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INFLUENCE OF EXPERIENCE AND RESEARCH TIMES ON THE PERCEPTION OF CSFs AFFECTING PROJECT MANAGEMENT IN THE CIVIL CONSTRUCTION INDUSTRY USING RNA

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Abstract: Efficient project management can ensure success and reduce the impacts of delays and changes that occur during the execution of the project. For this, there are the Critical Success Factors, which are essential for the company to achieve its mission. The objective of this study was to verify the influence of experience and research time on the perception of FCS in project management in the civil construction industry with the use of Artificial Neural Networks. To achieve this objective, data collected by a *survey* which resulted in 191 valid observations. Relative and global indices of importance were calculated. ANN was used to assess the most significant success factors using Neuro4 software with the algorithm: *Resilient Propagation* in the process of obtaining satisfactory RNA. The FCS: Unrealistic inspection and testing methods proposed in the contract were the most critical in project management in both perspectives and in the times considered by each of them, for the projects to achieve success. The ANNs produce subsidies to know the adopted input variables, they are efficient to order and transfer knowledge and they constitute a precise means for modeling non-linear variables.
Keywords: Strategy and Organization, Operations Research, Work Organization, Logistics and Production Management.

INTRODUCTION

In the current competitive environment, companies are required to work with a high degree of efficiency, optimizing existing resources, in order to achieve and maintain a strategic position in the face of pressure from competitors and the market (Delamaro & Rocha, 2006 and Takeuchi; Nonaka, 1986).

The growing competition in the civil construction sector has driven construction companies to seek strategies to establish management practices that make it possible to monitor changes in the environment, adding value to current businesses and innovating in new businesses (Medeiros, 2012). However, several characteristics, such as: difficulty in defining the scope, project interfaces, multidisciplinary teams and interdependencies of activities, make the construction environment challenging for any management methodology (Polito, 2010).

As it is an activity that involves several joint processes, an efficient management system is necessary, enabling control and increased productivity. Computerization, enabling the creation of databases, became one of the main changes that allowed the sector to have greater process management. Souza (2012) characterizes this first view of project management as a bureaucratic issue, serving only for internal support to organizations and without practical benefits. Some changes, such as the implementation of project management in the direct production of companies, provided an increase in the levels of efficiency, quality and values presented to customers. The author also emphasizes that project management has expanded the processes promoting resource gain, followed by the programming of activities that allows control of quantity, deadlines and costs.

According to Matos & Lopes (2013) project management has become an indispensable tool in the development of projects in many business areas, and according to Silva et al. (2014) emerges as an essential factor in determining the success of an organization. It is increasingly used by organizations to achieve their many and diverse goals (Meredith & Mantel, 2009). However, for the objectives to be achieved, it is necessary to distinguish the areas of the company that are essential to success, as well as the alignment of resources to direct the company in the same direction (Seixas, 2014).

This way, the Critical Success Factors (FCS) arise, which as a management tool, identify the set of key areas that are essential for the company to achieve its mission. They help to clarify what is most important and allow the autonomous execution of individual work, framed by the general objectives of the company (Carvalho, 2008; Seixas, 2014).

With regard to project management, it will also be necessary to ensure good results for their FCS, which are identified after obtaining the objectives or purposes of the project, translating into the needs to be satisfied in order to achieve them. (Amaral, 1994; Rockart, 1982). With the identification of the FCS, the more efficient the measures to be taken, avoiding poorly managed projects and enhancing their success. It is thus also possible to identify problems in current projects and trigger corrective measures in relation to them (Saqib, Farooqui, & Lodi, 2008).

The need to remain competitive generated the search for increased effectiveness and, therefore, was reflected in the area of project management as a motivator to seek, the incorporation of new capabilities that allow greater assertiveness to the person responsible for managing the project. Widespread statistical methods, such as multivariate linear regression (MLR), have shown limitations in describing the correlation between input and output data of nonlinear behavior (Foucquier et. al., 2013; Jimenez et. al., 2013; Kalogirou). , 2001; Melo, 2012). The approach of problems through Artificial Neural Networks is particularly suitable for very complex applications.

The use of RNA in the determination of FCS in project management in civil construction is still a little explored area due to the lack of an approach for the certification of such systems. Chua et. al. (1999) used ANN as an analysis method, where eight critical factors for the performance of the budget were identified, namely: the number of organizational levels of the project, amount of the detailed project completed at the beginning of construction, number of control meetings during the time, number of budget updates, implementation of buildability programs, team turnover, amount of money spent on project control, and technical experience of the project manager. The final model can be used as a predictive tool to predict the budget performance of a construction project.

Elwakil *et. al.* (2009) in their studies on modeling critical success factors using ANN at the project level 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 the ANNs to determine the most important critical success factors in evaluating the performance of organizations in the construction industry. They determined two performance prediction models that were developed with regression analysis and ANN, which show robust results when verified and tested. The analysis showed that the models developed are sensitive to the critical success factors identified.

In studies of modeling effectiveness in project management in construction using ANN, Apanaviciene and Juodis (2003) identified twelve key construction management factors (in areas related to the project manager, project team, project planning, organization and control). The model allows construction project managers to focus on FCS thereby reducing construction risk.

Constantine et. al. (2015) developed, through ANN, a decision support system to predict project performance for any set of FCS, classifying it in relation to the level of risk as successful and unsuccessful projects.

In addition, the use of Artificial Neural Networks to create a model to identify the FCS that affect the management of projects in the civil construction industry, determines the differential of this study because it was observed in the literature the lack of studies that investigated potentialities for the use of this method to model an extremely dynamic phenomenon such as FCS.

