APPLICATION OF KOHONEN MAPS FOR THE PRIORITIZATION OF MARKET AREAS: A PRACTICAL APPROACH

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ABSTRACT

This paper introduces a methodology based on neural networks to prioritize some market areas with a business approach. In this research, we try to resolve the uncertainty that exists in most organizations around the priority of a market area by conducting a search of the most relevant criteria businesses consider in order to assign priorities to certain clients. The problem is sustained by a lack of tools to estimate the priority of a market area and by the lack of an effective interface between logistics and marketing departments. To address this situation, we used Kohonen maps, a type of neural network that facilitates customer grouping and makes it possible to determine which of them most frequently impact the previously established priority criteria. Finally, three scenarios are proposed to validate the proposal made and see what behavior the neural networks have in terms of prioritizing marketing areas.

KEYWORDS: Neural networks; Kohonen maps; Market areas; Logistic; Marketing.

APLICACIÓN DE MAPAS DE KOHONEN PARA LA PRIORIZACIÓN DE ZONAS DE MERCADO: UNA APROXIMACIÓN PRÁCTICA

RESUMEN

Este artículo presenta una metodología basada en redes neuronales para realizar priorización de zonas de mercado visto desde un enfoque empresarial. En esta investigación se intenta dar solución a la incertidumbre que existe en la mayoría de las organizaciones en torno a la prioridad que tiene una zona de mercado; para ello se hace una búsqueda de los criterios más relevantes que las empresas tienen en cuenta para asignar prioridades a ciertos clientes. La problemática se sustenta por la ausencia de herramientas que permitan determinar la prioridad de una zona de mercado y la falta de una interrelación efectiva entre los departamentos de logística y mercadeo. Para ello se ocupan los mapas de Kohonen que son un tipo de red neuronal que facilita el agrupamiento de clientes y permiten determinar cuáles de ellos son los

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que impactan con mayor frecuencia los criterios de priorización previamente establecidos. Finalmente, se presentan tres escenarios con fin de validar la propuesta formulada y ver qué comportamiento tienen las redes neuronales en temas de priorización de zonas de mercado.

PALABRAS CLAVE: redes neuronales; mapas de Kohonen; zonas de mercado; logística; mercadeo.

APLICAÇÃO DE MAPAS DE KOHONEN PARA A PRIORIZAÇÃO DE ÁREAS DE MARCADO: UMA APROXIMAÇÃO PRATICA

RESUMO

Este artigo apresenta uma metodologia baseada em redes neurais para a priorização de áreas de mercado visto de uma abordagem empresarial. Nesta pesquisa tenta-se resolver a incerteza que existe na maioria das organizações em torno da prioridade de uma área de mercado; para fazer uma pesquisa dos critérios mais importantes que as empresas consideram a priorizar determinados clientes. A questão se suporta pela falta de ferramentas para determinar a prioridade de uma área de mercado e da falta de uma interface eficaz entre logística e departamentos de marketing. Para isto se fazem os mapas de Kohonen que são um tipo de rede neural para facilitar o agrupamento de clientes e permitir-lhes determinar quais são os critérios que impactam com mais frequentemente os critérios de priorização previamente estabelecidos. Finalmente, apresentam-se três cenários para validar a proposta e ver que o comportamento tem as redes neurais nas áreas de priorização de áreas de marketing.

PALAVRAS-CHAVE: Redes neurais; Mapas de Kohonen; Áreas de mercado; Logística; Marketing.

1. INTRODUCTION

The importance of logistics for company competitiveness has meant that they find themselves in need of establishing indicators for measuring the behavior of those variables that directly and indirectly have repercussions for them. In addition, changes in the business sector cause companies to see the need to measure themselves within the logistics field with the goal of designing competitive strategies that allow them to counteract those changes in their business. Given these circumstances, companies must be prepared through commercial strategies to maintain their markets; in fact, it is of vital importance that organizations keep logistical criteria in mind within their marketing plans as tools for improving their competitiveness.

