Determination of Internal Logistics Index using neural networks

Dr. O. P de Lima [1], * Dr. S.Santiago[2] , Dr. C. Taboada[3], Dr. J. Rodríguez[4]

[1] State University of Amazonas, [2] Federal University of Amazonas, [3] Federal university of Santa Catarina, [4] Federal University of Bahia
[1]orlempinheiro@gmail.com, [2]sbreval@gmail.com, [3]carlos.taboada@ufsc.br, [4]*jorgemoyar@gmail.com*

Abstract

There are few papers now at days that analyze how to quantify the level of performance of the internal logistics of a company. In recent years, it has been developed numerous applications of neural networks to solve the diverse problems of Engineering. The objective of this paper is to demonstrate the adhesion of the mathematical tool of neural networks to the measurement of the internal logistics index, considering 13 component parts and their respective properties. The study is considered descriptive, exploratory using a questionnaire, applied in 10 companies of the Industrial Pole of Manaus, and bibliographical research for the definition of the internal logistics components. The results demonstrate the value of the internal logistics index calculated by the neural networks through their synaptic weights and their adherence to the pre-established methods for the evaluation.

Keywords: Internal Logistic, Neural Networks, Industrial Pole of Manaus

Introduction

Internal logistics activities are necessary and vital to the operation of any enterprise regardless of the branch of economics that it belongs. The main task of internal logistics systems is often to provide the necessary supplies to the value-added processes of a company. A failure in the material flow can result in costly downtime, demonstrating the importance of a well-functioning system of internal logistics.

Despite the importance of internal logistics, it has not been completely understood, especially in the manufacturing industry. [1,2]. However, it constitutes a large part of the total cost for companies [3]; average logistics costs represent between 10% and 30% of the sales volume of a typical production company [4]. Logistics activities in general and internal logistics in particular, are often characterized by a high degree of manual handling; therefore, they have a high degree of utilization of employment, which strongly affects the cost of these operations.

Internal logistics is the part of logistics which includes all flows, physical movements and support operations that are performed within the warehouse or industrial unit.

There are various logistical operations performed in a warehouse or factory such as: receipt of material (raw material, packaging, etc.), storage, dispatch of finished product, production line supply, collecting of finished product, palletizing, labeling, etc.

Every day companies seek the improvement and optimization of the internal logistics processes, so as to eliminate all the tasks that do not increase the added value to the product.

It is very important that a company has clearly identified and defined its internal logistics, based on studies, observations, field research, interviews, etc., verifying the need for continuous improvement of the whole processes.

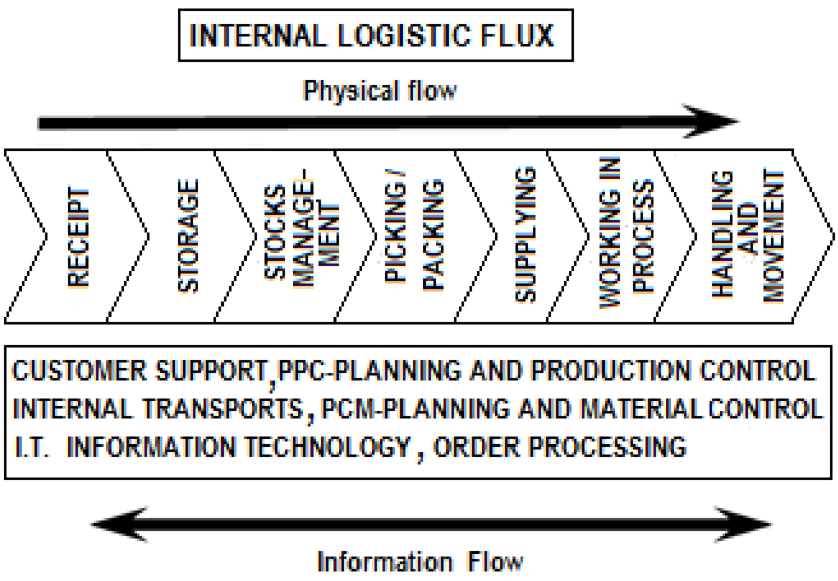
Both, the search and demand for products and services are in a continuous process of growth, therefore, companies tend to maintain minimum inventory of their products, with the aim of raising the level of services, because to have a high inventory becomes a disadvantage rising domestic costs. Many tests to find problems of disposal and storage that cause delays in the process can be done; these shortcomings need to be addressed effectively to achieve a good process and good customer service.

