Artificial Neural Network model for estimating the female and male Population in working age in Venezuela

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Abstract: This work presents an Artificial Neural Networks application for estimating the female and male population with working age in Venezuela. This model will predict future values of the Venezuelan population with working age, which will help in decision making at governmental, firms and institutions responsible for Venezuelan social security, in order to improve the functioning of the labor market both female and male. For the creation of the model it is used the previous year values related to the employed, unemployed and inactive population (out of the labor force).

Key-Words: Labor Force, Regression Analysis, Artificial Neural Networks.

1 Introduction

The labor market is comprised of three main actors: those who offer work, those who demand the work and government who regulate the exchanges, mainly through subsidies and taxes. The labor market theory is aimed at studying the behavior of bidders and working appellants against a set of monetary and non-monetary incentives [4]. This article will address the potential labor supply, represented by the working-age population, which is the set of people with 15 or more years of age that are potential to provide the available manpower for goods and services production to the market. The working age population is composed of the active labor force, commonly known as the economically active population (EAP) and the inactive labor force, commonly known as economically inactive population (EIP).

Recently, the Economic Commission for Latin America and the Caribbean (CEPAL) [3] has argued that the growth of the labor force in Latin America is mainly due to the strong tendency of women to enter the labor market, given that it has substantially increased their years of schooling. The increase in the labor force participation rate of women from 2002 to 2005 (55.5% to 58.1%) was significantly greater than that of men (82.7% to 83.2%). This demonstrates the increasing speed with which women are entering to the labor market.

The increase in female activity rate in Venezuela reflects the greater incorporation of women into the labor market, and there are two fundamental economic reasons for this addition: in 1970 the economic expansion is due to the increase in oil prices, and in the 80s is the economic crisis deepened and demanded the incorporation of women to compensate for the drop in real income of households [24]. Paredes [20], claims that Venezuelan women have entered to the labor market massively in the last three decades and are they who have contributed in large measure the net increase in the labor force. Their participation in the last thirty years has risen from 23.9% in 1971 to 52.5% in 2001, representing an increase in the rate of 28.6 percentage points. Iranzo and Richter [10] for the nineties, found that employment growth in Venezuela was higher among women than men and have been most affected by unemployment, whereas in 1990 its rate of unemployment was 20% higher than the male, in 1998 this ratio rose to 47%.

The Latin American Institute for Social Research (ILDIS) [9] when analyze the Venezuelan labor market, found that the increased participation of women in the Venezuelan labor market has been accompanied by a diminution in formal sector and growing up of informal sector: in 2000 the informal sector was 52% of all jobs and women's participation in its internal have increased 12-point in the decade and the male was only 1%.

For example, Acevedo [1] asserts that the limitations on women's access to the Venezuelan labor market do not match the educational levels achieved by them. Currently, women in the labor force are better prepared than men, because they have, on average, a better education standard than them. In his study Acevedo highlights three trends in gender inequalities at work in Venezuela; i) inequalities in access to employment; ii) precariousness of women's work, and iii) inequality in reproductive burdens.

The work of Lameda and Aguayo [12] focus on the relationship between education and employment for women, considering the impact it can have on the occupational structure (depending on type of activity) in the Venezuelan case. In the performed regressions they have used the of ordinary least squares method and they found that the educational variable has a statistically significant impact on the variable explained in most sectors, highlighting its impact on the cases of services and professionals, technicians and related workers.

Another interesting work is made by Lamelas [11]; in his work done for Venezuela during the 1975-2000 period, was focus on: i) analyze the evolution of women's total employment and by sector, and ii) analyze the evolution of certain educational indicators for illustrating the characteristics of the transition process. He found that the percentage of years invested at superior education by the female population increases the total female employment and some sectors of female employment.

Orlando and Zuñiga [20] conducted a very important investigation because it shows an approach to the women situation in the Venezuelan labor market focusing on two key issues, their participation and level of employment income earned. To do this, they have considered a general model of payment, using the ordinary least Square, with the purpose of determining the isolated influence of the sex on the payments. Additionally, they have decomposed the income gap between men and women, using the Oaxaca and Blinder technique, in a portion explained by human capital variables and labor market characteristics and an unexplained portion that is attributed to the presence of discrimination and/or lack of women mobility among different types of work. The results obtained by Orlando and Zuñiga show that men have incomes 20% higher than women with similar education and experience and performing in the same sector and occupation. Concerning the decomposition, they note that the differences in income among working men and women come from differences in the pay structure that can not be explained by differences in education, experience or economic sector.

