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Estimation Of The Unitary Cost Of The Square Meter Popular Housing In The City Of Manaus Based On The Most Important Inputs, Using Artificial Neural Networks

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Abstract: *Civil construction is one of the most expressive sectors in the economy, development and employability in the national territory. It is considered one of the branches that demonstrates the expansion and wealth of a country, where social housing is directly linked to socioeconomic development. According to the IBGE, in 2020, Manaus had 653,618 homes, of which 348,618 are classified as subnormal agglomerations, that is, stilt houses and unhealthy occupations and/or difficult to access. It can be said that one of the major obstacles to the construction of low-income housing is the lack of predictability of the behavior of costs during the execution of the work. This factor is even more pronounced in subdivisions and housing complexes, that is, in mass production, due to quantity. In order to mitigate these challenges, a tool was developed, based on the concepts of RNA - Artificial Neural Network, which compiles 2 civil construction price databases and predicts the cost of popular housing based on the value of the main inputs. This network seeks to estimate the cost per square meter of construction of popular housing in the city of Manaus. MATLAB® software was used, where data from the CUB and INCC databases were compiled. The inputs used were those contained in the so-called "basic batch", recommended by the CUB. Quickly and practically without cost, the developed tool can predict the price of the square meter of popular housing, in the city of Manaus, from the stipulation of the inputs. RNA was able to present a very strong correlation in the sources of its sample space, thus demonstrating that the databases, despite presenting different data collection and treatment, in addition to being elaborated by different institutes, present compatibility in their databases, which is reflected in the veracity and reliability of the data collected and processed. After estimating several statistical indices, it is clearly noted that this is a tool that has proven to be efficient and safe for estimating future costs.*

***Background**: The final cost of a work is one of the determining factors for carrying it out, especially in the more popular classes, where money is scarcer and any financial estimation errors can make the completion of the building unfeasible. In Brazilian territory, there are databases that predict the cost for the present, but none that estimate the cost for the future. This study develops an RNA to simulate the future value of a popular building in the city of Manaus.*

***Materials and Methods**: In this study, two databases were used as a national recognition database: the CUB and the INCC. The reference values were extracted from the databases, in monthly cadence, during the period from July 2009 to May 2022, to obtain an arithmetic medium for each item, thus allowing RNA simulation to predict the value of the square meter of the house.*

***Results**: Values for: MSE, NRMSE, MAPE, SER, MAE, RMSE, Medium Percent Error, and Pearson Correlation. All show adequate and correlated results. However, it can be stated that the most expressive result was the MSE, which was 91.14%, characterizing a well-adjusted RNA.*

***Conclusion**: The correlation between the data in the two databases was 91.14%, enabling the simulation of an artificial neural network with data from different sources and good accuracy.*

***Key Words**: Neural Network; Popular housing; Inputs, Price*

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I. Introduction

Civil construction is one of the sectors that most contributes to the increase in GDP - Brazilian Gross Domestic Product. Added to these factors, in Brazil, there is a housing deficit of 8 million homes in 2022 (JÚNIOR, 2022). Trying to generate support for builders and facilitate the budget forecast of works, databases and indexes begin to appear in the national territory, which are precisely intended to provide average prices of inputs and labor, the main ones being CUB and INCC. However, all these databases do not provide a forecast of future behavior with regard to prices. The longer the delivery time, the more variations can be accentuated. It is notorious that there is no price forecast that can serve as a guide for builders and financial preparation of consumers, only corrective measures after the price of inputs has already been changed in the market. In order to provide a corrected estimate of prices, the present work will create an RNA to correlate information from these two databases to generate a form of prediction of housing prices classified as "CP1Q – Popular House with One Bedroom", as it will be qualified accordingly. in the theoretical framework. The forecast will be based on the price of the main inputs used in the execution. The tool may prove to be very useful for quickly and inexpensively predicting the real price of the final construction. It becomes an interesting instrument for developers, builders and even for the final consumer, considering that they will have help in making the initial decision on whether or not the construction is viable.

II. Material And Methods

Data from the INCC and CUB databases were prospected, compiling a total of 157 data from the INCC database and 4553 data from the CUB database, for a total period of 157 months.

Study Design: According to the area of knowledge, this research can be framed in the area of engineering, since it deals with the application of a methodology that uses methodological tools focused on the development of a statistical prototype, with the purpose of application in the aforementioned area, through computational simulation.

Study Location: The present study was carried out in the city of Manaus, Amazonas, Brazil.

Study Duration: July 2009 to may 2022.

Sample size: 4710 samples

Sample size calculation: the sample size used in the study was obtained through what both databases made available. Naturally, the larger the sample, the greater the reliability. Aiming at this, we used all the samples to which we had access.

