Construction duration predictive model based on factorial analysis and fuzzy logic

Modelo de predição da duração do prazo de obras com base na análise fatorial e lógica Fuzzy

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Abstract

Setting the building construction duration for vertical residential works is made still in the study phase of economic and financial feasibility of the project and, in most cases, in an empirical way, increasing the uncertainties and the risks to fulfill the set deadline. However, there are computational intelligence tools that can contribute to reduce the degree of uncertainty. This study aimed to investigate the use of a hybrid system to estimate the deadline for vertical residential building works from design and production characteristics using factorial analysis and Fuzzy Systems. To this end, we used information of a database from the SEURB and in some buildings construction companies in Belém, a city located in the State of Pará, northern of Brazil. For the training and construction of the Fuzzy Forecast Model, data from 71 projects were used and 16 others residential buildings were used for its validation. The results showed a significant level of assertiveness, with 75% accuracy considering a range, whose upper and lower limits were calculated from MAPE and MASE. The model presented a prediction performance superior to other models already consecrated in the literature.

Keywords: Fuzzy modeling systems. Fuzzy systems. Building construction. Deadline.

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Resumo

A definição do prazo de execução de obras residenciais verticais ocorre ainda na fase de estudo de viabilidade econômica e financeira do empreendimento e, na maioria das vezes, de forma empírica, aumentando as incertezas e os riscos para o cumprimento do prazo estabelecido. No entanto, existem ferramentas de inteligência computacional que podem contribuir para a redução do grau de incerteza. Este trabalho tem como objetivo investigar o uso de um sistema híbrido para estimar o prazo de construção de obras verticais residenciais, a partir de características do projeto e produção utilizando análise fatorial e Sistemas Fuzzy. Para isso, utilizou-se de informações de um banco de dados oriundos da SEURB de Belém, no estado do Pará e empresas construtoras no município de Belém, cidade localizada no norte do Brasil. Para a construção e treinamento do Modelo de Previsão Fuzzy foram utilizados dados de 71 empreendimentos, e para a fase de validação foram utilizados 16 outras obras de edificações. Os resultados obtidos apresentaram nível significativo de assertividade, com acurácia igual a 75% considerando um intervalo cujos limites (superior e inferior) foram calculados a partir do MAPE e MASE. O modelo apresentou desempenho de predição superior a outros modelos já consagrados na literatura.

***Palavras-chave**: Modelo de Previsão Fuzzy. Sistemas Fuzzy. Construção de Edifícios. Previsão do Prazo de Obra.*

Introduction

Setting the construction duration of a real estate project can be considered an arduous and often imprecise task, influenced by a vast number of variables. However, it is important to minimize this inaccuracy because the term is one of the factors of success of the project, together with cost, scope and quality (WALKER, 1994; CHEN, 2007; AHSAN; GUNAWAN, 2010; RAMON; CRISTOBAL, 2013).

Construction projects involve risks at all stages of development (ZAVADSKAS; TURSKIS; TAMOSAITIENE, 2010; AHMADI *et al.*, 2017; TAVAKOLAN; ETEMADINIA, 2017). In this way, before deciding on the accomplishment of a real estate launch, economic and financial feasibility studies are usually conducted. However, at the moment, much information required to carry out the process of defining the building construction duration are not available, because at this stage even the architectural design is not detailed and the level of uncertainty is very high.

In general, in order to stipulate the construction duration, it is collected information on customer needs, construction projects, technical specifications, quantity of services to be executed, constructive method, among other aspects, depending on the nature of the development. Most of the time, the completion periods are calculated from the planner's own previous experience in similar projects (CHAN; CHAN, 2003).

One of the methods used to set the construction duration is the PERT/CPM technique, but it requires that the duration of the activities be known in the initial phase of the project, when the uncertainty is very high (CHANAS; ZIELIÃ, 2001; HEJDUCKI, 2003; ROGALSKA; HEJDUCKI, 2007; CHEN; HSUEH, 2008; RODRÍGUEZ *et al*., 2014).

The literature on forecasting in the estimation of the time of work is comprehensive and presents mainly statistical models. These models were designed, using characteristics of the works, mainly as: the constructed area, the cost, the number of floors. However there are other factors that influence decisively in the term of execution of a real estate project. This research seeks to fill this knowledge gap, where it was sought to adopt both the physical factors (Number of Bathrooms in the apartment, Number of rooms per apartment, Total Built Area, Number of towers, Number of apartments, Number of floors, Apartment per floor), as factors related to the management of the enterprise (Planned Term, Time of Company Existence, Works Delivered, Simultaneous Works, Manager Experience, Has Financing, Time between beginning of funding and construction, Complete Projects, Use of Planning, Outsourced work, and Planned construction deadline).

Therefore, in this scenario of inaccurate information and consequently of high risk the decision maker has to stipulate the building construction duration, which is a fundamental factor for the performance and success of the project. In this context, this study investigated the use of the combination between the factorial analysis (statistical procedure based on classical Aristotelian logic) and fuzzy logic (or diffuse/nebulous, which considers different possibilities of the classical view, such as shading), aiming to contribute to the prediction of the construction duration in a reasoned and not eminently empirical manner, in the initial phase of work planning, when much information of design and execution is not yet known in detail. In view of the above:

(a) this article presents as a highlight the use of a Fuzzy system combined with the method of factorial analysis to estimate the duration of vertical works, using as independent variables physical characteristics and management of real estate projects; and

(b) this article is composed by a conceptual review on prediction of the execution time of works and decision making based on fuzzy logic, then described the method used to elaborate the model, are also discussed the results found and the conclusions of this research.

Prediction of construction duration

The search for alternative methods that can provide a relatively simple, fast and accurate the building construction duration has been a field of research that aims, through the creation of models, to meet the need. This theme has been discussed in the last five decades by construction professionals, in large part, due to the difficulty of predicting the construction deadline.

According to Ng *et al*. (2001), the pioneer work and more cited in the literature was performed by Bromilow et al. in 1969 in Australia. The model created by Bormilow (1969) became known as BTC – Bromilow's Time-Cost Model. It was created from a database of - 309 projects of works, and had as objective to predict the duration through its cost of construction, which is the main variable independent or explanatory of the modeling.

Several studies were performed to improve this initial model, such as Skitmore and Ng (2003), Thomas

(2003), Walker (1994), Chan and Kumaraswamy (1996), Le-Hoai, Lee and Cho (2009) and Le-Hoai and Lee (2009). Although the research developed shows that there is indeed a correlation between cost and construction duration, they did not arrive at more conclusive or assertive answers on the subject.

In the survey conducted by Walker (1994), other variables were included: total gross area, number of floors, type of project and method of contracting resources, while Chan and Kumaraswamy (1996), Chan and Chan (2004) and Love, Tse and Edwards (2005) added the ratio of total area to number of floors, that is, the proportional area to be constructed in relation to the number of floors.