For all the studies mentioned above, it is necessary to have a model that allows predicting the Venezuelan population with working age (EAP and EIP) and thus being able to determine the number of Venezuelans who could be employed, unemployed or inactive in the short term. In other words, being able to predict the structure of the Venezuelan labor market, on the supply side. In this way, both the employer and the government having his role of regulator, may establish the actions and public policies necessary to achieve the best conditions for the functioning of the labor market and the most equitable way possible.

This paper presents a model, using artificial neural networks, which represents the structure of the Venezuelan potential labor supply, both male and female, during the period 1990 - 2007, a model for estimating Venezuelan potential labor supply by gender. Artificial Neural Networks (ANN) are techniques that have been widely used [2, 6, 7, 13, 14, 15, 17, 19, 22] for predicting values from known observations (patterns), based on the emulation of human brain capabilities.

The article is organized as follows: section 2 provides an overview on the Labor Force, in section 3 are generated models for estimating the Venezuelan population with working age, both male and female, including the statistics analysis and justification for the use of the ANN for modelling. Section 4 presents some conclusions, recommendations and possible future work.

2 Labor Force

Labor force is defined as all persons who provide the available manpower for goods and services production to the market. This population can be economically active population (EAP) or economically inactive population (EIP). The first of these called "active labor force," which comprises all those persons with 15 or more years old, who are working or are willing to work. To all persons who are outside the labor force, are called the "Inactive labor force", they are doing other activities such as home work, studying, living from the income, retirees, seniors or disabled, but could join at any time the active labor force.

The active labor force, is comprised of people who may be working or not. Those who are in the first situation are defined as employed population, because they are working and being paid for it. Those who are in the second situation, are defined as unemployed population, which may be with no work (they had a job but have lost it) or looking for work for the first time [16].

Finally, someone with 15 years or more may be working in two sectors of the economy: public sector or private sector. In the latter case, the worker can be found in the formal or informal sector of the economy. Those people who are working: on their own, as patron, employer, employee or worker in a company with fewer than 5 workers or as domestic workers are considered informal sector workers. Those who are working in enterprises with five or more people are considered in the formal sector of the economy.

The structure and dynamics of the labor force, explained in the paragraphs above, is depicted in Figure 1.

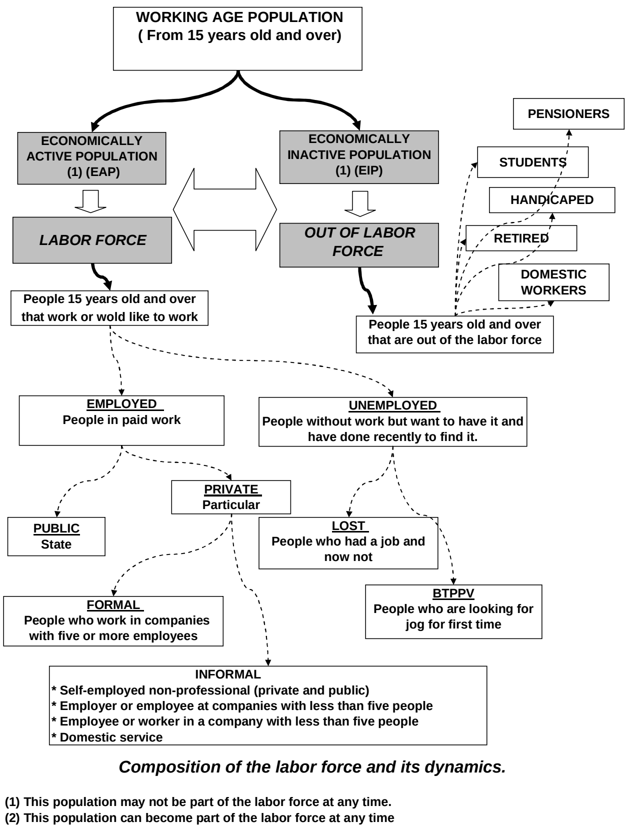

Figure 1. Composition of the Task Force and its dynamism

3 Artificial Neural Networks

Artificial Intelligence (AI) [2, 5] tries to emulate human intelligence capabilities, including expertise, decision making, autonomy, learning, classification, among others. The artificial neural networks [6] are part of the AI and have been widely used in various areas [7, 17, 19, 22, 25] due to its ability to learn and generalize by analogy with the functioning of the human brain. This generalization capability allows obtaining appropriate responses from different patterns to those used in the learning phase.
In the artificial model, the operations carried out in the neuron cell body (soma) can be seen as a process in which all signals are received through the dendrites, are added together and if they exceed the limit storage of the neuron, they are excited to generate an output signal using the axon, when the limit is not reached, the neurons remain in their inhibitory state.
Under the conditions of the neural network model, it can be introduced the following scheme (Figure 2).

