Proceedings of the 2011 Industrial Engineering Research Conference
T. Doolen and E. Van Aken, eds.

Aircraft Interior Failure Pattern Recognition utilizing Text Mining and Neural Networks

Abstract ID: 833

No Author 1 or 2 Yet
No Organization Yet
No Location Yet

No Author 3 Yet
No Organization Yet
No Location Yet

No Author 3 Yet
No Organization Yet
No Location Yet

Abstract

To remain competitive, airlines must promptly identify and correct failures found in their fleet. This study aims at reducing the time spent on identifying and correcting such failures logged. Utilizing Text Mining techniques during the pre-processing phase, our study processes an extensive database of events from commercial regional jets in Brazil. The result is a unique list of keywords that describes each reported failure. Later, an Artificial Neural Network (ANN) identifies and classifies failure patterns, yielding a respective disposition for a given failure pattern. Approximately five years of historical data was used to build and validate the present model. Results obtained were promising.

Keywords
Artificial Neural Network (ANN); Text Mining; Failure Pattern; Aircraft Log Book; Repair

1. Introduction
The aeronautical market faced by airlines is established in a complex environment, where the business perspective for operators relies on the scenario where minimum differences during the tender phase for companies that supply aircraft parts can lead in the end to airlines to different maintenance costs [1], guaranteed reliability and dispatchability figures [2,3], and availability of spare parts to support continued airworthiness, and other qualitative or quantitative aspects that sometimes are subjective measured [4].

Behind the rigid necessities to comply with the tight itinerary and schedules, the aeronautical sector focuses on the tripod of Reliability, Availability, and Maintainability (RAM)[5]. Due to the considerable number of variables, it would be complex to analyze the relationship and interaction of each other in the final impact on RAM [6]. The maintenance resources shall be allocated by aircraft operators on the best way possible, thus assuring the commitment management [7]. Finally, it is possible to keep the aircraft safe and reliable to flight. Now when it is analyzed from the airlines perspective, the practice has shown that the typical airline operational profile seeks a lean operation in terms of costs. To achieve this goal, there is not an absolute truth applicable to all the problems, such the proposed practices found on maintenance manuals, fault and isolation procedures, and so on to have the desired success.

Although a great effort is done to collect in-service aircraft data, an uncountable number of problems occur. Some problems can be mentioned such as to process and storage of the data [8], maintenance reports that were incorrectly or improperly filled out due to lack of training of the responsible mechanics, etc. Besides that, the problem is crescent of unstructured manners of storing information among the organizations. Some studies indicate that from 80% to 98% of all electronic data available in the organizations consist of unstructured data, *i.e.* data that is not available to be easily recovered by means of first hand methods [1]. Ref. [9] also relates that besides the maintenance operations segment, airlines operations can be based on three other disciplines (Flight Schedule Planning, Fleet Assignment, and Revenue Management). Ref. [10] reinforces the importance of survival of any business enterprise or organization depends on its ability to compete effectively on maintenance field.

This paper presents an analysis of a small portion of this scenario, limiting to the research of failure reports generated during the regular operation of commercial regional aircraft in Brazil whose parts (from passenger cabin) presented abnormal symptoms and conditions. Sections 2 and 3 present some recent literature review on the tools for the proposed problem; sections 4 and 5 describe the dataset and the performed analysis; the main conclusions are stated on section 6.

2. Background

One of the main consequences that can be enumerated about the reported events in an aircraft is the direct impact on the regular operation, which is measured by the increase of irregularity.

The aircraft operation generates records of failure events. These records are returned to the aircraft manufacturer and also to the authority. This helps on detecting in advance failure trends. It is recommended by the world authorities that the basic records of aircraft events should be handy available, so that it can be studied to prevent future failures.
When dealing with aircraft parts, it can be either analyzed evaluating the accumulated flight hours or a predetermined timeframe, whichever occurs first. This two-dimensional metric, which was not usual in the past, has been used more often in the recent present, as explained by [11]. Technical delays occur when malfunctioning of equipment and related checking and required corrective action causes the aircraft's departure to be delayed by more than a specified time after the scheduled departure time. Delays are deemed to have occurred if an originating flight departs later than the scheduled departure time, a turn round flight remains on the ground longer than the allowable ground time or if the aircraft is released late from maintenance. Lastly a cancellation occurs if a flight is canceled after being delayed for a longer than expected period of time or due to lack of flight critical and maintainability support.