Subjects and selection method: an indicator was extracted from the CUB database that made up the prices recommended by it, called “basic batch of inputs”. All the values of these inputs were collected, totaling 4553 samples and, subsequently, a factor indicated by the same database was used, demonstrating the consumption of each material for the building in question. It was placed in ascending order and the materials that represented less than 2% of the final cost of the building were eliminated, leaving 14 types of input.

Inclusion criteria: All values arranged in both databases which we had access. The information is necessarily from Amazon State.

Exclusion criteria: Total price of the input below 2% of the total cost of the work

Procedure methodology: Online, the CUB database has its own address containing the databases of all federation units and the Federal District. To collect data, you must: Access the page “www.cub.org.br”; access the “State CUB/m2” tab; it will be necessary to fill in some items to obtain the spreadsheet that the user wants; select the option “Generate PDF Report” and an automatic download will start.

The reports referring to the state of Amazonas were downloaded during the period from July 2009 to May 2022 (monthly reports).

For the INCC, several online portals and journals use the INCC as an indicative and, in turn, make the index available on their own pages. On the site “http://www.yahii.com.br/incc.html” the following database was already compiled.

In this compilation provided by this address there was already enough data to contemplate the same periods extracted from the other databases.

Soon after, the data were arranged in a database of the MICROSOFT EXCEL2015® program. In this way, it was possible to compile all the data available on the internet from different files and formats into one.

With the help of the MATLAB R2016® software, several RNA’s models were simulated, with the “Cascade forward” type being the model that most presented congruences with the problem in question.

The RNA uses a learning algorithm, which is improved each time new data is entered into the database. In the case in question, it was decided to simulate the 12 training functions, in order to verify which would perform better with the data provided, as shown in Table 1, in order of use:

Table 1: Training functions

ID	FUNCTION	ALGORITHM
1	'trainlm'	Levenberg - Marquardt
2	'trainbr'	Regulation Bayesiana
3	'trainbfg'	BFGS Quasi - Newton
4	'trainrp'	Resilient retroprogramming
5	'trainscg'	Scaled Conjugate Gradient
6	'traincgb'	Conjugate Gradient With Powell / Baele Reset
7	'traincgf'	Fletcher - Powell Conjugate Gradient
8	'traincgp'	Polak - Ribiere Conjugate Gradient
9	'trainoss'	One Step Secant
10	'traingdx'	Descending Grasdient of Variable Learning Rate
11	'traingdm'	Gradient Descent With Momentum
12	'traingd'	Gradient Descent

Each of the 12 RNA training functions is combined with the 3 transfer functions, classified in Table 2:

Table 2: Transfer functions

.	FUNCTION	ALGORITHM
1	purelin'	Linear Transfer Function
2	'tansig'	Hyperbolic tangent Sigmoid Transfer Function
3	'logsig'	Log-Sigmoid Transfer Function

Totaling 36 combinations and, consequently, 36 RNA's with the parametric combinations, for validation of the best results.

III. Results

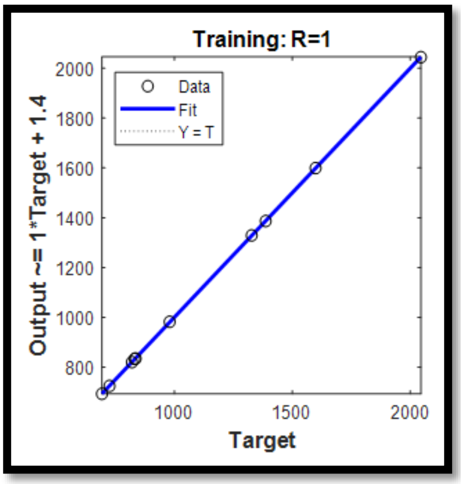
The medium square error has an optimal point when the result approaches 1, which in this case is the predicted value for the line. Two combinations showed excellent and identical results, as highlighted in Table 3:

Table 3: MSE

	purelin'	**'tansig'**	**'logsig'**
'trainlm'	59581,3914	49237,87	13776,31
'trainbr'	24,6808107	33,03905	200,0606
'trainbfg'	204,875229	204,8752	160,0405
'trainrp'	204,492424	204,4924	160,0405
'trainscg'	204,492424	218,5239	194,6041
'traincgb'	218,523872	218,5239	142,1148
'traincgf'	87,1043536	87,10435	9,018482
'traincgp'	2,35551097	1,042345	15,33881
'trainoss'	1,03028628	1,030286	8,214831
'traingdx'	5,91199643	4,085471	1,47649
'traingdm'	1,1923803	1,19238	1,47649
'traingd'	1,1923803	1,19238	1,47649

Graphs were also generated in order to illustrate and isolate the factors, with Figure 1 referring to network training, Figure 2 referring to validation, Figure 3 is the graph referring to the parametric test and, finally, Figure 4 is the compilation of all points on the same Cartesian plane. All points are on the same graph.

