Castillo, T., Jaramillo, K., Andrade, A., Zarate, A. (2024). Distribution of communication links in work teams of construction design offices. In Herrera, RF, Salazar, LA, (Editors), Proceedings of the IX Ibero-American Congress of Construction Management and Technology (IX ELAGEC2024).

DISTRIBUTION OF COMMUNICATION LINKS IN WORK TEAMS OF CONSTRUCTION DESIGN OFFICES

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SUMMARY

Social network analysis (SNA) has been used to characterize the organizations of work teams in project design. The statistics of the links constitutes a rich tool to unveil patterns of communication that are the main input in creative activities as project design. Studies have explored the communications within the social networks that are formed for the development of construction projects, one of their limitations is that they are a snapshot at a specific moment of network. Also, other researchers have proposed patterns of links distributions and models of ideal communications needed for the development of project`s design based on local data. There is a need to know whether these distributions are repeated in the design offices of other countries, assuming that the design process of construction projects is standardized and very similar regardless of the country. The purpose of this research is to identify communication patterns in the work teams of design offices in diverse countries and using social network statistics to obtain a mathematical model based on the probability distribution. The results show that there are common patterns of link distribution inside the design teams and a Poisson distribution function better describes such relations. The probability of 2 to 5 links occurring between its members was confirmed as a promising metric suitable for differentiating the small networks from design teams That information would be useful to generate to coordinate and manage design teams in the construction project offices.

KEYWORDS

Communication, social network, design office, statistics, links distribution.

INTRODUCTION

Social network analysis (SNA) has been used to characterize the organizations of work teams in construction and in project design (Herrera et al., 2020, 2023). SNA allows the use of metrics that characterize communication relationships in work groups and some of its characteristics have been associated with better communication and performance (Castillo et al., 2023).

In SNA, social networks are a representation of a system of links depicting interactions between persons also called nodes (Scott, 2013). The statistics of the links constitutes a rich tool to characterize nodes and networks and unveil patterns of communication that are the main input in creative activities as project design.

Although there is a particular interest in large and complex networks where the number of interactions forms intricated mathematical objects, the small social networks formed in the workplace are responsible for the everyday work done (Krackhardt & Hanson, 1993).

Studies have been carried out that seek to characterize the communications within the social networks that are formed for the development of construction projects. One of their limitations is that they are a snapshot at a specific moment of network development (Segarra et al., 2017). A social network model based on the efficiency of information and knowledge exchange, as critical factors in project success, was proposed by Chinowsky et al. (2008). In addition, a model has been proposed, that seek to identify the ideal amount of communication needed to carry out the construction project design, based on expert opinions (Herrera et al., 2023). However, the models that best fit reality are those that are developed from the information of the people involved in the task that generate the social network (Alarcon et al., 2013).

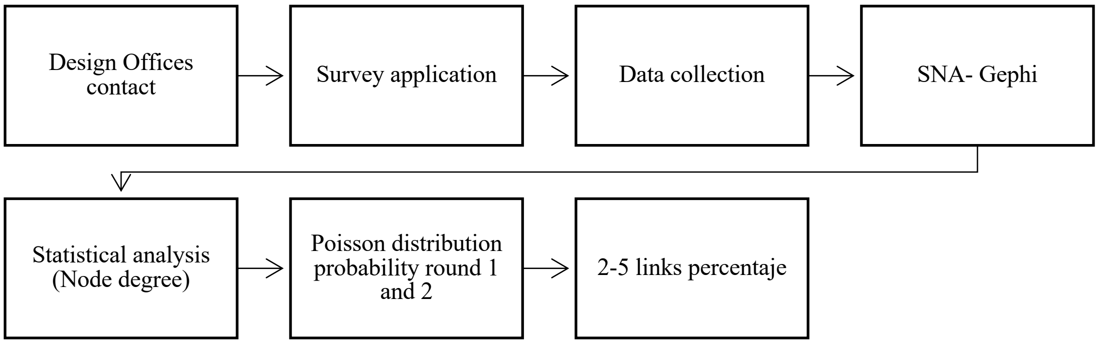
The social networks require tools to unravel their inner working to understand mechanisms that drive link formation (Lambiotte, 2019). Statistical models are often used as an idealized form that attempt to represent the stochastic mechanisms that produce relational ties and the complex dependencies between nodes (Handcock & Gile, 2012). A study carried out with design offices in Chile proposed a statistical distribution of links between the nodes of the work teams that is associated with their best performance (Castillo et al., 2023). This study was focused on a particular group of design teams, leaving open the necessity to explore whether these distributions are repeated in the design offices of other countries, assuming that the design process of construction projects is standardized and very similar regardless of the country (RAIC, 2022).