Although the progress is detected in the sector, there is still space to reduce recurrent costs due to delay. Studies from different authors and agencies show in numbers the impact of delays:

- Ref. [5] shows that in some cases flight delay costs can reach sums of US$ 775.00 per minute;
- Ref [12] discuss the difficulties and losses in planning the resources in airlines;
- The world's IATA (International Air Transport Association) airlines carried over 800 million passengers in three years (1990-1992), with losses on international scheduled services of US$11.5 billion;
- Ref [13] estimates that delays in 2007 cost airline customers more than $4 billion in lost productivity and wages. Meanwhile, at a rate of more than $60 per aircraft operating minute, ATA estimates that the 134 million system delay minutes experienced by U.S. airlines in 2007 cost the industry $8.1 billion.

Figure 1 shows the cost of delays per minute in some aircraft types.

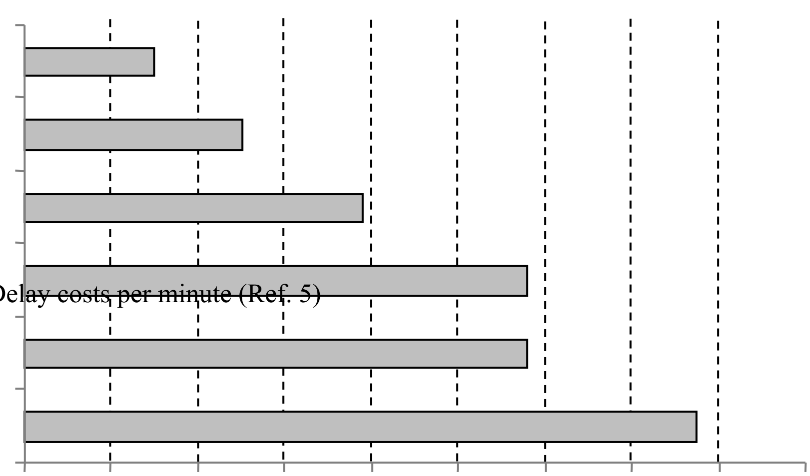

Figure 1: Delay costs per minute (Ref. 5)

In the United States, where it is based the major market of regional aviation in the world, the BTS (Bureau of Transportation) is responsible to collect and study such data.

The 15 minutes delay reference from the US is very aggressive when compared to other countries such as Brazil, where it is part of ANAC (National Civil Aviation Agency) to regulate the numbers and parameters for flights that can be classified in delay situations. In Brazil, the reference has been changed in the past years as a way to improve the services. Before 2008, it was considered an approximate reference value of 60 minutes. After May of 2008 and onwards the reference is considered as 30 minutes. To emphasize the importance of spreading the knowledge on solving problems, Ref. [5] mentions that airlines have a full understanding and great concern of these constraints. When it is not achieved, an undesirable situation of delay is in effect. Figure 2 shows the flight delay percentages for the U.S. and Brazil.

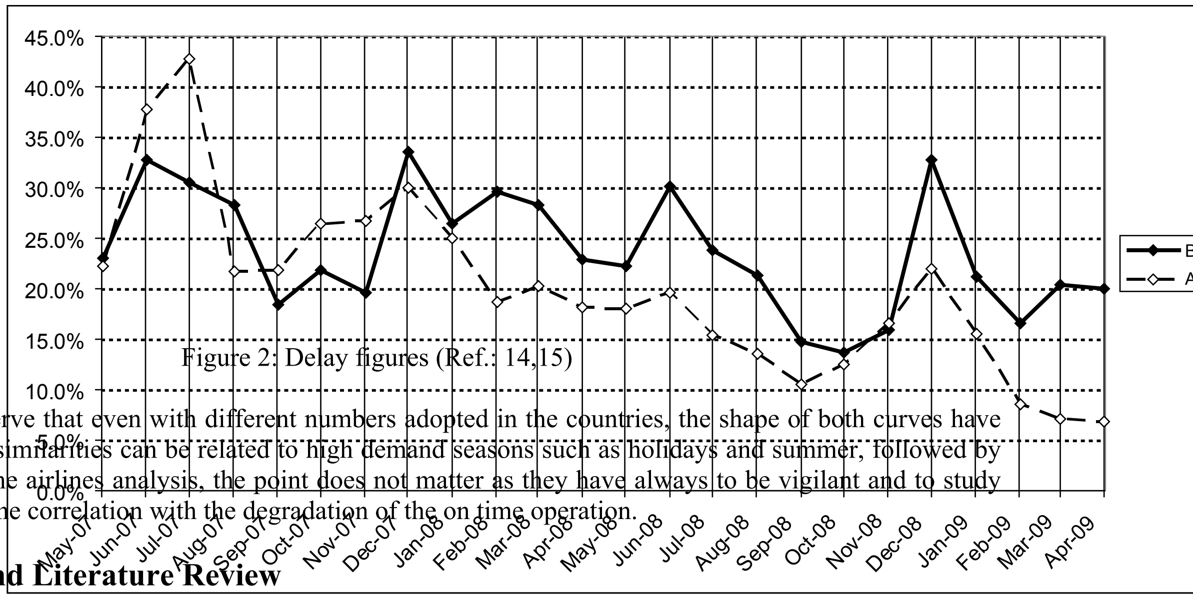

Figure 2: Delay figures (Ref.: 14,15)