The internal movement of materials and resources within production units is a complex and crucial activity for the competitiveness of a company. When executed properly, the internal logistics of a company, guarantees the reduction of stocks and an efficient use of labor, reducing the number of resources required for the implementation of transport tasks that do not add value through the costumer eyes. Achieving good performance of the Internal Logistics is decisive in reducing costs, whether equipment maintenance, stocks and human resources availability and also in the dramatic increase in productivity for ensuring the availability of materials and resources at the right time and in the proper amount.

Developed approach for evaluating the component parts of the Internal logistics

Now at days there are few systematic attempts proposals and techniques, that improving the manufacturing system and the internal logistics and related performance, are able to assess the dynamics of production and the corresponding enhancement. Based on the readings of the selected articles and a survey of 10 companies from different sectors of the Industrial Pole of Manaus, it was possible to identify the component parts of the internal logistics. They were made some adjustments through interactions with business professionals from different companies in order to obtain the widest possible pattern of component parts of Internal logistics. Figure 1 shows these parts. From this picture can be observed that there are component parts which have to do with the physical flow and other with the information flow.

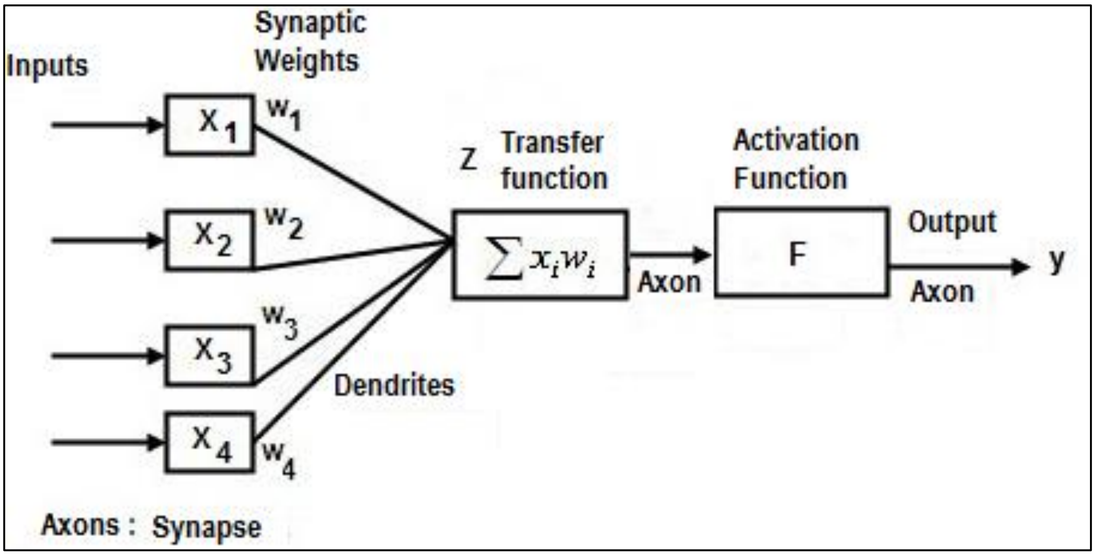
Figure 1 : Component Parts of the Internal Logistics.



Artificial Neural Network.

Artificial Neural Networks (ANN) is an area of computer science that emulates brain function and by training them, allow “in a certain way” computers to think. The ANN can be trained and they are able to accumulate experience and to make generalizations based on their prior knowledge. An artificial neuron acts in the same way as a biological neuron. The artificial neuron receives various input signals (x), calculates a weighted average of these signals (z), and when this average is applied to an activation function (F) an output signal (y) occurs (see Figure 2). [5]

Figure 2: Artificial neural Network Structure.



Set of inputs, $\boldsymbol{x_i}$. They can come from outside or from other artificial neurons.
Synaptic weights, $\boldsymbol{w_i}$. They represent the degree of communication between neurons.
Propagation rule, $\mathbf{Z}\ (\boldsymbol{x_i w_i})$. Integer the information from different artificial neurons and provides the potential post synaptic value from *i* neuron.
Activation Function, **F**. It provides the activation state of the *i* neuron.

Figure 3 shows a list of some of the activation functions more used in the different models of artificial neural networks.

ANNs are composed of a certain quantity of artificial neurons arranged in layers as shown in Figure 4. The first layer is called input layer and is the place where the input to the network occurs, here no calculation is performed. Calculations are performed in the hidden layer and in the output layer. The ANN shown in Figure 4 is a feed forward neural network, because all connections are in one way.