Guerrero, Villacampa and Montoyo (2014) carried out a research with 168 works executed in Spain, aiming to elaborate an equation to predict the construction duration of new works, encompassing several constructive typologies. The study adopted seven explanatory variables: total construction cost, total floor area above and below ground, number of floors (above and below ground), and ratios of total floor areas to number of floors and cost to the total floor area.

The result of this modeling pointed to two equations, with dependent variables the speed of production of the work and the time for execution. For these models, the independent variables are, respectively: for the speed of construction the total area of the floors, the number of floors, the ratio of the total cost of construction to total area of the floors; for the prediction of duration, the same previous variables along with the constructive typology (GUERRERO; VILLACAMPA; MONTOYO, 2014).

According to Walker (1994), the scope (represented by total area and cost of construction) and project complexity (defined as customer, project and environmental characteristics) represent challenging aspects for a project management team. They constitute risk formation factors and effectively influence the performance of construction duration. For Jarkas (2015), in many cases, the durations specified in contracts for execution of a work, are not able to meet a criterion of minimum time and necessary for the accomplishment of the construction in an appropriate way, and the term is stipulated in a random way by the decision maker, making it unfeasible or unrealistic for countless projects.

This is very negative because the definition of construction time, as already explained, is a very relevant factor, including to avoid future conflicts between the interested parties. In order to carry out its prediction, regression models have been proposed and adopted, the explanatory variables being generally the cost of construction and the size of the work, even though the literature has pointed out that other factors can significantly affect the execution duration of a project, such as the type of project to be constructed, the constructive method, the number of floors, the productivity, the quality standard, the type of management among others (CHAN; CHAN, 2003; COUTINHO *et al.*, 2012; JARKAS, 2015; SENOUCI; MUBARAK, 2016).

Without exhausting the possibilities of other variables that may influence the construction duration of an engineering venture, the following are some of the most referenced ones:

(a) size of the work (AHMADU *et al.*, 2015; JARKAS, 2015);

(b) cost of the work (BROMILOW, 1969; WALKER, 1994; CHAN; CHAN, 2003; SKITMORE; NG, 2003; CZARNIGOWSKA; SOBOTKA, 2013; AHMADU *et al.*, 2015);

(c) planning of the work (CHAN; KUMARASWAMY, 1996);

(d) execution time (SKITMORE; NG, 2003);

(e) characteristics of the executive project (WALKER, 1994; CHAN; CHAN, 2003; CRUZ; SANTOS; MENDES, 2018);

(f) productivity (KAMING *et al.*, 1998; HWANG; LIU, 2010; NASIRZADEH; NOJEDEHI, 2013);

(g) season of the year and managerial capacity (COUTINHO *et al.*, 2012).

However, some of these factors still cannot be defined or are very imprecise/vague in the phase of analyzing the feasibility of the project, when it is already necessary to predict the construction duration. In this sense, Cárdenas *et al.* (2014) and Li *et al.* (2013) state that risk assessment plays a key role in addressing the problem in the execution of the work in the time provided for the construction. Just as it is essential to evaluate the likely potential risk and its consequences (SALAH; MOSELHI, 2016).

Decision-making and fuzzy logic

Fuzzy decision-making

Decision-making by managers (entrepreneurs and executives) of organizations is a very important and recurring activity of these professionals. However, most of these decisions are made in a predominantly intuitive way, mainly based on the professional experience, the sensitivity and the feeling of each manager.

The first researches related to the decision making based on scientific and methodological appeared in this scenario. In the day to day of an organization, the decisions can be made with or without the use of formal methods of support to the decision. Due to this fact, the great concern is given, not to the use of methods, but the results achieved with the decisions made (ALMEIDA, 2013).

In agreement with Goldschmidt (GOLDSCHMIDT, 2010), the need for knowledge aimed at generating mechanisms that can be the basis for the generation of decision support systems is not a trivial task, since the capture of the facts occurs through subjective, abstract and inaccurate concepts coming from experts.

Therefore, through logical reasoning, one tries to construct arguments that may or may not validate certain prepositions or hypotheses. However, it is necessary to be careful with the false prepositions that can lead to the wrong conclusions, that is, one must be sure that all the premises are true so that the argument is correct and valid (MORTARI, 2001).

The traditional Boolean logic (dualistic, belongs or does not belong) served as a reference and basis for the improvement of a different logic, called fuzzy (diffuse, nebulous), capable of representing more realistically some phenomena, even approaching the human reasoning used in decision making. As fuzzy logic presents a broader concept in relation to traditional logic, it can be said that it also presents a more comprehensive field of application (RHEINGANTZ, 2002; SILVA, 2013).

This theory, created and presented to the world at the beginning of the twentieth century by European and American mathematicians and philosophers, was spread, became known and started to be applied from the publication of a paper that described the notion of diffuse sets in 1965, with the title “Fuzzy sets” or diffuse sets, by Lofti A. Zadeh, professor of engineering and computation at the University of California (GÜNDÜZ; NIELSEN; ÖZDEMIR, 2013).

Diffuse or Nebulous Logic (Fuzzy Logic) is, therefore, a theory based on solid mathematics, which allows modeling in a way similar to human reasoning, capable of representing this skill that is used in decision making, in uncertain and imprecise environments (GOLDSCHMIDT, 2010; LEAL, 2012; USTUNDAG; CEVIKCAN, 2016). It can be considered as an interesting alternative to be used in the construction industry due to its typical inaccuracies, risks and uncertainties (CHUN; AHN, 1992; GONZÁLEZ; FORMOSO, 2006; TAYLAN *et al.*, 2014; SADEGHI *et al.*, 2016).

Fuzzy Sets Theory

A fundamental concept of the Fuzzy Sets Theory, proposed by Zadeh (1965), is the pertinence. In the Classical Theory (Boolean), the concept of pertinence of the variable *x* in the set *A* is defined by (Eq. 1):

$$\mu_A(x) = \begin{cases} 1 \Leftrightarrow x \in A \\ 0 \Leftrightarrow x \notin A \end{cases} \quad \text{Eq. 1}$$

Where $\mu_A(x)$ pertinence of the variable *x* in the set *A*.

So, a variable *x* only "belongs" ($\mu_A(x) = 1$) or "non-belongs" ($\mu_A(x) = 0$) to the set *A*. However, for the Fuzzy Sets Theory, this concept of pertinence is presented as follows (Eq. 2):

$$A = \{(x, \mu_A(x)) |\ x \in U\} \quad \text{Eq. 2}$$

Where:

$\mu_A(x)$: Degree of pertinence of the variable *x* in the set *A*;

A: Fuzzy set formed by ordered pair (x, $\mu_A(x)$);

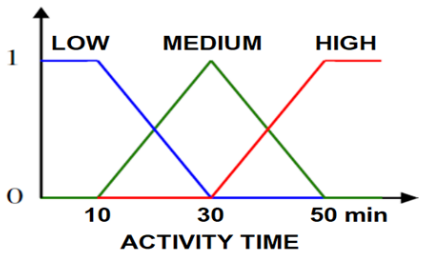
x: Variable of interest; and

U: Universe of speech.

