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Self-Organizing Maps to Analyze Value Creation in Mergers and Acquisitions in the Telecommunications Sector

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Abstract

A great effort has been made in recent years to refine the study methods that emerged in the 1990s to assess long-term abnormal returns in the stock markets as a way to evaluate the value creation or destruction of merger and acquisition (M&A) in the sector of telecommunications. It is regularly addressed in generic merger and acquisition studies, with a short-term time horizon or just with a qualitative focus. In this work, we use a visual data-mining tool, Self-Organizing-Maps (SOM), to analyze mergers and acquisitions in telecommunications sector. The relationship among variables influencing the M&A was only observed due to the capabilities of the visual neural map method that allow to relate variables, which is not possible with other classical methods. In this work, the relationship obtained with the SOM linking M&A language, M&A cross-border, and size of the acquiring company is an important result.

Keywords: Self-Organizing Maps, data, merger & acquisition, abnormal returns, telecommunications

1. Introduction

The long-term analysis of merger and acquisition (M&A) is a new avenue of research that started in the last decade of twentieth century. Currently, we can often find more researches devoted to this issue in order to understand the long-term corporate performance of these operations, but

it is still quite infrequent in the telecommunication sector. It is regularly addressed in generic merger and acquisition studies, with a short-term time horizon or just with a qualitative focus. Specifically, the analyses of M&A in this sector normally focus on the following:

- Short-term studies using an event-oriented methodology, where the stock market performance of a group of telecommunications firms involved in M&A processes is analyzed [1–3]. Specific studies by countries such as Taiwan [4], Korea [5], Turkey [6], or Brazil [7].
- Concrete examples of M&A operation involve different actors, such as the study of the unsuccessful M&A of Telia and Telenor [8], the Cingular—AT&T Wireless merger [9], the acquisition of Voice Stream by Deutsche Telecom [10], the SBC-Pacific Telesis merger, and the Bell Atlantic-Nynex merger analyzed by Sung and Gort [11].

In telecom, there is an observable shortage of statistical and econometric analyses of a sectorial nature in M&A. Moreover, except for Ref. [12] who studied the sector before liberalization, all of them are short-term studies.

As for results, the evidence is mixed: the assessments that indicate negative abnormal returns stand out [3, 13]. For instance, [5], supported by empirical evidence, suggest that M&A generally do not reward the participants on stock markets primarily because of the dynamic nature of the telecommunications sector, which is characterized by frequent changes of a technical and regulatory nature, market globalization, new product definition, and entry of new competition. However, another group of researchers reveal the positive market reaction to announcements of M&A in telecommunications [2, 14, 15]. There is a certain tendency to recognize, as is customary in the general literature on mergers and acquisitions, that the acquirers are negatively impacted by the M&A. Additionally, the factors involved in the M&A remain unclear. Our work thus aims to throw more light on this issue, especially since long-term research is, as we have seen, practically inexistent for this industry, and the methodological controversy between long-term and short-term analysis remains open.

In order to answer the question: do the M&A in telecommunications create or destroy value in the long term? Nowadays, there are three fundamental methodologies for analyzing the specific returns of the M&A:

- BHAR, *Buy-and-Hold Abnormal Returns*.
- CAR, *Cumulative Abnormal Returns*.
- CTAR, *Calendar-Time Portfolio Approach*.

The calendar-time portfolio approach when constructing the comparison portfolios allows the variance in each of the periods to automatically incorporate the cross-sectional correlation of the individual returns of the sample firms. This is a relevant advantage against the other analyzed methodologies. According to Mitchell and Stafford [16], the use of large samples and the careful construction of benchmark portfolios can partially mitigate the negative effects of the BHAR methodology, but it cannot solve the serious problem of cross-sectional dependence [17].

The calendar-time portfolio methodology results very solid and statistically robust for the analysis of value creation in M&A by evaluating the stock abnormal returns, but the relationship

among possible variables to explain it remains unclear. With classical statistical analysis, further studies of dependences and causes for the values creation or destruction are not conclusive. Other methodologies are required.