Training Process of ANN

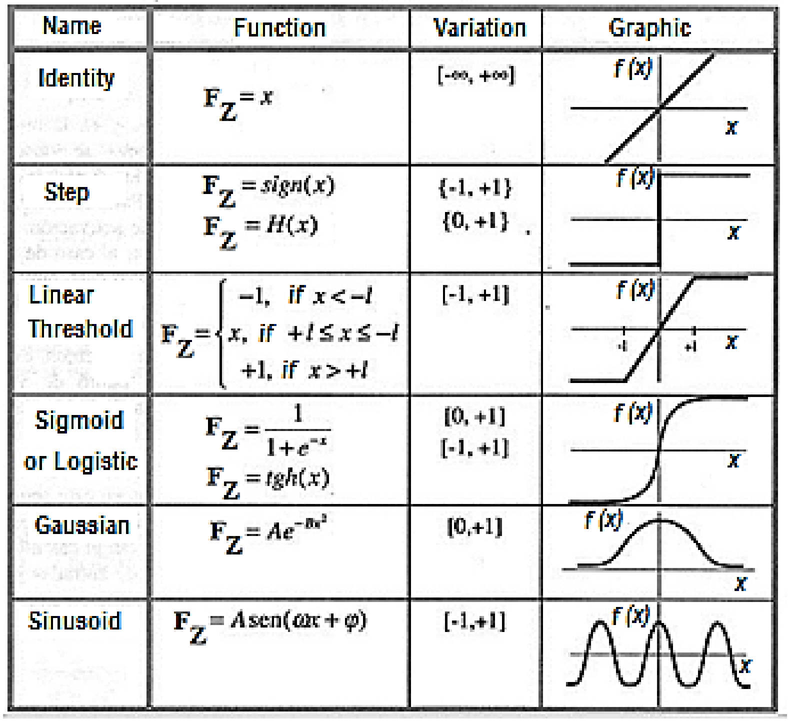
Training or Learning is the process whereby the parameters of a neural network are adapted by means of a constant stimulation from the environment in which the network is operating. The kind of learning is defined by the way the settings of the network parameters is performed [7].

Undoubtedly the main attraction of neural networks is their learning ability, in which the network extracts relevant information from established patterns, generating its own representation of the problem: "The artificial neural networks learn by their mistakes" [5].

Usually the process of learning or training of the neural network involves three phases:

1- Calculating the value of the output function
2- Comparing the values of the output function with the desired responses
3- Adjusting the weights and repeating the process.

Figure 3: Artificial Neural Network activation functions.



Name	Function	Variation	Graphic
Identity	$F_Z = x$	$[-\infty, +\infty]$	
Step	$F_Z = sign(x)$ $F_Z = H(x)$	$\{-1, +1\}$ $\{0, +1\}$	
Linear Threshold	$F_Z = \begin{cases} -1, & \text{if } x < -l \\ x, & \text{if } +l \le x \le -l \\ +1, & \text{if } x > +l \end{cases}$	$[-1, +1]$	
Sigmoid or Logistic	$F_Z = \frac{1}{1+e^{-x}}$ $F_Z = tgh(x)$	$[0, +1]$ $[-1, +1]$	
Gaussian	$F_Z = Ae^{-Bx^2}$	$[0,+1]$	
Sinusoid	$F_Z = A sen(\omega x + \varphi)$	$[-1,+1]$	

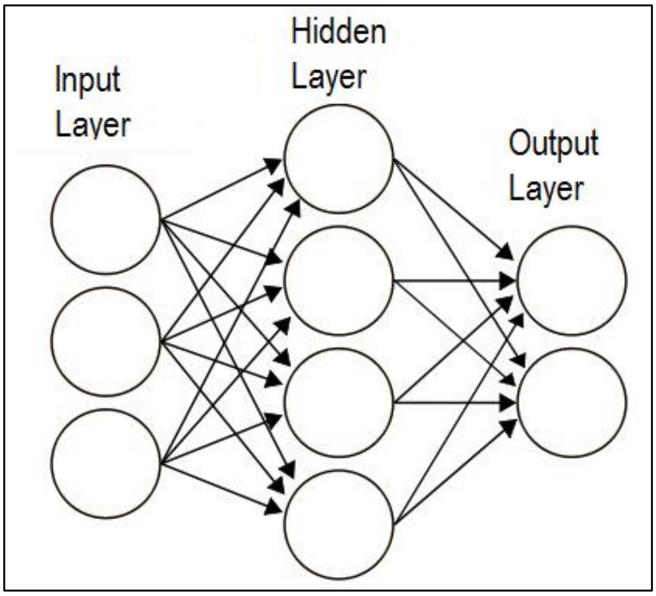
According to figure 3, can be observed that:

$$Z = \sum_{i=1}^{4} x_i w_i \qquad (1)$$

The activation function can take many forms and expressions as seen in the above table, but the most used in practice is a logistic function of the form:

$$F_Z = \frac{1}{1+e^{-z}} \qquad (2)$$

Figure 4 : Feed Forward Neural Network Architecture



Ordinarily the training or learning process starts with arbitrarily assigned weights. The difference between the actual output (y) and the desired output (d) is then calculated. This difference Δ must have a minimum value, and if possible to be reduced to zero. The process of reducing the difference is performed by changing the weights.

One of the most important issues in the ANNs is how to get the weights (w) corresponding to the synapses that are really established in biological neurons. This requires establishing a learning process to determine the values of the weights that connect the artificial neurons. The training process of the ANN is divided into three groups according to their features [8, 9]:

- Supervised training. A set of input patterns is presented to the Network with the expected output. The weights are modified in proportion to the error that occurs between the actual output of the network and the expected output.
- Unsupervised Training. A set of input patterns is presented to the Network. No information is available regarding the expected output. The training process in this case will have to adjust their weights based on the correlation between the input data.

Table 1 : Artificial Neural Networks training forms

Main Training Algorithm				
Training form	**Training Rule**	**Architecture**	**Training Algorithm**	**Uses**
Supervized	Error correction	Perceptron and Multilayer Perceptron	Perceptron, backpropagation, ADALINE, MADALINE	Pattern classification, function approximation, prediction, control.
		Elman and Jordan Recurrents	Backpropagation	Time series synthesis
	Boltzman	Recurrent	Boltzman	Pattern classification
	Competitive	Competitive	LVQ	Intraclass categorization, data compression
		ART	ARTMap	Pattern Classification, intra-class categorization
Non supervized	Error correction	Hopfield	Associative Memory training	Associative Memory
		Multilayer without feedback	Shannon projection	Data analysis
	Competitive	Competitiva	VQ	Categorization, data compression
		SOM	Kohonen SOM	Categorization, data analysis
		ART	ART1, ART2	Categorization
Reinforcement	Hebbian	Multilayer without feedback	Linear discriminant analysis	Data analysis, pattern classification
		Without feedback or competitive	Main component analysis	Data analysis, data compression

- Reinforcement training. This type of learning is located in between the two precedent trainings. It is presented to the network a set of input patterns and it is indicated to the network whether the output obtained is or not correct. However, there is not provided the value of the expected output. This type of learning is very useful in cases where it is not known what is the exact output to be provide to the network.

It is necessary to train the ANN until it is able to recognize patterns and regularities in the data, so that it can then extrapolate them to the desired values. The training algorithm most used in the literature is that known as back propagation [11-13]. Through this algorithm, the weights are adjusted so as to minimize errors in the solution according to the input data and expected values.

The "back propagation" algorithm was created in 1986 [14] and is the most widely used method of training feed forward networks. It is a supervised learning method of descent gradient; where there are distinguish clearly two phases: first an input pattern is applied, which spreads through the different layers composing the network to produce its output. This output is compared to the desired output and the error for each output neuron is calculated. These errors are passed backwards from the output layer to all neurons of the intermediate layers [15]. Each neuron receives an error that is proportional to its contribution to the total network error. Based on the error received, the errors of the synaptic weights of each neuron are adjusted.

Results

Evaluation of the weights of the component parts of the Internal Logistics by the companies

To evaluate the weight of each component part of the internal logistics was sent a survey to 10 companies to analyze and to assign a weight according of its importance in a Likert scale of 1-5 where 1 was attributed to the less importance part and five to the most important one according to the particularity and priority represented by the component parts for the mentioned companies. In Table 3 there are offered the results of three of the companies investigated.