The hypothesis is that the time in years of experience or research in project management directly affects the responses of respondents in relation to which critical success factors influence project management in the construction industry.

In view of the above, this work aims to verify the influence of experience time and research time of respondents on the perception of FSC that affect project management in the construction industry with the use of Artificial Neural Networks, from the perspective of the academic universe. used for this the identification and analysis of the most relevant FCS in project management.

METHODOLOGY

According to Creswell (2003) the three elements of investigation (i.e. methods, strategies and alternatives of knowledge claims) combine to form different approaches to research, which are converted into processes in the research project, with the determination of the steps in designing a research proposal, and carrying out the assessment of knowledge claims, in order to consider the investigation strategy and then identify specific methods (Figure 2).

Initially, a systematic review was carried out on the identification of FCS with emphasis on project management in the construction industry, according to the methodology presented by Yi *and* Chan (2013) e Freitag (2015). It was made from qualitative data in the scientific bases Scopus and SciELO, and the use of both indicators prevents the evaluation of publications from being restricted to a single metric.

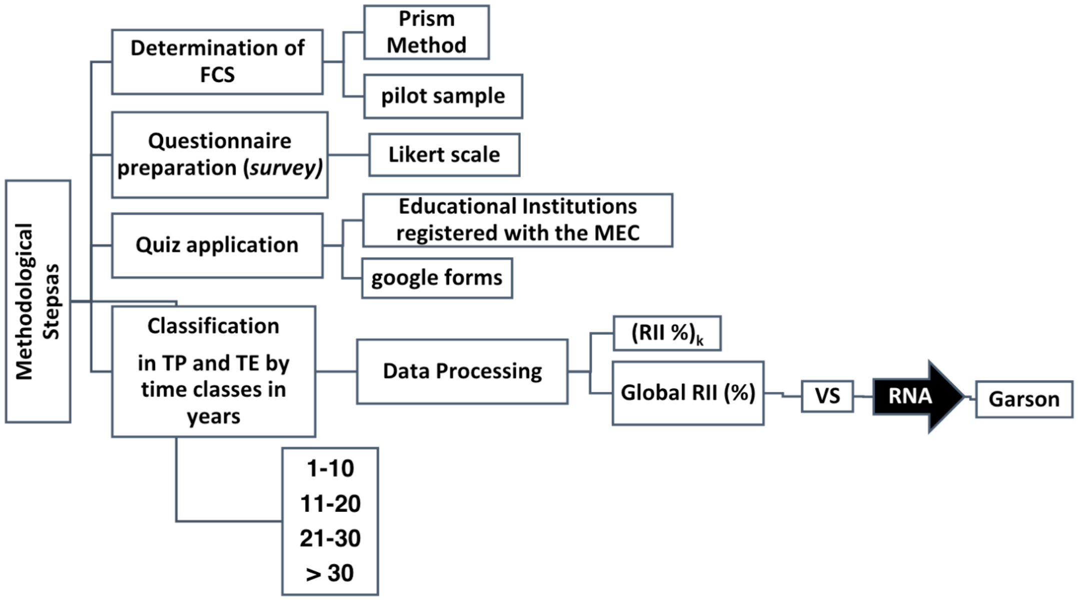


Figure 2: Research Methodological Steps

In addition, both indicators are able to act in a really complementary way, in addition to being public metrics and with their published calculation methodologies. All works were listed with reference to project management in civil construction, critical success factors (FCS) and artificial neural networks (ANN) applied in civil construction until the year 2018.

The documents were analyzed using the PRISMA method (Key Items for Reporting Systematic Reviews and Meta-analyses in English). "*Preferred Reporting Items for Systematic Reviews and Meta-Analyses*"), where this analysis is composed of four distinct parts: Identification, Selection, Eligibility and Inclusion. This phase of using the Prisma method consists of a *checklist* with 27 items with the objective of helping to improve the reporting of systematic reviews and meta-analyses, with the reading of abstracts and elimination of incomplete or non-adherent records, where only documents that, after content analysis, are considered of relevant contribution will remain to the proposed work.

With this base, a pilot questionnaire was prepared with a set of 120 selected FCS and sent to professionals and researchers of the undergraduate and graduate courses of Civil Engineering registered at MEC in a total of 90 emails (about 10% of the total population), randomly selected, where after the return of 43 respondents (47.7% of the total), the 20 most impacting factors in project management were determined, where another questionnaire was prepared as a research instrument (*survey*) for data collection , to assess and validate the effect of each factor.

This questionnaire is composed of two parts, where the first part (I) refers to the time of experience in the civil construction area and their time in research related to project management in the civil construction industry of the respondents. In the second part of the questionnaire, respondents are invited to assess a series of factors that impact project management in the construction industry. To evaluate these practices, the use based on the Likert scale (Likert, 1932) of 5 points was chosen, because it is a perception where the opinion based on their experience is required, the possible answers are: Very Low impact; Low impact; Medium impact; High impact; Very high impact.

The search for respondents was carried out in all undergraduate and graduate courses in Civil Engineering at the Teaching Institutions registered with the Ministry of Education (MEC). The characterization of the sample is based on the randomness and heterogeneity of the return of the questionnaires, since the sending reached the entire population described, and as the data collection was carried out exclusively by electronic means (*google forms*) with a link sent by e-mail. email and/or cell phone using the WhatsApp application, to fill out a virtual form, between May and June 2018, there is no possibility of interference by the author in this return, characterized by the impartiality and randomness of the sample collected.

