Networks, obstacles, and resources for innovative performance: An analysis via neural networks for prediction in the manufacturing industry

Fernando Barrios[1], Sandra Mora[2], Luis Gutiérrez[1], Martha Amado[1]*

Abstract

This document aims to predict the level of innovation in manufacturing companies in Colombia between the years 2017-2018. A forecasting mechanism for innovation performance has been constructed using Neural Networks (NNs). This model considers the objectives of innovation, the obstacles to innovation, the knowledge networks, and the technical information of each one of the firms. Results show that demand push, vertical sources, financial obstacles, and, qualified personnel are the most important variables in predicting innovative performance. Our empirical analysis uses firm-level innovation survey data from the EDIT (Encuesta de Desarrollo e Innovación Tecnológica in Spanish, Technological Development, and Innovation Survey in English) for Colombia for the years 2017-2018.

Keywords: Knowledge Networks, innovative performance, neural networks.

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Introduction

Technological innovation is a key factor in the growth of countries and firms (Freeman, 1997; Nelson and Winter, 1982; Schumpeter, 1935; Sterbeng and Arndt, 2001). However, the uncertainty faced by companies due to the cost-benefit of developing innovation can slow down or cause projects to fail. The innovation capacity of a company represents a task that is difficult to predict, but is important for the public policy to allocate resources that lead to the greatest social benefit (private social of return). Although an innovation's impact may not be known until it has been implemented, a forecasting model is a key factor to evaluate the relationships between the determinants of both, the innovative effort and the results of innovation. Thus, this research presents a forecasting model for predicting innovation outcomes using as determinants the knowledge networks, the technical information resources, and, the objectives to innovate manufacturing firms in Colombia between 2017 - 2018.

This research presents a neural network with a perceptron and a hyperbolic tangent activation function to predict innovation performance using technical informational resources, and, the firm's innovation objectives. This model was trained on a sample of 15.936 manufacturing industries from the Technological Development and Innovation Survey (EDIT) of Colombia between the years 2.017 and 2.018. This survey is carried out on companies and allows to identify whether a company is innovative or not. For each of the variables included in the model, a sensitivity analysis was carried out to study the accuracy and the estimation error of the neural network when including or excluding inputs.
The results of the research indicate that demand push, vertical sources, financial obstacles, and qualified personnel are the most important variables in predicting innovative performance in manufacturing firms in Colombia between these years. The positive impact of demand push on innovation is not a new issue. In the Schumpeterian tradition, increasing sales allow the financing of expensive and uncertain research and development (R&D) activities, while, at the same time the suitability and potential profitability of innovation rise with market size (Schumpeter, 1942).

Many researchers have tried to analyze the relationship between technological performance and other influencing factors, such as strategic management, and information resources. However, they do not mention the questions regarding how each dimension influences innovation results and, how to predict these results. Therefore, the main contribution of this study is to predict the probability of innovation from the determinants of obstacles to innovation, the knowledge networks of competitors, the universities and research centers, the demand push, and, the qualified personnel related to innovative performance. Finally, the results of this research can be a relevant resource for both, economic analysts and policymakers, because it helps to understand the innovation performance from the potential of data models, and the adjust allocated resources to match a company's innovation goals.

The organization of this work is as follows: the detail of the results of the innovation through the prognostic neural networks described in Section two. The constructions of the neural training network are presented in section three. Section four presents the data analysis results. Finally, the conclusions and recommendations for future research are given in Section five.

Literature Review

Artificial neural networks have been applied to different research fields given their effectiveness in modeling, especially in those cases where no mathematical or empirical model allows the simulation of processes involving all the variables of the system. These models

(1) School of Management, Business, and Economics Sciences, University Foundation of the Andean Area, Bogotá, Colombia
(2) School of Economic, University of the Andes, Bogota, Colombia
* Corresponding author: fbarrios4@areandina.edu.co

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classify the data through learning algorithms and parameters that minimize the error function between inputs and outputs. (Kengpol and Wangananon , 2006). The novelty of neural networks lies in their ability to model nonlinear processes with few a priori assumptions about the nature of the process that generates the data. This is particularly useful in forecasting innovative performance, where much is assumed, and little is known about the nature of the processes that determine innovation outcomes. All these advantages make neural networks an optimal model to develop this research to forecast the innovation results of Colombian manufacturing firms.