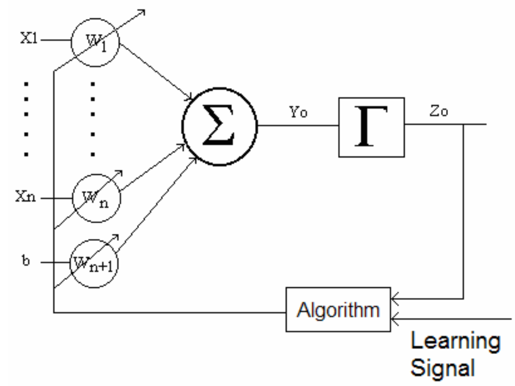

Figure 2. adaptive artificial neuron Scheme

Artificial neural networks consist of one or more adaptive neurons that contain the following elements:
- A sum of weighted inputs and generates a corresponding output signal using an activation function.
- An output of each neuron (axon).
- A group of post synaptic interconnection weights.
- A learning algorithm.

Representation capabilities of a neural network depend on the intensity of the interconnections between neurons (synapses) and the learning algorithm used for training or updating of the weights.
In Figure 2 can be found the following expressions:

$$Y_0(t) = \sum_{i=1}^{n} W_i(t) X_i(t) + W_{n+1}(t) b \quad (1)$$

$$Z_o = \Gamma(Y_0) \quad (2)$$

Where "xi" are the neuron inputs, "Wi" are the synaptic interconnection weights and "b" is a bias or deviation signal. Γ Is the activation function, among which the most commonly used are the sigmoid functions or logistic, Hyperbolic Tangent and linear.

The learning algorithm updates the interconnection weights and of course, the operation of the neural network depends on this task.

4 Model with gender perspective for the estimation of Venezuelan population with working age using artificial neural networks

4.1 Data Source

For the estimation of the model it was used data provided by the Venezuelan National Institute of Statistics (INE), which include the period from 1990 to 2007. The variables included in the study correspond to the total population with working age (PET), the total employed population (PTO), the total unemployed population (PTD) and the total inactive population (PTI), all of them discriminated by sex and measured each semester, for a total of 4 variables and 36 observations that correspond to the semester measurements obtained through the Sample House Survey.

The values of total population with working age, the total employed population, the total unemployed population and inactive population represent the millions of Venezuelans who are in each of these sectors.

4.2 Statistical Analysis

Considering that the objective of the study is the estimation of the Venezuelan male and female population with working age in terms of employed, unemployed and inactive women and men respectively, is given exploratory univariate analysis for detecting atypical cases, select the independent or explanatory variables for each model and verify the assumptions on which it is based linear regression that arises as the first estimation method. For this analysis it was used the statistical computational package SPSS version 13 [23].

In the exploratory analysis there was no evidence of atypical observations. Figure 3 illustrates a joint temporary chart with the female population with working age and male population with working age that have been measured in the same time periods. That chart shows that both variables present growing trend and there is no evidence of other components (cyclical or seasonal). It also notes that the female population with working age is slightly higher than the male. As the objective is making a short term estimation, it is better using linear regression that time series, which could also be used.

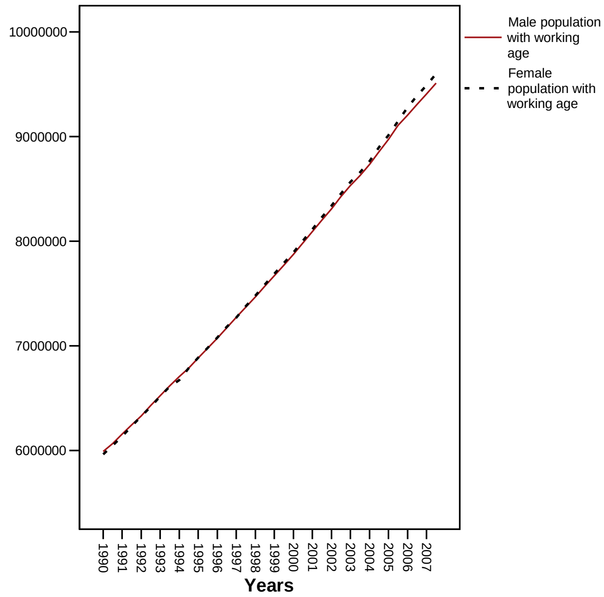

Figure 3. Temporary chart of male and female population with working age

There are made joint temporary sets graphics for female and male population concerning the total employed population, unemployed population, and for the total inactive population variables. From these graphics is important to emphasize the following points:

- Employed Population: This variable is clearly bigger the amount of male employed population that the female employed population; in percentage terms, the female employed population is only 54.24% of the male employed population, as can be seen in Figure 4. In both series it can be seen a general upward trend. The female employed population graph shows a minimal point occurred in the second half of 1993 and that value can be attributed to the economic and political crisis experienced in Venezuela in the early 90’s; in the male population is detected an irregular movement that produces a minimum in the first half of 2003 and can be attributed to the effect of the oil strike occurred in Venezuela in late 2002 and early 2003 that had a significant impact on the country's economy.
- Unemployed Population: In both series is evident decline in the unemployed population in the period between the first half of 1992 and the last half of 1994. Subsequently from 1995 it shows an increasing trend of female and male unemployed population that reaches a peak in the first half of 2000. In the case of

the female population shows a decrease of the unemployed population since the second half of 2000 that extends until the second half of 2002 and the first half of 2003 both sets reach the maximum number of men and women unemployed in the period study, which is attributable also to the effects of the oil strike. Subsequently, starting in the second half of 2003 both series have decreased. In percentage terms, the unemployed female population represents only 70.55% of the male population unemployed (see Figure 5).

- Inactive Population: In the case of the female inactive population, the series presents certain movements that start with an upward trend until the second half of 2004 where it reaches a maximum, and then another peak in the second half of 1995. There is a decrease of the female population inactive since the beginning of 1996 until 2000, when it returns to experience a growth that continued until the second half of 2002, and from 2003 the inactive female population increases again, which can be attributed to the government social programs (named missions) established for the training and education of the population. The male inactive population has remained during the study period with a slight tendency to grow, as shown in Figure 6. In percentage terms, the female inactive population represents the 299.26%% of the male inactive population.

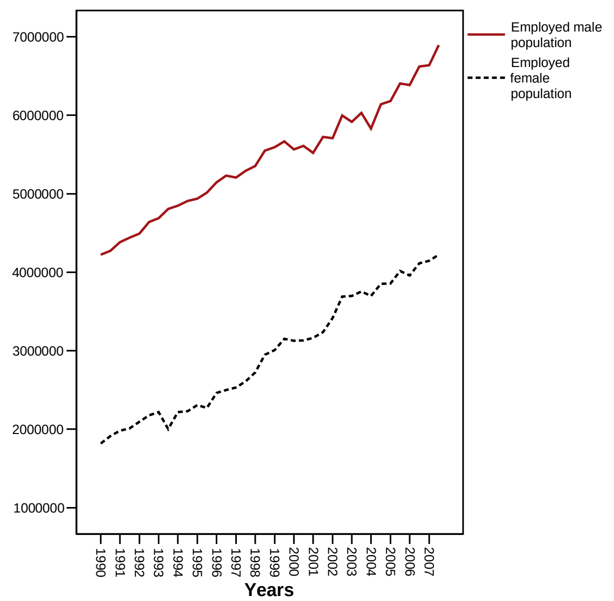

Figure 4. Temporarily Chart of employed male and female population in Venezuela

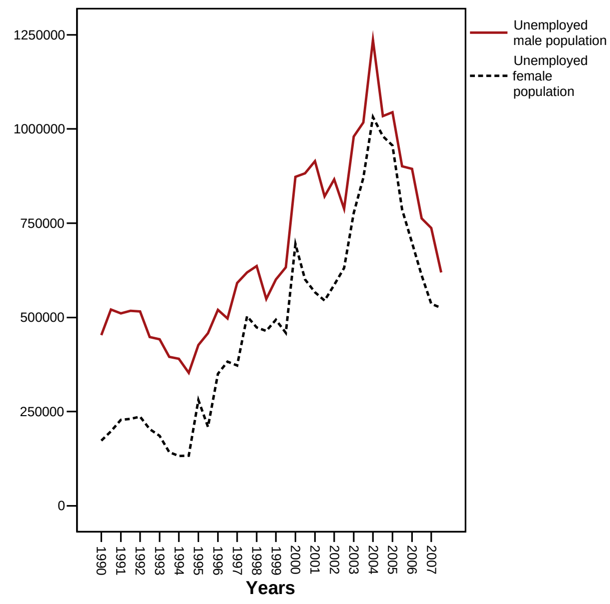

Figure 5. Temporarily Chart of unemployed male and female population in Venezuela.

