Proceedings of the 2015 International Conference on Operations Excellence and Service Engineering
Orlando, Florida, USA, September 10-11, 2015

Application of the Restricted Boltzmann Machine for the planning of maintenance in databases

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Abstract

Restricted Boltzmann Machine (RBM) is one of many stochastic models that helps IT organizations to make different kinds of predictions, events programming, among other uses. Taking into account the four learning methods most used in the neural networks applications, RBM uses supervised offline learning, which means that the weights of the connections stay fixed after the end of the training stage of the network. This model was adapted into two different codes: one with supervised online learning and the other with supervised offline learning, after the code is adapted, its effectiveness and efficiency are evaluated. The before mentioned, was analyzed with a database maintenance plan model, and as a result, it is obtained that there is no significant difference in the effectiveness of learning methods, resulting in a difference of 0.52% in the average prediction error; instead, it is found that each method have different processing times. Furthermore, as part of the future lines of research, it would be helpful to use a larger data set with the actually needed information and a real set to train the network according to the problem analyzed.

Key Words: Restricted Boltzmann Machine, Artificial neural network, database maintenance, Offline learning, Online learning, Stochastic programming.

1. Introduction

The worlds' economy is now dependent on information systems and telecommunications, the economy use data or information which is processed to be interpreted and take all kinds of actions and decisions (Suárez 2007). In order to analyze these data, it is of the utmost importance a proper management of the same, by which the information technologies are an effective tool for resolving the different needs of processing, storage and distribution of information in the various areas of development.

It is important to note that at the time of processing the information, this is not always known or deterministic, and sometimes must work with uncertainty and probability functions associated by which the stochastic models come to be a possible solution to this variant (Birge J.R. & Louveaux F., 2011). Between the stochastic models are genetic algorithms, programming with fuzzy logic, artificial neural networks and expert systems.

Currently there is a growing need to plan and predict events. A method of resolution that is compliant with raised are artificial neural networks, due to the fact that the main strength of the same is its high ability to recognize

patterns, to make predictions, learn from the experience and make conclusions (Li 2004). Due to this characteristic of the artificial neural networks, these have been used to perform various functions in the industry such as forecasting, programming or scheduling of events, image recognition, data mining, among others (Hilera and Martínez, 2000).

In this research we want to analyze and criticize the method of learning of the Restricted Boltzmann Machine, for which is set using only a method of learning off-line and not one on line, the working group raised the uncertainty, why is that it is not used the method of learning on line, which is the reason to present a comparison between the two methods. To achieve this, it sets a code that simulates the model of a Restricted Boltzmann Machine and evaluates the efficiency and effectiveness of prediction of the two forms of learning of the network. Once adjusted the code uses an interface to run the same in the Python programming language and obtain the results of the program, which were the mean error in the prediction of the input variable. For the implementation of the code were used two programs; Canopy Express and Tutorialspoint.

Then, to evaluate learning methods, it is estimated a sample size from the initial results of runs and compares the average error of samples between the two methods.

Conclusions section focuses on summarizing the findings obtained from the development and validation of the present work. Finally in section of future lines of research recommendations are made in case of a post at midlevels in research.

2. Theoretical framework

2.1 Stochastic Programming

Muñoz and Cerdá (2006) defined the stochastic programming as an analysis of the resolution of problems of mathematical programming in which some parameters are unknown, but it is known the probability distribution associated with them, and therefore, the situations that are analyzed using the same are situations of risk. The stochastic programming treats parameters as random variables hold to uncertainties and errors in its measurement or estimation of what is known its probability distribution.

For its part, (Prékopa 1995) defines stochastic programming as the resolution of mathematical problems in which some or all of the parameters are random variables.

Due to these reasons, in the stochastic programming, relaxes the assumption that all the parameters of a problem are deterministic, thus allowing to deal with random variables, parameters hold to uncertainty or to possible errors in its estimation or measurement; of which knows its probability distribution (Caballero, Cerdá, Muñoz & Rey,2004).

2.2 Artificial Intelligence

Romero, Dafonte, Gómez and Penousal (2007) define artificial intelligence as the branch of science that is responsible for the study of intelligence in artificial elements and, from the point of view of engineering, proposes the creation of elements that possess an intelligent behavior.