On this subject, research has shown that neural networks can accurately predict results in the innovation patterns of firms, indicating non-linear patterns in firm innovation activities (de la Paz-Marín et al., 2012; Hajek and Henriques, 2017, Saberi and Yusuff, 2012; Wang and Chien, 2006). More specifically, Wang and Chien (2006) found that neuronal back propagation network techniques outperformed traditional statistical regression models, regarding the accuracy of innovation forecasting at the firm level in Taiwan. Similarly, Saberi et al.(2012), developed and trained a neural network with a back-propagation algorithm and showed that the model can classify company performance as high, low, or poor in technology adoption with a 72% accuracy rate in the three clusters.

In Colombia, Gómez (2021) used artificial neural networks to analyze the determining factors of the global innovation index. This research started with quantitative research to explore determinants of firm´s behavior in developing innovation, namely the intensity of local competition, foreign investment, human capital, and other variables. After categorizing the most important variables to diagnose the global innovation index of firm´s behavior in developing innovation, a back-propagation neural network classification model was developed. The model demonstrates the usefulness of the 98% classification rate in classifying firms according to their level of innovation and showed the most important variables to diagnose the global innovation index were intensity of local competition, foreign investment, access to credit and human capital.

This evidence coincides with the specialized literature on determinants of innovative performance. This literature usually shows that innovation is determined by two main drivers: on the one hand, the technology push builds on external and internal research, factors that increase the supply of technological options by directly promoting advances in science and technology, and, on the other hand the demand push that emphasizes the role of customers in the development of R&D activities through the market shares of a firm in different industries (Cohen, 2010, Di Stefano et al., 2012, Saviotti and Pyka, 2013). In addition, other research has found that the innovative performance can be determined by the compose innovation strategy and the extent to which innovation activities are carried out in conjunction with other institutions suppliers, clients, public assistance agencies, industry associations, competing companies, larger firms, vertical partners, universities, and public laboratories. (Peeters and van Pottelsberghe de la Potterie, 2006; Romijn and Albaladejo, 2002). In emerging countries, firms with broader knowledge networks work closely with universities, research centers and business incubators, on average they get better innovation results (Blalock and Gertler, 2005; Moran et al, 2005; Romijn and Albaladejo, 2002; Schmitz, 2004). In addition, firms need an adequate stock of technically qualified personnel to absorb new technologies, modify, create, and transfer new technological information, particularly scientists and engineers (Becker 2003; Crawford et al, 2004; Griffiths, 2000; Romijn and Albaladejo, 2002). Nevertheless, policies and practices on innovation are going to vary very generally depending upon the size of the firm. Specifically, larger firms have easier access to financing, can spread the fixed costs of innovation over a higher volume of sales, and benefit from economies of scale and complementarities between R&D and other activities in increasing the probability to participate in risky projects (Cohen and Keppler, 1996).

Furthermore, the generation of self-financing and the availability of own resources would condition R&D in companies. Likewise, a greater intensity of capital and better infrastructure endowments, as well as more sophisticated equipment goods could favor investments in R&D. Usually, in an emerging country, companies with a greater presence of foreign capital tend to innovate more. In addition, in these emerging countries, innovation activity is aimed at adopting foreign technology, which requires adaptation costs to the national context.

Methodology

The research uses a neuron network to classify the results of innovation in firms to obtain information allowing more precise diagnoses of innovation status in each company. This neural network has a single-layer perceptron and a hyperbolic tangent activation function. The data set used to train this neural network was the manufacturing companies with information in the Technological Development and Innovation Survey between 2017 and 2018, since this survey has as its main objective to measure innovation by contemplating several variables; this method will show the most important variables to promote strategies in innovation policies.