As consequence, a variable *x* came to belong to a set *A* in a gradual way, in an interval [0, 1]. This implies that a variable can belong to more than one fuzzy set, with different degrees of pertinence.

Another fundamental concept is the concept of a linguistic variable. In the Fuzzy Sets Theory a linguistic variable uses natural language values, which give the name to Fuzzy Sets. For example, for a linguistic variable called "Activity Time", it could assume values: low, medium and high, as shown in the Figure 1.

Figure 1 – **Fuzzy sets of the variable "Activity Time"**



Source: adapted from Ross (2016).

Complementing the concept of linguistic variable there is the concept of membership function that assigns values of fuzzy pertinence to discrete values limiting of the discourse universe of the linguistic variable. Thus, considering the previous example, see Figure 1, a time of activity of up to 10 minutes presents a degree of pertinence equal to 1 in the Fuzzy Set "LOW", but for values of time between 10 and 30 minutes, it is perceived that the degree of pertinence for the Fuzzy Set "LOW" decreases and for the Fuzzy Set "MEDIUM" grows, and for the time of 30 minutes we have a degree of pertinence equal to 0 for the Fuzzy Set "LOW" and equal to 1 for the Fuzzy Set "MEDIUM". The shape or configuration of the Fuzzy Set (Triangular, Trapezoidal, among others) will depend very much on the boundary conditions of the problem involved. Operations can be performed between the Fuzzy Sets, as shown in Figure 2.

These concepts are fundamental to understand a Fuzzy Inference System (FIS) that basically is a model that allows solving problems that have inaccuracies in the values of the variables of interest. The standard configuration of a FIS, shown in Figure 3, is composed of 3 steps: Fuzzification (conversion of the inputs from the real domain to the fuzzy domain); Rules and Fuzzy Inference (logical implications that relate converted entries); and Defuzzification (interpretation of the logical implications in outputs converted from the fuzzy domain to the real domain), see Figure 3.

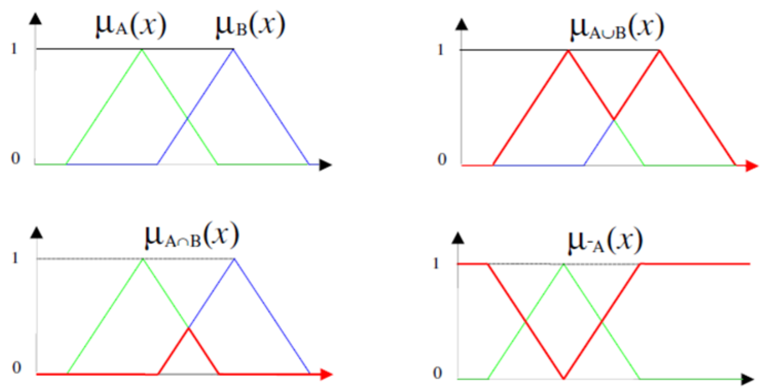
An example of rule in a Fuzzy Inference System would be: SE *x* is *A* AND *y* is *B*, THEN *z* is *C*. Where, *A* and *B* are the input Fuzzy Sets, relative to the part known as antecedents or premises, while *C* is the output Fuzzy Set, relative to the part known as consequent or conclusion.

Figure 2 - **Operations in Fuzzy Sets**

Union : $\mu_{(A\cap B)}(x) = \max(\mu_{(A)}(x), \mu_{(B)}(x))$

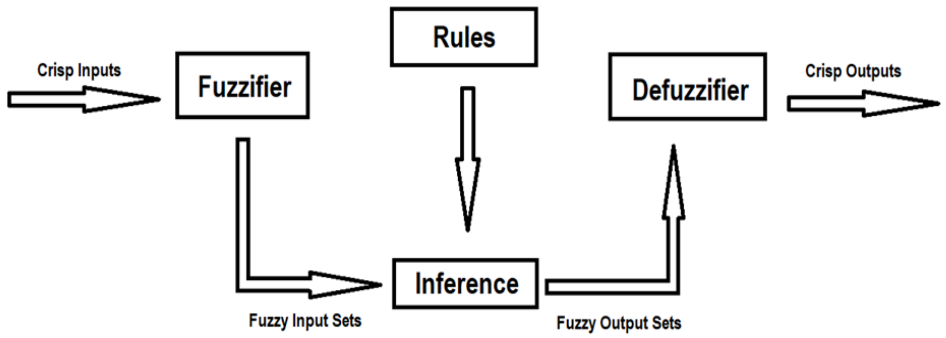
Intersection : $\mu_{(A\cap B)}(x) = \min(\mu_{(A)}(x), \mu_{(B)}(x))$

Complement : $\mu_{(\bar{A})}(x) = 1 - \mu_{(A)}(x)$



Source: adapted from Ross (2016).

Figure 3 - **Fuzzy Inference System (FIS)**



Source: adapted from Ross (2016).

In the literature there are several models of Fuzzy Systems, the most known being the Mamdani Model and the Tagaki-Sugeno Model. The basic feature of the Mamdani Model is the fact that both antecedents and consequents are mapped in the Fuzzy Domain. For example, a typical rule in a Mamdani Model is: SE *x* is "High" AND *y* is "Low" THEN *z* is "Medium".

In the Takagi-Sugeno Model, the output of the Fuzzy System is represented as a function of the input variables. A typical rule of the Takagi-Sugeno Model is: SE *x* is "High" AND *y* is "Low" THEN $z = f(x,y)$.

In this model, the fuzzification of the inputs with the application of the Fuzzy Operators is done in the same way as the Mamdani Model, with the difference that the output is a function in the real domain. Further details of these models can be found in Ross (2016).

Methodology

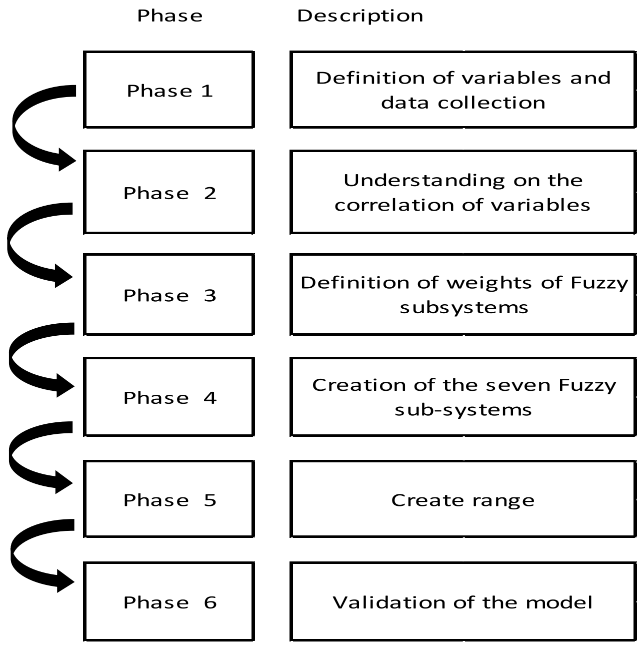
The present work is a research evolution previously published in scientific journal "Ambiente Construído", see Maués *et al.* (2017). The research consisted of a case study based on quantitative and qualitative information of residential buildings from several construction companies operating in Northern Brazil, in order to propose a hybrid modeling method based on factorial analysis and Fuzzy systems to assist decision makers to forecasting the construction duration of vertical residential works (with multiple floors) still at the stage of analysis of economic and financial feasibility of the project. For a better understanding of the research method, Figure 4 shows the phases of research development.