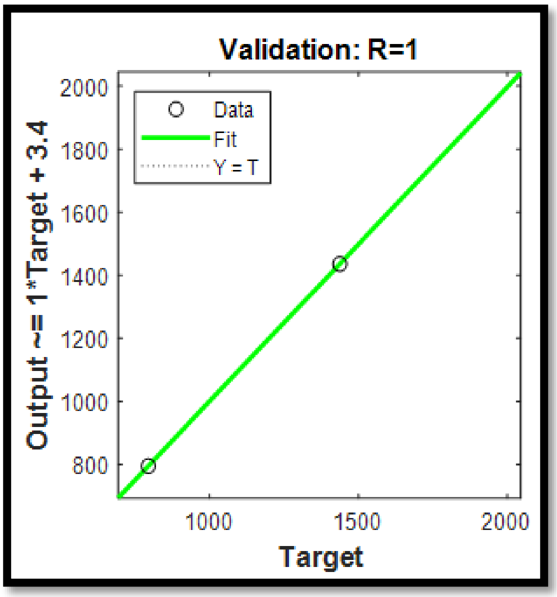
Figure 1: Training



Note that the points on the training function graph coincide with the straight line, considered "optimal", with no "outlier" points.

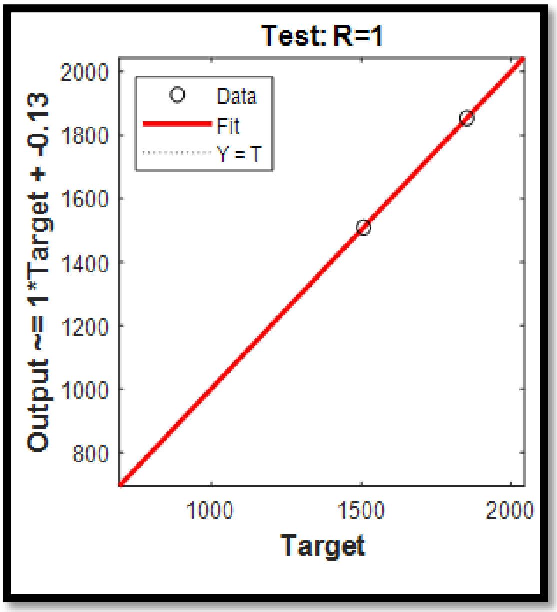
In the validation graph, shown in Figure 2, it is possible to notice characteristics similar to the previous one, that is, points well adjusted and coincident with the straight line.

Figure 2: Validation



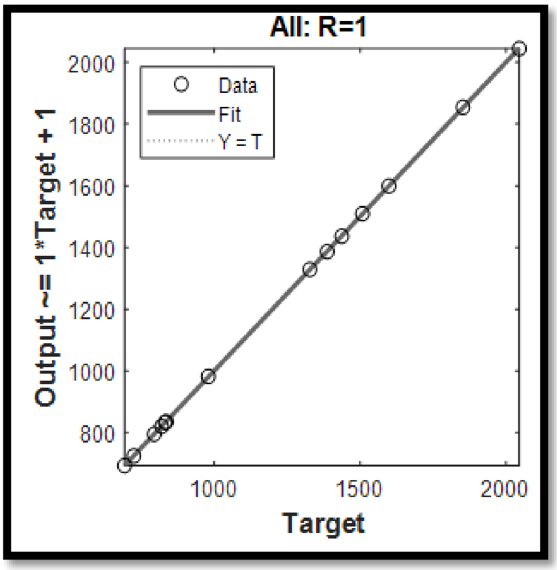
Validation proves that the function is well adjusted and with points superimposed on the straight line of the Cartesian plane.

Figure 3: Test



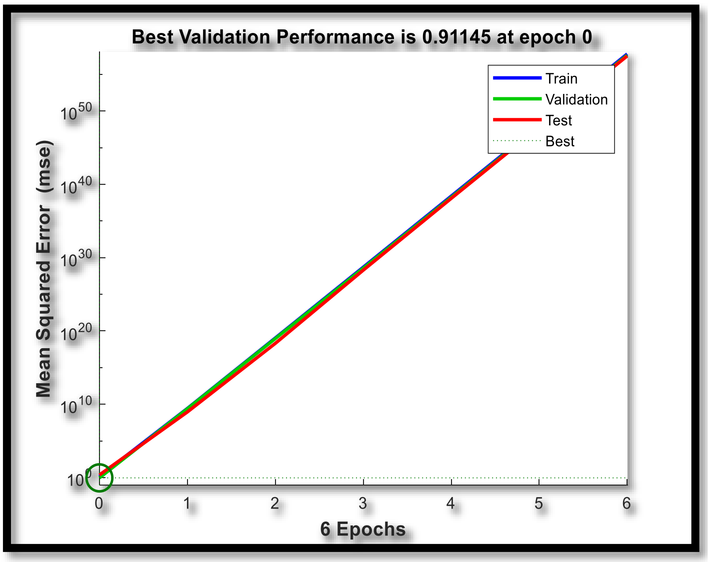
Placing all assumptions in a single graph, the one shown in Figure 4, it can be seen that the lines overlap, which is a prerogative and, together with that, the points overlap with slight deviations.