From the marketing perspective, the classic variables that normally intervene and help to counteract changes are the following: price, understood as the value of the exchange of a product as determined by its usefulness or the satisfaction derived from the purchase; place, or elements that make it possible to ensure a product arrives satisfactorily to the customer; product, which would be any type of goods, service, idea, location, organization or institution with offerings in the market for acquisition, use or consumption and that satisfies a need; and promotion, the form in which the company determines how it will communicate with the client.

These variables allow businesses to have a good indicator for measuring their competitiveness, which obliges the logistics area to be aware of said variables to establish and schedule their communication delivery in a timely manner, at the right moment, in a suitable location, at the right cost, in the hands of the end customer, and fully satisfying their needs. Thus, the need arises to generate criteria for the companies that permit them to measure the market priority each one of their geographic zones has. So far, it can be said that no direct work has been done in market area prioritization, but studies have been developed to achieve it through mathematical tools and/or statistics for describing customer behavior to facilitate the decision-making process.

Keeping the same information in mind, several projects can be highlighted for their attempts to approach customer research and to that end the prioritization of marketing areas, such as the work of Kiang and Kumar (2001), who utilized Kohonen maps to find clusters within a data set obtaining good results when they were asked to do research on mining with these types of tools. Curry et al. (2001) also used self-organizing maps (SOMs) to classify customer groups in the hotel industry with the aim of finding correlations between customers and hotel performance. The same Curry et al. (2003) conducted a general analysis of the market segmentation process, as well as an analysis of clusters using Kohonen maps, demonstrating the advantages of utilizing this type of neural network compared to other traditional segmentation methods.

A study conducted by Chul and Ho (2004), examines a market segmentation in video games using SOMs and is one of the first studies to take a formal approach with marketing area prioritization, given that they use segmentation as a tool for determining the location of customers with certain characteristics and focus the market strategies on those segments to then determine a more exact level of importance for each segment. Being that the objective of the study is to identify the characteristics of the video game market in Japan and South Korea, it further identifies the segments of age, gender, education, and a large quantity of customer characteristics in the market using SOMs to efficiently segment and reduce the impact presented by the atypical data generated by analyzing two different countries. Additionally, Kiang and Kumar (2004) have conducted a comparison between Kohonen maps and k-means algorithms to achieve marketing segmentation by showing that SOMs elicit better results in all cases and situations evaluated. Kuo

et al. (2006), meanwhile, present a methodology in their research for identifying the characteristics of specific groups of customers in a determined area, as well as the process of clustering in subgroups with specific characteristics.

One study that comes a bit closer to area prioritization is that conducted by Bravo, Orejuela and Osorio (2007) in which they target indicators to measure prioritization in transportation and subsequently present the need to establish certain indicators in market area prioritization. Similarly, Montoya (2007) segmented customers through factor analysis, which made it possible to validate data from a previous market study utilizing matrices with (*n*) variables and (*k*) factors. This was done to reduce the number of variables that appeared in the market area analysis, which further aided the study. Finally, a customer classification can be obtained based on some characteristics identified in market research, thus facilitating decision making on the part of marketing departments.

Additionally, Bigné et al. (2010) make a comparison between neural networks and traditional methods to create an approach to market segmentation that demonstrates the superiority of SOMs over hierarchical clustering to achieve segmentation. Soldic-Aleksic (2012) propose a combination of the two models of data mining to conduct market segmentation, for which they used Kohonen maps and decision trees, where the first was used for visualization and clustering and the second for an improved visualization from a statistical point of view, achieving favorable results with the combination of both methods.

Seret, Verbraken and Baesens (2014) implemented a new method for customer clustering that directly impacts marketing decisions. The authors propose a method of variable prioritization that, according to their attributes, makes it possible to understand the differences between certain customers. Meschino et al. (2015) posit the use of fuzzy data for data clustering through SOMs, reaching important conclusions in the field given that the data normally exhibit stochastic behaviors and are not always deterministic.

Finally, the majority of studies in existence to date are primarily based on market segmentation using various tools and methodologies to facilitate decision making, while in the case of market area prioritization there are only approximations and suggestions regarding the importance of considering a market area prioritization criterion for decision making in terms of resource allocation.