Definition of variables and Data Collection

For the elaboration of the proposed model, initially a theoretical revision was made in several articles that deal with the theme of the term of execution of work. From this research it was possible to extract among the most cited authors, the factors that influence the execution period of an enterprise, see more details in Maués *et al.* (2017).

The sample used in this research consisted of residential vertical buildings with multiple pavements. Data collection was carried out in the period between 24/08/2015 and 01/09/2015, from information gathered from SEURB (Municipal Department of Urbanism of the city of Belém), a public agency responsible for building permits, and from real estate sector and construction companies. A total of 274 residential and commercial real estate projects were identified. Of these, 142 were included in the present study because they were residential type, they were completed and they provided consistent information/data.

Figure 4 - **Summary of research development**



Factor analysis

In order to obtain better representativeness for the dependent variable, we chose the use of Factor Analysis to identify factors that best represent the proposed Fuzzy model. According to Fávero *et al.* (2009), this technique seeks to perform a synthesis, when the sample presents a strong correlation in order to determine the relationship between the variables, as well as allows the reduction of multiple variables to a smaller number of factors, of an abstract nature, (ÖCAL *et al.*, 2007; BUZZI, 2010; PALLANT, 2011).

Therefore, the first step in the construction of the model used this technique to facilitate the understanding of the variables and their correlations. In this way, when analyzing the results generated by this factorial analysis, we obtained the number of factors that represented the number of subsets in the construction of the diffuse model, see Table 1.

With the use of factorial analysis it was established that the model would have seven Fuzzy subsets, since the factorial analysis generated seven factors. Each factor grouped the variables that presented correlations with each other. In this way, the definition of the number of Fuzzy subsystems to be used in the modeling was established, as shown in Table 2.

Then, the sum of all factorial loads generated as a factorial analysis response for each of the factors was analyzed (see Table 1). Subsequently, we defined the weight of each of the subsets that is obtained by the ratio between the sum of the factor loads of each factor and the total sum of the factors.

These weights were used to aggregate the results obtained with the defuzzification process of each of the subsets constructed in the model proposed in this research. A better description and identification of the subsets and variables are described in detail in Maués *et al.* (2017).

Process of Data Fuzzification and Defuzzification

The creation of the model using fuzzy logic for the prediction of the construction duration initially used the subsets presented in Table 1, for the creation of the seven fuzzy sets. For each, the input variables were generated by the factorial analysis result. The seven subsets containing their respective linguistic variables, membership functions and domains are shown in Table 3.

Table 1 - **Rotational component matrix**

Variables	Variables with factor loading > 0.5						
	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**
V1-Number Bathrooms Apt	.903						
V2-Number Bedrooms Apt	.841						
V6-Number of Floors	.749						
V17-Apartaments Per Floor	-.537						
V14-Completed Construction		.918					
V13-Time Completed Construction		.898					
V16-Outsourced Construction		.751					
V5-Number Apt			.947				
V3-Total Construction Area			.886				
V4-Number Towers			.756				
V7-Planned Time				.937			
V18-Construc Duration				.913			
V9-Delivered Construction					.857		
V10-Simultaneous Construction					.688		
V11-Manager Experience					.594		
V8-Time Company Exists						.912	
V12-Funding Available							.875
V15-Used Planning							.506

Source: Maués *et al.* (2017).

Table 2 **- Variables and fuzzy subset in vertical buildings**

Fuzzy Subsets	Variables
F1 - Physical characteristics of the apartments	V1- Number of Bathrooms in the apartment V2- Number of rooms per apartment V6- Number of floors V17- Apartment per floor
F2 - Management decisions	V14- Complete Projects V13- Time between beginning of funding and construction V16- Outsourced work
F3 - Size of the work	V5- Number of apartments V3- Total Built Area V4- Number of towers
F4 - Time for the execution of the work	V7- Planned Term V18- Construction duration
F5 - Expertise of the Construction Company	V9- Works Delivered V10- Simultaneous Works V11- Manager Experience
F6 - Time of operation of the company	V8- Time of Company Existence
F7 - Startup conditions	V12- Has Financing V15- Use of Planning

Source: Maués *et al.* (2017).

Table 3 **– Domain and linguistic variables of fuzzy model**

Input variable	Domain range	Linguistic variable
V1- Number of bathrooms	1 – 6 (unit)	Few, intermediate and many
V2- Number of rooms	1 – 5 (unit)	Few, intermediate and many
V3- Total Built Area	4,301 – 75,624 (m^2)	Small, medium and large
V4- Number of towers	1 – 9 (unit)	Few, intermediate and many
V5- Number of apartments	21 – 432 (unit)	Few, intermediate and many
V6- Number of floors	4 – 37 (unit)	Few, intermediate and many
V7- Deadline for construction	24 – 62 (months)	Short, intermediate and long
V8- Company Experience	2 – 61 (years)	Little, medium and much
V9- Number of works delivered	0 – 67 (unit)	Few, intermediate and many
V10- Number of works built simultaneously	0 – 10 (unit)	Few, intermediate and many
V11- Experience of the project manager	3 – 26 (years)	Little, medium and much
V12- Has financing	0 (no)-1 (yes)	Small, partially and large
V13- Time for Financing Release	0 – 19 (months)	Short, intermediate and long
V14- Have complete projects	0 (no)-1 (yes)	No, partially and yes
V15- Use of planning technique	0 (no)-1 (yes)	No, partially and yes
V16- Outsourcing of construction	0 (no)-1 (yes)	No, partially and yes
V17- Number of apartments per floor	1 – 12 (unit)	Few, intermediate and many
V18- Construction duration, city hall term	18 – 70 (months)	Short, intermediate and long

The membership functions used in this model were triangular and trapezoidal, since they are the most frequently used in Fuzzy Systems (ZENG; SMITH, 2007; CHENG *et al.*, 2012). After the construction of the seven fuzzy subsets and seeking to validate their respective support, a questionnaire was produced, containing the possibilities of varying the support of each variable.

This questionnaire was applied through a survey to 40 professionals who work in civil engineering, obtaining 31 filled questionnaires, generating a return of 77.50%. The characteristics of the interviewees are listed in Tables 4 and 5.

This research had the objective of validating the elaboration of membership functions, seeking the opinion of a diversified public. It is understood that the profile of the interviewees with an average of

21.23 years of experience in the market in different roles in their organizations contributes to the definition of variables of residential real estate projects in the construction of the model.