To classify the perception of FCS in years by time of experience and research time, respondents were separated according to their performance and then the amplitude was determined and the number of classes by Strugers was calculated and their respective intervals were obtained through the formulation de Struges, cited by Hoaglin et al. (1983). Each distribution was adjusted for the period of four observations (ages), distinguishing the different classes of time of experience in years.

To analyze the data, the Relative Importance Index (RII) was used. This index is calculated for each specific factor for each year of experience of the participants, using Equation 1 (Lim and Alum, 1995; and El-Gohary and Aziz, 2013):

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

Equation 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 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 global Relative Importance Index (RII (%) for each factor of all respondents, considering all years of experience of respondents together, which is calculated as a weighted average of (RII%)_k obtained from equation 2.

$$GRII(\%) = \frac{\sum_{k=1}^{k=K}(k \times RII_k)}{\sum_{k=1}^{k=K} k} \quad \text{Equation 2}$$

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

ANN was used to determine FCS weights, in all training layers, using Neuro4 software version 4.0.2. For insertion, an output value is required for these variables, for this reason the Weighted Average was chosen according to Equation 3:

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

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

The training algorithms used were *resilient propagation*, a learning rate of 0.01 was used, as well as a momentum parameter of 0.005, with 500 networks processed, with 10 hidden layers with 4000 cycles in each network, totaling 2,000,000 of cycles. One (1) weight was generated for each factor in each of the layers, generating a total of 200 weights per network, totaling 100,000 weights.

The validation sample allows an estimate of how the artificial neural network will behave in a real environment, as it uses an unused dataset in training and testing the model. In this sense, in this research, a minimum accuracy of 70% of the data (134 respondents) was randomly required for training and 30% (57 respondents) were allocated. In machine learning, statistics and feature selection, Garson's algorithm was used. It 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 occur in the output variable when there is a change in the input variables. (Valencia, 2007).

Initially, the desired inputs and outputs are provided to the network. The inputs are propagated through the layers of the network and the respective outputs are generated. These outputs are compared with the desired outputs and the errors between them are calculated. If the error value obtained is not in accordance with the objective, the values of the weights of the network are changed in order to reduce this value. For this, the chain rule is used to back propagate the error value, starting from the output layer until reaching the input layer, allowing the updating of the weights according to the error obtained. After updating the weights, a new iteration begins, propagating the entries through the network and calculating the error again.

The choice of the best configuration and the ANN training process was carried out by evaluating the mean square error and the standard deviation of the mean square errors of each simulation, with the simplest and most consistent configurations being chosen. As a stopping criterion for the training algorithms, the following were used: the total number of cycles (4000) and the mean square error of less than 1%. Therefore, training was terminated when one of the criteria was met. The ANN estimates and were evaluated based on the correlation coefficients with the observed values and the square root of the mean error (RQME) (Equation 4), as well as on the graphic analysis of residuals (percentage errors) and histogram of percentage errors.

$$RQME\ (\%) = 100\sqrt{\frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2}{n}} / \bar{Y} \quad \text{Equation 4}$$

Where: Y = Output Value, $\hat{Y}$ = *estimated output*, $\bar{Y}$ = *average of the observed output*, n = number of data.

RESULTS AND DISCUSSIONS

To determine which FCS would be used in the questionnaire, a literature search was carried out in the last 5 years for several keywords used alone and together (Chart 1). To select the articles to be used, the Freitag methodology (2015) was followed, which checks the qualitative data through the analysis of documents using the PRISMA method (Main Items to Report Systematic Reviews and Meta-analyses in English). "*Preferred Reporting Items for Systematic Reviews and Meta-Analyses*"), where this analysis is composed of four distinct parts: Identification, Selection, Eligibility and Inclusion. This phase of using the Prisma method consists of a checklist with 27 items with the objective of helping to improve the reporting of systematic reviews, with the reading of abstracts and elimination of incomplete or non-adherent records, where only documents remained that, after analysis of content, were considered of relevant contribution to the proposed work.

In the pilot questionnaire stage, respondents were asked to select the 20 most relevant FCS according to their perception. After analyzing the responses to the pilot questionnaire, the 20 most relevant CSFs (Chart 2) that were used to prepare the final questionnaire were listed.

874 e-mails were sent to all educational institutions registered in the e-mec system available on the MEC website, resulting in a total of 191 answered questionnaires, not having an exact number of people affected because the vast majority of these do not list the professors by area of activity in their courses.

The sample size for the intended objective 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 they say that the most acceptable number is a ratio of ten to one and by Malhotra (2001), who recommends that the sample size have at least four to five times more observations than the number of variables.

Another important analysis to determine the adequacy of the sample is the statistical significance. Factor loadings greater than 0.30 are significant only for sample sizes greater than 350; for a sample of 100 respondents, the factor loading must be at least 0.55 to have an adequate degree of significance; for 50 respondents, the factor loading must be at least 0.75 (Hair et al., 1998).

Considering the 191 questionnaires obtained and the 20 FCS included in the field research, a questionnaire/variable ratio of 9.55 is obtained, which is greater than the upper limit suggested by Malhotra (2001) and meets Hair et al. . (1998), this is further reinforced by Guadagnoli and Velicer (1988) apud Laros (2012), who, in challenging Gorsuch's criterion, argued that no theoretical or empirical basis exists for recommendations on the relationship between the number of participants and the number of participants. of variables.

In the descriptive statistics, considering the time in years of experience and the research time in the area of project management of the respondents, high variability is observed, proving the heterogeneity of the data. With the values obtained from the asymmetry and kurtosis coefficients, the two times evaluated have a positive asymmetric distribution, that is, where the highest frequency of age is on the left side of the distribution, that is, the respondents have experience and research time shorter than the average time observed. With the kurtosis values, we observed that for TE the kurtosis is platykurtic, that is, it has a flatter curve at the top in relation to the normal curve and for TP it is leptokurtic, it has a more tapered distribution function curve with a higher peak than the normal curve. than the normal distribution.