It was found that depending on the company and its respective sector, the priorities and the degree of importance may be subject to changes and therefore affect the performance index of internal logistics. The maximum score that each company can get is 65 points, which is the result of the multiplication of the 13 items by the maximum value of each item according to the Likert scale. It is noted for example that the company 1 attributed a very low note for the items: Storage, WIP and internal transport, while companies 2 and 3 attributed notes 5, 5 and 4 respectively for these same items, therefore, it follows which depending on the sector and the type of production, whether continuous or discrete, the degree of importance may change. An arithmetic mean of the 3 companies values was also developed in this tabulation and it was noted that from the maximum possible score of 65 points, the company 1 scored 35 points, followed by 61 points by the company 2, then the company 3 with 59 points, and the arithmetic average was 51.67 points.

Evaluation of the index of each property of Internal Logistic by companies

Based on the literature investigated was developed the structure of the model of the diagnostic of the component parts of the internal logistics, its filling, its testing and its subsequent validation. There were developed 10 questions to assess each property and the survey was conducted in different companies. These questions were developed based on the literature review, and according to the criteria of a group of specialists on logistics management and consulting and business managers. It was developed an Excel tabulator to evaluate the performance of each of the component parts of the internal logistics as well as the index of internal logistic of a company.

Table 2 : Answers from the companies on the degree of importance of the elements of Internal Logistics.

Property	Assigned weight by each company				
	Company1 weight	**Company2 weight**	**Company3 weight**	**arithmetic mean**	**Company3 Peso %**
Receipt	3	5	4	4,00	6,8%
Handling and movement	2	4	3	3,00	5,1%
Picking/Packing	4	4	4	4,00	6,8%
Storage	1	5	5	3,67	8,5%
Stocks management	2	5	5	4,00	8,5%
Supplying	5	5	5	5,00	8,5%
PMC- Planning and Material Control	2	5	5	4,00	8,5%
PPC - Planning and Production Control	2	5	5	4,00	8,5%
WIP- Working in process	1	5	5	3,67	8,5%
Order Processing	4	4	5	4,33	8,5%
Internal transports	1	4	4	3,00	6,8%
Customer Support	5	5	5	5,00	8,5%
Information technology	3	5	4	4,00	6,8%
Internal Logistic Index	35	61	59	51,67	100%

The Excel Tabulator was based on the following equations:

$$ILI = \sum_{i=1}^{13} \left[\left(\frac{Z_i}{100} \right) . W_i \right] \qquad (3)$$

Where:

ILI = General Index of Internal Logistic performance;

W_i = Weight assigned to each component part i ;

i = Each one of the properties analyzed;

Z_i = Reached value in % by the i property based on the sum of all the assigned values of each parameter from the correspondent property of the Likert scale from 1 to 5and divided by the maximum value to achieve expressed in % :

$$Z_i = \sum_{j=1}^{10} \left(\frac{P_j . L_j}{50} \right) . 100 \qquad (4)$$

Where:

P_j = Each of the parameters that assess the Z_i property (always it going to assume the value 1 in the above expression)

L_j = Value assigned to the parameter P_j at the Likert scale from 1 a 5.

It was chosen randomly the company three to answer questionnaires regarding the 13 elements or components parts of internal logistics. This company filled the Excel tab, reaching a score in% of each property that was multiplied by the weights assigned in Table to each property. This company reached a general index of 79.17% for Internal Logistics as it is shown in Table 3.

Application of neural networks to determine the rate of internal logistics of an industrial company

One problem with the method applied in the previous section is that the user of Excel tab has to assign a weight to each component part of the internal logistics based on in his own experience, which naturally influences the overall index of internal logistics of a company. Attempting to avoid subjectivity in determining this rate, it was looked to the technique of artificial neural networks. To analyze the Internal Logistics of an industrial company was used the Internal Logistics Index (ILI), evaluated between 0 and 100%. This index is calculated based on the values assigned to each of the internal logistics properties between 0 and 50 according to the 10 parameters of evaluation of each property in the Likert scale of 1 to 5. There were selected 10 companies of the Industrial Pole of Manaus for their study and analysis, all of them belonging to the productive sector.