The answers that presented the highest percentage index were chosen to elaborate the membership functions of each fuzzy subset. See example in Table 6, the final configuration of the Fuzzy subset 1. As well as the final configuration of the output membership functions of each subset shown in Figure 5.

Later, the IF-THEN rules of the model were created. An important aspect taken into account in the design of the model is the fact that sampling has a large number of independent variables (18 in total). The fuzzy method, among other aspects, directs to set the number of rules that the system must have, where it is taken into account the number of variables, the number of fuzzy sets and the linguistic variables to be used.

Since there are three fuzzy sets for each input variable and 18 variables in total, then we must have the number of 3^{18} = 337,420,489 rules, that is, a very high number. As an alternative to perform the modeling in a more dynamic and compatible with the reasonableness of execution of the model, the seven fuzzy subsets were created, using factorial analysis, as previously described. In this way, the number of rules has decreased dramatically, as shown in Table 7.

Table 4 **- Profile of the interviewee**

Profile of the interviewee	Number per category
Professor	1
Consultant	1
Planning Engineer	3
Construction Engineer	4
Director	9
Manager	13
Total	31

Table 5 **- Time of experience of the interviewee**

Experience (years)	Number of interviewees per period
From 1 to 5 years	3
From 5 to 10 years	6
From 10 to 15 years	2
From 15 to 20 years	2
From 20 to 25 years	4
From 25 to 30 years	3
More than 30 years	11
Total of interviews	31

Table 6 **- Definition of membership functions, linguistic variables and domain of variables of Fuzzy Subset 1 (F1)**

Variables	Support	Linguistic variable	Membership functions
V1- Number of bathrooms	01-06	Few, intermediate and many	Trapezoidal and triangular.
V2- Number of rooms	01-05	Few, intermediate and many	Trapezoidal and triangular.
V6- Number of floors	03-40	Few, intermediate and many	Trapezoidal.
V17- Number of apartments	01-08	Few, intermediate and many	Trapezoidal and triangular
Fuzzy subsystem 1 Output	0 - 90	Very small, small, medium, long and very long	Triangular

Figure 5 - **Fuzzy subset output**

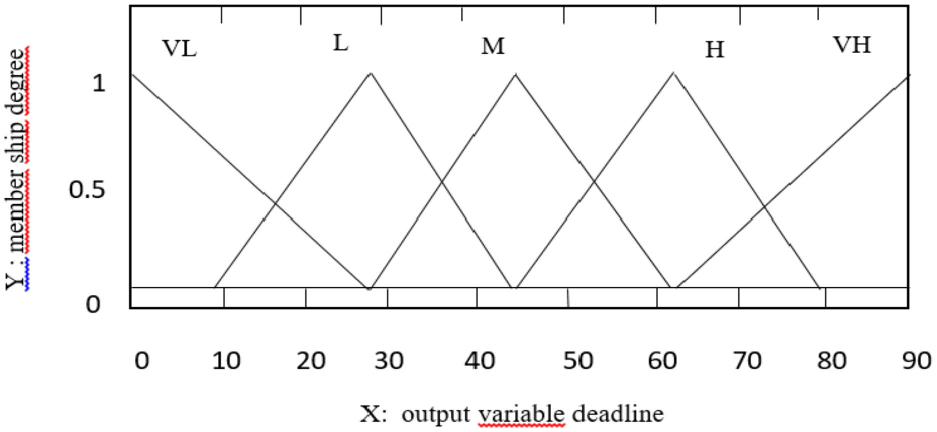


Table 7 - **Number of rules per fuzzy subsystem**

Fuzzy Subsystem	Number of rules
F1 - Physical characteristics of the apartments	81
F2 - Management decisions	27
F3 - Size of the work	27
F4 - Time for the execution of the work	9
F5 - Construction Company Expertise	27
F6 - Time of operation of the company	3
F7 – Startup conditions	6

From this method, the number of rules used was 180. Therefore, the IF-THEN rules were generated from the combination of the three membership functions for each of the variables of each of the fuzzy subsets of the model. For example, subset 1:

1. If (total area is small) and (number of floors is low) and (funding is no) and (simultaneous works are few) then (duration is short) (1);

5. If (total area is small) and (number of floors is low) and (funding is partial) and (simultaneous works are intermediate) then (duration is medium) (1);

9. If (total area is small) and (number of floors is low) and (funding is total) and (simultaneous works are many) then (duration is long) (1);

(...)

81. If (total area is large) and (number of floors is high) and (funding is total) and (simultaneous works are many) then (duration is long) (1).

This logic was applied to each of the seven fuzzy subsets that constitute the model proposed in this study.

Model structure

Here, we chose to perform the modeling using the Mandani method, because in addition to being more frequent in the literature (WANG, 1997), this method is better suited to the solution of this research problem. In this research, the operator "E" was used with the minimum method, minimum implication, maximum aggregation and defuzzification by center of gravity or centroid method. Using the combination of factorial analysis, each of the fuzzy subsets were grouped. In this way, the system began to be constituted of several subsets that are being incorporated due to its peculiarities, as shown in Figure 6.

As shown in Figure 6, the final result of the model is obtained from the sum of each of the fuzzy output values, multiplied by the weight of each factor. This weight was calculated by the sum of modules obtained with the factor loading of each of the seven factors generated in the factorial analysis.

Results of the model

The dependent variable of this research is the construction duration, defined as the time interval between the installation of the construction site and the final cleaning.

The comparison of the results predicted by the model and the deadlines observed in the sample indicates that the behavior between the output and the actual values of the construction durations present a homogeneous behavior. This fact is also verified when analyzing the box-plot graph of the sample and the fuzzy model, in Figures 7 and 8.