In this work, we propose a new approach: Self-Organizing Maps (SOM), a visual data-mining tool to analyze (M&A) in telecommunications sector. We will obtain visual information about the time evolution (short to long term) of the stock cumulative abnormal returns of the M&A acquirer company as a way to evaluate the operation's value creation or destruction and the behavior of different related parameters. This analysis will make possible to draw qualitative conclusions in such operations.

Self-Organizing Maps are a very useful and effective visualization tool nowadays [18]. It is based on neural networks and its goal is to search and show patterns in high-dimensional data sets. In classical approximations, data are represented in two or three dimensions. However, when the dimension number is higher, the representation of all obtained data is difficult. The dimension restriction in the visualization space makes necessary restrictions in the variables to show, as, for example, to fix some of them and to represent the rest. This limitation gives rise to a partial representation of the representation and important information could be hid or ignored. Nevertheless, SOM enables to visualize all the dimensions (variables) from the data with no restrictions and to find relations in data sets with high dimensionality, allowing to maintain topographical relations between the input and output spaces. Patterns near the original space will be near to the output space [19, 24].

The chapter is structured as follows: Section 2 describes the SOM algorithm. Section 3 describes the data set used to extract the conclusions. Section 4 presents the results obtained with the SOMs used over the data set described. And finally, the conclusions of the work are summarized in Section 5.

2. Self-Organizing Maps

In Ref. [19], Teuvo Kohonen proposed a special neural network: The Self-Organizing Map. After that, SOM has been widely used and analyzed. Most recent reviews can be found in Refs. [20, 21]. This technique and its variants are used often in a broad variety of domains: financial [22], medical [23], and engineering applications [24, 25]. Also in animal sciences SOMs have been applied [26–28]. As a neural network, SOM is formed by neurons, in this case organized in two layers (**Figure 1**): N neurons disposed in the input layer (each input variable has assigned a neuron) and a second layer used to process the information, named output layer. The output layer is disposed in a regular low-dimensional structure, normally, a two-dimensional grid.

Each neuron is represented by an N -dimensional weight vector $\mathbf{m} = [m_1, \dots, m_N]$, where N is equal to the dimension of the input vector.

The most important principle in the SOM is to maintain a neighborhood relation between the N -dimensional data space original and the regular low-dimensional grid. In fact, for this

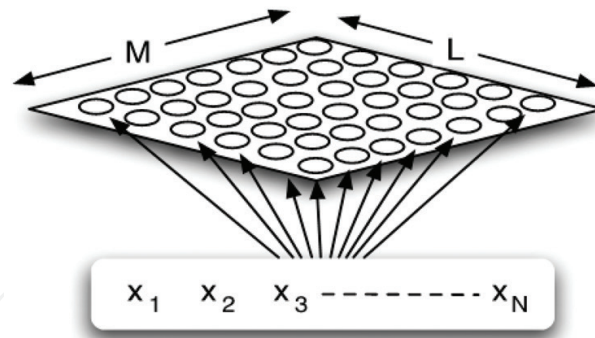


Figure 1. Self-Organizing Map scheme.

paper and this particular case, similar M&A behavior (characterized by the observed variables) will be placed near areas in the low-dimensional output space.

A learning algorithm is used now to calculate the corresponding coefficients for each neuron, called synaptic weights. First, the algorithm makes a weight initialization. With this initial values of synaptic weight selected, the following is to get them closer to the optimum. An iterative procedure is used to obtain these new values. For each training step, the distances between all the weight vectors of the SOM and a random sample vector \mathbf{x} from the input data set are calculated using some distance measure. The neuron with the weight vector nearest to the input vector \mathbf{x} is called the *Best-Matching Unit (BMU)*, denoted here by c :

$$\|\mathbf{x} - \mathbf{m}_c\| = \min_i \{ \|\mathbf{x} - \mathbf{m}_i\| \} \quad (1)$$

where $\| \cdot \|$ is the distance measured, typically Euclidean distance.

Once BMU is found, SOM's vectors weight are updated in order that the BMU is moved closer to the input vector in the input space. All topological neighbors of the BMU are treated in the same way.