The above gives a clear demonstration of the need to design a methodology for market area prioritization. For that reason, this study introduces a methodology that to some extent attempts to provide a solution to the problems with finding a tool for prioritizing customer areas. In section 2, the entire theoretical framework for the tool used to conduct the prioritization process will be explained. In section 3, the case study will be presented. In Section 4 the most relevant results and findings will be shared, and finally the conclusions will be presented in section 5.

2. THEORETICAL FRAMEWORK

2.1. Neural networks

Neural networks are responsible for the relative weights that make it possible to measure the importance the distinct prioritization criteria have within market areas, thus one is able to emulate the behavior in such zones in any way.

For the development of the methodology a short description of the neural networks is presented, as well as the behavior exhibited both in the biological setting and in its application in the marketing and logistics areas. The SOM is the visual tool employed by the neural networks to visualize the behavior based on the relative weights. Finally, a case study will be presented involving an analysis of three scenarios with their respective computational results simulated in Matlab.

Per Caicedo and López (2009) artificial neural networks (ANN) came about as an attempt to emu-

late the function of the neurons we have in our brains. In this sense ANNs follow a different trend than classic approaches in artificial intelligence, which try to model human intelligence by seeking to imitate the thought processes that occur in our brains.

The classic structure of a neural network can be seen in **Figure 1**, where the input vector is defined as $X=[x_1, x_2, ..., x_n]$. The information received by the neuron is modified by a vector with synaptic weights whose role is to emulate the synapses that exist between biological neurons. The parameter θ_j is known as the bias or threshold of a neuron, and finally the parameter y_j is the final output or outcome of the neural network.



2.2. Kohonen SOMs

SOMs were introduced by Teuvo Kohonen in 1982, and are also known as Kohonen self-organizing maps or Kohonen neural networks. These maps are modeled after the capacity of the human brain to recognize and extract relevant features or characteristics in the world around them (Caicedo and López, 2009).

The basic idea behind an SOM is to create the image of a multidimensional input space in the output space with the smallest size. It is a model made up of two layers of neurons as can be observed in **Figure 2**. The first layer is the input layer and the second is the processing layer. The neurons for the input layer are limited to collecting and channeling

the information. The output layer or processing layer is linked to the input layer through the synaptic weights of the connections.



The Kohonen SOM is made up of two levels of neurons, one for input and one for output. However, only at the output level is the information processing conducted, which is why it is referred to as the output layer and the network is therefore considered a monolayer type. The connectivity is complete, meaning that all the neurons in the output layer receive stimuli from the input neurons.

Learning in the Kohonen SOM model is governed by **Equation 1**, which defines the variation of the weights as δw_r in this algorithm, wherein the winning neuron and its neighbors modify their weights vector by adding a fraction of the existing distance between the input vector and the weights vector in instant t of the algorithm.

$$\delta w_r = \alpha(t) h_{rs}(t)(x - w_r)$$
(1)

Where *x* is the input vector, δw_r is the variation of the vector weights for the rth neuron, $\alpha(t)$ is the learning rate, $h_{rs}(t)$ is the neighborhood function, w_r is the vector weights of the rth neuron, and *t* is the iteration index.

In a neural network, the connections between neurons have a determined weight w_r which has as its principal function the mitigation or amplification of the values desired to spread towards the neuron. The learning rate is calculated using **Equation 2**, where α_r and α_i correspond to the final and initial learning rates respectively. t_{max} is the maximum number of iterations.

$$\alpha(t) = \alpha_i = \left(\frac{\alpha_f}{\alpha_i}\right)^{\frac{1}{t_{max}}}$$
(2)

With this expression, what is sought is that the learning rate follow an exponential function with the aim of having strong variations in the weights at the beginning of the process, and as that process advances the variations decrease, thereby guaranteeing that, at the beginning, the neurons fan out as quickly as possible between the representative data forming the basis of the training.