The independent variables for the construction of the neural network are selected based on the sensitivity analysis to know the effect of each predictor variable on the dependent variable. The sensitivity analysis used in this research consists of setting the value of all the input variables at their mean value and varying the value of one of them throughout its entire range to observe the effect it has on the network output. This measure represents the relative effect that an input variable has on the output of the network. Thus, a value close to 0 would indicate little effect or sensitivity and as it moves away from 0, it would indicate that the effect is increasing.

The process of transforming inputs into outputs, in an artificial neural network, with r inputs, a single hidden layer, composed of q process elements, and one output unit can be summarized by the following formulation of the function network output:

$$\hat{f}(x,W) = F(\beta_0 + \sum_{j=1}^{q} \beta_j G(x'\gamma_j))$$

$f.(x,W)$i is the output of the network, the vector $x = (1,x_1,x_2,\ldots,x_r)'$ represents the inputs of the network (1 corresponds to the bias of a traditional model), $\gamma_j=(\gamma_{j0},\gamma_{j1},\gamma_{ji},\ldots,\gamma_{jr})' \in R^{(r+1)}$ are the weights of the neurons from the input layer to the intermediate or hidden ones, β_j, $j=0,\ldots, q$, represents the connection force of the hidden units to the output ones (j=0 indexes the bias unit), q is the number of intermediate units, that is, the number of nodes in the hidden layer, $F:R \rightarrow R$ is the activation function of the unit output and $G:R \rightarrow$ corresponds to the activation function of intermediate neurons. W is a vector that includes all the weights of the network, that is, γ_j and β_j.

Data

The empirical analysis uses firm-level innovation survey data from the EDIT compared to the CIS – Community Innovation Survey in Europe, we can notice that the Colombian EDIT survey allows us to avoid the overlapping periods between two different waves of the survey. In other words, we are then able to observe and identify firm´s innovation behavior specifically for each period without any doubtful imbrication.

The sample is made up of the number of companies reported by EDIT, for the years 2.017-2.018. This database is made up of a cross-section of 7.529 industrial companies, which are part of the DANE directory. The objective of these surveys is to characterize the dynamics of technological development of the manufacturing and service companies in Colombia, in terms of intensity and trajectory of innovation and technological development activities, to evaluate the incidence of public policy instruments, and to establish the types of occupational profiles applied in the different areas or departments of the companies.

In this study, innovative performance in products, processes, markets, and organizations is used as a dependent variable, in a binary context (1= yes, it innovates; 0= otherwise) and on a discrete, non-negative scale (innovation count).

From the information available in the EDIT, the dependent and independent variables to use are the following:

Dependent variables

Binary of innovating in products, processes, markets, and organizational firms (1= innovate; 0= does not innovate).

Independent variables

·Company size: Number of company employees in logarithms.
Source of vertical ideas: Equal to 1 if the company uses customers or suppliers as sources of information for innovation. Equal to 0 otherwise.

·Source of ideas from universities and research centers: Equal to 1 if the company uses universities and R&D centers (Technological Development Centers -CDT and Research Centers) as sources of information for innovation. Equal to 0 otherwise

·Demand Drive: It is a binary variable, equal to one if the company expresses as very important the improvement in the quality of the goods or services and the expansion in the range of goods or services offered (Griffith et al., 2006). Equal to 0 otherwise.

·Highly qualified personnel refer to employed personnel with masters and doctoral degrees over the total personnel.

·Qualified personnel: Refers to employed personnel with undergraduate training and specialization over the total personnel.
R&D expenses: Logarithm of the investment in internal and external R&D activities.

·Obstacles to Innovation: five dummy variables related to the category's knowledge, cooperation, demand, regulation, and financing self-reported obstacles. In each of them, the value of the variable is one if the company self-reports an obstacle related to that category and cero otherwise.