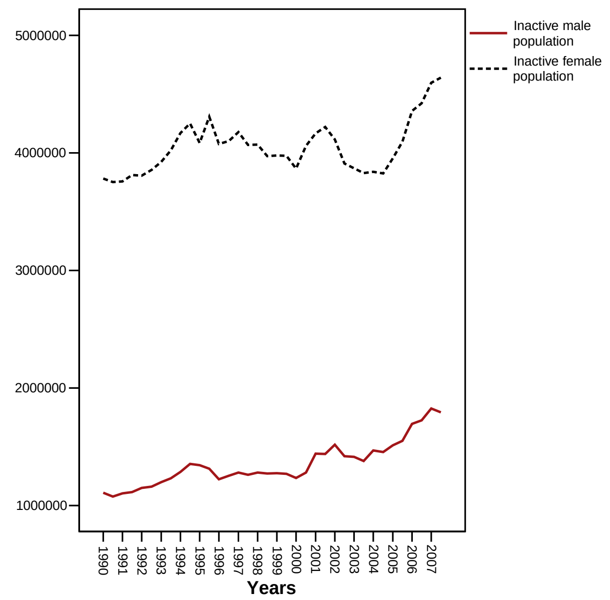

Figure 6. Temporarily Chart of inactive male and female population in Venezuela.

Reviewing the correlation matrix for the variables studied in men and women it can be mentioned the following:

a. In the correlations matrix for women (see Table 1) almost all coefficients are positive, there are very high and significant correlations among the female population of working age with a female population and female population unemployed, it can be said that the relationship between the first pair of variables is almost perfect because the ratio is close to 1. The female population with working age coefficient with the inactive female population is 0493, although they are significant is not indicative that the linear relationship between these two variables is very strong. The correlation coefficient between employed female population and unemployed female population is 0,841 indicating that these two variables are highly correlated. It is interesting that the inactive female population variable shows low correlation coefficients with other variables, it can be even say that there is no linear association between this variable and the unemployed female population because the coefficient is negative, near zero and was not significant.

		Female population with working age	Employed female population	Unemployed female population	Inactive female population
Female population with working age	Pearson Correlation	1	.992**	.841**	.493**
	P Value		.000	.000	.002
	N	36	36	36	36
Employed female population	Pearson Correlation	.992**	1	.860**	.409*
	P Value	.000		.000	.013
	N	36	36	36	36
Unemployed female population	Pearson Correlation	.841**	.860**	1	-.004
	P Value	.000	.000		.982
	N	36	36	36	36
Inactive female population	Pearson Correlation	.493**	.409*	-.004	1
	P Value	.002	.013	.982	
	N	36	36	36	36

**. Significant correlation at level 0.01

*. Significant correlation at level 0.05

Table 1. Correlation matrix: Female Case

b. Reviewing the correlations matrix for men (see Table 2), all coefficients are positive and significant. For the male population with working age Variable there are observed high coefficients with other variables, whether there is a nearly perfect direct linear association with male population employed, and also a very strong relationship with inactive male population, the lowest coefficient between male population of working age population variable is observed with unemployed male population. There are two identical correlation coefficients (0,902) between inactive male population and male population with working age, and between inactive male population and employed male population, which is attributed to almost perfectly previously described relationship between male population with working age and employed population. The lowest coefficients are presented between the unemployed men population variable and the rest of the variables included in the study.

		Male population with working age	Employed male population	Unemployed male population	Inactive male population
Male population with working age	Person Correlation	1	.988**	.780**	.902**
	P Value		.000	.000	.000
	N	36	36	36	36
Employed male population	Person Correlation	.988**	1	.690**	.902**
	P Value	.000		.000	.000
	N	36	36	36	36
Unemployed male population	Person Correlation	.780**	.690**	1	.523**
	P Value	.000	.000		.001
	N	36	36	36	36
Inactive male population	Person Correlation	.902**	.902**	.523**	1
	P Value	.000	.000	.001	
	N	36	36	36	36

**. Significant correlation at level 0.01

Table 2. Correlation matrix: Male Case

Reviewing the regressions there were found some interest results regarding the assumptions, which are described below:

a. Women regressions model:

i. The normal distribution assumption for the residuals is not met. In this situation, it should be applied mathematical transformations in the female population with working age variable, It is suggested the use of logarithmic transformation or a power transformation such as $\frac{1}{X}, \frac{1}{X^2}, \ldots, \frac{1}{X^p}$ because the residuals presents positive asymmetry, which can be seen in Figures 7 and 8.