Figure 6 **- Final configuration of the proposed hybrid model**

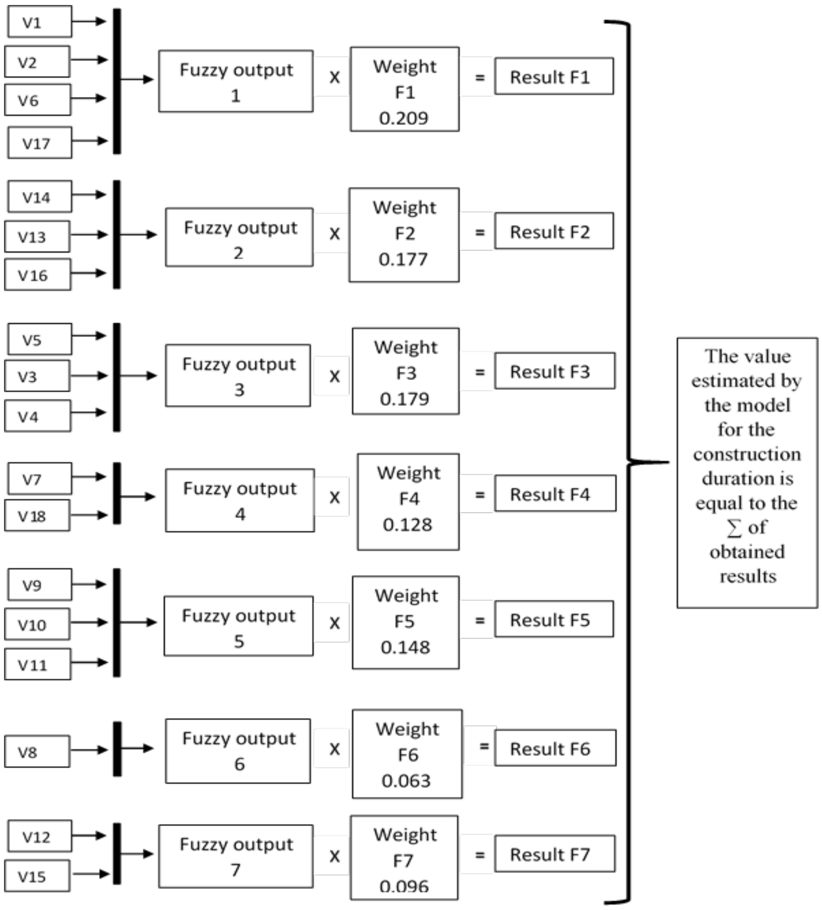


Figure 7 **- Box-plot of the actual construction durations**

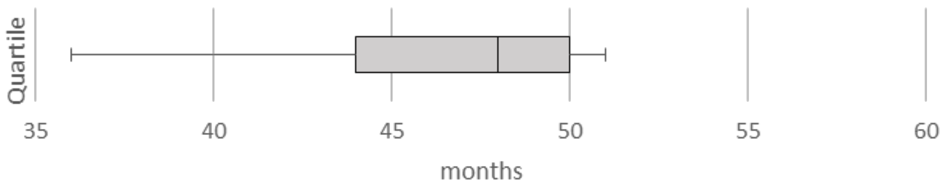
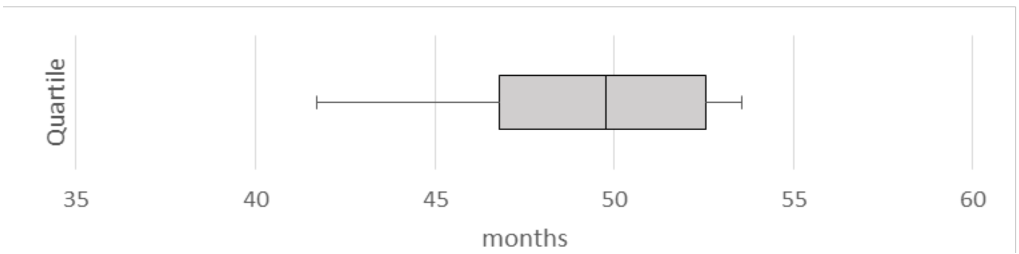


Figure 8 **- Box-plot of the construction duration from fuzzy modeling**



In order to analyze the level of assertiveness of the results generated by the proposed model, a comparative study of the same and values established within the upper and lower limits was performed, using the mean absolute percentage error (MAPE), as well as adopting the method of the Absolute Minimum Error in Scale (MASE), to validate the use of the model in function of its greater precision, because this method is less sensitive to outliers and more easily interpretable in relation to other methods of accuracy (HYNDMAN; KOEHLER, 2006; CARVALHO; COSTA, 2017).

We attempted to compare both the results generated by the proposed model as well as the results generated by a traditional and pioneering method known as BTC (Time-Cost Model of Bromilow), in relation to the upper and lower interval established by the MAPE for a percentage of assertiveness every 5% of variation. In the phase, the value attributed to the MASE method was also verified, which in this case was obtained a value of 0.89, which was lower than 1, demonstrating the possibility of using the model. The result of assertiveness can be seen in Figure 9.

In the first range, where the maximum allowed deviation was 5% in relation to the actual construction duration, the Fuzzy system generated 49 positive results, while the BTC (Bromilow's Time-Cost Model) generated four results. This behavior was repeated in all comparison ranges. To finalize the analysis of the results generated during the construction of the Fuzzy model, it was defined for each value of the sample a range with the construction duration generated by the modeling, assigning a minimum and maximum value to each result found with the modeling.

For this purpose, we used comparison indicators among estimators, also known as risk or error that demonstrates when there was an error between the actual values and the values assigned to the construction duration through fuzzy logic.

The calculated Mean Absolute Scaled Error (MASE) was 0.8864 (MASE<1 then can be used) and the calculated mean absolute percentage error (MAPE) was 8.56%, which means that on average a deviation of this order is occurring between the actual value and the value generated by the Fuzzy system. We used this value to set the upper and lower limits of an accuracy assessment range of the regressor.

After identifying the limits for each of the values, we obtained the results shown in Table 8.

As can be seen in Table 7, 49 results generated by the Fuzzy system were within the range of the model construction duration, which represents a percentage of hit of the order of 69.01%. These values can be observed individually in Figure 10.

Model validation

For validation of the proposed model, a new sample was used, which came from the initial database of 274 projects, but composed of works that until September of 2015 had not yet been completed, so they were not part of the initial samples used in the construction of the model.

This new database with independent samples consists of 16 real estate projects that were completed between October 2015 and December 2016. In this sense, the criteria used were the same applied by the researchers when the model was constructed.

The analysis of the results of some statistical values showed that the results are very close, both in relation to the measures of the mean, median and measures of central tendency, according to Figure 11, which shows the results obtained for the actual sample.

Figure 9 – **Comparison of hits of the models (Sample 01)**

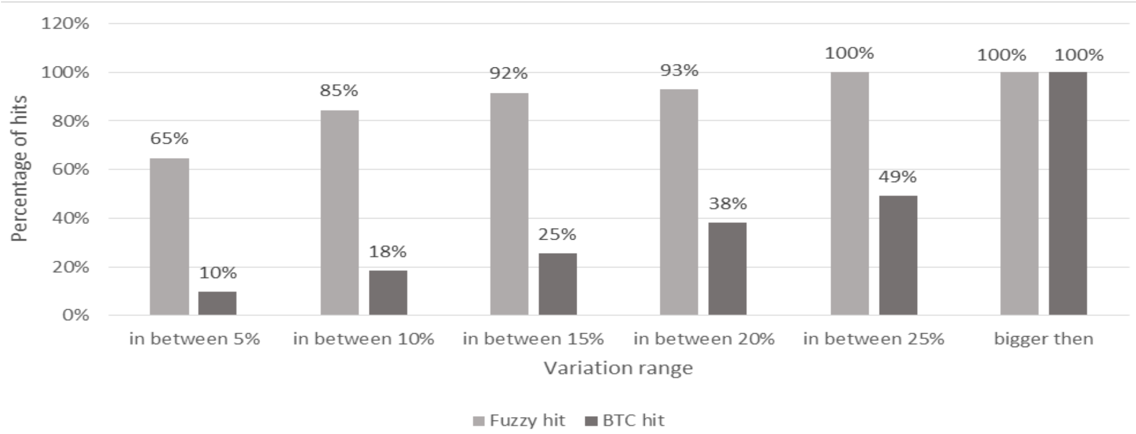


Table 8 – **Performance Measurements between actual and Fuzzy values**

Hit condition for the construction duration range	Number of works	Percentage
Between the limits	49	69.01%
Below the lower limit	19	26.76%
Above the upper limit	3	4.23%