Table 3 : General Internal Logistic Index of a company (Internal Logistics´ Components)

Property	**Performance**		
	Percent	**Weight**	**Points**
Receipt	96,00%	6,8	6,53
Handling and movement	88,00%	5,1	4,49
Picking/Packing	90,00%	6,8	6,12
Storage	86,00%	8,5	7,31
Stocks management	86,00%	8,5	7,31
Supplying	46,00%	8,5	3,91
PMC- Planning and Material Control	94,00%	8,5	4,62
PP - Planning and Production Control	92,00%	8,5	4,62
WIP- Working in process	88,00%	8,5	7,48
Order Processing	88,00%	8,5	7,48
Internal transports	90,00%	6,8	6,12
Customer Support	88,00%	8,5	7,48
I. T. Information technology	84,00%	6,8	5,71
General Internal Logistic Index		79,17	

It was proposed to the ANN to determine the Internal Logistic Index of 10 companies in the industrial pole of Manaus. The values of the properties of the component parts of the 10 companies are given in Table 5. The desired Internal Logistics Indexes for the aforementioned companies (supervised training), in order to train the ANN are given in Table 6. In figure 4 it is showed the Architecture of the ANN implemented in MATLAB, In order to achieve reliable results, the network was trained five times (Figures 6 and 7 the training process is displayed).

Figure 5 : Artificial Neural network implemented in MATLAB

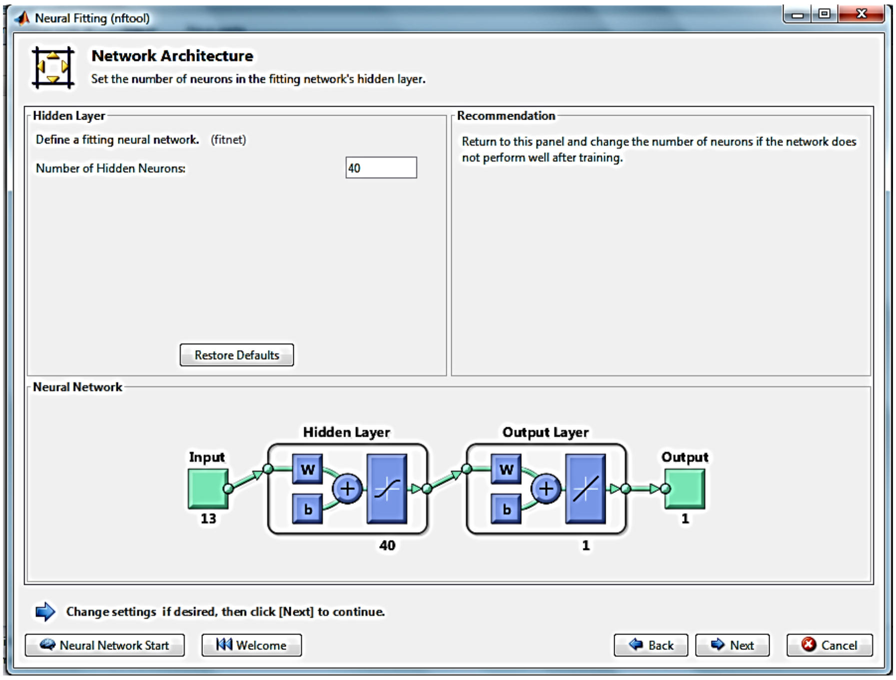


Figure 6 : Neural Network Training state.

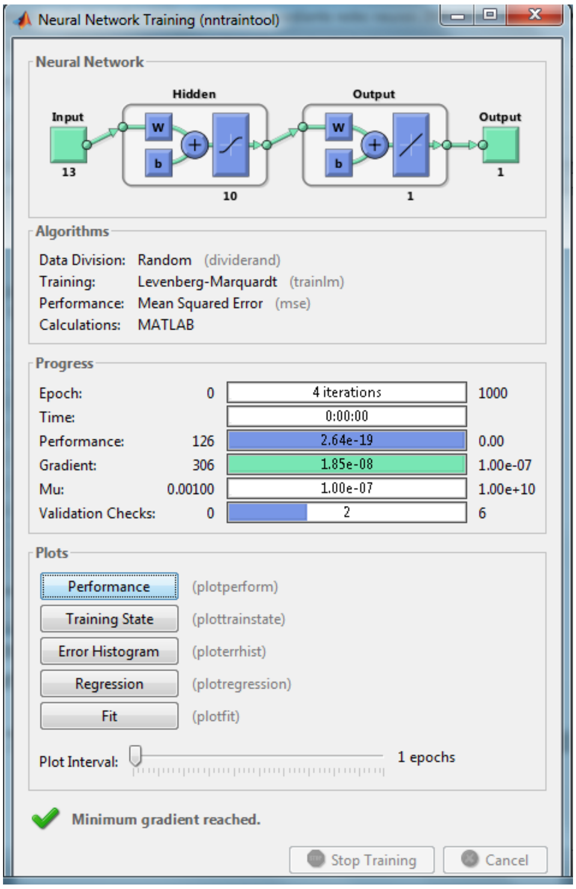


Figure 7 : Training and Retraining of the ANN.