It is interesting to observe that even with different numbers adopted in the countries, the shape of both curves have some similarity. Such similarities can be related to high demand seasons such as holidays and summer, followed by off-peak seasons. To the airlines analysis, the point does not matter as they have always to be vigilant and to study the failure events and the correlation with the degradation of the on time operation.

3. Methodology and Literature Review

Ref. [16] says that from the perspective of the authorities, aircraft manufacturers, and operators, a good database system has to show - in a convenient time basis - the trends about the failures reported in the field. The roadmap adopted as the methodology to be used in this paper can be summarized by the following steps:

a. Collection of raw field data;
b. Populating and pre-processing of raw data utilizing text mining;
c. Failure pattern recognition utilizing artificial neural networks;
d. Prediction of future dispositions based on historical data.

The main concepts of text mining and neural networks are described next.

3.1 – Text Mining

Unstructured text is very common, and in fact may represent the majority of information available to a particular research or data mining project. Ref. [1] discusses the available information in the corporations, where it is normally stored as unstructured text.

Prior to the data being introduced, it was necessary to mine the meaningful data from the reports [17]. Ref. [18] mentions that with the advent of digital content, databases have received attention in information retrieval. Ref. [19] proposes the combination of human expertise and text-mining techniques to extract the data. There are other techniques to process Natural Language Processing (NLP) as discussed by [1] that have been used successfully to extract information from unstructured text using the content analysis. Ref. [20] mentions that extracting meaningful data from databases can be useful for management and decision purposes. Ref. [21] and [22] discuss about text mining techniques, where all words found in the input documents generates a table to summarize the information. Inverse Document Frequency and Log-Frequencies are efficient techniques to represent a text by means of a numerical representation; such techniques show the concept of vector space model (VSM). Then, each document D is punctuated similar as cited in [23], where the documents D can be converted to a vector representation as a function. After the proper transformation is applied to a set of registers, it can be converted to a table where each row represents an event registered and the columns represent each descriptor (keyword) that describes a given event. Figure 3 shows how this transformation is after the text mining applied:

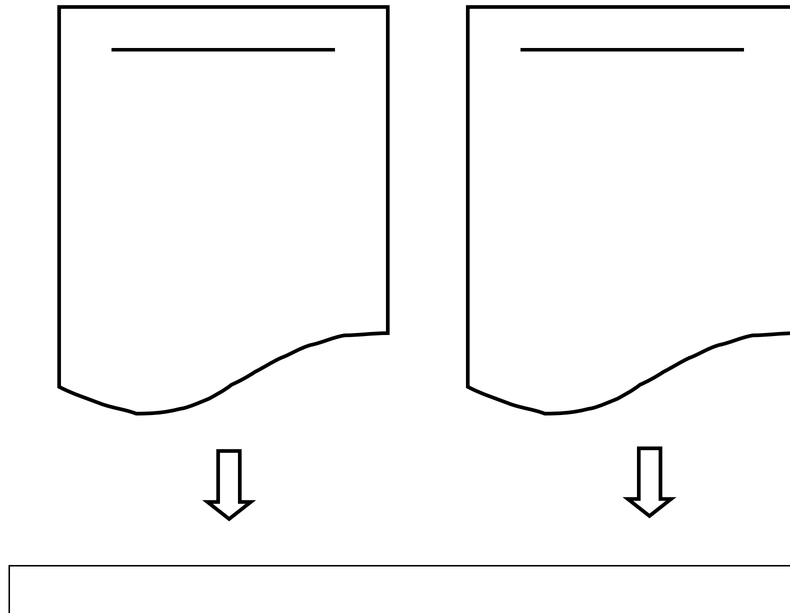

Figure 3: Text mining

When text mining is implemented, it is possible to convert unstructured (textual) information, extract meaningful numeric indices from the text, and, thus, make the information contained in the text accessible to other learning algorithms such as Artificial Neural Networks (ANN).