Once the map training is completed, the visualization of the two-dimensional map named "components plane" provides qualitative information about how the input variables are related to each other for the data set used to train the map. In this figure, the weight vector of neurons that form the map is represented separately using a color code. In this way, establishing relationships among variables is immediate.

3. Data set

The telecommunications M&A occurred between 1995 and 2010 have been counted as samples, to conduct the analysis. These samples have been obtained from the Thomson Reuters One-Banker database, including 10,459 announcements. Only operators of the telecommunications sector (SIC codes 4812, 4813, and 4899) with effective date of M&A have been included. In this way, we obtained the specific data for each M&A. Of these data, 4337 are M&A made

“between operators.” Financial information has been obtained from the S&P’s COMPUSTAT database, obtaining the most significant book values (3878 annual records of fiscal data), and from the University of Chicago CRSP database on monthly stock evolution (18,425 records of monthly listings). All the information was consolidated in a single database. We proceeded to a manual consolidation as the databases are indexed in different ways, and to elaborate the book-to-market ratio.

After the processing, we have obtained 402 samples with all the required data: deal information, the acquirer’s stock market data, and its financial book data. A sample of this size is equivalent or larger than those generally analyzed in the studies of M&A in this market. For instance, [1] with 275 operations and [3] with 144 short-term studies and also in the levels of key studies based on long-term generic post-M&A analyses: 399 in [29] and 230 in [30].

To evaluate value creation or destruction, we analyze the short- and long-term abnormal returns provided by the financial markets. We calculate the calendar-time cumulative abnormal returns ($CTAR_t$), which are defined as the mean abnormal return calculated each month for each firm (R_{pt}), subtracting from the monthly portfolio returns of each firm the reference expected portfolio return ($E[RP_t]$) and we cumulate them with different time horizons (3, 6, 12 months, and so on). The final variables used to be analyzed are shown in **Table 1**.

Before proceeding to use the SOM to analyze the data set, possible dependencies between variables were searched. For this purpose, an independent analysis was carried out for discrete variables (χ^2 -test) and correlations for the continuous variables. Regarding continuous variables, correlations higher than ($p < 0.05$), in absolute value, were not found, so none of them were removed. Regarding the discrete variables, the next dependencies were found:

- *Dependence Size-Language*. The observed dependence of size and language indicates the influence of proceeding with M&A of same language to guarantee their corporate success [31].

Name of variables	Meaning
Size	Acquirer market: 1 (64%) 0 (36%) 1 big company; 0 small company
Domestic	In-country (25%) Cross-border (75%)
Experience	Number of previous acquisitions (same acquirer, 3-year period)
Language	M&A language: same language (46.5%), different language (53.5%)
Target company’s market situation (GDP, penetration of Internet, Mobile before Telephone)	Interannual growth of GDP, internet, mobile and fix penetration (2 years the M&A)
Intangible	Acquirer’s intangible assets/total assets ratio
European	European M&A or not: 1 (61.5%) 0 (38.5%)

Table 1. Variables analyzed in this study. The frequency of occurrence of the discrete variables listed.

- *Dependence Size-Spanish.* With the same idea of merging or acquiring companies with same language, the main acquirers in Spanish are Telefonica and America Mo'vil, both are large in size and with preference to proceed with M&A in Spanish.
- *Dependence Domestic-Spanish.* Typically, the M&As in a country use the country language to complete the operation.
- *Dependence European-Spanish.* This dependence was expected because it relates a geographical area (Europe) with one of the languages spoken in this area.

After this analysis, the variables Size and Domestic and European were disregarded.

To analyze the temporal dynamics of the acquisitions, it was considered to modify the CTAR index defining a new input variable to the SOM. Eq. (2) determines the difference in values of the CTAR variable in different temporal instants (6, 12, 24, and 36 months) versus the value initially taken (3 months). In this way, the temporal variation of this index can be integrated into the SOM. As we prefer performing a qualitative analysis, it is important to normalize the initial value from the beginning. It was noted that other approaches used, and not presented in this paper for lack of space, did not present good performance. These approaches were, on one hand, to use CTAR values as variables and, on the other hand, to use the increments without normalize

$$CTAR_i = \frac{CTAR_i - CTAR_3}{|CTAR_3|} \quad (2)$$

After that, the SOM was trained with the selected variables, which is discussed in Section 4.