The artificial intelligence allows simulate the thought processes and the actions of the man, using procedures that achieve a proper behavior and decision-making accurate and immediate manner (Andrade, 2013).

There are various areas of application of artificial intelligence, in which methods are applied different resolution for each application. Within the main areas are the genetic algorithms, fuzzy logic, expert systems and neural networks (Salao, 2009)

Moujahid, Inza and Larrañaga (2007) define genetic algorithms such as adaptive methods that can be used to solve problems of search and optimization; its operation is based on the genetic processes of living organisms; and through the imitation of this process, the genetic algorithms manage to be able to create solutions for real-world problems.

The fuzzy logic is an extension of classical logic that not only imposes it set for false and true values; it also procures to create mathematical approaches in the resolution of certain types of problems. In other words, intend to produce accurate results from inaccurate data, which are particularly useful in electronic or computational applications (Morales, 2002).

León (2007) defines the expert systems as a computer program based on knowledge and reasoning that

performs tasks that usually only performs a human expert; in other words, it is a program that imitates the human behavior in the sense that uses the information that it provided in order to be able to give an opinion on a special topic.

Finally, neural networks are a model based on the complex information processing systems whose structure and function are inspired in the biological neural networks; they consist of a set of simple processing elements called nodes or neurons connected to each other because of the connections that have a numerical value called modifiable weight (Montaño 2002).

As previously mentioned, genetic algorithms have as main function the optimization, the fuzzy logic the approximation, the expert systems the imitation and the neural networks the processing or the recognition of patterns.

Since it is intented to plan the maintenance in a database, it requires the processing of information where it is comparing a series of entries and is obtained as these a response given depending on the data that the same result. Which is why according to the main function of each area of application of artificial intelligence, choose the neural networks; because, as Montaño (2002) mentions these allow to add the values of the inputs that it receives from other units connected to it, compare this amount with the threshold value and, if it equals or exceeds, send activation or outlet for the units to which they are connected. Also both outflows and inflows that sends depend on the weight or strength of connections by which those transactions are carried out.

2.3 Artificial Neural Networks

Neural networks have specific characteristics, among them four main aspects, which are: topology, learning mechanism, type of association between the input and output, and finally the form of representation of this information (Rodríguez & Sierra 2005)

Topology refers to the organization and layout of the neurons in network, forming clusters calls layers; the parameters to take into account are the number of layers, the number of neurons per layer, the degree of connectivity and the type of connections between neurons (Andrade,2013).

Learning mechanism: is the process by which a neural network modifies its weights in response to an input information (Rodríguez & Sierra, 2005). During this process the weights of the network connections are modified, when these remain stable means that the network learned (Andrade, 2013). There are four types of learning that determine this criterion, first is the supervised learning and unsupervised; the difference between them lies in whether or not there is an external agent (supervisor) to control the learning process of the network. Also within the types of supervised learning are: learning by error correction, learning by reinforcement and stochastic learning (Row & Martínez 2000). As to the unsupervised learning there are two types of learning, the hebbiano and the cooperative learning and competitive. On the other hand has the learning on line and off line, the difference between these two types of learning is that learning on line do not distinguish between a training phase and the phase of operation, causing the weights vary dynamically each time new information enter into the system. While the off line learning, has a definite stage for training and another for implementation; it will first be trained by the network, and then this works with weights already established, that is to say, the weights remain fixed once that ends the training phase (Rodríguez & Sierra, 2005)

Type of association between the input and output information: This refers to the data that the network learns, and associates the entries with an output. There are two ways for obtain this association, the heteroassociation and autoassociation. In the first the network learns by pairs of data and responds by generating an output and the second network learns certain information, so that when the information is displayed in the form of input, performs an autoassociation with one of the stored data (Andrade, 2013).

Form of information representation: This feature makes reference to the nature of the entered data as to the data generated in the output; can be of two types, or analogues or discretes. The first ones are continuous values, normalized to a specific range; while the discretes are of binary type what means that they can be represented only with 0 and 1 (Rodríguez and Sierra, 2005).