Figure 4: Compilation



In Figure 5, a graph was generated in which the points were equated in 2nd degree, generating the lines of the figure. The maximum performance obtained for the MSE- Medium Squared Error was 0.911.

Figure 5: Best result for the validation



In Figure 6, there is a histogram of errors generated during the creation of all RNAs until the best functioning one is found.

Figure 6: Histogram of error

This indicator shows the ratio between the root medium square error and the root medium square of the original values. The result closest to 0 will represent the most qualitative data for the creation of the RNA, according to Table 4.

Table 4:NRMSE

	purelin'	'tansig'	'logsig'
'trainlm'	244,093	221,8961	117,3725
'trainbr'	4,967979	5,74796	14,14428
'trainbfg'	14,31346	14,31346	12,65071
'trainrp'	14,30008	14,30008	12,65071
'trainscg'	14,30008	14,78255	13,95006
'traincgb'	14,78255	14,78255	11,92119
'traincgf'	9,332971	9,332971	3,003079
'traincgp'	1,534767	1,020953	3,916479
'trainoss'	1,01503	1,01503	2,866153
'traingdx'	2,43146	2,021255	1,215109
'traingdm'	1,091962	1,091962	1,215109
'traingd'	1,091962	1,091962	1,215109

The medium absolute percentage error is a relative error indicator that uses absolute values to prevent positive and negative errors from canceling each other out, as shown in Table 5:

Table 5: MAPE

	purelin'	'tansig'	'logsig'
'trainlm'	0,159003	0,064665	0,035801
'trainbr'	0,002003	0,001104	0,006166
'trainbfg'	0,010006	0,010006	0,009291
'trainrp'	0,009166	0,009166	0,009291
'trainscg'	0,009166	0,007031	0,010331
'traincgb'	0,007031	0,007031	0,009961
'traincgf'	0,007917	0,007917	0,001201
'traincgp'	0,001116	0,000931	0,001531
'trainoss'	0,00077	0,00077	0,001334
'traingdx'	0,001761	0,001553	0,000896
'traingdm'	0,000864	0,000864	0,000896
'traingd'	0,000864	0,000864	0,000896

The values obtained for the residual standard error analysis are shown in Table 6:

Table 6: RSE

		v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14
'trainlm'	**'purelin'**	16,17278	6,951462	13,74109	16,32432	34,36827	8,446454	5,344988	5,855813	32,65733	16,36082	38,72622	13,10386	4,629082	9,921219
'trainlm'	**'tansig'**	0,039187	0,046153	0,09608	0,069257	0,065469	0,042773	0,015191	0,014564	18,06158	0,020742	0,010394	39,07486	11,69681	21,27808
'trainlm'	**'logsig'**	0,713887	0,082135	1,001094	1,384984	1,041079	2,968945	0,920415	3,416437	0,63112	1,037822	21,37394	1,12018	0,149508	14,27986
'trainbr'	**'purelin'**	3,07E-10	5,57E-10	5,60E-11	0,681758	7,19E-10	2,121869	1,46E-10	3,34E-10	1,82E-10	2,82E-11	7,05E-11	3,59E-11	2,38E-11	1,05E-10
'trainbr'	**'tansig'**	2,08E-08	4,15E-08	5,88E-09	0,048749	2,33E-08	1,26E-07	8,89E-08	3,39E-08	1,54E-08	1,49652	2,95E-09	2,46E-09	6,33E-09	1,18E-08
'trainbr'	**'logsig'**	5,89E-10	7,093373	5,04E-10	1,539594	4,83E-09	3,60E-08	2,13E-08	6,13E-09	2,09E-09	1,81E-10	6,29E-11	5,35E-10	1,38E-09	1,85E-09
'trainbfg'	**'purelin'**	1,426864	5,64516	0,725486	2,129857	0,586615	0,472945	0,238502	0,09883	0,128969	0,06788	0,183163	0,465485	0,907682	0,931

