 and 30 years, and only 2% over 30 years.

There is a predominance of respondents in the lowest times both for Research time and Experience time. Moreover, none of the respondents reached the highest times in the states of São Paulo and Minas Gerais, probably due to the expansion of Universities and Institutes throughout the interior of Brazil.

To prioritize the 20 CSF, the relative importance indexes were calculated according to the perceptions about how much the factors influence project management, enabling to rank the importance of each factor. Calculations considered the research times and the experience times of each of the respondents. Factor 4 had a high impact rate considering both the research time and the experience time of respondents, with percentages of 87.1% and 83.8% respectively. Factor 8 also had a high index, with the highest value for research time (88.7%) and the third highest value for experience time (82.8%) (Table 2).

Table 2. Classification of Factors considering Research Time and Experience Time according to the relative importance index.

Research Time		**Experience Time**	
Factor	**Ind (%)**	**Factor**	**Ind (%)**
8	88.67	4	83.80
4	87.10	19	82.98
19	87.07	8	82.75
3	86.72	5	82.31
5	86.09	3	81.70

Table 2. Continued...

Research Time		Experience Time	
Factor	**Ind (%)**	**Factor**	**Ind (%)**
18	85.28	16	81.60
16	84.47	18	81.28
1	83.76	11	81.06
14	83.48	15	80.38
11	82.06	1	79.96
15	81.55	10	75.98
2	81.37	14	75.57
6	79.32	20	75.20
20	79.11	2	74.82
10	78.49	6	72.48
7	75.11	7	70.93
12	73.38	17	70.59
17	73.36	12	69.54
13	69.29	13	66.25
9	66.43	9	63.27

A similar result was found by Saqib et al. (2008), who applied a questionnaire to the common public and to the professionals involved in the civil construction industry. The authors considered the following CSF in project management: effectiveness in decision making, planning effort, and the previous experience in project management.

When assessing critical success factors in the performance of civil construction projects, Paschoal (2014) determined four dimensions of success (efficiency, operational learning, customer satisfaction, and preparation for the future) and their CSF in project management. The factor ‘manager competence’ appears in the first three dimensions; the factor ‘manager experience’ does not appear only in the dimension of customer satisfaction. Conflicts between team members appear in the dimension of learning and preparation for the future.

Jordão et al. (2015) determined critical factors in civil construction project management with the application of a questionnaire to managers and employees involved in project activities. The items considered most critical were those related to management planning and support, incuding the setting of goals, customer involvement, planning definition, planning completion, communication between members, acquisition of materials, work feedback, managerial support, risk management, and expense management.

When analyzing CSF in international civil construction projects with the application of a questionnaire to 27 management professionals, Kikuti (2016) determined that the ten CSF in projects proposed by Pinto & Slevin (1988) contemplate the processes to be considered in the execution of projects.

Leite (2018) evaluated CSF in civil construction projects using the method of systematic literature review and its subsequent validation with the application of a semistructured questionnaire to Portuguese project managers. The most relevant CSF in project management were project monitoring and feedback, project risk management, and project change management. These findings corroborate this study.

Adequacy to planning and specifications is considered a CSF that depends not only on the conduct of the project manager responsible for the contract, but also on the team and people involved with the project. When adapting a project, the manager is aligning the execution schedule.

After the classification of the Factors according to the Relative Importance Indexes (Equations 2 and 3), and with the definition of the output values (V_s), the data to be inserted in Neuro4 were obtained as shown in Table 3.

Table 3. Matrix of responses to the use of ANN considering Experience Time in the area of civil construction and Research Time in project management.

Experience Time					Research Time				
Resp	**F1**	**F2**	**F20**	**Vs**	**Resp**	**F1**	**F2.......**	**F20**	**Vs**
1	4	4	5	4.09	1	4	4	5	4.27
2	5	3	4	4.30	2	5	3	4	4.26
3	5	3	5	3.84	3	5	3	5	4.03
188	4	5	4	4.26	188	4	5	4	3.97
189	3	5	1	4.07	189	3	5	1	3.62
190	4	5	3	4.35	190	4	5	3	4.02
191	5	5	3	4.14	191	5	5	3	3.89

With the insertion of the collected data, classified according to the Relative Importance Indexes, statistical results were analyzed, evolving from one to 12 neurons in the hidden layer. After adjusting the configuration to 10 neurons in the hidden layer, as shown in Figure 1, processing (training) of Neuro4 was carried out. In this step, 100 networks were trained with the Resilient Propagation algorithm with stopping criteria after an average error of 0.0001 and 3000 cycles with a convergence value of 20, which is considered a sufficient value for the research objectives and the number of cycles (Barros, 2018). In setting the stopping criteria, variations of the average error were initially tested. Then, the configuration was tested with variations in the number of cycles. It became clear that, after 3000 cycles, error convergence does not show major changes in the average values.