Due to the approach of the theme in the stochastic programming, it'll push out into the type of stochastic supervised learning. Hilera and Martínez (2013) propose that this learning is basically perform with random changes

in the values of the weights of the connections of the network and evaluate its effect on the desired goal and probability distributions.

Within the thirteen types of neural networks, the most important are: Avalanche, Adaptive resonance theory, Adaline/Madaline, Back Propagation, Bidirectional associative memory, Boltzmann and Cauchy Machine, Brain-Estate -in-a-box, Cerebellatron, Counter-propagation, Hopfield, Neocognitron, Perceptron and Self-Organizing-Map (SOM) and Topology-Preserving -Map (TPM). However, only one of these types (Boltzmann and Cauchyt Machine) are stochastic networks. In such a way as to be classified within the type of supervised learning, specifically in the stochastic learning.

For its part, the Boltzmann Machine is a network with different alternative topologies, but always with hidden neurons that allow, through a probabilistic setting, enter a noise that is being decreased during the process of learning to escape from the minimum (local) of the energy function of encouraging the search of the overall minimum (Hilera & Martínez, 2013). Specifically this network uses the technique of the temple as simulated procedure to escape local minimum using noise and combines it with the probabilistic assignment (stochastic learning) through the hidden layer of the network.

On the other hand, the Cauchy Machine is a refinement of the Boltzmann, which uses a faster procedure in search of the global minimum and a different probability function. However, based on Andrade (2013) its use is not as required, due to the fact that during the learning stage and functioning need too much time, in addition its functioning is very complex and much less intuitive than the other networks. These stochastic networks are used in the recognition of patterns, voice processing and image processing of knowledge and to solve optimization problems (Hilera & Martínez, 2013).

Agree with Row and Martinez (2013) the stochastic networks Boltzmann Machine and Cauchy Machine have learning off line. However, the stochastic learning based on reality in search for the combination of weights that establish a minimum value of the function of relative entropy of the network. Therefore, if the on-line learning has the capacity to vary the weights dynamically and the aim of the stochastic learning is to find for the optimum combination of weights, ¿why not use the on-line learning? Questioning on the basis of which it develops later criticism of the model and the validation of the proposal.

Of the stochastic neural networks existent the Boltzmann Machine is the most recognized and is classified in different types which finds the Restricted Boltzmann Machine (RBM). In relation with Fischer and Igel (2012) the Boltzmann Machine can be used to learn important aspects on a probability distribution unknown based in samples of this distribution. In general, this process of learning is difficult and comports time. However, the learning problem can be simplified imposing restrictions in the topology of the network, which comports to the creation of the RBM.

With base in of De La Rosa (2014) the Boltzmann Machine is a model the sufficiently powerful to represent distributions complicated (that is to say, go for a parametric configuration limited to one no parametric), considers that some of the variables that describe to the representation never observed (called hidden). Having hidden variables, increases the modeling capability of the Boltzmann Machine (although also increases its computational cost).

2.4 Databases

The databases have become the preferred method for structural storage of data; from the big multi-user applications, until the mobile telephones and electronic organizers use database technology to ensure the integrity of the data and facilitate the work of users and facilitate the works of user and programmers that develop them. (Camps et al. 2005)

A database such as it mentions it Deuai Z. (2012) is a collection of data of archives related, that permit the management of information from some company or entity. Likewise, each one of these archives can be seen as a collection of registers and each register is composed of a collection of fields, where each one of these fields allows carry information of some attribute of an entity of the real world.

Besides, although the database has to allow varied and simultaneous utilizations, the representation of the same will be unique and integrated (Camps et al. 2005).

The databases have become essential part of almost all the current companies, proof of this are the most representative applications of the same, which are: banking, airlines, universities, credit card transactions, telecommunications, finances, sales, production and human resources (Silberschatz, Korth and Sudarshan, 2002).

There are also, database management systems, which are a system based in computers, whose general purpose is register and maintain data using a database management system, allowing to the user and applications the query and manipulation of data, through the use of a structured query language, also known as SQL (Structured Query Language) (Deuai Z. 2012).