Table 1: For the construction of the obstacles to innovation, the following classification was used

Obstacle	Obstacle Type
Lack of qualified personnel	Knowledge
Lack of market information.	Knowledge
Lack of technological information.	Knowledge
Lack of information on public support instruments	Knowledge
Limited possibilities for cooperation with other companies or institutions	Cooperation
Uncertainty in the demand for innovative goods and services	Demand
Uncertainty about the success in the technical execution of the project	Demand
Lack of internal resources	Finance
Low profitability of innovation.	Finance
Difficulties in accessing external financing for the company	Finance
Low supply of inspection, testing, calibration, certification and verification services	regulator
Difficulty complying with regulations	regulator
Ease of imitation by third parties.	regulator
Insufficient capacity of the intellectual property system to protect innovation	regulator

Sources: The authors, based on theoretical review

Results

The data set was divided into two subsets, one for training and the other for testing. The number of observations in each subset has a similar distribution of firms with and without innovation.

Table 2. Case Processing Summary- one perceptron

		N	percentage
Example	Training	5.262	69,9%
	tests	2.267	30,1%
Valid		7.529	100,0%
excluded		0	
Total		7529	

Source: The authors, based on EDIT database

Table 3. The network information

Input layer	factors	1	Knowledge obstacles
		2	Cooperation obstacles
		3	demand obstacles
		4	financial obstacles
		5	regulatory hurdles
		6	Demand Push
		7	Competitor information
		8	Information Universities and Research Centers
	Covariate	1	Natural logarithm of the number of employees biannual
		2	qualified personnel
		3	highly qualified staff
	Number of units to		20
	Rescaling method for covariates		standardized
hidden layers	Number of hidden layers		1
	Number of units in hidden layer 1 to		7
	activation function		hyperbolic tangent
output layer	Dependent variables	1	Is the company innovative? 1=yes; No=0
	Number of units		2
	activation function		soft max
	bug function		cross entropy
a. Bias unit is excluded. Source: The authors, based on EDIT database			

Source: The authors, based on EDIT database

The results of the model indicate that the data obtained by the network in its prediction was significantly close to the real data provided for training of the neural network. The performance of the network in its training and testing phase shows an error of 2,4% and 2,2%, respectively.

Table 4. Model Summary

Training	Cross entropy error	531.262
	Percentage of incorrect forecasts	2,4%
	Stop rule used	1 consecutive step(s) without error decrease to
	training time	0:00:01,16
tests	Cross entropy error	221.425
	Percentage of incorrect forecasts	2,2%
Dependent variable: is the company innovative? 1=yes; No=0		
a. Error calculations are based on the test sample.		

Source: The authors, based on EDIT database

Table 4. Classification

Example	observed	predicted		
		0	one	percent correct
Training	0	3.830	0	100%
	1	128	1.304	91,1%
	overall percentage	75,2%	24,8%	97,6%
tests	0	1.640	0	100%
	1	51	576	91,9%
	overall percentage	74,6%	25,4%	97,8%
Dependent variable: Is the company innovative? 1=yes; No=0				

Source: The authors, based on EDIT database

The model demonstrates the usefulness of the 97,8% classification rate in classifying whether a company is innovative. To select the most important variables and those with the greatest influence on the prediction of innovation in a company, the importance of the independent variables was used through their weighted percentage of importance and, their percentage of normalized importance, both measures indicating how much the value changes of the dependent variable by the ANN model for different values of the independent variable. The importance indicator consists of weighting each of the analyzed variables in percentage terms and ordering them from highest to lowest. The normalized importance is the result of the values divided by the highest importance values expressed as a percentage. Thus, the created model of ANN, responds to the classification of factors and the importance of the variables on the influence of the output in the model. Table 5 presents the independent variables in the model and their importance in the model to predict innovation in a company. Demand push, vertical sources, financial obstacles, and qualified personnel are the most important variables in predicting innovative performance.