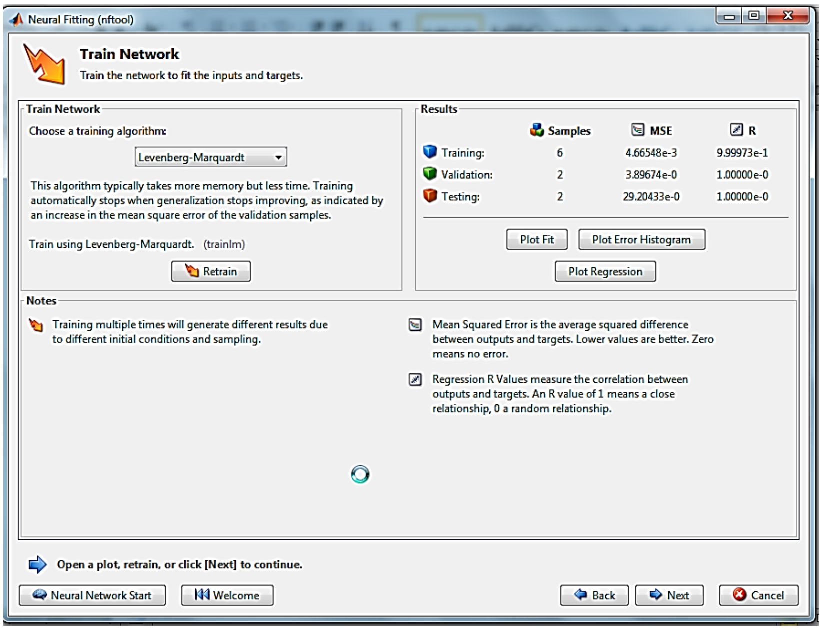


Table 4 : Different properties that compose the Internal Logistic Index of a company and heir values for the 10 companies evaluated.

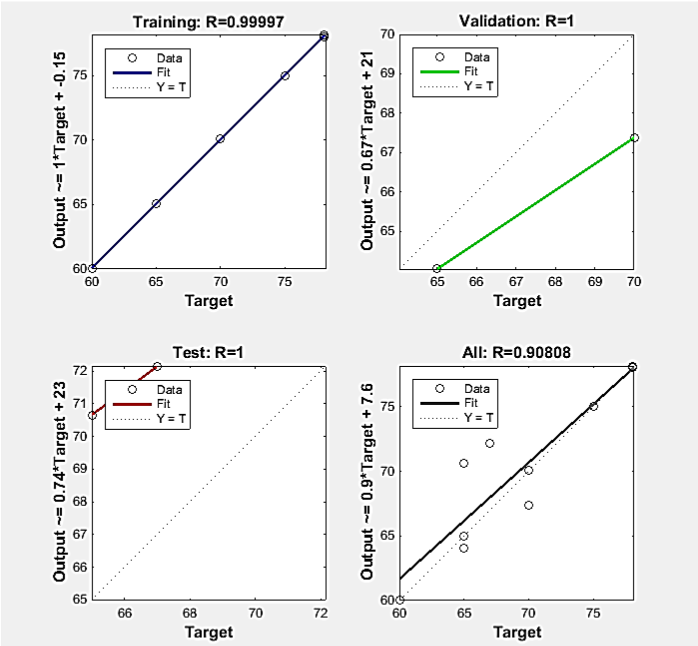
Property	Company number and value of the performance of each property									
	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
Receipt	30	35	36	50	42	47	32	18	50	22
Handling and movement	20	44	23	50	35	45	34	15	39	19
Picking/Packing	50	22	32	48	26	34	45	21	40	23
Storage	40	33	41	43	12	50	23	32	35	34
Stocks management	30	11	25	21	18	16	15	18	18	35
Supplying	24	44	18	50	22	24	18	43	25	23
PMC- Planning and Material Control	33	50	15	39	19	35	22	32	35	41
PP - Planning and Production Control	28	33	21	40	23	32	18	19	28	19
WIP- Working in process	16	22	32	35	34	18	34	42	47	32
Order Processing	41	11	18	18	35	33	45	35	45	34
Internal transports	33	33	43	25	23	22	35	26	34	45
Customer Support	23	45	32	35	41	43	25	12	50	23
I. T. Information technology	33	44	19	28	19	21	18	18	16	15

Table 5 : Possible Internal Logistics Indexes (ILI) for each company (targets) based ANN

ILI	**Company number and Internal Logistic Index possible according to the performance value of each property**									
	E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**
	65	75	70	67	78	60	70	65	78	65

Validation errors of the neural network are shown in figure 8.