Figure 10 **- Inference of the fuzzy model of construction deadlines and variation range for the model construction process**

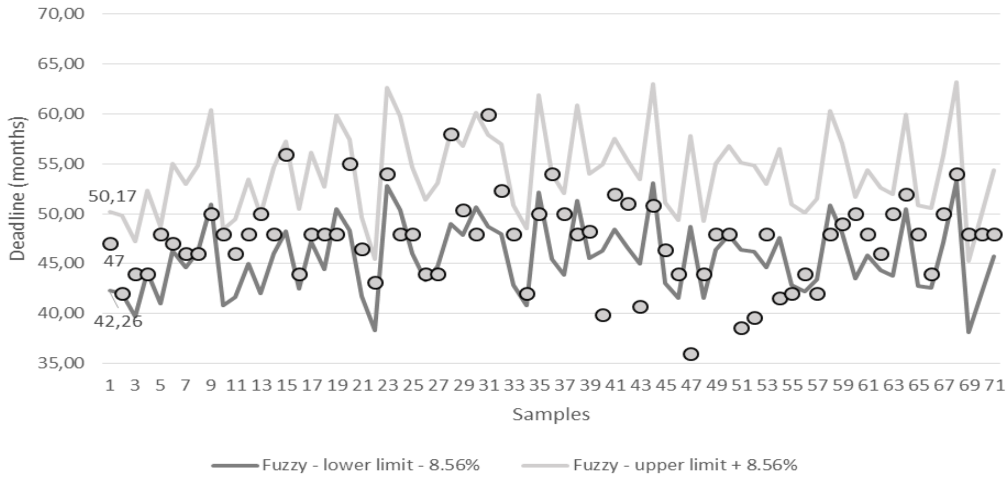


Figure 11 **- Box-plot of the sample deadline**

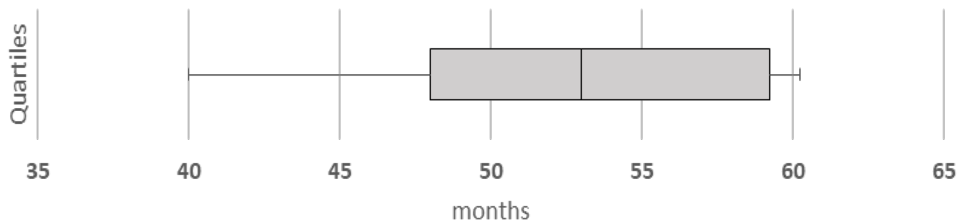


Figure 12 illustrates the results obtained with the values inferred by the proposed Fuzzy system, also in relation to the mean, median and measures of central tendency.

The data obtained with the Fuzzy system generated a smaller amplitude than that found in the actual data, which was 29.00 months, while the modeling result showed an amplitude of 20.81 months, with all the values generated by the model within the actual range of the construction duration. These values reveal that the works of this new database were executed over a longer period of time than the other 71 projects, characterized by projects that had delayed completion. Even so, the model was able to estimate values close to reality.

With the actual values of the construction duration, the values generated by the Fuzzy method and the BTC method, a comparative study was made. This comparison evaluated the deviation between the actual value and the values generated by the two methods, at intervals varying every 5% of deviation from the sample data. As shown in Figure 13.

In the first range, where the maximum allowed deviation was of the order of magnitude up to 5% in relation to the actual construction deadline, the Fuzzy system generated 12 positive results from the 16 samples, resulting in a 75% success rate in this range. The BTC method produced four results in this range generating a 25% hit percentage.

As the deviation tolerance increased every 5%, the behavior of the results of both Fuzzy and BTC models showed the same behavior, that is, the hit level of the proposed Fuzzy model was significantly better than that generated by the BTC.

In the analysis of the results generated during the construction of the Fuzzy model, we defined for each value of the sample an interval with the range of the construction duration, assigning a minimum and maximum value to each value found with the modeling.

To this end, we used statistical performance indicators that indicate the variance between actual values and those assigned to construction duration by the model suggested in this study. Frist was calculated Mean Absolute Scaled Error (MASE) was 0.5594 (MASE<1 then can be used).

Because the MAPE value was 6.83%, it was used to stipulate the lower and upper limits of each of the generated values. In this way, it will be able to stipulate the range of the construction duration. As can be seen in Table 9, 12 results generated by the Fuzzy system were within this range, which represents a percentage of hit of the order of 75.00%.