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'trainbfg'	**'tansig'**	1,426864	5,64516	0,725486	2,129857	0,586615	0,472945	0,238502	0,09883	0,128969	0,06788	0,183163	0,465485	0,907682	0,931468
'trainbfg'	**'logsig'**	1,701303	5,407774	0,808645	2,205635	0,674561	0,446427	0,21146	0,199436	0,230068	0,030265	0,0686	0,242641	0,415823	0,365088
'trainrp'	**'purelin'**	0,799745	6,269718	0,022259	1,44386	0,076719	0,300947	0,425802	0,270652	0,219852	0,46456	0,482406	0,632946	0,752527	0,669977
'trainrp'	**'tansig'**	0,799745	6,269718	0,022259	1,44386	0,076719	0,300947	0,425802	0,270652	0,219852	0,46456	0,482406	0,632946	0,752527	0,669977
'trainrp'	**'logsig'**	1,701303	5,407774	0,808645	2,205635	0,674561	0,446427	0,21146	0,199436	0,230068	0,030265	0,0686	0,242641	0,415823	0,365088
'trainscg'	**'purelin'**	0,799745	6,269718	0,022259	1,44386	0,076719	0,300947	0,425802	0,270652	0,219852	0,46456	0,482406	0,632946	0,752527	0,669977
'trainscg'	**'tansig'**	0,31627	7,255176	2,105678	1,30E-09	7,37E-09	2,19E-09	6,26E-09	1,95E-09	1,11E-09	5,17E-09	5,30E-09	2,81E-09	2,40E-10	0,165631
'trainscg'	**'logsig'**	1,217998	6,393058	1,319107	0,761942	0,751411	0,747501	0,637367	0,470166	0,449995	0,434363	0,41387	0,39036	0,336747	0,139301
'traincgb'	**'purelin'**	0,31627	7,255176	2,105678	1,26E-09	7,35E-09	2,22E-09	6,27E-09	1,95E-09	1,11E-09	5,17E-09	5,30E-09	2,81E-09	2,51E-10	0,165631
'traincgb'	**'tansig'**	0,31627	7,255176	2,105678	1,30E-09	7,37E-09	2,19E-09	6,26E-09	1,95E-09	1,11E-09	5,17E-09	5,30E-09	2,81E-09	2,40E-10	0,165631
'traincgb'	**'logsig'**	3,020967	4,094327	0,256572	2,019554	1,748736	1,19896	0,668991	0,217075	0,151161	0,067146	0,061705	0,259147	0,13531	0,045675
'traincgf'	**'purelin'**	1,346538	3,191415	0,336755	1,955674	1,402727	0,305124	0,69942	0,069061	0,46651	0,222945	0,372492	0,217509	0,238959	0,258675
'traincgf'	**'tansig'**	1,346538	3,191415	0,336755	1,955674	1,402727	0,305124	0,69942	0,069061	0,46651	0,222945	0,372492	0,217509	0,238959	0,258675
'traincgf'	**'logsig'**	0,010203	0,017646	0,104296	0,076402	0,040335	0,034784	0,506988	0,087297	0,061113	0,052217	0,654854	0,021241	0,004973	0,00894
'traincgp'	**'purelin'**	0,101712	0,050284	0,095431	0,143561	0,108433	0,253276	0,069618	0,209184	0,22078	0,141923	0,029572	0,106238	0,006438	0,026189
'traincgp'	**'tansig'**	0,161213	0,13701	0,080096	0,16318	0,123078	0,175064	0,161965	0,122044	0,003261	0,046816	0,04523	0,052905	0,011677	0,019272
'traincgp'	**'logsig'**	0,046823	0,169605	0,048589	0,076271	0,098213	0,315162	0,015539	0,074769	0,040758	0,143185	0,034965	0,083097	0,433647	0,563475
'trainoss'	**'purelin'**	**0,113669**	**0,006322**	**0,035943**	**0,059012**	**0,204881**	**0,180622**	**0,11385**	**0,058456**	**0,038933**	**0,14461**	**0,015142**	**0,064567**	**0,000608**	**0,041937**

'trainoss'	**'tansig'**	**0,113669**	**0,006322**	**0,035943**	**0,059012**	**0,204881**	**0,180622**	**0,11385**	**0,058456**	**0,038933**	**0,14461**	**0,015142**	**0,064567**	**0,000608**	**0,041937**
'trainoss'	**'logsig'**	0,161302	0,032738	0,002608	0,179041	0,054455	0,157761	0,157823	0,071259	0,060171	0,189248	0,055152	0,0634	0,26972	0,41351
'traingdx'	**'purelin'**	0,333226	0,38404	0,230165	0,334366	0,082172	0,290827	0,104348	0,000924	0,142047	0,18939	0,003557	0,018279	0,045429	0,306649
'traingdx'	**'tansig'**	0,212609	0,18357	0,279443	0,154967	0,383815	0,070974	0,35964	0,12776	0,026859	0,034438	0,095634	0,02041	0,014849	0,208876
'traingdx'	**'logsig'**	0,030888	0,004732	0,142374	0,033139	0,255563	0,081729	0,236727	0,095707	0,044448	0,051363	0,088759	0,042674	0,090422	0,056005
'traingdm'	**'purelin'**	0,073462	0,104491	0,051353	0,055033	0,16861	0,168234	0,162967	0,0413	0,096521	0,101628	0,040864	0,002499	0,051453	0,091292
'traingdm'	**'tansig'**	0,073462	0,104491	0,051353	0,055033	0,16861	0,168234	0,162967	0,0413	0,096521	0,101628	0,040864	0,002499	0,051453	0,091292
'traingdm'	**'logsig'**	0,030888	0,004732	0,142374	0,033139	0,255563	0,081729	0,236727	0,095707	0,044448	0,051363	0,088759	0,042674	0,090422	0,056005
'traingd'	**'purelin'**	0,073462	0,104491	0,051353	0,055033	0,16861	0,168234	0,162967	0,0413	0,096521	0,101628	0,040864	0,002499	0,051453	0,091292
'traingd'	**'tansig'**	0,073462	0,104491	0,051353	0,055033	0,16861	0,168234	0,162967	0,0413	0,096521	0,101628	0,040864	0,002499	0,051453	0,091292
'traingd'	**'logsig'**	0,030888	0,004732	0,142374	0,033139	0,255563	0,081729	0,236727	0,095707	0,044448	0,051363	0,088759	0,042674	0,090422	0,056005