Table 5. Importance of independent variables

	Importance	Normalized importance
Knowledge obstacles	.104	64,1%
Cooperation obstacles	.026	16,3%
Demand obstacles	.029	17,8%
Financial obstacles	.134	82,8%
Regulatory obstacles	.098	60,5%
Demand Push	.162	100%
Competitor information	.149	92,2%
Information Universities and Research Centers	.078	48,4%
Natural logarithm of the number of employees biannual	.072	44,4%
qualified personnel	.040	24,7%
highly qualified staff	.108	66,4%

Source: The authors, based on EDIT database

The results obtained show that the neural network with a perceptron correctly predicts the probability that a company with certain characteristics innovates or not. The innovative firm ranking model performs well within the test set of firms with a surveyed innovation status.

According to this research, financial, knowledge, and regulatory obstacles are important barriers for innovation activities, while demand and cooperation obstacles are less important to determine the performance of innovation. Innovation projects often involve high financial risks for the investor, which directly implies the need to secure funding. So, it is not surprising that lack of access to credit is a key hurdle for innovation projects, which makes them more expensive and would not be chosen by firms facing knowledge or financial obstacles. Regarding the demand push indicator, it seems that the firm reveals key factors for its performance to look and develop new markets. In this case, the demands and, the needs of consumers drive the growth innovation process in the firms. Results are consistent with the literature that demand may benefit the diffusion of new products and innovation output (Di Stefano et al., 2012). Moreover, the capacity to anticipate changes in the demand market trends in new products may be crucial to successful innovation.

Similarly, the results show that size has a positive effect on the probability to invest in innovation. These effects are greater in firms that hire more skilled personnel. This result is linked to the Schumpeterian hypothesis, which states that innovation is favored in a climate where companies are large. One of the reasons that large companies tend to be more innovative than their smaller counterparts, is because the returns to scale prevail in them. Moreover, larger companies have easier access to financing, can spread the fixed costs of innovation over a higher volume of sales, benefit from economies of scale and, complementarities between R&D and other activities in increasing the probability to participate in risky projects (Cohen, 1996).

Conclusions

In this research, to predict whether a company innovates according to its innovation objectives and characteristics, a single-layer neural network model was used, which correctly classified 97,8% of the sample. This neural network model is relevant to classify firms with a probability of innovating and those that are not likely to innovate, and select the variables that determine and influence the most on innovation of a manufacturing company in Colombia. Through the study, it was identified that the demand push, vertical sources, financial obstacles, and qualified personnel are the most important factors for an innovative company. Regarding the tool used, it is important to clarify that, within the method of application of neural networks, there is a disadvantage, which is the fact that there is no single known procedure guaranteeing that the global solutions found manage to find a weight configuration for the problem. That minimizes the error criterion, therefore, one of the multiple possible local minima is obtained through one of the many rules proposed in the literature.

The key to an industry's innovation performance is for corporations to calibrate their effective variables in innovation performance and adjust their innovation targets information resources and technical resources through demand push, financial obstacles, and qualified personnel that includes collaborative relationships with other allies. In future research, a more detailed study can be developed, one that focuses on a specific industry or sector to predict innovation performance, considering the presence of different input variables.

One of the recommendations is to implement neural networks for the estimation of innovation forecasts in sectors of different companies and, compare their performance with other statistical methods since only in this way could their usefulness be verified compared to traditional methods. Although a company's capacity for innovation represents a task that is difficult to predict but is important for public policy. The lack of information on the capacity of a company to innovate can generate social losses if public resources for innovation are allocated to companies with a low probability of innovation. These institutions surely have a strong interest in avoiding a misallocation of resources to prioritize the companies most likely to innovate. Very often, in public policies, the allocation of resources for innovation in companies is based on the following factors: size and economic sector, with the largest companies being the beneficiaries of these subsidies.

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