4. Results

This section presents the results obtained with the data set put forward in Section 3. The SOM was trained varying the following training parameters [20]:

- *Initialization.* Two different types of parameter initialization of the model (synaptic weights) were conducted. On one hand, random initialization and on the other, principal component analysis of the inputs was used.
- *Neighborhood function.* The *Gaussian*, *bubble*, and *cut-gauss* functions were used as neighborhood functions to update the neuron coefficients close to the winner.
- *Learning algorithm.* Two types of algorithms were used for training the SOM:
 - *Sequential.* In this way, the synaptic weights are updated with each pattern of the database.
 - *Batch.* Here, the weights are updated when all the patterns of the database are passed. This algorithm is faster than the previous one because it requires fewer updates. However, this algorithm usually provides worse results.

After varying these parameters, 4000 different SOMs were obtained; the selection of the best SOM was based on two different error measures: the topographic and quantization errors

[20]. The topographic error evaluates the neighborhood relationships; that is, it quantifies if patterns close in the original space remain close in the output space (defined by the SOM).

The quantization error measures the quality of the mapping established by the SOM and calculates the norm among the input patterns and the corresponding winner's neurons. As both are important measures, that which presented the best balance between the two measures was chosen. Therefore, the geometric mean between the quantization and topographical errors was chosen as a measure of the quality of SOM. The only problem with this measure is if one of them is zero (this case did not happen). The SOM finally chosen presented a random initialization, sequential learning mode, and Gaussian neighborhood function (**Figure 2**).

The following conclusions can be drawn from **Figure 2**:

- The normalized increase in CTAR index at 6 months is different to that presented at 12–24 months. This indicates that an M&A has a transitional period exceeding the value of 6 months. It shows that any attempt to draw conclusions in that period of time can lead to errors as seen in the subsequent evolutions. Also, there are delimited areas with best performance (top-center part of the map) and with the lowest one (bottom-left part of the map).
- The largest variations of normalized CTAR occur in the same position (top-center part). It is worth mentioning that both Spanish language and language of M&A are found in this area.
- After 36 months, the situation is very similar to the initial one except for the extreme behaviors, or M&A has gone very well or very badly. This fact is proved by the last component which presents values near to zero in almost the entire map.