For the case in question, the medium absolute error is a good metric, mainly because it eliminates "outliers" quite successfully. The values obtained follow in Table 7.

Table 7: MAE

	purelin'	**'tansig'**	**'logsig'**
'trainlm'	190,1324	109,338	55,10087
'trainbr'	1,6655	1,564485	4,572613
'trainbfg'	9,665642	9,665642	8,08831
'trainrp'	9,190015	9,190015	8,08831
'trainscg'	9,190015	5,347751	9,322097
'traincgb'	5,347751	5,347751	8,196375
'traincgf'	7,258616	7,258616	1,463722
'traincgp'	1,241495	0,902294	2,228326
'trainoss'	0,818097	0,818097	1,854287
'traingdx'	1,854178	1,605598	1,017377
'traingdm'	0,953761	0,953761	1,017377
'traingd'	0,953761	0,953761	1,017377

The values obtained by this statistical tool are the square root of the predicted medium subtracted from the found squared. Low values are well seen in this analysis, which is explained in Table 8.

Table 8: RMSE

	purelin'	'tansig'	'logsig'
'trainlm'	244,093	221,8961	117,3725
'trainbr'	4,967979	5,74796	14,14428
'trainbfg'	14,31346	14,31346	12,65071
'trainrp'	14,30008	14,30008	12,65071
'trainscg'	14,30008	14,78255	13,95006
'traincgb'	14,78255	14,78255	11,92119
'traincgf'	9,332971	9,332971	3,003079
'traincgp'	1,534767	1,020953	3,916479
'trainoss'	1,01503	1,01503	2,866153
'traingdx'	2,43146	2,021255	1,215109
'traingdm'	1,091962	1,091962	1,215109
'traingd'	1,091962	1,091962	1,215109

The values obtained in the study of the average percentage error (deviation of each value in percentage) are shown in Table 9:

Table 9: Error Average Percentage

		v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14
'trainlm'	**'purelin'**	0,161728	0,069515	0,137411	0,163243	0,343683	0,084465	0,05345	0,058558	0,326573	0,163608	0,387262	0,131039	0,046291	0,0992122
'trainlm'	**'tansig'**	0,000392	0,000462	0,000961	0,000693	0,000655	0,000428	0,000152	0,000146	0,180616	0,000207	0,000104	0,390749	0,116968	0,2127808
'trainlm'	**'logsig'**	0,007139	0,000821	0,010011	0,01385	0,010411	0,029689	0,009204	0,034164	0,006311	0,010378	0,213739	0,011202	0,001495	0,1427986
'trainbr'	**'purelin'**	3,07E-12	5,57E-12	5,6E-13	0,006818	7,19E-12	0,021219	1,46E-12	3,34E-12	1,82E-12	2,82E-13	7,05E-13	3,59E-13	2,38E-13	1,046E-12
'trainbr'	**'tansig'**	2,08E-10	4,15E-10	5,88E-11	0,000487	2,33E-10	1,26E-09	8,89E-10	3,39E-10	1,54E-10	0,014965	2,95E-11	2,46E-11	6,33E-11	1,179E-10
'trainbr'	**'logsig'**	5,89E-12	0,070934	5,04E-12	0,015396	4,83E-11	3,6E-10	2,13E-10	6,13E-11	2,09E-11	1,81E-12	6,29E-13	5,35E-12	1,38E-11	1,847E-11
'trainbfg'	**'purelin'**	0,014269	0,056452	0,007255	0,021299	0,005866	0,004729	0,002385	0,000988	0,00129	0,000679	0,001832	0,004655	0,009077	0,0093147
'trainbfg'	**'tansig'**	0,014269	0,056452	0,007255	0,021299	0,005866	0,004729	0,002385	0,000988	0,00129	0,000679	0,001832	0,004655	0,009077	0,0093147
'trainbfg'	**'logsig'**	0,017013	0,054078	0,008086	0,022056	0,006746	0,004464	0,002115	0,001994	0,002301	0,000303	0,000686	0,002426	0,004158	0,0036509
'trainrp'	**'purelin'**	0,007997	0,062697	0,000223	0,014439	0,000767	0,003009	0,004258	0,002707	0,002199	0,004646	0,004824	0,006329	0,007525	0,0066998
'trainrp'	**'tansig'**	0,007997	0,062697	0,000223	0,014439	0,000767	0,003009	0,004258	0,002707	0,002199	0,004646	0,004824	0,006329	0,007525	0,0066998
'trainrp'	**'logsig'**	0,017013	0,054078	0,008086	0,022056	0,006746	0,004464	0,002115	0,001994	0,002301	0,000303	0,000686	0,002426	0,004158	0,0036509
'trainscg'	**'purelin'**	0,007997	0,062697	0,000223	0,014439	0,000767	0,003009	0,004258	0,002707	0,002199	0,004646	0,004824	0,006329	0,007525	0,0066998
'trainscg'	**'tansig'**	0,003163	0,072552	0,021057	1,3E-11	7,37E-11	2,19E-11	6,26E-11	1,95E-11	1,11E-11	5,17E-11	5,3E-11	2,81E-11	2,4E-12	0,0016563
'trainscg'	**'logsig'**	0,01218	0,063931	0,013191	0,007619	0,007514	0,007475	0,006374	0,004702	0,0045	0,004344	0,004139	0,003904	0,003367	0,001393
'traincgb'	**'purelin'**	0,003163	0,072552	0,021057	1,26E-11	7,35E-11	2,22E-11	6,27E-11	1,95E-11	1,11E-11	5,17E-11	5,3E-11	2,81E-11	2,51E-12	0,0016563
'traincgb'	**'tansig'**	0,003163	0,072552	0,021057	1,3E-11	7,37E-11	2,19E-11	6,26E-11	1,95E-11	1,11E-11	5,17E-11	5,3E-11	2,81E-11	2,4E-12	0,0016563
'traincgb'	**'logsig'**	0,03021	0,040943	0,002566	0,020196	0,017487	0,01199	0,00669	0,002171	0,001512	0,000671	0,000617	0,002591	0,001353	0,0004567
'traincgf'	**'purelin'**	0,013465	0,031914	0,003368	0,019557	0,014027	0,003051	0,006994	0,000691	0,004665	0,002229	0,003725	0,002175	0,00239	0,0025867
'traincgf'	**'tansig'**	0,013465	0,031914	0,003368	0,019557	0,014027	0,003051	0,006994	0,000691	0,004665	0,002229	0,003725	0,002175	0,00239	0,0025867
'traincgf'	**'logsig'**	0,000102	0,000176	0,001043	0,000764	0,000403	0,000348	0,00507	0,000873	0,000611	0,000522	0,006549	0,000212	4,97E-05	8,94E-05

'train cgp'	**'purelin'**	0,001017	0,000503	0,000954	0,001436	0,001084	0,002533	0,000696	0,002092	0,002208	0,001419	0,000296	0,001062	6,44E-05	0,0002619
'train cgp'	**'tansig'**	0,001612	0,00137	0,000801	0,001632	0,001231	0,001751	0,00162	0,00122	3,26E-05	0,000468	0,000452	0,000529	0,000117	0,0001927
'train cgp'	**'logsig'**	0,000468	0,001696	0,000486	0,000763	0,000982	0,003152	0,000155	0,000748	0,000408	0,001432	0,00035	0,000831	0,004336	0,0056348
'train oss'	**'purelin'**	0,001137	6,32E-05	0,000359	0,00059	0,002049	0,001806	0,001139	0,000585	0,000389	0,001446	0,000151	0,000646	6,08E-06	0,0004194
'train oss'	**'tansig'**	0,001137	6,32E-05	0,000359	0,00059	0,002049	0,001806	0,001139	0,000585	0,000389	0,001446	0,000151	0,000646	6,08E-06	0,0004194
'train oss'	**'logsig'**	**0,001613**	**0,000327**	**2,61E-05**	**0,00179**	**0,000545**	**0,001578**	**0,001578**	**0,000713**	**0,000602**	**0,001892**	**0,000552**	**0,000634**	**0,002697**	**0,0041351**
'train gdx'	**'purelin'**	**0,003332**	**0,00384**	**0,002302**	**0,003344**	**0,000822**	**0,002908**	**0,001043**	**9,24E-06**	**0,00142**	**0,001894**	**3,56E-05**	**0,000183**	**0,000454**	**0,0030665**
'train gdx'	**'tansig'**	0,002126	0,001836	0,002794	0,00155	0,003838	0,00071	0,003596	0,001278	0,000269	0,000344	0,000956	0,000204	0,000148	0,0020888
'train gdx'	**'logsig'**	0,000309	4,73E-05	0,001424	0,000331	0,002556	0,000817	0,002367	0,000957	0,000444	0,000514	0,000888	0,000427	0,000904	0,0005601
'train gdm'	**'purelin'**	0,000735	0,001045	0,000514	0,00055	0,001686	0,001682	0,00163	0,000413	0,000965	0,001016	0,000409	2,5E-05	0,000515	0,0009129
'train gdm'	**'tansig'**	0,000735	0,001045	0,000514	0,00055	0,001686	0,001682	0,00163	0,000413	0,000965	0,001016	0,000409	2,5E-05	0,000515	0,0009129
'train gdm'	**'logsig'**	0,000309	4,73E-05	0,001424	0,000331	0,002556	0,000817	0,002367	0,000957	0,000444	0,000514	0,000888	0,000427	0,000904	0,0005601
'train gd'	**'purelin'**	0,000735	0,001045	0,000514	0,00055	0,001686	0,001682	0,00163	0,000413	0,000965	0,001016	0,000409	2,5E-05	0,000515	0,0009129
'train gd'	**'tansig'**	0,000735	0,001045	0,000514	0,00055	0,001686	0,001682	0,00163	0,000413	0,000965	0,001016	0,000409	2,5E-05	0,000515	0,0009129
'train gd'	**'logsig'**	0,000309	4,73E-05	0,001424	0,000331	0,002556	0,000817	0,002367	0,000957	0,000444	0,000514	0,000888	0,000427	0,000904	0,0005601