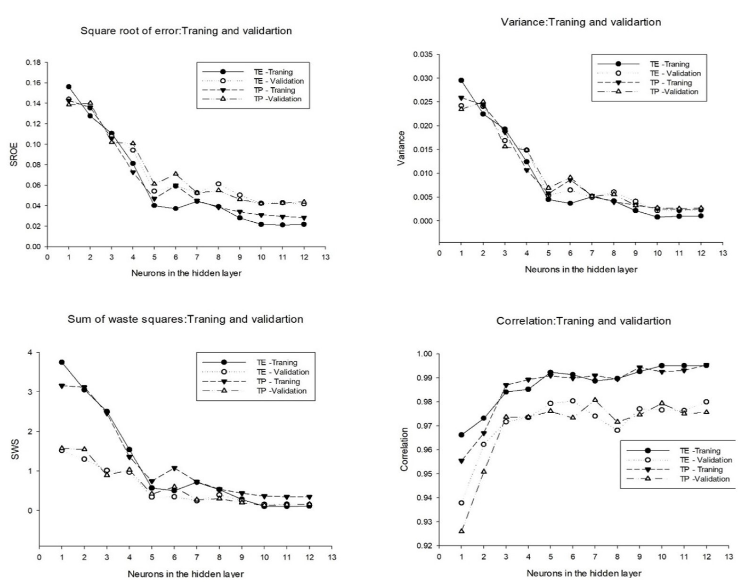

Figure 1. Statistical analysis of the processing, considering experience time (ET or 'TE') and research time (RT or TP').

Insertion of the collected data, classified according to the Relative Importance Indexes, makes it necessary to understand the functioning of Neuro4, as shown in Figure 2. Characterizations of the inserted variables are necessary for the training. Thus, all the variables “Factors” were characterized as quantitative, and the “V_s” variable as the output variable.

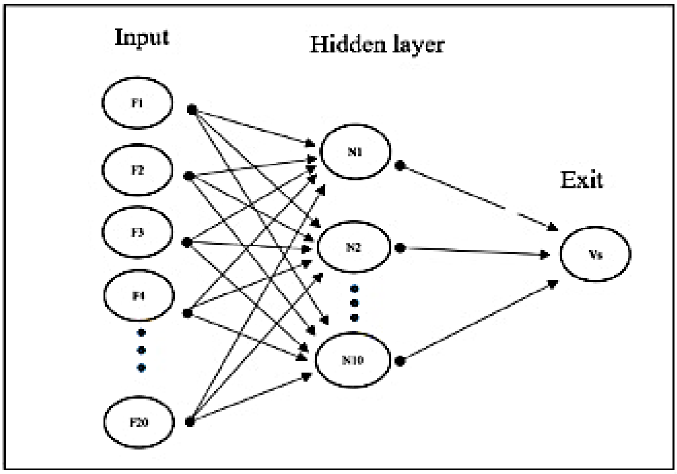

Figure 2. Trained network architecture.

After processing (training) according to the architecture, the statistical values Root Mean Square Error (RMSE), Variance, Residual Square Sum (RSS), and Correlation were used.

With these data, we searched for networks with more significant statistical results using the Excel software. In this search, 29 processes were carried out at Neuro4 for Research Time, and 32 for Experience Time.

Regarding statistical results, correlation was quite high, while RMSE, RSS, and Variance were considerably low. Thus, this study adopted the correlation reference value of 0.989 for training and validation. The networks that met these criteria were selected, totaling 100 networks for each period, to which the Garson algorithm was applied.

For this phase, it is necessary to extract the values of each weight assigned to determine the CSF by using the Garson algorithm. Factor 20 appears primarily in both interpretations, demonstrating that for respondents it was undoubtedly the factor with the greatest impact in civil construction project management. The “Unrealistic inspection and test methods in the contract” (factor 20) was the factor that most appeared in the first 4 positions. For RT and ET, it appeared 50 and 58 times, respectively, in 100 networks as the factor that most influences project management. For RT, this factor appeared 19 times in the second position, 8 times in the third position, and 3 times in the fourth position. For ET, it appeared 16 times in the second position, 10 times in the third position, and 3 times in the fourth position.

Experience time (ET) is directly related to the experience of the project manager, which is a critical factor of great importance to guarantee success. It assesses whether the manager has the necessary skills to face critical situations in the project. Manager experience can affect the perception of the importance of aspects that influence the work environment.