Given the importance of the database, is paramount the management and maintenance of the same. The management of a database does reference to the security, that is to say, the allocation of the levels of access to this to safeguard the information that it finds. The maintenance by its part includes from backups, to prevent the loss of information in case the hardware or software fail; until a plan of periodic maintenance. In this maintenance plan typically realize the following tasks: analysis of archives of control, analysis of the page of the basic data, transactions in limbo, index management, user management, management of permissions and backups (Dorado, 2010). Well same Dorado (2010) explains every aspect of the maintenance of the database:

1. Analysis of control files: When it generates some type of problem that cause the fall of the database, this generates a message in a file, giving a kind of binnacle, that goes to allow by means of these messages know the stability of the database, as well as access to the same.
2. Analysis of the database pages: The database has three types of page (structure of the table, indexes, and the page of data), the verification of the integrity of these pages with the tools of the system, helps to the control that it do not duplicate the information doing inefficient the database or causing failures by the no integrity of the same.
3. Transactions in limbo: In a once initiated database a transaction; these can then be finalized or refused. However, some transactions remain slopes or in the limbo, so that the elimination of these transactions is desirable to avoid load on the database with information or files without importance.
4. Management of indexes: The indexes in general are going to be saved in the form of binary tree, once that the data suffer changes, the indexes begin to occupy more pages, increasing the depth of the same; therefore, the reconstruction of the same, relocates the indexes again, improving the benefits that would make the database.
5. User Management: The high and low of users that access to the database, it is an aspect of must be performed periodically to monitor the security of the same.
6. Management of permissions: In a database, not all users have the same privileges, so that must be managed permissions to tables, views, and other factors.
7. Backups: The backups have to do periodically to protect the database, these copies can be made in hot or cold, hot, means that users still connected to the database while generating the copies, however not all database systems allow for this, so you can make in cold means that only the ABD is connected to the base, without users.

3. Model Explanation

3.1 Evaluation of the Restricted Boltzmann Machine in maintenance of databases

The technologies of information covers a range of services associated with it, such as: the provision of services of software, software maintenance, database migration, database transmission models, database maintenance, and telecommunications, among others.

As mentioned above, given the contribution that the databases have had in the daily actions of the organizations, as well as the massive use of these, databases are chosen as the branch of information technologies to study, focusing especially on its maintenance. Due to the malfunction of these, it can cause problems for the organization, given that in them is where all the information that is used to operate this entity is stored.

Artificial intelligence and its functions were mentioned before and from these, it was determined that since artificial neural network have a great pattern recognition system, these were appropriate to predict how often a

database has maintenance. These networks will compare an input set and a result will be obtained from these inputs, in this case, the output would be how much time until the database needs maintenance.

There are also different types of neural network, as explained above; we are going to be working with the Boltzmann machine because it is a stochastic neural network with its restricted version, due to the fact that learning process can be simplified by imposing restrictions on the topology of the network.

Given that the learning stochastic searches for the optimal combination of weights, and online learning have the capacity to vary the weights dynamically, a question arises from the reason of why isn't online learning used in the implementation of the RBM. Which it is intended to train the network using learning on-line and off line, with the purpose of determining the prediction errors associated with each type of learning and compare the same.

3.2 RBM with learning off-line

For the elaboration of the RBM with off-line learning, we took an existing programmed code of RBM, which was modified by the working group, to achieve the desired result.

For the current paper, initially the network is trained with a set of six data arrays of size six each set. The network then runs five thousand times to train itself, you will introduce these vectors to the network five thousand times, so that she learns how to recognize them.

Once the network is trained you enter a vector and run the network one hundred times, to determine the capacity of recognition of the same, in this part the prediction error is calculated. As mentioned previously, each vector has six fields; the model determines how many of these six fields the network was mistaken in the prediction. For example if the vector was introduced (1,0,1,0,0,1) the model runs one hundred times, resulting the amount of times the network correctly predicted that vector and was not mistaken for example, that the vector was (1,1,1,0,1,0). If it correctly predicts the vector, then zero error is obtained as a result.

The error obtained shall be the amount of fields in the vector that the network did not predict well. Therefore, the maximum errors the network can get is six; as they are six fields, and the least is zero (if all the fields were predicted correctly).

In summary, the RBM network is trained to determine the degree of accuracy in the prediction of data, given an input variable. The resultant error is going to represent this accuracy. What this research wants to find out is which learning methods has lower error, and then through a comparison, determine which learning method should be used.