Figure 8 : Validation of the Artificial Neural Network errors.



Internal Logistic Indexes of the studied companies.

The ANN enabled in MATLAB with data values of the 13 Internal Logistic Properties from the 10 companies was processed. The values of the indexes of Internal Logistics as well as their possible are given in Table 6.

Table 6 : Obtained values of the Internal logistics Indexes and errors of these values in the 10 companies studied.

Company	1	2	3	4	5	6	7	8	9	10
ILI	70,65	75,00	67,37	72,13	78,15	60,03	70,05	65,00	78,00	64,04
Error in %	-2,65	-0,006	2,62	-3,13	-0,15	-0,03	-0,059	-0,004	-0,009	0,95

Conclusion

In this paper two approaches and their expressions to assess the internal logistics of a company is established. The first method was based on dividing the internal logistics in 13 properties, having each property 10 indicators that were evaluated between 1 and 5 points. This leads to the maximum value of Internal Logistics Index (ILI) for each company can reach up to 100 points.

When assessing this parameter, using the Excel tab developed or by the method of Artificial Neural Networks, very similar values consistent with the reality of the companies studied were obtained, demonstrating the validity of both methods.

The methodological approach developed for the definition of both models contains all the steps and procedures, allowing replication of the research, which is as important as the application of the developed models at the companies.

References

1. Mentzer, J. T., & Konrad, B. P. (1991). An efficiency/effectiveness approach to logistics performance analysis. *Journal of business logistics*, *12*(1), 33.
2. Olavarrieta, S., & Ellinger, A. E. (1997). Resource-based theory and strategic logistics research. *International Journal of Physical Distribution & Logistics Management*, *27*(9/10), 559-587.
3. Rouwenhorst, B., Reuter, B., Stockrahm, V., van Houtum, G. J., Mantel, R. J., & Zijm, W. H. (2000). Warehouse design and control: Framework and literature review. *European Journal of Operational Research*, *122*(3), 515-533.
4. Gattorna, J., Day, A., & Hargreaves, J. (1991). Effective logistics management. *Logistics Information Management*, *4*(2), 2-86.
5. Trippi, R. R., & Turban, E. (1992). *Neural networks in finance and investing: Using artificial intelligence to improve real world performance*. McGraw-Hill, Inc..
6. Lipton, Z. C., Berkowitz, J., & Elkan, C. (2015). A critical review of recurrent neural networks for sequence learning. *arXiv preprint arXiv:1506.00019*.
7. Haykin, S. (1994). *Neural networks: a comprehensive foundation*. Prentice Hall PTR.
8. Isasi Viñuela, P., & Galván León, I. M. (2004). Redes de neuronas artificiales. Un Enfoque Práctico, Editorial Pearson Educación SA Madrid España.Yao X (1999) Evolving Artificial Neural Networks. En Proceedings of the IEEE. Vol 87(9), pp.1423-1447.
9. Efendigil, T., Önüt, S., & Kahraman, C. (2009). A decision support system for demand forecasting with artificial neural networks and neuro-fuzzy models: A comparative analysis. *Expert Systems with Applications*, *36*(3), 6697-6707.
10. Rojas, R. (2013). *Neural networks: a systematic introduction*. Springer Science & Business Media.
11. Goyal, A., Walia, G. K., & Kaur, S. (2012). IMPLEMENTATION OF BACK PROPAGATION ALGORITHM USING MATLAB. International Journal of Information Technology, 5(2), 429-431
12. Gupta, J. N., & Sexton, R. S. (1999). Comparing backpropagation with a genetic algorithm for neural network training. *Omega*, *27*(6), 679-684.
13. Rumelhart, D. E., Hinton, G. E., & Williams, J. R. (1986). Learning Internal Representations by Error Propagation. Parallel Distributed Processing, Vol. I, Rumelhart, D. E. and McClelland, JL.
14. Fritsch, J. (1996). *Modular Neural Networks for Speech Recognition* (No. CMU-CS-96-203). CARNEGIE-MELLON UNIV PITTSBURGH PA DEPT OF COMPUTER SCIENCE.