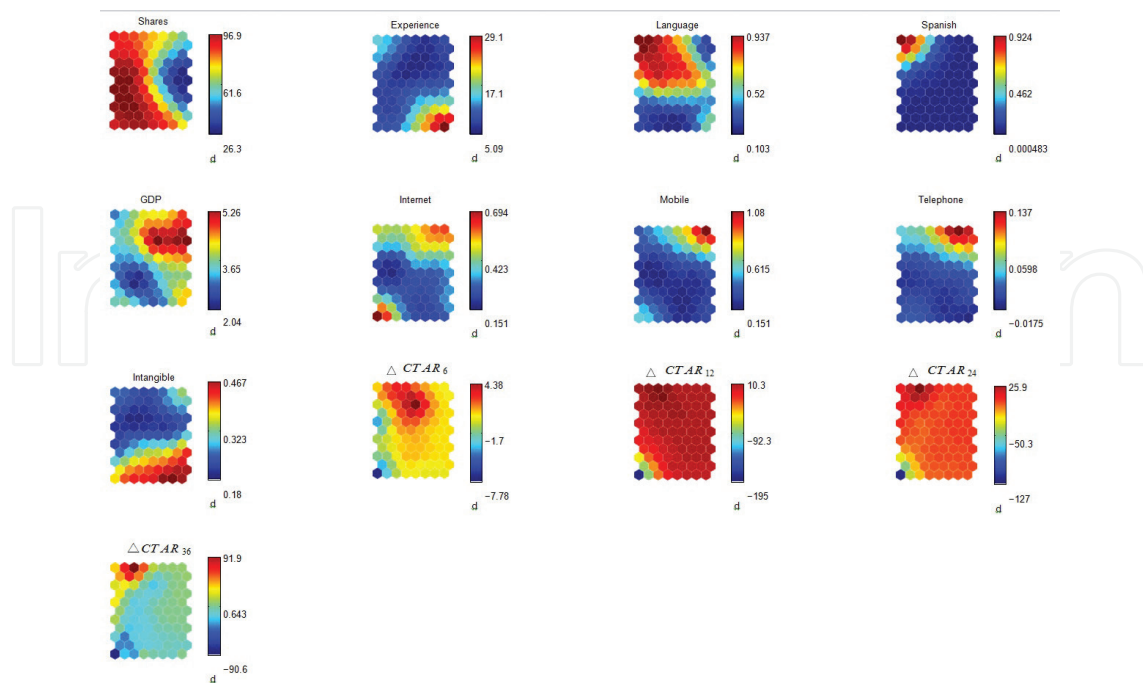


Figure 2. Components plane obtained after the SOM training.

- These regions (bad/good evolution) have different values in the variables *Language*, *Spanish*, and *Intangible*.

The results have relevant methodological implications in the discussion of the analysis of value creation timing (short-term vs. long-term analysis). In this sense, several studies are supported against short-term methodologies stressing that the short-term event studies results only reflect the market reaction in a very limited period of time, by evaluating fluctuations around the date of the event. It therefore does not appear that value creation is properly addressed from the structural and sectorial perspective. We can identify several reasons why the evolution of stock market prices in short term does not reflect properly a solid long-run value creation for the acquirer and the market could include the following:

1. It is generally accepted that short-term researches are devoted to M&A announcements around the date of the announcement more than real situations of M&A with an effective date [32].
2. Short-term value changes may reflect speculative or ephemeral changes. The M&A may affect not only the acquirer but also the competitive position, the situation of the rest of the industry and its rivals and even the likelihood of other competitors being acquired [33–35].
3. A short-term analysis window may not capture all the effects on stock markets [35, 36].
4. Supporting the M&A performance conclusions in the analysis of short-term returns means considering that the investors fully understand the determining factors of a successful acquisition and have enough information to accurately predict how the process of integration is going to affect the future results of the acquirer. This assumption is not always possible [37].

Therefore, the validity of our long-term approach in the study of mergers and acquisitions is also supported by these results.

Due to the temporal evolution of the index CTAR, it was decided to carry out a cluster analysis of neurons in the SOM to further clarify the above conclusions. The obtained clusters (10) are shown in **Figure 3**.

Moreover, to study the problem in more depth, the cluster centroids are represented by parallel coordinates (standardized centroids are calculated to jointly represent all variables). This visualization method is useful for data analysis when you need to discover or validate a group structure. **Figure 4** shows such representation. This figure shows the evolution of the variables related to CTAR. Three different behaviors can be observed: one upward, another downwards and other one with constant evolution (where clusters from 8 to 10 are included).

To determine the differences of a good and bad M&A, a new parallel coordinate figure was used (**Figure 5**). For this purpose, the centroids of clusters for good and bad M&A are used. The biggest differences between a successful and a bad M&A are clearly represented in **Figure 5**. The main differences are corresponding to variables 3 and 4 (*Language* and *Spanish*), having lower incidence at the ninth, eighth, and second variables (*Intangible*, *Telephone*, and *Experience*) in that order.