Figure 12 **- Box-plot of the Fuzzy system deadline**

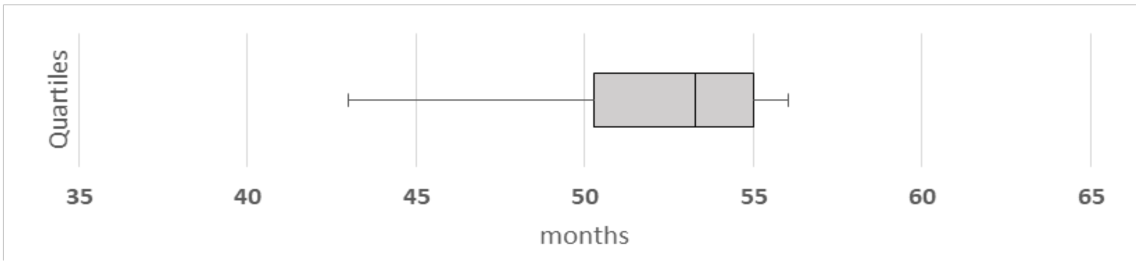


Figure 13 **– Comparison of hits of the models – Sample 02**

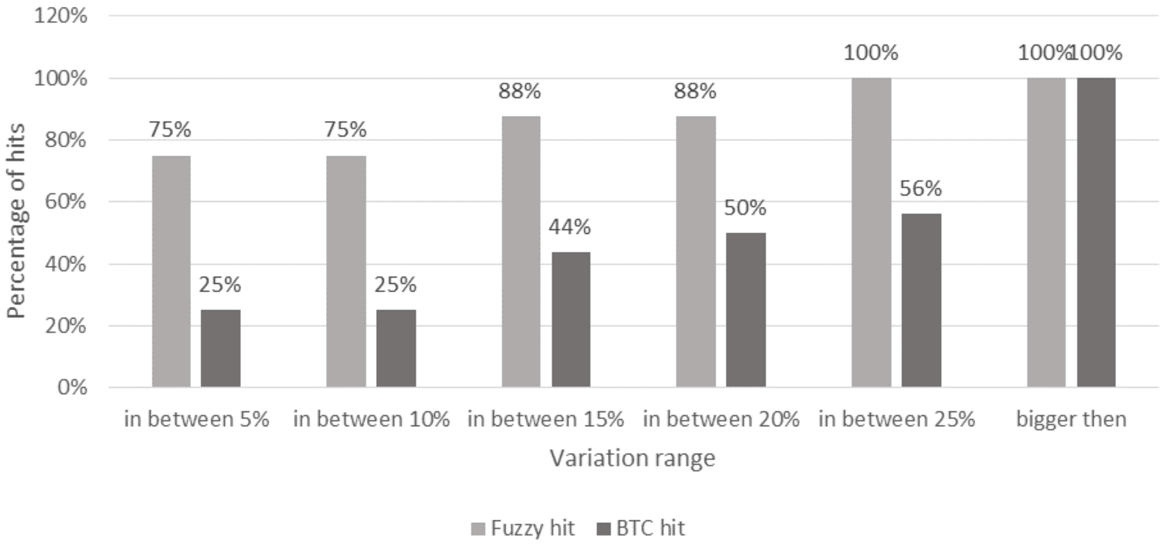


Table 9 **– Performance measurements between actual and Fuzzy values**

Hit condition for the construction duration range	Number of works	Percentage
Between the limits	12	75.00%
Below the lower limit	02	12.50%
Above the upper limit	02	12.50%

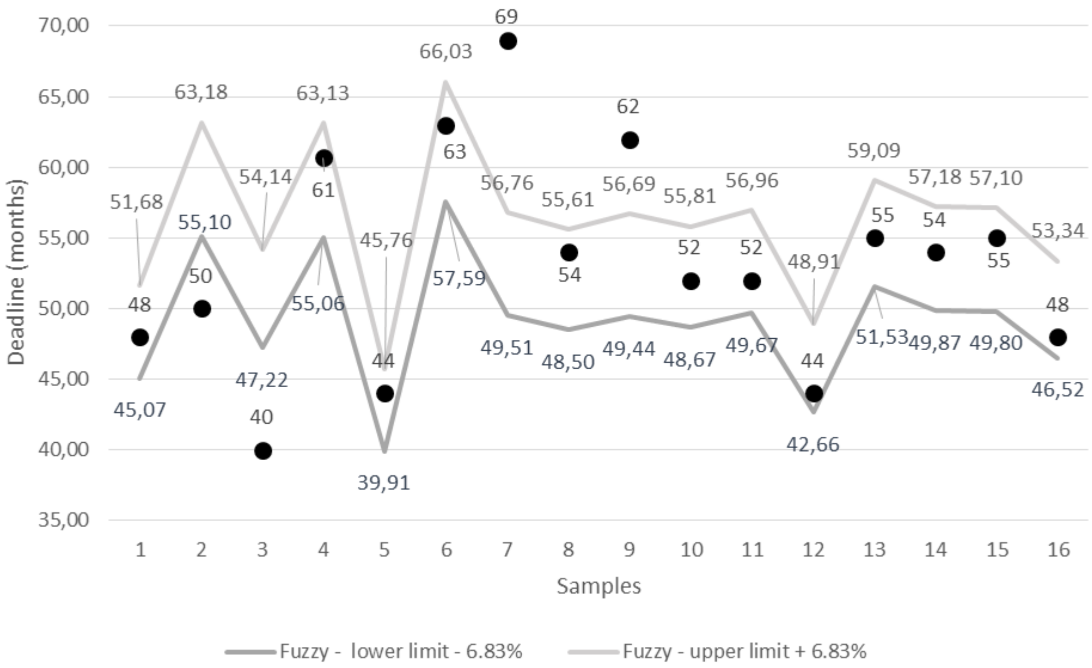
These values can be observed individually in Figure 14. It should be noted that in the validation phase the value calculated for the MASE was 0.56, this value was lower than that found in the model construction phase (0.89), showing that for this new set of samples the model was more assertive.

Nevertheless, it can be seen that two results presented the actual construction duration below the lower limit, representing that the works were completed in a period shorter than the value estimated by the Fuzzy model, already taking into account the limit. This is not a negative factor, since it represents that these works, when anticipating the date of their completion, benefited the entrepreneur in a certain way, making it possible to add more value in their rate of return, due to the anticipation of the delivery of the project to the buyers.

Considering these two results, that is, those predicted within the range of acceptance and values that were below the lower limit of the model, but which are acceptable values, since it shows that the work was completed in a shorter period than predicted by the model, the assertiveness value rises to 87.5%.

On the other hand, 12.5% works were completed with a deadline longer than the maximum limit generated by the Fuzzy system, representing a risk in the performance in relation to the delivery date of the work.

Figure 14 – **Inference of the fuzzy model of construction deadlines and variation range for the model validation process**



Conclusions

The objective of this research was to propose a model to estimate the construction duration of vertical residential works, even in the initial stage of the real estate implementation process, when the uncertainties regarding the characteristics of the projects are significant. A hybrid model was created with the use of factorial analysis (statistical) and fuzzy logic (artificial intelligence).

At first, data were collected from 142 works, using the statistical technique of factorial analysis, grouping 18 independent variables considered in the study into seven subsets or factors, which were used, in a later step, as input variables in the fuzzy model. The use of this technique provided an expressive reduction in the number of rules used in fuzzy modeling, since it reduced the number of rules from 3^{18} = 337,420,489 to only 180, demonstrating that the combination of these two techniques (statistical and artificial intelligence) was an important strategy in the modeling.

However, in constructing the fuzzy model, the second stage of modeling, only 71 of the 142 projects had planning and control of the work, and therefore, we can use them to define the actual construction duration and compare it with the result obtained through the fuzzy inference generated in the modeling. In order to evaluate the assertiveness of the model, three different forms were used:

(a) through descriptive statistics;

(b) by comparison with the BTC method - already consecrated and considered a model of great assertiveness; and

(c) by establishing a range with reference to the mean absolute percentage error (MAPE).

Inferring with other 16 real estate projects, it can be concluded that the suggested methodology provided satisfactory results for the prediction of the building construction duration of the residential work, since the percentage of assertiveness was 75% in relation to the minimum and maximum range of the construction deadline. This percentage rises to 87.5% if considering only those projects that were completed before the deadline predicted by the model. One of the limitations of the proposed model is the need to make adaptations, depending on the particularities of each region.

The elaborated model has the potential to be applied pragmatically in the search for solutions to real engineering problems, and although it has been studied in a specific construction segment and in a single city, if considering the particularities and differences, especially in choice of the explanatory variables and in the definition of the domains of membership functions of each of the factors that will be used in fuzzy systems.

It can be applied also in other segments, typologies and regions, being able, in this way, to contribute, to reduce subjectivity and empiricism so frequent in defining the deadline of construction works and, consequently, reduce the uncertainties and the risk of non-compliance with this deadline.

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