The purpose of the present research is to identify communication patterns in the work teams of design offices in diverse countries. Then, by using social network statistics, to obtain a mathematical model based on the probability distribution of the links within the social networks that make up the design teams and establish whether the metric proposed by Castillo et al., (2023) is applicable in design offices in general. Such information would be useful to generate to coordinate and manage design teams in the construction project offices.

This paper is organized as follows. First the introduction section presents the background and need for this research. Next, the research method is reviewed and then the discussion of results is presented. Lastly, conclusions and limitations are drawn.

METHOD

The methodology applied in this research is detailed in the next diagram:



In this study 7 design offices from Colombia, Perú, México, Ecuador, United Kingdom and Honduras, each one with 3 project design teams, agreed to participate. The research team applied an online survey to the design team members, asking who they communicated with to provide relevant information for the performance of their work in the last six months, relevant means the necessary information which provides added value and is not openly available. Adjacence matrices were obtained showing the edges formed between team members and were processed by Gephi 0.10.1 software to obtain the degree of each node. The 21 social networks studied were debugged, leaving only the confirmed connections between nodes (Krackhardt & Hanson, 1993). The study is based on the analysis of undirected networks since they depict better the communication relation between team workers (Easley & Kleinberg, 2010). A total of 21 networks from 7 design offices with members between 5 and 10 were used for analysis based on the average degree of each node, there were values between 0 and 7 as can be seen in Table 1.

Table 1. Degree of the node by design firm (Ei) and project (Pi)

Node	E1			E2			E3			E4			E5			E6			E7		
	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3
1	4	2	3	4	1	1	1	0	2	3	3	2	4	1	1	2	2	2	3	3	4
2	2	2	2	4	2	2	1	0	3	1	2	2	3	1	2	3	3	2	3	5	3
3	4	3	2	5	2	3	0	1	4	2	4	2	0	0	1	3	2	2	7	6	5
4	4	1	0	1	1	1	1	2	3	2	2	1	0	0	1	0	0	0	4	2	3
5	1	0	0	1	1	1	0	0	0	0	1	0	3	2	2	2	1	0	2	1	0
6	1		1	4	3	3	1	2	2		2	1	3	2	1				1	2	2
7	1			0	1	1	0	1	0				1	0	0				2	4	3
8	2			0	1	1	0	2	0										4	5	4
9	1			4	2	2															
10				1	0	1															

For the analysis, 21 density curves were created with the degrees of the nodes using R 4.4.1 statistical software. The methodology used consisted of fitting each density curve to a Poisson distribution, assuming in a first attempt that are random networks, each connection is an independent event with a low probability of occurrence and the links do not follow a preferential growth pattern (Perianes-Rodríguez et al., 2008), and then averaging the 21 individual fits to obtain a first average curve fitted to the Poisson distribution. This adjustment process allowed to accurately obtain the variability and particularities of each network under study since these characteristics of the networks directly influence the degree distribution. Individual fitting decreases the bias that could arise from averaging the 21 density curves and then adjusting. Because each network has a better Poisson fit, the average of these fits generates a model with better characteristics and properties of the Poisson distribution.