Exploratory analysis was performed (Table 1), verifying data normality, with a significant Kolmogorov-Smirnov test at the level of 0.01. The analysis of asymmetry and kurtosis confirmed these data, but showed that the variables presented, in general, values close to normality, with asymmetry presenting values between -0.66 and 0.107, with variable 17 presenting a value of 0.107. Kurtosis, on the other hand, presented values that varied between values between -1.479 and -0.097, with variable 4 presenting a value of -1.479. For asymmetry with the exception of the FCS. The analysis of Pearson correlations for the observed data indicated that the 20 FCS presented statistical significance.

The relative importance indexes were determined according to the perceptions

Research Phrases	Quantity of documents
Project Management	37.882
Critical Factors AND Project Management	997
Critical Factors AND Artificial Neural Networks	200
Project Management AND Artificial Neural Networks	125
Project Management AND Critical Factors AND Artificial Neural Networks	4
Success in construction	1913
Success in construction AND productivity	62
Critical factors for success in construction	157
Critical factors for productivity AND profitability in construction	3
Critical factors for reducing waste in buildings	4
Critical factors for efficiency in construction	84
Efficiency AND productivity in construction	232
Efficiency in the construction of large buildings	282
Achieving better profitability in construction	1
Management AND Critical Success Factors	58
Management AND Artificial Neural Networks	165
Construction AND Critical Success Factors	142
Construction AND Artificial Neural Networks	465
Construction AND Productivity AND Artificial Neural Networks	9
Construction AND Productivity AND Critical Success Factors	13
Effectiveness AND Critical Success Factors	199
Effectiveness AND Construction AND Critical Success Factors	17
Effectiveness AND Building AND Artificial Neural Networks	36
Effectiveness AND Building AND Critical Success Factors	12
Effectiveness AND Artificial Neural Networks	1512

Chart 1: Keywords used in the search to determine the FCS

Cód.	Impact Factors
F1	Increase in the scope of work
F2	Ambiguity in specifications and/or conflicting interpretation
F3	Rework due to design change
F4	Unrealistic schedule imposed in contract
F5	Rework due to a runtime error
F6	Inaccurate specification of site condition
F7	Difficulty accessing information, materials and equipment in the project office
F8	Poor coordination between stakeholders (Stakeholders)
F9	Lack of registration of companies for subcontracts

F10	Engineer or architect reluctance to change
F11	Conflict between owners and other parties
F12	Obtaining authorization from local authorities
F13	Changes in government regulations and laws
F14	Simplicity and Clarity in specifications between projects
F15	Poor coordination between project parties
F16	Lack of feedback on project information
F17	Lack of knowledge of quality requirements
F18	Clear definition of project scope
F19	Lack of experience of the project team
F20	Unrealistic inspection and test methods proposed in the contract

Chart 2: List of Critical Success Factors selected for research.

FCS	Average	Standard Error	Median	Mode	D P	Kurtosis	Asymmetry	Minimum	Maximum	K-S
1	4.28	0.0571	4	5	0.7890	-0.672	-0.666	2	5	0,088
2	4.12	0.0583	4	5	0.8061	-1.239	-0.273	2	5	0,088
3	4.30	0.0531	4	5	0.7341	-0.970	-0.546	3	5	0,088
4	4.46	0.0376	4	4	0.5200	-1.479	-0.047	3	5	0,088
5	4.29	0.0524	4	5	0.7240	-0.953	-0.510	3	5	0,088
6	3.90	0.0606	4	3	0.8370	-1.230	0.026	2	5	0,088
7	3.61	0.0784	4	4	1.0842	-0.579	-0.406	1	5	0,088
8	4.20	0.0578	4	5	0.7981	-1.329	-0.384	3	5	0,088
9	3.21	0.0839	3	3	1.1599	-0.756	-0.110	1	5	0,088
10	3.93	0.0608	4	4	0.8402	-1.234	-0.031	2	5	0,088
11	4.20	0.0578	4	5	0.7981	-1.329	-0.384	3	5	0,088
12	3.91	0.0626	4	4	0.8654	-1.079	-0.111	2	5	0,088
13	3.52	0.0771	4	3	1.0653	-0.809	-0.167	1	5	0,088
14	4.02	0.0625	4	5	0.8642	-0.934	-0.337	2	5	0,088
15	4.23	0.0534	4	4	0.7374	-0.759	-0.463	2	5	0,088
16	4.04	0.0593	4	4	0.8197	-1.194	-0.193	2	5	0,088
17	3.88	0.0590	4	3	0.8151	-1.235	0.107	2	5	0,088
18	4.25	0.0539	4	5	0.7449	-1.087	-0.433	3	5	0,088
19	4.20	0.0573	4	5	0.7915	-0.603	-0.574	2	5	0,088
20	3.88	0.0683	4	4	0.9444	-0.097	-0.525	1	5	0,088

Table 1: Descriptive statistics considering time of experience in civil construction and research time in project management in years.

about how much the FCS has an impact on project management and considering the research times and experience times in years (Table 2) of each of the respondents to rank the importance of each FCS thus providing the initial weight of each factor.

It can be seen that FCS 4, 3, 5, 16 and 1 had a high global impact index considering both research time and experience time by classes of respondents,

A similar result to this study was found by Saqib et. al., (2008) that with the application of a questionnaire to the public in common and to the professionals involved in the Civil Construction industry. They considered effectiveness in decision making, planning effort and previous experience in project management as FCS in project management.