The neighborhood function is defined using **Equation 3**, where *d* is the Euclidian distance between the winning neuron (*s*) and the neuron (*r*) to which the weights are modified. Neighborhood range $\sigma(t)$ is variable and defined with **Equation 4**, where σ_i and σ_f correspond to the initial and final neighborhood ranges respectively.

$$h_{rs}(t) = e^{\left(-\frac{d(r,s)^2}{2\sigma(t)^2}\right)}$$
(3)

$$\sigma(t) = \sigma_{i} = \left(\frac{\sigma_{f}}{\sigma_{i}}\right)^{\frac{t}{t_{max}}}$$
(4)

A neuron will become winning when its Euclidian distance towards the input vector (in this case the values for prioritization criteria) are the minimum. **Equation 5** shows the result.

$$s = \min(x - w_i) \tag{5}$$

The neighborhood is an exponential function whose characteristic makes it possible to see that the neurons farthest from the winning unit are affected in their synaptic weights in a lower proportion than those that are closer.

In summary, Kohonen maps are a type of unsupervised neural network where there is no training pattern for the input data, which is different from supervised networks if they possess that training pattern or teacher for the data entered.

2.3. Prioritization criteria

To estimate the priority of a market area the following prioritization criteria must be defined based on fieldwork; in this case, different types of experts who work in logistics and marketing were interviewed, as well as academic experts in the same fields who provided their input for the selection of the prioritization criteria from the perspective of academia. The resulting criteria were the following:

- Average demand (by the various SKUs)
- Average safety inventory (safety stocks)
- Lead time: transit time

• Company regional participation level (per the distribution of the demand classified by areas)

• Regional permanence (total time the company has serving the market area in question)

• Establishment of competition in the region (number of companies that serve the region in question with similar or substitute products)

• Distance to the distribution center (how far the market area is from the company's closest distribution center)

2.4. Simulation algorithm

Having identified the final prioritization criteria, a case study is designed for three geographic areas. Random values are generated between a series of ranges (maximum and minimum) for each of the defined criteria, and in turn replicated for the three pre-established scenarios.

The algorithm for the Kohonen map consists of the following six steps:

1. The architecture of the network is defined with N neurons in the input layer and M neurons in the output layer. The control parameters are then randomly defined: $\sigma_{\rho} \sigma_{\rho} \alpha_{\rho} \alpha_{f}$ and t_{max}

2. An input vector is randomly selected $X = [x_1, x_2, ..., x_n]$, so that it belongs to the training pattern set.

3. The index of the winning neuron *s* is determined based on the minimum distance between the

input vector and the neuron weight vectors: $s = min (x - w_i)$.

4. The neuron weights are modified rth in accordance with: $\delta w_r = \alpha(t) h_{rs}(t)(x - w_r)$

5. Parameter is increased *t*

6. If $t < t_{max}$ we return to step 2.

The Kohonen neural network is programmed in the computing environment Matlab, making use of the neural network application in the toolboxes.

3. CASE STUDY

For the case study, a decision had to be made regarding which of the (n) market areas with a company can be the most prioritized in a determined period to ensure that the distribution resources would be successfully administered and assigned in the most efficient way (to be understood as distribution resources: personal, storage, communication systems, cargo trucks, etc.).

Based on the selected criteria the case study is conducted under the following conjectures and conditions:

• The seven previously mentioned prioritization criteria are used.

• Three geographic regions are considered and designated A, B, and C, each one having specific characteristics.

• For the demand criteria, the total average demand of the customers in the three geographic regions was considered.

• The average security inventory on the part of the customers located in the three geographic regions was considered.

• For the reset time, the time from when the cargo came out of the CD of the supplier until arrival at the end client located in any of the three geographic regions was considered.

• The participation level criteria refer to the total (%) participation the supplier has in each of the three geographic regions.

• The potential region criterion is maintained as the total demand potential that exists in the region.

• Regional permanence refers to the time the supplier has been distributing its products in each of the three regions.

• For the freight criterion, it is assumed that the supplier funds 100% of the freight. For this case the value of this criterion would be associated with the quantity of the cargo and the total distance between the supplier and the end customer.

• In total 50 customers for each region were studied, so 150 customers total for the three geo-graphic regions together.