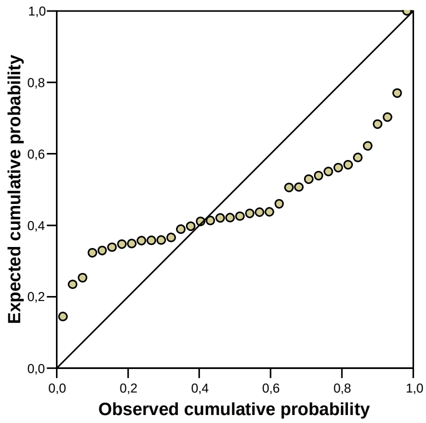

Figure 7. Normal Probability Chart for residuals. Female Case

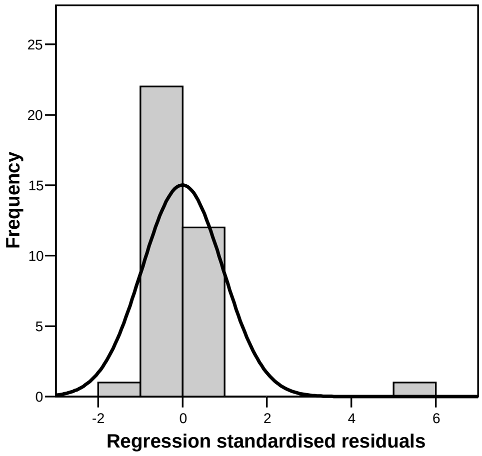

Figure 8. Residuals Histogram. Female Case

ii. The Durbin Watson statistic is close to 2 ($DW = 2{,}264$) which indicates independence between the residuals.

iii. It is made the White contrast for detecting heterocedasticity due to the independent or explanatory variables, and it is not rejected the hypothesis of constant variance of the residuals, the value of the statistic test is W = 6,948.

iv. Since there is not normality in the residuals, it must be applied a mathematical transformation on the dependent variable (female population of working age), taking care that the functional relationship between the dependent variable and independent or explanatory is maintained. In this regard several functions are tested and the result shows that the best is the logarithmic transformation, which is applied in the four variables considered in the study and is adjusted by a ordinary least squares regression method. Is not obtained the convergence to the normal distribution of residuals, but present an improvement compared to the original regression as can be seen in figures 9 and 10.

v. In this regression it is deteriorated the Durbin Watson statistical whose value is *DW=1,400* and indicates that there is a positive first-order autocorrelation in the residuals, and in the White contrast (W=5.76) is not detected heteroscedasticity.

vi. Considering all points previously presented, is not desirable to adjust a regression model using the ordinary least squares method, and it is suggested to use a different estimation method.

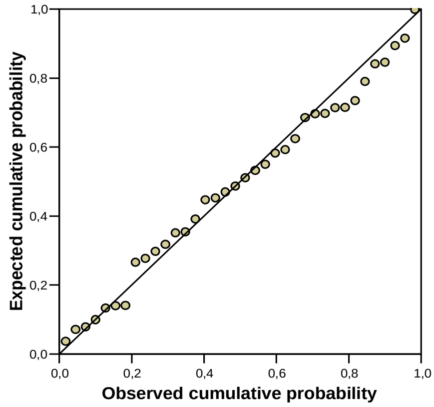

Figure 9. Normal Probability Chart for residuals. Case Female - Dependent Variable Transformed

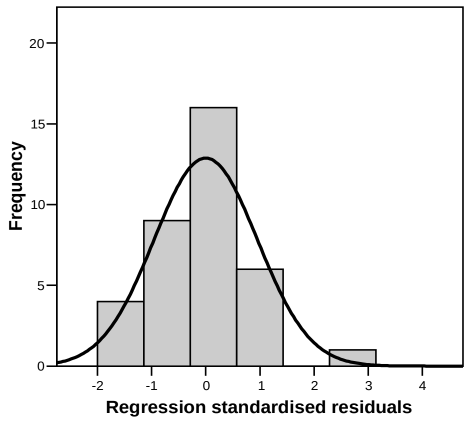

Figure 10. Histogram of the residuals. Case Female - Dependent Variable Transformed

b. Men regressions model:

i. For checking the normal distribution assumption of the residuals, it was used normal probability graph and the histogram (see Figures 11 and 12), which reveal that the residuals distribution was close to be normal, although a slight positive asymmetry is evident in them.

ii. The Durbin Watson statistical is close to 1 (DW=1,060), indicating that there is autocorrelation, and is suspected first-order positive autocorrelation.

iii. It was made the White contrast for detecting heteroscedasticity, and it was rejected the hypothesis of residuals variance, the value of testing statistical is W=18.00 therefore there is heteroscedasticity.

iv. The consequences of heteroscedasticity and the residuals autocorrelation are serious. In the presence of these problems the estimation of the coefficients using the ordinary least squares method are not the best and all inference procedures about them are inadequate, as well as the interpretation of the goodness of fit measures.

v. It is recommended to use another estimation method.