Paschoal (2014) when evaluating FCS in the influence on the performance of Civil Construction projects, determined four dimensions of success (efficiency, operational learning, customer satisfaction and preparation for the future) and their FCS that affect project management. Since the project manager's competence factor appears in the first three dimensions, the project manager's experience factor only does not appear in the customer satisfaction dimension and conflicts between team members appears in the learning and preparation for the future dimension.

Jordão *et. al.* (2015) in determining critical factors in project management in civil construction using the methodology of questionnaires applied to managers and employees involved in project activities, they determined that, in general, the items considered most critical by the team were those related to planning and managerial support , such as definition of objectives, customer involvement, definition of planning, ability to follow the plan, communication between members, acquisition of materials, work *feedback*, managerial support, risk management and expense management.

Leite (2018) when evaluating FCS in civil construction projects using the methodology of systematic literature review and its subsequent validation with the application of a semi-structured questionnaire, composed of closed and open questions, Portuguese project managers found with regard to the project management category, the three CSFs considered most relevant are project monitoring and feedback, project risk management and project change management. Being factors that corroborate with this study.

It is observed that the adequacy to planning and specifications is considered another FCS which depends not only on the conduct of the project manager responsible for his contract, but also on the team and people involved with the project. When adapting a project, the manager is aligning the schedule of the execution stages. According to Toor et al. (2009) the planning and control of projects reaches a series of other aspects such as objective definition, contractual risk of contracts. Large-scale construction needs a very careful plan and design.

With the definition of the output values (Vs), for the Research and Experience Times, the matrix to be inserted in Neuro4 was made according to tables 3 and 4 for the respective training.

With these data inserted in Neuro 4 , the FCS variables were characterized as quantitative and the variable V_s as an output variable and after the configuration adjusted with 10 neurons in the hidden layer, the processing (training) of Neuro4 was performed, where 500 networks were trained with *Resilient Propagation* algorithm with stopping criteria after an average error of 0.0001 and 4000 cycles with 20 of convergence, with a value above 0.96 as a correlation for both training and validation.

TE (years)								TP (years)							
1 a 10		11 a 20		21 a 30		>30		1 a 10		11 a 20		21 a 30		>30	
FCS	GRII%	FCS	GRII%	FCS	GRII%	FCS	GRII%	FCS	GRII%	FCS	GRII%	FCS	GRII%	FCS	GRII%
4	0.90	3	0.88	4	0.91	5	0.92	4	0.90	4	0.90	16	0.96	1	0.97
1	0.87	4	0.87	8	0.89	1	0.92	5	0.86	3	0.86	3	0.96	11	0.95
5	0.86	1	0.85	16	0.88	19	0.91	2	0.85	1	0.86	8	0.95	16	0.95
11	0.85	5	0.84	19	0.87	18	0.91	15	0.85	11	0.85	14	0.89	3	0.93
3	0.85	19	0.84	3	0.87	11	0.91	1	0.85	5	0.85	15	0.89	18	0.91
18	0.84	18	0.84	14	0.85	16	0.88	18	0.84	8	0.85	4	0.88	5	0.88
15	0.84	15	0.83	5	0.83	8	0.87	3	0.84	2	0.84	6	0.87	19	0.88
8	0.83	11	0.83	15	0.83	15	0.86	11	0.82	15	0.83	18	0.86	8	0.86
2	0.81	8	0.83	20	0.83	7	0.85	8	0.82	16	0.81	10	0.85	15	0.82
19	0.80	2	0.82	11	0.82	4	0.84	19	0.82	18	0.81	19	0.84	4	0.82
17	0.80	16	0.81	18	0.82	10	0.83	6.06	0.80	19	0.80	2	0.84	7	0.82
7	0.80	17	0.79	2	0.81	3	0.82	16	0.80	10	0.79	1	0.82	20	0.80
12	0.78	14	0.79	6	0.79	20	0.77	12	0.80	12	0.79	5	0.81	10	0.79
16	0.78	10	0.78	10	0.78	6	0.73	14	0.80	17	0.77	20	0.81	14	0.77
10	0.77	12	0.77	1	0.76	17	0.72	10	0.79	6	0.74	13	0.79	6	0.75
6	0.77	20	0.75	12	0.75	14	0.72	17	0.79	14	0.74	11	0.78	17	0.73
20	0.77	6	0.74	13	0.73	2	0.69	20	0.75	20	0.72	7	0.74	12	0.71
14	0.76	13	0.68	9	0.71	13	0.65	7	0.68	7	0.71	12	0.71	2	0.71
13	0.71	7	0.67	17	0.70	12	0.64	13	0.67	13	0.68	17	0.65	9	0.64
9	0.62	9	0.65	7	0.69	9	0.63	9	0.63	9	0.59	9	0.51	13	0.60

Table 2: Classification of FCS according to TE and TP in years in relation to the global importance index

Resp	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	Vs
1	4	4	5	4	5	5	4	4	2	5	4	5	3	5	4	4	5	4	4	5	4,09
2	5	3	4	4	5	4	5	4	5	4	5	3	3	4	4	5	4	5	5	4	4,30
.																					
.																					
190	4	5	3	4	5	4	2	5	4	3	4	3	4	5	5	4	5	3	5	3	4,35
191	5	5	5	5	5	2	2	4	4	5	5	5	1	3	4	4	3	3	4	3	4,14

Table 3: Matrix of responses for the use of the Artificial Neural Network considering TP

Resp	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	Vs
1	4	4	5	4	5	5	4	4	2	5	4	5	3	5	4	4	5	4	4	5	4,27
2	5	3	4	4	5	4	5	4	5	4	5	3	3	4	4	5	4	5	5	4	4,26
.																					
.																					
190	4	5	3	4	5	4	2	5	4	3	4	3	4	5	5	4	5	3	5	3	4,02
191	5	5	5	5	5	2	2	4	4	5	5	5	1	3	4	4	3	3	4	3	3,89

Table 4: Matrix of responses for the use of the Artificial Neural Network considering ET

For the processing of the data, some tests of the configuration in the structure of the software were necessary, the selected algorithm was the *Resilient Propagation* for being characterized in one of the algorithms that best adapt in the determination of independent and non-linear variables, the configuration of the training structure was necessary. In this selection, the statistical results such as the correlation was quite high while the values of RQME, SQR and Variance were considerably low, so the reference value of correlation of 0.995 for training and 0.989 for validation was adopted in this work.