After, the mean absolute error (MAE) of the data was obtained from the respective density curves, formed with degrees between 0 to 10, and fitted to the Poisson distribution to validate the first approximation. To discriminate social network data, the MAE was used, due to robustness against outliers. From the results obtained, those networks with MAE values greater than 10% were not considered and again was performed a fit of 9 curves that met this criterion. Due to the complex interactions between network members and the expected variability in social network analysis, a 10% threshold for mean absolute error (MAE) is a good balance between accuracy and flexibility. This approach, commonly used in other research areas, serves as a reliable starting point for validating fits or predictions, particularly in the context of social network analysis from count data (Chuquin-Vasco et al., 2024; Hart et al., 2022).

With the 9 curves, a new approximation to the Poisson distribution was obtained and a curve graph was created. The MAEs were calculated and values lower than 10% were used as an indicator that the model has a good fit for the networks analyzed.

Using the last curve obtained, the probabilities of links within a range of 2 to 5 was calculated.

RESULTS AND DISCUSSION

As a result of the first approximation, an average Poisson curve was obtained with a mean value λ = 2.191572, see Figure. 1.

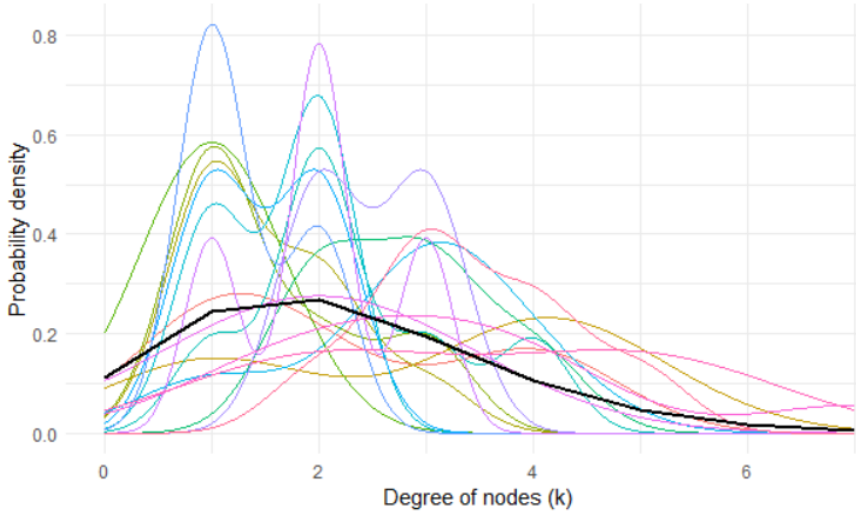


Figure. 1 First Poisson distribution approximation

The second approximation to the Poisson distribution was obtained for the 9 curves with a mean value λ = 2.814903. The MAEs were calculated, and the results shown in Table 2 were obtained. Values of MAE lower than 10% resulted in all cases, so it is assumed that the model has a good fit for the networks analyzed. Between the first approximation and the second approximation, a growth of the average by 28.44 % is observed.

Table 2. Results of the second Poisson fit

Firm	Number of nodes	Mean absolute error (MAE)
E1_P1	9	7,29
E2_P1	8	4,51
E3_P3	5	9,02
E4_P2	6	9,59
E5_P1	5	6,13
E6_P3	3	7,08
E7_P1	8	2,00
E7_P2	8	3,27
E7_P3	7	7,52

Also, a Poisson fit curve was generated showing a smoot adjustment better than the result obtained in the first approximation, as is shown in **Figure. 2**.