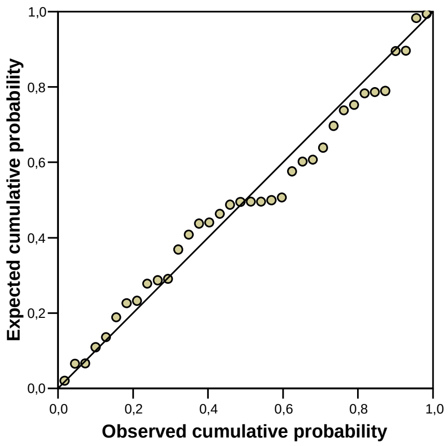

Figure 11. Normal Probability Chart for residuals. Male case

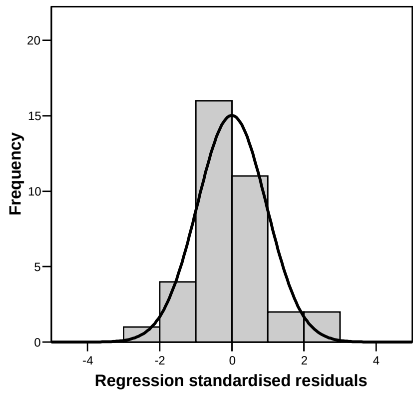

Figure 12. Histogram of the residues. Male case

Given all this, and considering that in both cases it is wanted to estimate the population with working age (male and female), it has total relevance the use of artificial neural networks.

4.3 Artificial Neural Networks Model

Using the semestral data from 1990 to 2007, being a total of 36 patterns; there were used the first 27 patterns (75%) for training the artificial neural network and the 9 remaining patterns (25%) for testing the obtained model. For training the neural network it was used the computer program Statistica Neural Networks [26] using the backpropagation algorithm [6, 8] and next it will be presented the obtained results:

4.3.1 Neural Model for estimating the female population with working age

The neural network that achieved the best results was the one shown in Figure 13.

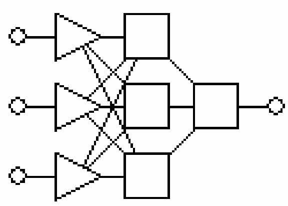

Figure 13. Neural Network for estimating the female population with working age

This model has three (3) inputs: the female employed, unemployed and inactive population in the previous year to the one wanted to be predicted, a hidden layer with three (3) neurons and logistic activation function

and an output layer with one (1) linear neuron for the female population with working age (PET_F) estimated for Venezuela.
It was calculated both for training and for testing the absolute error percentage, described as:

$$Error\% = \left|\frac{Error}{PET_F}\right| * 100$$

where:
"Error" is the difference between the real value and the estimated by the neural network value of the female population with working age.

Mínimum Error%	Máximun Error%	Average Error%	Median Error%
0,0241121	1,87910709	0,40286884	0,28745221

Table 1. Errors percentages obtained in Training phase for PET_F

Mínimum Error%	Máximun Error%	Average Error%	Median Error%
0,1657284	2,5845536	1,22422833	0,9729529

Table 2. Errors percentages obtained in Testing phase for PET_F

The artificial neural network model obtained for estimating the female population with working age (PET_F) is as follows:

$$z_1 = w_{11} PTO_F + w_{12} PTD_F + w_{13} PTI_F + w_{14}$$
$$z_2 = w_{21} PTO_F + w_{22} PTD_F + w_{23} PTI_F + w_{24}$$
$$z_3 = w_{31} PTO_F + w_{32} PTD_F + w_{33} PTI_F + w_{34}$$
$$PET_F = w_{41}\frac{1}{1+e^{-z1}} + w_{42}\frac{1}{1+e^{-z2}} + w_{43}\frac{1}{1+e^{-z3}} + w_{44}$$

where:
PTO_F= female employed population in the previous year to the one wanted to be predicted
PTD_F= female unemployed population in the previous year to the one wanted to be predicted.
PTI_F= female inactive population in the previous year to the one wanted to be predicted

w_{11}= -1.656484 w_{12}= -2.6817
w_{13}=-3.447295 w_{14}= 2.669685
w_{21}= -1.797642 w_{22}= -2.662924
w_{23}=-0.003204 w_{24}= 3.033486
w_{31}= -1.681529 w_{32}= -0.7323
w_{33}= -0.5118 w_{34}= -1.795575
w_{41}= -2.795503 w_{42}= 1.741478
w_{43}=-1.793574 w_{44}= -1.596806

Next table presents the obtained female population with working age using the Artificial Neural Networks and the real values.