• To generate each value, the Excel tool for obtaining random values according to the minimum and maximum range given to each criterion for each geographic region was used.

• A hypothetical value range case was defined for each of the seven criteria, based on the conjecture that said values must be in conflict initially, which is to say that the value of the criteria must not demonstrate an immediate preference for one region compared to the others. A field study was done through detailed surveys where experts (people who work in marketing and logistical roles) were asked which of the prioritization criteria were most relevant at the moment of defining the priority of a market area. The survey consisted of two specific questions that led to the determination of the percentage of each prioritization criterion's participation according to the role of the expert surveyed. In addition, a statistical study was conducted whose result was a specific number of surveys to conduct to ensure the sample was significant. **Table 1** shows the consolidated results of the surveys conducted.

3.1. Scenario 1: case in conflict

In this scenario, the case is shown to be in conflict with the criteria, where determination by visualizing the prioritized region with the naked eye would be impossible. **Table 2** shows the value ranges for each of the seven criteria in the three market areas.

3.2. Scenario 2: demand and inventory variation

In this scenario, the attempt is to see how much the final results would vary in the event that the demand and inventory values are modified, knowing ahead of time that these criteria have a weight of 25% and 15% respectively in the election of the prioritized region.

TABLE 1. PERCENTAGE OF EACH PRIORITIZATION CRITERION										
Dema	nd Effective inventory	l Lead Tin	ne Part	ticipation level	Region potential	Permanence in region	Freight			
25%	25% 15%		8%		7%	9%	20%			
TABLE 2. VALUE RANGE: CASE IN CONFLICT										
		Effective	Lead		. .					
Region	Demand (und)	inventory (und)	Time (hrs)	Participation level (%)	Region potential (%)	Permanence in region (years)	Freight (millions \$)			
Region A	Demand (und) [1,450;1,600]	inventory	Time		potential		5			
		inventory (und)	Time (hrs)	level (%)	potential (%)	region (years)	(millions \$)			

Table 3 shows the changes made in the criteria mentioned; then, the rest of the criteria remain equal as in scenario 1.

3.3. Scenario 3: lead time and freight variation

This scenario is similar to the previous one, but in this case the criteria modified are lead time and freight, which have percentage weights of 16% and 20% corresponding to the second and third criteria in order of importance for the final prioritization decision.

Table 4 shows the percentage variation each criterion presents and how in the previous case the value range for the five remaining criteria stay the same as in the case in conflict.

TABLE 3. DEMAND AND INVENTORY VARIATION							
Region Demand (%) Effective inventory (%)							
А	[-3.45 ;4.38]	[-5.0 ; 4.0]					
В	[-27.5 ; -14.5]	[-3.33 ; -13.0]					
С	[-35.7 ; -26.8]	[-22.2 ; -26.5]					

TABLE 4. LEAD TIME AND FLEET VARIATION							
Region	Lead time (%)	Freight (%)					
A	[-16.7 ; 3.75]	[15.0 ; 33.3]					
В	[3.33 ; 12.5]	[-40.0 ; -33.3]					
С	[-40.0 ; -28.6]	[30.4 ; 78.6]					

4. **RESULTS**

The neural network was programmed in Matlab, which processes and emits two main results, an SOM and a map with the plane analysis. Below, each individual scenario and its corresponding prioritization analysis will be presented.

4.1. Scenario 1 Results: case in conflict

The results for the neural network programmed in Matlab normally give two principal results as displayed in **Figures 3** and **4**. The first of them (**Figure 3**) provides the visualization of the categories detected by the SOM, meaning the three market areas (a representation on a plane for the market areas studied), while **Figure 4** corresponds to the plane analysis for the different inputs used, which for this case are the seven prioritization criteria. The results in this figure show the intensity each prioritization criterion has in the SOM (market areas). The darker it is, the more intense the criterion in question within the region it falls into. For example, criterion number 4 has a high level of intensity in the red region according to **Figure 3**.

To validate the sample and part of the results of each scenario, 20 uniformly distributed replicas were conducted according to the ranges within which the prioritization criteria values move, while in the case of results training and validation the same set of data was used. For greater ease in attaining the results, in all of the scenarios the topology of the networks used was 10 x 10 for a total of 100 neurons in each case.