After selecting the networks that presented the established statistical values, it was necessary to visualize the weights assigned by Neuro 4 in all 10 hidden layers of neurons. considering only the networks that presented, simultaneously, a correlation at least equal to this selection criterion, in which Garson was applied. After classifying the factors in descending order, in each processing, we found that Factor Number in years of operation in the 100 networks as the factor that most impacts project management in the civil construction industry (Table 4).

In the division into time classes in years of experience and research in project management in the construction industry (Tables 5 and 6) it can be observed that in both cases and for all time classes, FCS number 20 is the most affect project management.

The evaluation of the distribution of residuals is important so that the estimation process maintains the same distribution of the observed data, thus avoiding distortions and alterations in the behavior of the original variable. Graphical analysis was performed for FCS 20, which was the most impactful, showing that the selected networks presented unbiased and bias-free results, which indicates that the assumption of constant variance is correct, or the homoscedasticity condition was met. ANNs 238, 45, 462 and 335 were selected for different periods of experience in years and ANNs 12, 388, 18 and 348 were selected for different research periods (Figure 1).

The normality of the SV data was tested for experience time and research time and comparing with the Shapiro-Wilk probability table, the calculated value (0.940) is between probabilities 0.10 and 0.50, therefore, the hypothesis of normality of errors, at the level of 5% of significance, is not rejected.

Person's correlation (r = 0.992) between experience time and research time indicates that it has a strong positive correlation, that is, the values tend to increase according to the time in years of working in the areas.

It can be seen in Table 8 that in classes 21-30 and ≥ 30, where the number of respondents is smaller, the RQME% values are greater than 5%. And that at ages 1-10 and 11-20, where the number of respondents is much higher, the highest RQME% value is around 1 to 10% for ANN, showing that the FCS estimated by the ANN are very close to the FCS real values obtained in the answers to the questionnaires. This table also illustrates the lowest and highest coefficients of linear correlation between FCS 20 responses and its VS. Practically, all these coefficients are in the range of 0.64 to 0.99 indicating a positive linear correlation.

These results obtained here corroborate those found by Constantino et al (2015) who developed, through ANN, a decision support system to predict project performance for any set of FCS, classifying it in relation to risk level as projects successful and unsuccessful and also by Waziri et al. (2017) on the use of ANNs in Construction Engineering and Management, who concluded the possibility of finding successful applications of ANNs in cost prediction, optimization and scheduling, risk assessment, claims resolution results and making. The integration of ANN

TE		TP	
FCS	Weights	FCS	Weights
20	67,24	20	55,79
7	6,66	6	9,05
18	3,94	4	4,73
1	3,28	14	4,30
14	2,96	17	3,93
10	2,22	2	2,63
3	2,09	8	2,50
4	2,03	10	2,31
5	1,76	3	1,77
16	1,75	9	1,73
8	1,21	12	1,62
9	1,03	16	1,36
2	1,03	19	1,32
15	0,95	1	1,26
19	0,61	11	1,21
13	0,57	15	1,20
17	0,23	18	1,02
6	0,21	13	0,96
12	0,20	7	0,87
11	0,03	5	0,44

Table 4: Determination of weights considering Experience time and research time in project management in the civil construction industry.