Pattern	ANN PET_F	REAL PET_F
1	6004223	5964287
2	6022958	6051027
3	6130079	6133856
4	6263329	6234382
5	6317056	6327154
6	6425352	6420957
7	6538569	6515797
8	6487202	6611438
9	6774217	6672678
10	6862844	6785343
11	6869377	6886608
12	6999105	6981534
13	7060017	7078876
14	7155647	7179458
15	7254316	7268398
16	7367619	7380492
17	7450080	7481563
18	7552135	7583211
19	7664747	7686843
20	7760751	7790942
21	7924244	7894317
22	8018671	8002834
23	8121008	8113074
24	8227431	8230267
25	8342221	8340210
26	8457518	8454170
27	8595549	8565490
28	8718885	8657907
29	8851180	8765892
30	8914711	8895216
31	8997400	9012336
32	9063969	9146582
33	9136816	9275405
34	9213673	9387053
35	9286595	9488411
36	9351802	9599917

Table 3. Female population with working age estimation

4.3.2 Neural Model for estimating the male population with working age

The neural network that achieved the best results was the one shown in Figure 14.

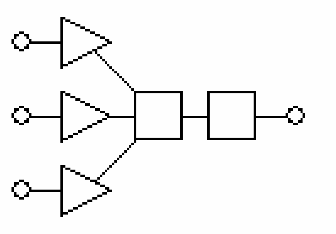

Figure 14. Neural Network for estimating the male population with working age

This model has three (3) inputs: the male employed, unemployed and inactive population in the previous year to the one wanted to be predicted, a hidden layer with one (1) neuron and logistic activation function and an output layer with one (1) linear neuron for the male population with working age (PET_M) estimated for Venezuela.
It was calculated both for training and for testing the absolute error percentage, described as:

$$Error\% = \left|\frac{Error}{PET_F}\right| * 100$$

where:
"Error" is the difference between the real value and the estimated by the neural network value of the male population with working age.

Mínimum Error%	Máximun Error%	Average Error%	Median Error%
0,007805	0,3333164	0,0883472	0,0743189

Table 3. Errors percentages obtained in Training phase for PET_M

Mínimum Error%	Máximun Error%	Average Error%	Median Error%
0,0936063	0,656058	0,37414262	0,44093493

Table 4. Errors percentages obtained in Testing phase for PET_M

The artificial neural network model obtained for estimating the female population with working age (PET_M) is as follows:

$$z_1 = w_{11}PTO_M + w_{12}PTD_M + w_{13}PTI_M + w_{14}$$

$$PET_M = w_{21}\frac{1}{1+e^{-z1}} + w_{22}$$

where:
PTO_M= male employed population in the previous year to the one wanted to be predicted
PTD_M= male unemployed population in the previous year to the one wanted to be predicted.
PTI_M= male inactive population in the previous year to the one wanted to be predicted

w_{11}=0.7888733 w_{12}=0.2759482
w_{13}=0.1992676 w_{14}= 0.7238753
w_{21}= 3.668776 w_{22}= 1.250508

Next table presents the obtained male population with working age using the Artificial Neural Networks and the real values.

Pattern	ANN PET_M	REAL PET_M
1	5982230	5992408
2	6060180	6069305
3	6178337	6157812
4	6252291	6245759
5	6338650	6329540
6	6425636	6430549
7	6509001	6523538
8	6610593	6617315
9	6704845	6707268
10	6801103	6787776
11	6891639	6885390
12	6973187	6979340
13	7071382	7074676
14	7168884	7172644
15	7266723	7271307
16	7367558	7370395
17	7469917	7469334
18	7573429	7569635
19	7675321	7671180
20	7778560	7771919
21	7880027	7874175
22	7983999	7981969
23	8090446	8091540
24	8200830	8202208
25	8311860	8309908
26	8421778	8424788
27	8526205	8533372
28	8637662	8627457
29	8741560	8733385
30	8833191	8854309
31	8933640	8973206
32	9047664	9107414
33	9157817	9200876
34	9279098	9306057
35	9362295	9405568
36	9453253	9510519

Table 4. Male population with working age estimation

These results illustrate that with extremely simple neural structures, it can be obtained estimated of the Venezuelan with working age population both male and female with errors that in no case are over 2.6% of real value.

5 Conclusions

In this work it have been developed two models for estimating the population with working age, men and women, in Venezuela using the previous year values of employed, unemployed and inactive people based on artificial neural networks. It has been justified from a statistical point of view the relevance of the use of artificial neural networks for obtaining the prediction models.

The worst errors made in the neural models are quite small (0.65% for estimating the male population with working age and 2.58% for estimating the female population with working age), in addition that neural networks topologies obtained are very simple. This allows its easy use without needing special computing and data processing requirements.

The estimation of the population with working age, men and women, with the obtained precision, can be used for evaluating the structure of the Venezuelan labor market, on the supply side, that allow deploying the appropriate actions and public policies necessary to achieve the best conditions for the labor market functioning and in the most equitable way possible. Knowing the potential number of women and men to be employed, unemployed or inactive, the government can take strong action for reducing the gap for those conditions in which the woman has been incorporated into the labor market, despite its high levels education, compared with men.

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