It should be noted that for all practical purposes the five thousand iterations used, were defined by the working group; however, depending on the required target you can define the number of iterations that are deemed appropriate, according to the training that you may want to give; under equal criterion the hundred runs to determine the error was defined.

3.3 RBM with learning on line

Online learning method in the Restricted Boltzmann Machine, is used using the same code applied to the learning off-line. The difference between these lies in the fact that the network is trained every time a user performs an iteration to adjust the weights of the network. In the same way as the offline model, the network will trained five thousand times using the same vectors of the earlier case. It introduces an input variable, for example the vector (1,0,1,0,0,1), and now instead of making one hundred runs, determining the error in each vector, according to the previous training, the network is going to do a run, train itself, performs a second run then trains itself again, and so on, up until the hundred runs are completed.

To achieve this, a change in the programming code was made; this change calls the training phase within each run. What causes that the weights of the network for each run will be adjusted and trained a hundred times.

It should be noted, that the same vectors of training are used, as well as the same amount of times that the network is trained (five thousand) and the runs where compare well to achieve equality of conditions in the errors present in each type of learning.

Analyzing on line and off line learning, it can be determined if the choice of the learning type has a significant effect on the training of the network, because according to Cai, Hu y Lin (2012) it is difficult to develop fast learning algorithm for the Boltzmann Machine.

4. Validation of the model

Once the two neural networks of the restricted Boltzmann machine was programmed for both off line and on line learning method, a sample size is calculated in order to compare the mean error of the network already trained for both methods of learning.

To obtain the sample size, each of the networks is executed ten times to obtain a population. This data (mean errors) was introduced in the Minitab software to run a normality. Considering a confidence interval of 95% and an error of type alpha of 5 %, a Shapiro-Wilk normality test was used for the network off-line because according to Bee and Mohd (2014) this test is restricted to a sample of size less than 50, in this way it applies to this case. Furthermore, it was established as null hypothesis (H0) that the data behave as normal, while as an alternative hypothesis (H1) that these are not normal. As a result, it was observed that the p-value was 0.064; therefore there is not enough information in order to refute the null hypothesis that the data behave as normal due to the p-value is greater than alfa error type, which can be seen in appendix 1. Similarly, the calculations were performed for the on-line network, where using the same confidence interval, the same error alpha type and the same null hypothesis and an alternative; the resulting p-value was greater than 0.1. It is therefore concluded that there is not enough information in order to refute the null hypothesis that the data behave as normal due to the p-value is greater than alfa error type, the foregoing can be seen in appendix 1.

Then to prove that the data are normal, we can calculate its sample size using (1) so that the values behave in accordance with this distribution. It is estimated the population deviation which turned out to be 1.22 for the network with off-line learning and 1.27 for the network with on line learning. An error of 10 % is used, which according to De la Vara and Pulido (2009), these are considered acceptable, in a way that allows the samples away from the population at a maximum of 10 %. In addition, for the alpha of 5% is determined that the z value is -1.96. With these data, we proceeded to calculate the sample size, which turned out to be 573 for the network off-line and 620 to the network on line.

To explain how the Restricted Boltzmann Machine network is used in database maintenance, we proceeded to run the code for the off-line network using the variables that will be observed below and the assumptions defined for the specific case of a database. It should be noted that the values that indicate the maintenance are included in the code in binary symbology:

1. Amount of faults or messages in the file: 1 =eight thousand messages, 0 =messages<eight thousand.
2. Number of transactions in limbo: 1 =four thousand transactions, 0 =transactions<four thousand.
3. Number of pages per index: 1 =mil, 0 =pages<thousand.
4. Backups: 1 =updated in the last two weeks, 0 =time without updating the copy<two weeks.
5. Number of queries: 1 =thirty thousand, 0 =consultations<thirty thousand.
6. Number of users: 1 =twenty thousand, 0 =users<twenty thousand.

The above assuming that in this case the database being used has capacity for up to ten thousand messages in the file, six thousand transactions in limbo, two thousand pages per index, maintain the backup by three weeks, forty thousand consultations and thirty thousand users.