The results of **Figure 3** indicate that region A (light blue) is located in the upper right area of the map, region B (yellow) is located in the lower right of the map, and region C (red) is on the left side of the map. Lastly, the dark blue color indicates the neurons that did not form a pattern and for that reason did not successfully activate. For this case, there are some neurons that activated but stayed outside of the assigned zone, as in the case of region B, which has two neurons located in the lower left area.



Figure 4 indicates the intensity of the prioritization criteria in the final representation of the SOM, where said intensity indicates higher participation or higher relevance of the criterion within the market area. The criterion established for classifying the intensity results of the maps is done using a scale of 1 to 5 (defined a priori to estimate the classifications). In this case the higher the intensity of the criterion, the higher its classification will be.



In its first column, **Table 5** shows the weight of each criterion (taken from **Table 1** above). Then, it shows the classification each criterion obtained in each of the regions according to **Figures 3** and **4**. This is followed by the relative weight corresponding to the product of the weight by the classification to then calculate the amount by region and obtain the total for each one.

The 3.2 figure obtained by region A in the demand criterion is due to the intermediate intensity displayed by the first grid in **Figure 4**, which refers to the SOM (**Figure 3**). This intermediate intensity (the mean value of the 1 to 5 scale, or 3) is represented by the yellow color of the demand Criterion over the total for region A. The 3.2 value is determined by the fact that the yellow color in that grid is tending towards red. The same is done for regions B and C, and for the rest of the six prioritization criteria.

In **Table 5** it can be observed that region C obtained a 3.9, which corresponds to the highest classification; therefore, it can be concluded that said region is the most highly prioritized for this scenario. The location of the zone in the first part of the map was due in large part to the freight criterion, which allowed the majority of the neurons located in that region to immediately activate, an attempt at representation through a closer approach to the central datum.

Validating the selection results for region C a bit, as the prioritized zone, it must follow that said region would display the most intermediate data of the three, meaning it wasn't particularly high nor low in the majority of the prioritization criteria. Although it was the scenario in conflict, those small differences that the other two regions had affected them to the extent that their priority wasn't as marked as that of region C.

4.2. Scenario 2 Results: demand and inventory variation

The principal results for this scenario can be seen in **Figures 5** and **6**, and in **Table 6**.

Criterion))(ai aib t		Classificatio		Relative Weight		
Criterion	Weight	А	В	С	Α	В	С
Demand	25%	3.2	2.8	3.5	0.8	0.7	0.9
Effective inventory	15%	3.5	3	4	0.5	0.5	0.6
Lead time	16%	3.5	3.5	3	0.6	0.6	0.5
Participation level	8%	3.6	5	4.5	0.3	0.4	0.4
Region potential	7%	3.5	3	5	0.2	0.2	0.4
Permanence in region	9%	2.5	3	3.5	0.2	0.3	0.3
Freight	20%	4.8	2	4.8	1	0.4	1
Prioritization results						3.0	3.9



In **Table 6** it can be observed that priority lies in region A with a relative weight of 3.5, which is due in large part to the 0.75 result it received from the demand criterion. Unlike the previous scenario where the priority fell in region C, here it can be observed that the changes made in demand and inventory play an important role in priority moving to region A.

For this scenario, the criterion that most influenced the final location of the regions was the level of participation, generating an average classification of 3.86, while the criterion for which the least weight was generated for the location of the regions was demand, with an average classification of 2.5. Part of the final conclusion regarding why region A was chosen as the priority region is that said region was the one that had the highest positive variation in the demand criterion, which succeeded at moving it 4% forward, while the other regions didn't have positive growth in this criterion. On the other hand, although the aforementioned region did not have the highest benefit from the inventory variations, it can be concluded that the weight the demand criterion has is much more relevant for bending prioritizing decisions towards a particular market region or area.