3.2 – Artificial Neural Networks

ANNs, first used in the fields of cognitive science and engineering, are universal and highly flexible function approximators. As cited by [24, 25] ANNs are general and flexible tools for forecasting applications. An ANN is a computer program that can recognize patterns in a given collection of data and produce a model for that data. The training process comprises of presenting data to it. Then, it is computed an output, which is compared to desired output. Ref. [6] comments the algorithm that provides paired examples of input and output for training the network. Finally, the network weights are modified to reduce error. To use the network, it is necessary to present new data to it, and then the network will compute an output based on its training.

4. The Dataset

When an event is observed, the flight crew must register the event (problem) on the aircraft log book. Later on, the event is analyzed by the mechanic and an action is carried out, closing the reported problem. It is mandatory that the operators keep the activities tracked, because inspection and diagnostic activities are integral components of an effective maintenance.

Often, operators may have different dataset architecture to store the information, but it will follow at least the recommendation from local. The minimum required information for a reported event contains:

a. Aircraft manufacturer, aircraft model, aircraft serial/tail number, engine or propeller;
b. Aircraft registration;
c. Airline name;
d. Date when the failure or defect was identified;
e. What flight phase the failure was identified;

f. What failure or defect identified;
g. Applicable ATA system chapter and subsystem;
h. Total flight hours or flight cycles accumulated by the defective part;
i. Part manufacturer, part number, part description, part serial number;
j. What actions or emergency precautions where performed;
k. Other relevant information that can help to find the failure cause, malfunction or defect, including time since last maintenance action, revision, repair or inspection.

According to ATA [13], a unified database to track such failures can contribute greatly for reducing administrative time involved in aircraft operation. The idea is to keep the data as simple as possible and at the same time complying with the regulatory requirements. Figure 4 shows how it works:

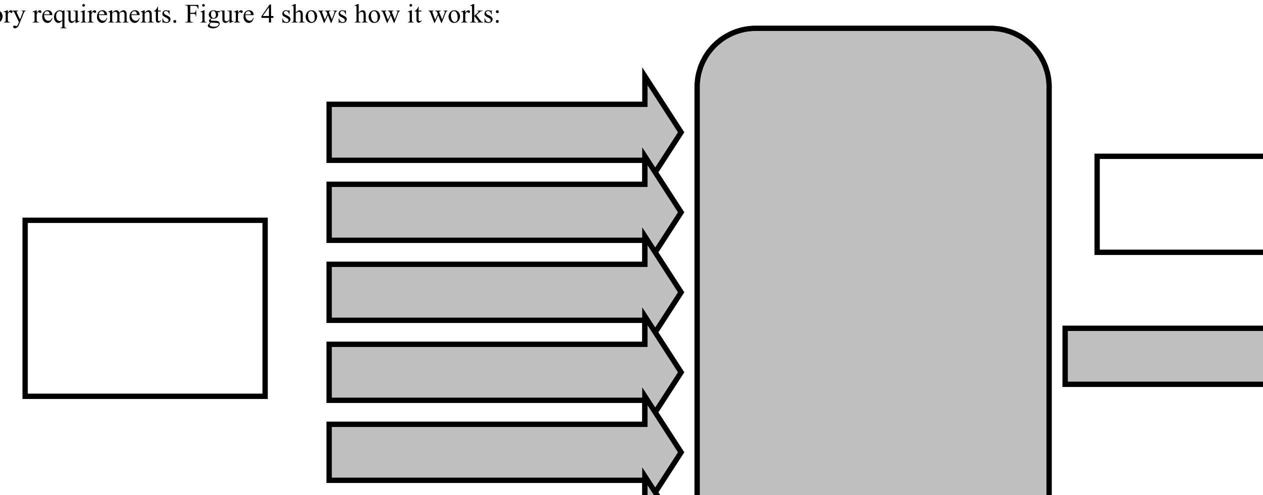

Figure 4: Reported failures structure

As the uncountable control carries variables, a repair process can have aside from dates, an Air Transport Association (ATA) reference number, name of the operator who sent the part, aircraft data, accumulated flight hours, in-and-out dates, response from engineering from each given discrepancy found, cost and warranty analysis, etc. Ref [25] mentions that there exist difficulties on defining the factors that control the process. The log book process studied in this paper seems to have many factors that can be interesting when running an experiment at first time using as much factors as available, respecting time and cost restrictions.

5. The Dataset Analysis and Results

The efforts to always improve the maintenance techniques have attracted the attention of several research workers. Ref. [26] mentions that increase on availability can be achieved using the maintenance techniques and preventive maintenance programs. Following this practice, Ref. [16] mentions that the failure information follows patterns that are cyclic or repeated. Taking these premises, the text mining used in conjunction with artificial neural networks (ANN) as approximation models are promising when compared to analytical techniques.