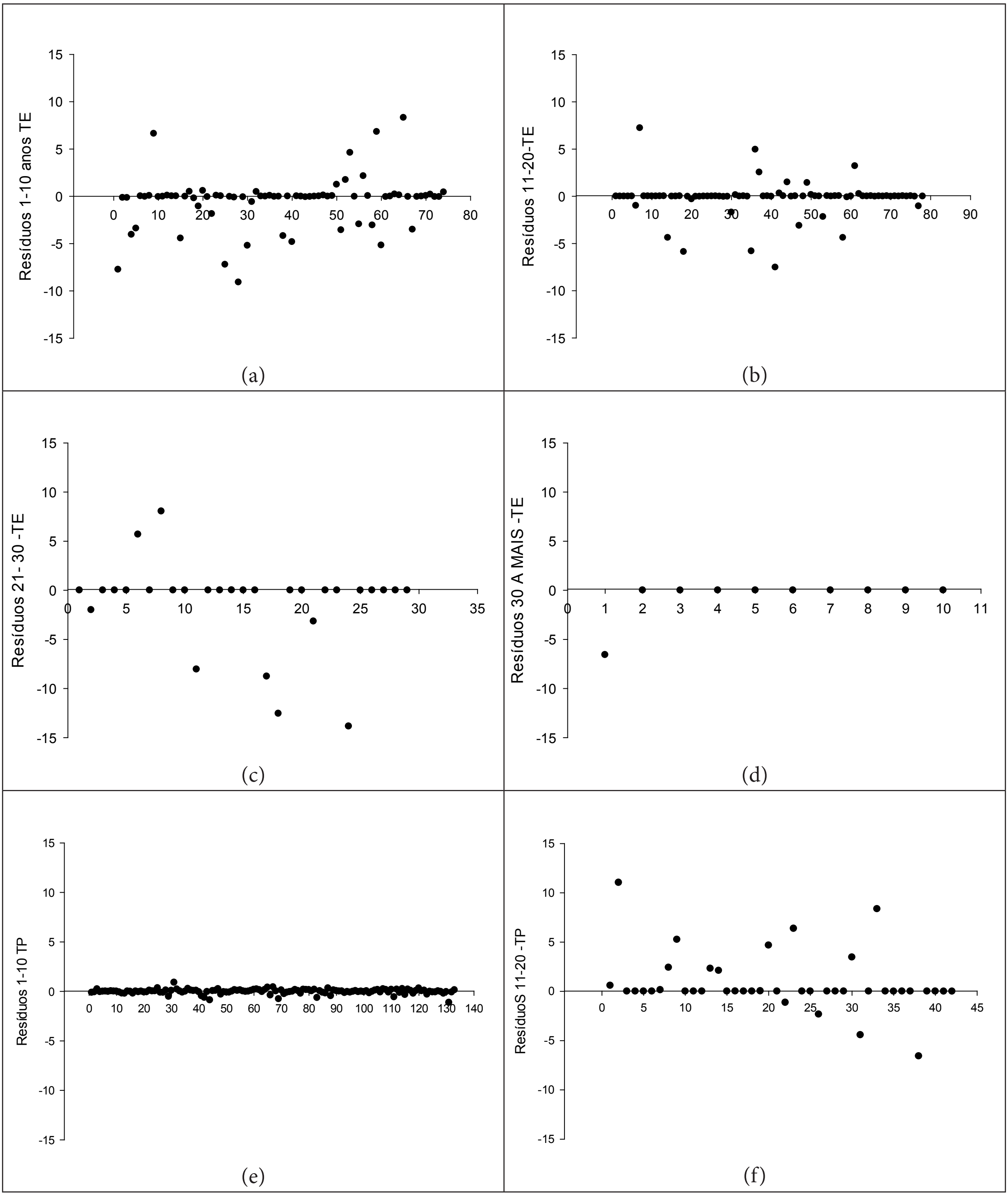
Time of experience							
1- 10 years		11 - 20 years		21 - 30 years		>30	
FCS	Average weight	FCS	Average weight	FCS	Average weight	FCS	Average weight
20	56.517	20	46.053	20	58.643	20	92.327
16	8.790	15	10.110	8	14.208	7	6.910
18	4.270	6	8.486	1	5.293	3	0.707
7	4.152	9	4.735	11	4.041	6	0.022
10	3.616	18	4.509	6	3.972	8	0.011
5	3.238	14	4.018	14	2.742	15	0.010
4	2.885	11	3.528	12	1.823	16	0.004
3	2.483	8	2.836	13	1.429	9	0.002
9	2.042	2	2.743	16	1.161	5	0.001
8	1.967	1	2.135	3	1.046	10	0.001

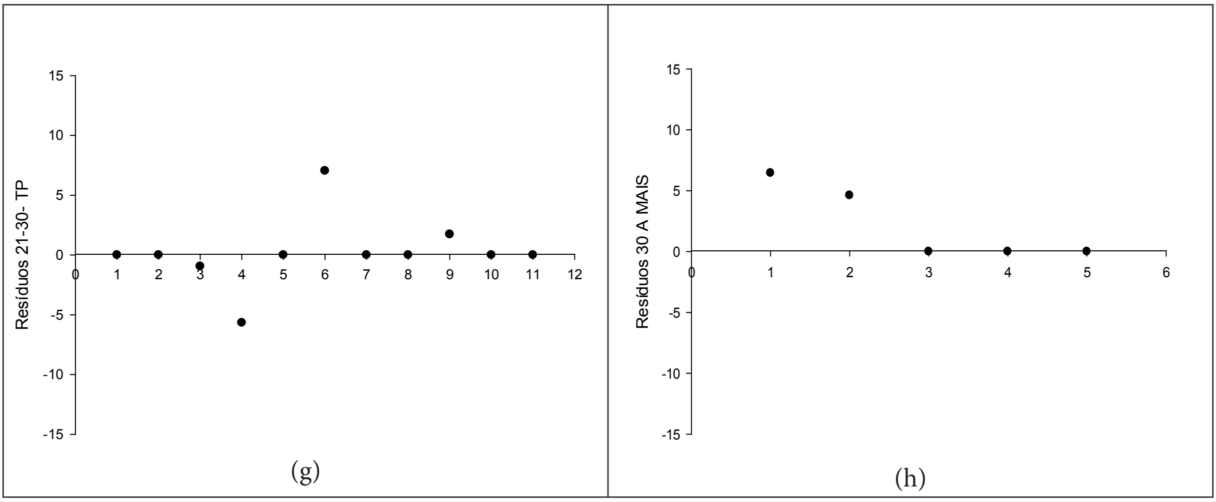
1	1.840	3	1.677	9	0.999	19	0.001
12	1.330	16	1.511	15	0.800	12	0.001
17	1.165	7	1.368	10	0.752	2	0.001
11	1.081	19	1.320	4	0.721	1	0.001
14	1.008	17	1.260	7	0.719	4	0.001
15	1.000	5	1.146	17	0.605	18	0.000
6	0.932	13	0.804	5	0.580	17	0.000
19	0.769	10	0.657	2	0.299	14	0.000
2	0.765	4	0.559	18	0.091	13	0.000
13	0.149	12	0.546	19	0.073	11	0.000

Table 5: Determination of average weights considering time of experience by time classes in years in project management in the civil construction industry.