When considering RT, factors 17, 5, and 9 (“Lack of knowledge of quality requirements”, “Rework due to an error in execution”, and “Lack of registration of companies for subcontracts”) appeared 28, 23, and 22 times in the first 4 positions, respectively. Factor 17 appeared 6 times in the first position, 9 times in the second, 4 times in the third, and 9 times in the fourth. Factor 5 appeared 3 times in the first position, 3 times in the second, 6 times in the third, and 11 times in the fourth. Factor 9 appeared 9 times in the first position, 5 times in the second, 3 times in the third, and 5 times in the fourth. The most impacting factors in the 100 selected networks were, in decreasing order: Factor 20, Factor 9, Factor 8, and Factor 17.

Research and Experience times directly influence the respondents’ perceptions. For ET, factors 1 and 3, namely “Increased scope of work” and “Rework due to project change”, appear 39 times in the first 4 positions; and Factor 14, “Simplicity and clarity in project specifications”, appears 34 times in these positions. Factor 1 appeared only 3 times in the first position, 14 times in the second, 9 times in the third, and 13 times in the fourth. Factor 3 appeared 4 times in the first position, 10 times in the second, 17 times in the third, and 8 times in the fourth. Factor 14 did not appear in the first position, but appeared 16 times in the second position, 7 times in the thirs, and 11 times in the fourth. The most impacting factors in the 100 selected networks were, in decreasing order, Factor 20, in the first position; Factor 7, in the second position; and Factors 3, 5, and 15, all in the third position.

In this way, it is clear that both the delimitation of the scope and the clarification of the main objectives strengthen the link between the project participant and his/her commitment. Knowledge of what should be done contributes to motivate or discourage the team and can bring more expressive results in terms of performance.

The critical success factor that most appeared according to the experience time and research time corroborates Kog & Loh (2012). In their study, incentive mechanisms in the contract with suppliers, realistic obligations, motivations, and contractual incentives are among the ten most important critical success factors in civil construction projects.

The results also corroborate Costantino et al. (2015), who developed an ANN-based decision support system to predict project performance for any set of CSF, classifying projects as successful or unsuccessful according to the level of risk; and Waziri et al. (2017), who used artificial neural networks in construction and management engineering. The latter authors demonstrated the possibility of successful applications of ANNs in cost prediction, optimization and scheduling, risk assessment, claims and dispute resolution outcomes, and decision making. The ANNs were applied to problems that are difficult to solve with traditional mathematical and statistical methods. The authors also explored the integration of ANN with other soft computing methods like Genetic Algorithm, Fuzzy Logic, Ant Colony Optimization, Artificial Bee Colony, and Particle Swarm Optimization, which generally indicated better results in comparison to conventional ANNs. The study provides comprehensive repute of ANN in construction engineering and management for application in different areas for improved accuracy and reliable predictions.

When studying Critical Success Factors in projects with the use of ANNs in the macroindustry of energy in Civil Construction, Asgari et al. (2018) determined ten indicators of project success, divided into five categories (financial, interaction processes, labor, contract configurations, and project characteristics). After training the ANN, the model of project success was provided with the factors “Insertion of realistic commitments", "Description of services and purposes specified in the contract", and "Professional competence of project manager client" as those that most affect the success of projects in the energy area.

The arguments used in the present study make it relevant from a socioeconomic point of view since the findings can improve project management in CCI, which is one of the most relevant sectors in the Brazilian GDP. The study is also relevant from the business point of view since studies in project management allow advances in the area; hence, the results can improve management practices especially in the development of Civil Construction projects. Moreover, this study is relevant from a scientific point of view since bibliographic survey showed that there is still no consensus in the literature on CSF in civil construction project management.

The use of ANNs produced subsidies to know the relevance of the input variables adopted. This occurred from the subsequent use of the Garson method, which proved to be an important tool for the classification of nonlinear variables.

Validation was verified by the proximity of the results obtained in the two processes where the Research and Experience Times were considered. Notwithstanding, future research in this line should apply the multidimensional vision of the project to analyze other perceptions of CSF in projects so as to extend the validation of the results obtained here.

5 **Conclusions**

The selection of critical factors already consolidated in the bibliography led to the construction, formulation, and application of the questionnaire, which achieved its objective of providing subsidies for the analysis of the study.

The classification method (Relative Importance Index - RII) provided a valid and consistent matrix for ANN processing. Considering the Experience Time in civil construction and the Research Time in project management, the Resilient Propagation algorithm proved to be effective in the training of ANNs since it provided a matrix of consistent weights for the application of the Garson Algorithm.

In the model with 3000 cycles, 100 networks, and 10 hidden layers with the described CSF, the factor "Unrealistic inspection and test methods in the contract" (Factor 20) is the one that most impacts project management in the civil construction industry.

The results obtained after the training allowed us to conclude that the ANN is an effective tool in the estimation of nonlinear functions.

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