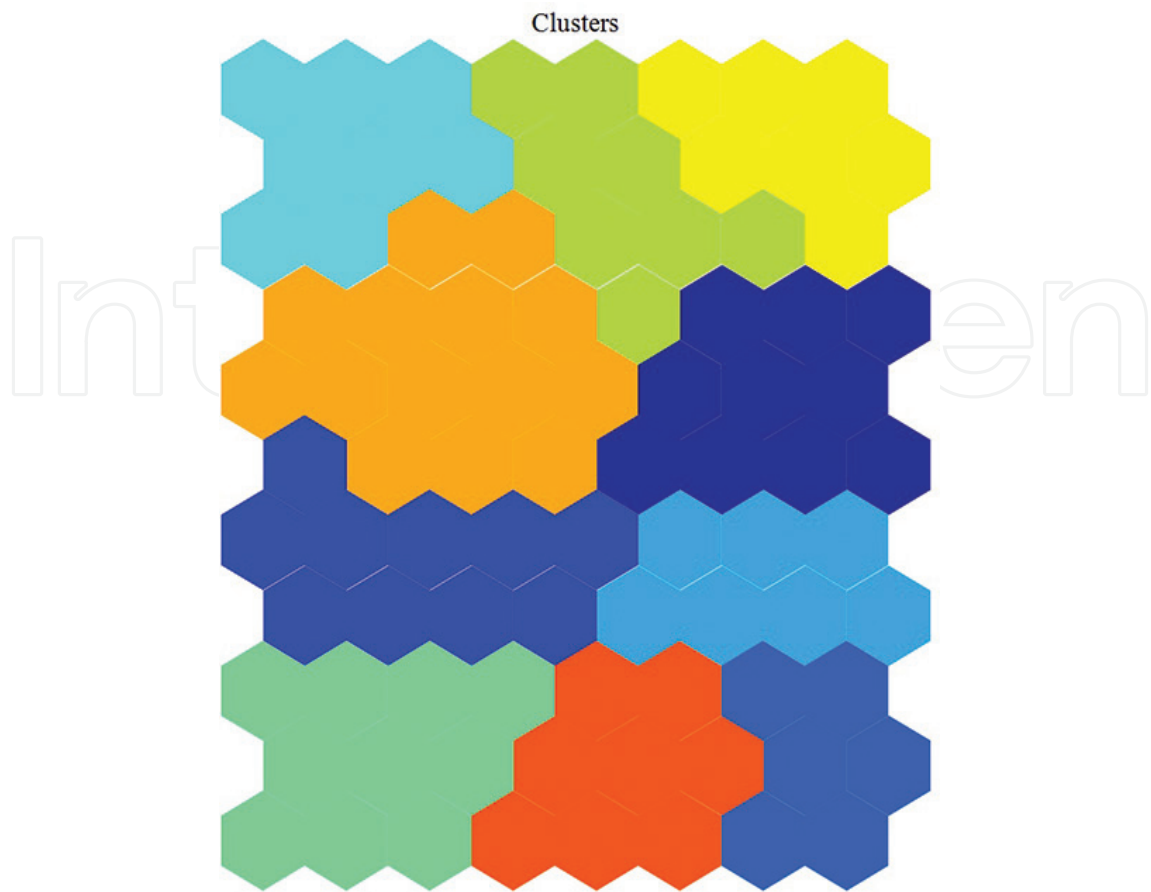


Figure 3. SOM clusters obtained.