In such a way that each vector of the six used in the training bar correspond respectively to the before mentioned variables. The vectors used are the following: (1,1,1,0,0,0), (1,0,1,0,0,0), (1,1,1,0,0,0), (0,0,1,1,1,0), (0,0,1,1,0,0), (0,0,1,1,1,0). For example, for the first vector we would conclude that the database has eight thousand messages in the file, four thousand transactions in limbo, a thousand pages per index, less than two weeks with the latest version of your backup, less than thirty thousand queries and less than twenty thousand users; and so on.

Once defined the input variables, we define the output variables associated with each entry, so that when the model predict adequately achieved also get associate the correct output variable.

To define the output values, initially a Likert scale is used in order to establish the importance of each value in the vector. For the first vector is defined as the first value has a relative weight of 0.10 , the second value of 0.15 , the third value of 0.05 , the fourth and fifth value of 0.20 and the sixth value of 0.25 . This in order to quantify the total importance depending on the set of input values. Then the following logic is used; if the sum of the set of values multiplied by each weight of entry is less than 0.3 means that you have not reached the maximum value defined with variables described above, and proceed to link it with a maintenance in 3 months, if it gets a value greater than 0.3 but less than 0.5 maintenance is being performed in 2 months, if this value is greater than 0.5 and less than 0.7 , maintenance is carried out in a month and increased to 0.7 in 15 days. In the case of the network performed both on line and off line, is reflected in the following way, if when you insert the vector (0,0,1,1,1,0) the model achieves predict this same vector, it is determined that the model achieved associate your output variable properly.

Given that what is required is to determine the error for the prediction of artificial neural networks with the two types of learning, was introduced the same input variable for each type of learning, the input variable was used: (0,0,1,1,1,0); which indicates that there are fewer than eight thousand messages in the file, less than four thousand transactions in limbo, a thousand pages per index, up-to-date backup in the past two weeks, thirty thousand queries and less than twenty thousand users. This vector represents as defined by the working group, which the maintenance is required within one month. For this reason they want to determine which model of learning has greater efficacy in the prediction of the fields according to the input variable, so that with this prediction is correct you can determine which is the time of next recommended maintenance.

After running the off-line network 573 times, it was determined that the average of the mean error resulting was 1.9642. Knowing that the maximum error is 6, because that is the amount of spaces in the vector that can have different values with respect to the input vector, it is established that the RBM is mistaken in average 1.9642 fields each run. Then we ran the online network 620 times and it was determined that the average of the mean error resulting was 1.9694. Again it is established that the RBM is mistaken in average 1.9694 fields each run. Also, when comparing the average of the mean error for each of the networks we could observe that the difference is 0.52 %.

5. Conclusions

1. The database maintenance is extremely important in the current businesses because relevant information is managed in this. A shutdown in the database could cause consequences in a small, medium or large-scale according to the error that is presented and the amount of information that is being stored. Therefore maintenance just in time reduces the chances of failure, while safeguarding the information and the actions of the companies that make use of these database systems.
2. The learning methods (on-line and off line); presented results very close between them, it was found that on average each run is mistaken 1.9642 fields for the offline learning method and 1.9644 for the on line one, in terms of the prediction error. Concluding that the use of one or the other method does not generate a marked difference. The discrepancy between the two methods was discovered in the response time of each model; given that online learning method trains itself every run, it takes more to give a final answer, on average it takes approximately 142 seconds more than the off line method.
3. Based on the results obtained in the validation of the models, it is not considered optimal to use one or another model, but it is also advisable to have a combination of the same, if the network is trained only once, not taking into account changes in the environment information updates, would be critical. While the on-line method considers these factors, given that it saves each output obtained during the training phase and updates its training, varying the weights of the variables dynamically. So a combination of these types of learning would be recommended. Such combination would consist in training the network in an offline way at the beginning because, as noted above we can achieve results in a shorter period of time, but each period of time, depending on the need to update the data and the variability of the same, the network would be trained again (on-line) to adjust the weights and provide better results.

6. Future research lines

In regard to the future research lines, it would be beneficial to use a set of larger data with the necessary and real information to train the network and perform a more representative maintenance plan, in order to perform an analysis of costs and profitability from the implementation of the model, considering the costs of deployment and operation, as well as the savings of that implementation. Additionally with these data used to train the network, it can be determined with greater certainty the prediction errors of the model, the efficiency and effectiveness of the same to analyze if even with a larger scale of data, it is feasible using the RBM.