The values obtained for the study of Pearson's correlation are shown in Table 11. It is worth noting that only data representing more than 2% of the overall value of the work were used, discarding inputs of lesser significance. The correlation value, considering INPUT’s x INCC, is shown in the last column of Table 11.

Table 11: Pearson Correlation

Nº	BASIC COMPONENTS (PER M2 OF CONSTRUCTION)	MED	PEARSON
1	Manson	**h**	0,151181263
2	Helper	**h**	0,146095636
3	Cement CP-32 II	**kg**	0,833504195
4	Plastified Plyward Sheet 18 mm 2,20 x 1,10 m	**m²**	0,532149259
5	Ceramic Brick 9 cm x 19 cm x 19 cm	**un**	0,42088354
6	Internal door without paint (wood) 0,60 x 2,10 m	**un**	-0,250767814
7	Ceramic plate for floor ~30 cm x 40 cm, PEI II, White color	**m²**	0,415316168
8	windom 1,20 m x 1,20 m em 2 opens, made in steel with paint	**m²**	0,408302229
9	Rock number 02	**m³**	0,466515036
10	Pipe of PVC-R for sewage ø 150 mm	**m**	0,517232657
11	Steel bar for concrete CA-50 ø 10 mm	**kg**	0,780989155
12	Roof tile 6 mm 2,44 x 1,10 m	**m²**	0,330334697
13	PVA Paint	**l**	0,699365438
14	Tripolar Key 70 A	**un**	0,083022827

It is noted that some items have a strong correlation, especially those of consumption. The items with the highest correlation are cement and steel.

IV. Discussion

In this study, a neural network was created in which data from two major civil construction indices were correlated in order to create price forecasts for the construction of popular houses, based on inputs commonly consumed in this type of work.

The correlations calculated between the databases carried out in this research are perfectly synergistic. The degree of correlation between the two databases is quite expressive, according to the data shown in Chapter 4, thus demonstrating that, despite not being administered or created by the same institution, the collected data prove to be reliable to reality, in view of the conformation of the same.

The result obtained proves that the model can be an effective tool for decision-making during the period characterized as an economic feasibility study, a stage in which there is still not much information regarding the project and deadlines, which in the context of civil construction can mean several years.

V. Conclusion

The implementation of the sample space for the creation of an RNA that would demonstrate the costs of the square meter of popular construction in the city of Manaus was successful. Although the two databases used in this work were collected and treated in completely different ways, by different institutions, the synergy and correlation between the data proved that there is a certain degree of confidence in the tool generated here for predicting the price of “RP1Q”.

The model has good indications in all the statistical parameters measured in the development of the work, thus showing that there is some reliability in the results of the tool to predict the value of the square meter of the property type “RP1Q”. The tool allows the user to estimate the price of inputs and obtain the final unit value.

Furthermore, it is worth highlighting the values obtained in the “MSE” for the “optimal point”: the functions “trainoss x purelin” and “trainoss x tansig” both presented a value of 1.030. It is precisely this value very close to 1 that indicates the degree of linear adjustment between the two variables in the Cartesian plane. It is one of the main indications of the correlation between the data in both databases. It is noteworthy that the data were compared for the same period.

Can be noted in all graphical results that the points obtained are easily “fitted” into a straight line derived from a 2nd degree equation. This behavior indicates that there is a linear proportionality between the values, so that the statistical experiments can be considered successful, as they presented values considered good to ideal within the proposed parameters.

The best validation performance is 0.91145 at epoch 0, for simulation of 6 epochs with “trainoss x purelin” and “trainoss x tansig”. The maximum possibility is “1”.

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