TABLE 6. FINAL PRIORITIZATION RESULT – DEMANDAND INVENTORY VARIATION								
Criterion	\\/a;akat	Classification			Relative weight			
	Weight	А	В	С	А	В	С	
Demand	25%	3	2	2.5	0.75	0.5	0.6	
Effective inventory	15%	4	1	3.6	0.6	0.2	0.5	
Lead Time	16%	3.6	3.9	3.6	0.6	0.6	0.6	
Participation level	8%	3.5	3.6	4.5	0.3	0.3	0.4	
Region potential	7%	4	3.4	3	0.3	0.2	0.2	
Permanence in region	9%	3.5	3.2	3.8	0.3	0.3	0.3	
Freight	20%	3.5	4.5	3	0.7	0.9	0.6	
Priori		3.5	3.0	3.3				





The principal results for this scenario can be observed in **Figures 7** and **8**, and in **Table 7**.

Table 7 indicates that in this scenario the priority falls into region A, with a relative weight value of 3.4. In terms of the most representative criteria, in this case they are demand and freight, with values of 0.88 and 0.84, meaning they bring the most benefit to region A. Regions B and C obtained values closer to each other (2.9 and 3.1), possibly due to region B successfully activating the neurons, then those neurons immediately activating the neurons in region C or vice versa.



TABLE 7. FINAL PRIORITIZATION RESULT – LEAD TIMEAND FREIGHT VARIATION								
Criterion	Waight	Classification			Relative weight			
	Weight	Α	В	С	А	В	С	
Demand	25%	3.5	3.8	3.5	0.88	1.0	0.9	
Effective inventory	15%	3	2.5	3.5	0.5	0.4	0.5	
Lead Time	16%	3.2	3	1	0.5	0.5	0.2	
Participation level	8%	3	4.5	4	0.2	0.4	0.3	
Region potential	7%	3.8	3.5	3	0.3	0.2	0.2	
Permanence in region	9%	2.5	3.2	3.8	0.2	0.3	0.3	
Freight	20%	4.2	1	3.2	0.8	0.2	0.6	
Prior	3.4	2.9	3.1					



Detailing the varying criteria, it can be observed that lead time doesn't generate good results for the three regions in general, where even region A reached a maximum of only 0.51 in its relative weight, surpassing region B's 0.48 by a small margin. The previous criteria variation revealed a priori that region C would be the one with the highest benefit for this criterion, given that its variation indicated a decrease in lead time by more than 33%. This value indicates that the neural network is based on how the data at the beginning of the simulation are distributed, thus affirming whether a criterion had an increase not necessarily identified by the network and shown as a benefit, but based on the percent variation and on how far apart the data are dispersed from each other.

As a final result of this scenario it can be observed that the priority lies in region A, given that it had the highest positive variation with respect to the lead time criterion, meaning the delivery times reduced considerably to tend to customer demand. This was expected given the importance of this criterion for prioritizing regions.

5. CONCLUSIONS

Basically, the importance that logistical and marketing decisions have regarding issues like prioritizing customer zones is highlighted. Normally these types of decisions are independent from each other, but this research project emphasized the importance of combining these departments for joint decision-making.

The importance that statistical and/or mathematical tools have for company decision-making was highlighted. In this way, the SOMs or Kohonen maps make it possible to successfully utilize important approaches when it is necessary to study a certain amount of data that facilitate the decisionmaking process.

The logistical and marketing criteria identified in the research conducted provide an initial visual of the behavior of each market area. This allows the states in conflict that each individual region displays to be seen. In addition, the importance that each of them has regarding prioritization can be recognized, given that, upon varying their values in a certain way the priorities change from one region to another.

It can be said that the variations of the input parameters modify the location of the market areas in the SOM and consequently the change in the region's priority. Analysis of the scenario demonstrated that any modifying input pattern can cause a variation in the region's priority and likewise their redistribution within the map. What is proven is the great utility that artificial neural networks have for assimilating the behavior of a determined number of data that situations in conflict present, unlike other tools that wouldn't achieve the same in a clear way. For the purpose of these cases, the neural networks function with unsupervised learning in which the previously discussed pattern or supervisor doesn't exist, thus the initial weights of the network are activated randomly and attempt to find the initial datum closest to the next neurons to be activated.

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