It should be noted that in terms of the efficiency of time in learning methods, it was identified that this also depends on the software that runs the model, in this case it is determined that between Canopy Express and a terminal of Python in line, the latter 81 seconds faster, representing 56% of the total processing time in Canopy Express, by which it is important to take into account the software in which you are running the model and thus choose which option is more efficient.

Also, it is worth mentioning that the proposed model can be used in different applications in industry where required recognize a pattern of data, such as predictions, in cases where appropriate data to train the network is available.

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9. Appendix 1

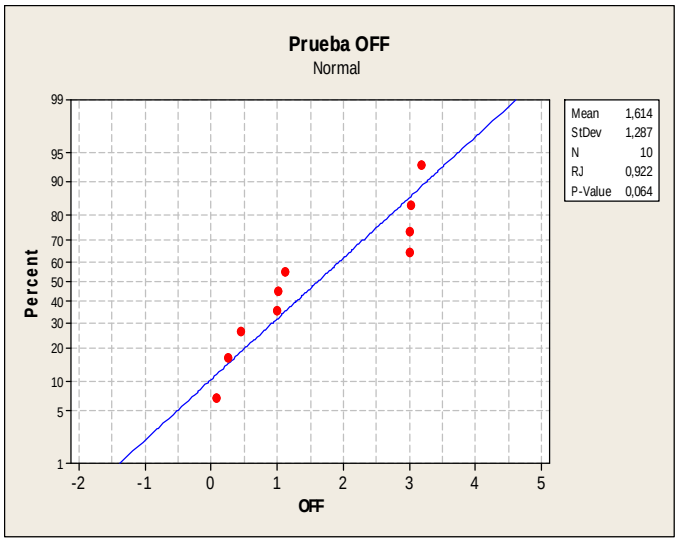

Figure 1. Normality Test for RBM with learning off-line

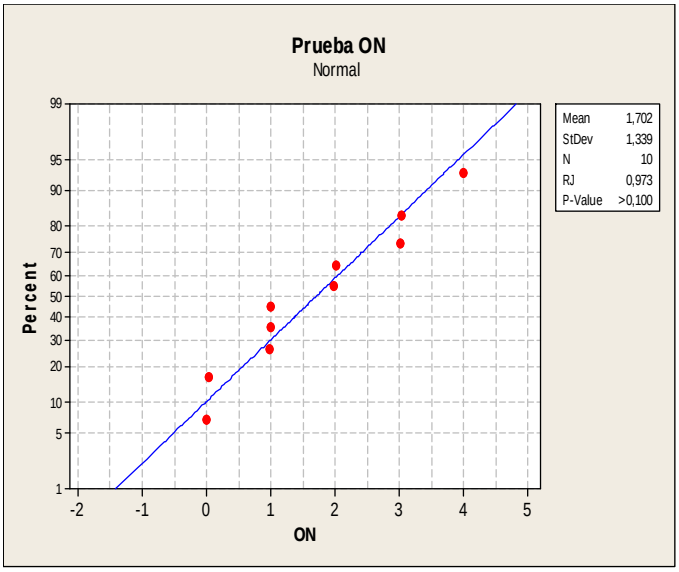

Figure 2. Normality Test for RBM with learning on line

Table 1. Likert scale for the input variables

Variable	Importance Assigned
Amount of failures or messages in the files.	0,1
Amount of transactions in the limbo	0,15
Amount of pages every index	0,05
Security copies	0,2
Amount of searches	0,25
Amount of users	0,25
Total	1

Table 2. Output variables with their respective interpretation

Time until next maintenance	Output
3 months	00
2 months	01
1 month	10
15 days	11

Table 3. Interpretation of the variables of training

Input	Output	Meaning
[1,1,1,0,0,0]	01	2 months
[1,0,1,0,0,0]	00	3 months
[1,1,1,0,0,0]	01	2 months
[0,0,1,1,1,0]	10	1 month
[0,0,1,1,0,0]	00	3 months
[0,0,1,1,1,0]	10	1 month