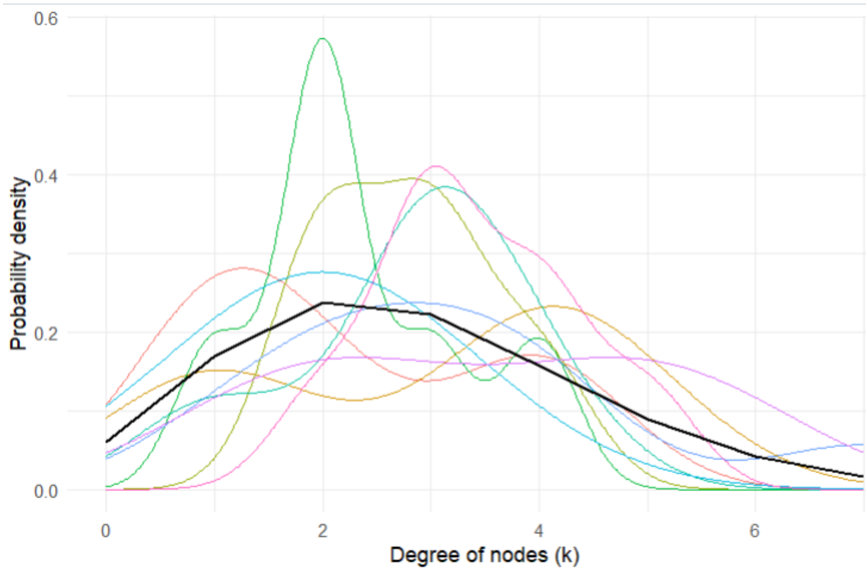


Figure. 2 Second Poisson distribution approximation

Through this procedure the equation of the curve that best fits the 9 of the 21 networks studied was obtained, which is

$$P(k) = \frac{\lambda^{k} e^{-\lambda}}{k!} \qquad \textbf{Formula 1}$$

Where k is the number of random events (degrees) and

λ is the mean of the degree distribution (2.814903 links).

Furthermore, to test the quality of the network, with the adjustment to the Poisson distribution, link probability between 2 and 5 of 70.50% was obtained. The probability of less than 2 edges for a node was estimated in 22.86% and probability of edges more than 5 was 6.64%, so a distribution with a positive bias is observed. High percentages of 2 to 5 links in a small social network are related to better performance of the design teams as in Castillo et al., (2023).

In the first approximation, the networks that did not fit the first Poisson model were established by MAE with the errors greater than 10%. Those networks form a second group that may belong to Poisson model with a lower mean than λ = 2.191572. Besides, in the original 21 social networks link distribution, there is a third group that tends towards a normal distribution with a mean greater than λ = 2.191572.

The results show that design teams social networks form diverse communication patterns at work. The differences between these groups of networks may be originated in the type of project they develop or the company's own ways of working. Although the offices are different, by converting the degrees of the nodes to link probability distributions, the probabilities within a range of 2 to 5 can be used as a standard indicator that could evaluate the composition of the networks during their evolution over time, complementing the results of previous studies such as Herrera et al., (2023).

The equation (1) describes the most frequent pattern of distribution of links between the members, of the design teams studied, that is produced when they communicate to provide relevant information and knowledge needed for the performance of their work. Such a finding is unexpected since non-random link distributions should be more suitable for the social networks of design teams with a fixed number of members and that carry out their activity under a pre-established command structure (Barabási, 2009).

However, in this study 12 of the 21 social networks did not fit the Poisson distribution so other distributions should be tested, such as Pareto or Adjoint Preferential, which are more suitable for networks where the probability of a new link is not totally random and a large portion of knowledge and information is held by a small fraction of the design team or have a high hierarchical influence (Zhou et al., 2017).

CONCLUSIONS

This research appointed to stablish a mathematical model that depict the pattern of distribution of edges inside the work social networks of the team working in the development of construction designs. The results show that there are a few distribution patterns in the studied networks, one of those fit a Poisson distribution with different mean values which respond to different forms of internal organization of the offices during the development of their work. A mathematical equation based on the Poisson distribution was established for a representative group of work teams and the probability of between 2 and 5 links occurring between its members was estimated with a result of 70.50%, confirming that this percentage can be a metric suitable for differentiating small networks from these work teams.

The proposed distribution associated with a high percentage of people with links between 2 and 5 can be used as a predictor of successful teams in project design tasks. Otherwise, adjustments should be made to improve communication between its members.

Although one limitation of this study is the small sample of design offices and projects, it is remarkable that an important group of design teams has similar configuration to develop their work. Analyze other distributions of links within the design offices and increasing the sample size is a future pending task.

ACKNOWLEDGMENTS

The research team thanks the international design offices that voluntarily joined this research.

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