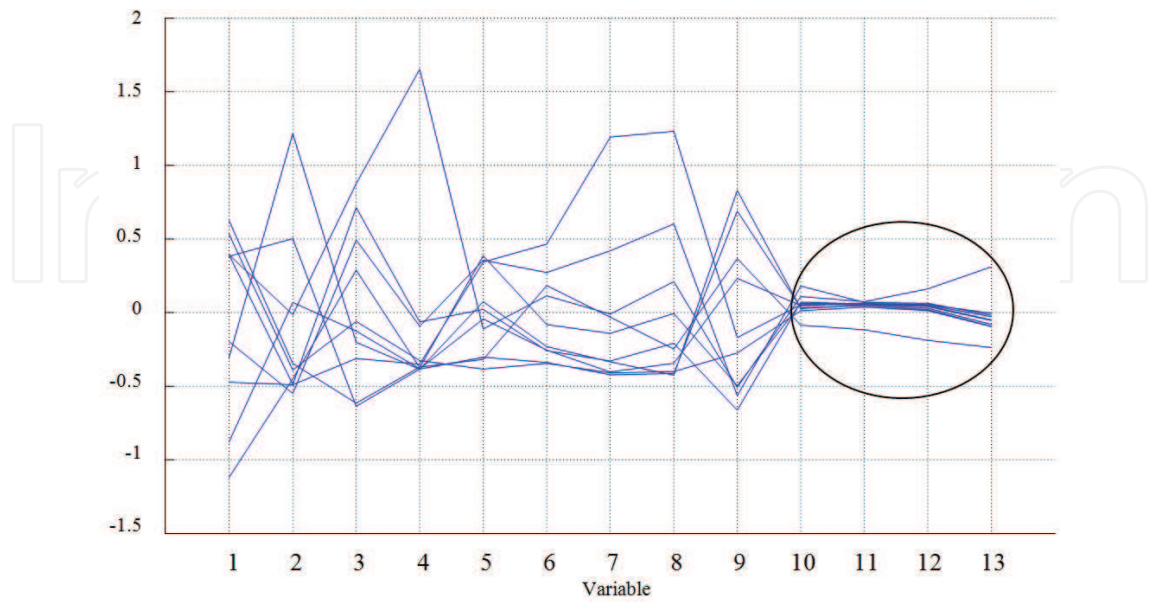


Figure 4. Parallel coordinates of the clusters obtained within the SOM.

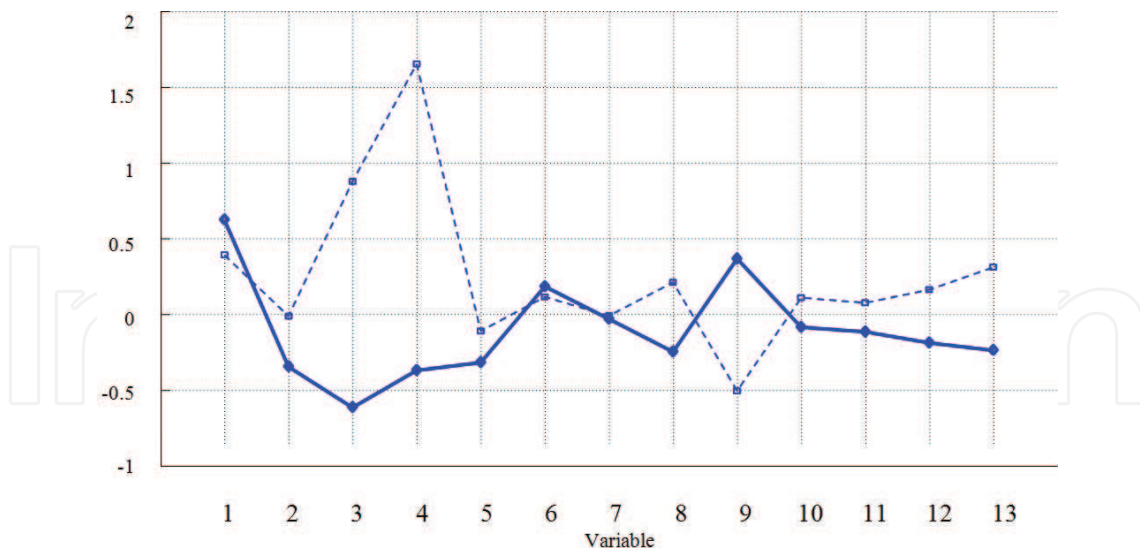


Figure 5. Parallel coordinates of clusters corresponding to a good M&A and bad M&A.

5. Conclusions

This paper proposes the use of a Self-Organizing Map to extract qualitative information about the different variables in M&A operations in the field of telecommunications. The relationship between the variables is complex and highly nonlinear. The Self-Organizing Map together with the parallel coordinate method shows the most important factors in this problem. The current study is relevant for deepening in the study of the variables that influence telecommunications mergers and acquisitions, which, as we saw, is a relatively young field of research. Highlight the importance of language in such transactions, especially when the language, as explanatory value of M&A, is not a factor lavish too much [38, 39]. The chapter discussed the role of the acquirer's size, which is not a factor extensively studied in the acquirer's value creation [30] and internationalization [40]. Also, this paper especially relates these factors all together, thanks to the visual analysis and SOM. Additionally, new areas of future research were identified, thanks to the centroids analysis, as the role of post-acquisition degree of control and also the acquirer's intangible value that usually present the opposite behavior, as the literature points out.

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