Time of searching							
1- 10 years		11 - 20 years		21 - 30 years		>30	
FCS	Average weight	FCS	Average weight	FCS	Average weight	FCS	Average weight
20	72.123	20	39.897	20	53.779	20	47.973
8	10.139	15	11.730	1	7.740	7	22.561
3	4.756	17	8.130	7	6.846	9	20.610
10	2.797	9	7.055	6	6.722	18	1.176
7	2.590	8	4.899	13	3.946	14	0.941
12	2.539	19	4.229	11	2.680	17	0.832
6	1.693	14	4.086	12	2.568	1	0.722
9	1.366	7	3.043	17	2.435	5	0.719
17	0.527	18	2.674	14	2.343	4	0.682
1	0.402	6	2.344	4	2.203	8	0.625
11	0.358	3	2.336	16	1.972	12	0.612
4	0.299	16	2.290	10	1.478	16	0.475
15	0.107	2	1.623	2	1.185	19	0.470
18	0.097	11	1.334	3	0.978	10	0.433
14	0.082	5	0.969	9	0.734	3	0.421
2	0.051	12	0.936	19	0.536	6	0.261
5	0.040	10	0.768	5	0.532	15	0.205
16	0.014	13	0.648	15	0.519	2	0.158
13	0.013	4	0.578	8	0.406	13	0.104
19	0.010	1	0.432	18	0.397	11	0.019

Table 6: Determination of average weights considering research time by time classes in years in project management in the construction industry


Resíduos 1-10 anos TE
(a)
Resíduos 11-20-TE
(b)
Resíduos 21- 30 -TE
(c)
Resíduos 30 A MAIS -TE
(d)
Resíduos 1-10 TP
(e)
ResíduoS 11-20 -TP
(f)



(g) (h)

Resíduos = Residues

Figure 1: Graphical analysis of residuals for FCS 20 according to selected networks by time of experience (a, b, c and d) and by time of research (e, f, g and h) in years

Age Years	Number	Estimated time of research Observed	Average	Number	Estimated time of experience Observed	Average
1-10	133	4,00[a]	4,046[a]	74	4,00[a]	4,080[a]
11-20	42	4,00[a]	4,053[a]	78	4,00[a]	4,080[a]
21-30	11	4,00[a]	4,070[a]	29	4,00[a]	4,093[a]
>30	5	4,00[a]	4,087[a]	10	4,00[a]	4,097[a]

Note: Averages followed by the same letter do not differ from each other in the lines by Tukey's test (P < 0.05).

Table 7: Effect of research time and experience time in years in relation to FCS 20

Age Years	RQME% Time of experience					RQME% Time of reserach				
	N	Min.	Max.	DP	r	N	Min.	Max.	DP	r
1-10	74	0,38	8,57	1,93	0,88	133	0,09	7,52	1,60	0,99
11-20	78	0,16	9,72	2,12	0,92	42	0,80	9,21	2,38	0,79
21-30	29	1,31	10,29	2,68	0,65	11	1,21	15,24	5,02	0,73
>30	10	2,39	19,36	5,25	0,89	5	21,33	22,44	0,43	0,64

Table 8: Prediction errors by age class in years and Standard deviation

with other soft computing methods such as Genetic Algorithm, Fuzzy Logic, Ant Colony Optimization, Artificial Bee Colony and Particle Swarm Optimization were also explored, which generally indicates better results when compared to conventional ANNs. The study provides a comprehensive reputation for ANN in construction engineering and management for application in different areas for better accuracy and reliable predictions.

Asgari et. al. (2018) when studying the CSFs that affect projects with the use of ANN in the macro energy industry of civil construction, determined ten indicators of project success divided into five categories (financial, interaction processes, labor, contract settings and design feature). After training the ANN, the project success model was provided having the factors "Entry realistic commitments", "description of services", purposes specified in the contract" and "Professional competence of the project manager" as the ones that most affect the project. success of projects in the energy area.

This way, it is clear that the delimitation of both the content of the scope and clarification of the main objectives ends up strengthening the bond of the project participant with their commitment. The knowledge of what must be done helps to motivate or demotivate the team and can bring more expressive results in terms of performance. The results obtained show that the presence of factors such as unrealistic inspection and test methods proposed in the contract, increased scope of work and lack of knowledge of quality requirements significantly contribute to explaining project performance.

FINAL CONSIDERATIONS

Considering that the proposed objective was to identify the critical factors for success in project management in the construction industry by the perception of academic managers considering time in years of experience and research in the area, it was observed that from 1 to 30 years or but the perception is the same.

It was also found that the respondents agree that the FCS Unrealistic Inspection and test methods proposed in the contract provide an improvement in project management in the civil construction industry, contributing positively, where the hypothesis was not confirmed because it is perceived that there was no divergences considering the Experience and Research Times in project management in the civil construction industry.

With the proximity of the results obtained in the two processes where the Research and Experience Times were considered, we realized that the validation is verified, however future works in this line must apply the multidimensional vision of the project to analyze other perceptions of FCS in projects, in order to extend this validation of the results obtained here. The analysis undertaken here provides a basis for a more conscious and detailed definition of strategies to succeed in project management in the construction industry.

The use of a methodology based on statistical treatment is fundamental for the validation of results and identification of the factors that effectively have weight in the decision-making process of the main players in a segment.

The scope of the study does not allow the generalization of results, however this study contributes to greater effectiveness of planning experiences in project management, and can be used as a reference in processes of implementation and evaluation of strategic planning in the construction industry.

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