5.1 – Dataset pre-processing utilizing Text Mining

In this paper, the dataset under investigation contains data collected from airlines from 2004 to 2008. The total of collected cases amounts to 15,760; in the dataset, the variables eligible for text mining techniques are the reported problem and the reported action.

For this analysis, elimination of all words that do not pertain to English language was performed to simplify it [27]. The dataset presents particular terms from aircraft, it was constructed a specific dictionary table to translate them into complete words. Table 1 shows some of these customized forms:

Table 1 – List of Synonyms (Example)

Descriptor	Synonyms	Descriptor	Synonyms
adjust	readjusted, repositionned, repositioned	lach	latch
aircraft	acft, airplane	light	lt, lamp, lights, ligh,

The final matrix from text mining has the dimension *m x n*, where *m* means the number of analyzed events and *n* the number of used descriptors.

With the text mining results, it was found the total of 88 word descriptors, which can represent approximately 99.24% of the dataset, i.e. 15,640 failure events (these events had at least one descriptor different than zero). The analysis could be redone, but due to the origin of the dataset it was considered sufficient and the discarded part is negligible.

5.2 – Dataset failure pattern recognition utilizing ANN

To start the neural failure pattern recognition, some pre and post processing, selection, and variable coding were done, like transformation of nominal variables to numbers, and normalization. The majority of variables are categorical ones, i.e. they had to be proper coded as output variables 120 through 124 show the different states. This precaution makes the ANN learning more effective. Moreover, it was considered the NFF (No Fault Found) cases [28]. Therefore, after the coding and normalization, the dataset can be represented as shown on Table 2:

Table 2 – Input and Output Variables

Input Variables		**Description**			
1-88		Descriptors originated from pre-processing phase utilizing text mining (variables : problem reported / action reported)			
89-92		Aircraft model / type (A, B, C e D)			
93-97		ATA System-chapter			
98-119		ATA Sub-chapter			
Output Variables		**Description**			
120		Interruption? (Yes/No)			
121		Interruption = *delay*			
122		Interruption = *cancellation*			
123		Interruption = *return from runway*			
124		Failure concordance			
		Description - Assigned failure category			
125	CM01	Attachment Problem	135	CM11	Improver Servicing
126	CM02	Drain Problem	136	CM12	Latch Problems
127	CM03	Electrical Failure	137	CM13	Lock Problems
128	CM04	External Induced Failure	138	CM14	Mechanical Failure
129	CM05	Failure related to Galley Equipment	139	CM15	NFF (No Fault Found)
130	CM06	Heater Problem	140	CM16	Seat Recline Mechanism Problem
131	CM07	Improper Cleaning	141	CM17	Routine Check
132	CM08	Improper Handling	142	CM18	Seat Belt Problem
133	CM09	Improper Lubrication	143	CM19	Wearout
134	CM10	Improper Maintenance	144	CM20	Wrong Troubleshooting

As per the Table 2, it can be shown that it was possible to condensate a considerable dataset into a reasonable number of variables (119 input variables and 25 output variables).

As the modeling consists of classification of events, it was chosen the MLP network type. This type of network is flexible to model this sort of problem. Other important heuristic considerations were also considered to start the ANN modeling [29], such as updating of backpropagation error rate in stochastic (sequential) or batch, maximize the information content utilization of an example set to maximize the training error, normalization of inputs and outputs, training by mean of *tips*, and the learning rate.

Additionally, it was used the classical proportion of 2:1:1 (50% for training, 25% for test, and 25% for validation). The summary for the neural networks are shown on Table 3:

Table 3 – ANN Results

MLP Arrangement	**119-33-25**	**119-43-25**	**119-53-25**	**119-63-25**	**119-73-25**
Parameters					
Activation Function					
Layer 1 (input)	Hyperbolic	Hyperbolic	Hyperbolic	Hyperbolic	Hyperbolic
Layer 2 (hidden)	Hyperbolic	Hyperbolic	Hyperbolic	Hyperbolic	Hyperbolic
Layer 3 (output)	Logistic	Logistic	Logistic	Logistic	Logistic
Error Classification Function	MSE	MSE	MSE	MSE	MSE
Efficiency					
Training	0.930196	0.934415	0.934543	0.937867	0.924827
Test	0.925319	0.926854	0.934271	0.930179	0.937340
Validation	0.931202	0.933503	0.927621	0.923017	0.931969
Error Rate					
Training	0.166373	0.167903	0.167232	0.170275	0.174229
Test	0.173939	0.176193	0.176450	0.180737	0.183264
Validation	0.172378	0.178355	0.179919	0.181283	0.182995
Training Algorithm	BP	BP	BP	BP	BP
Trained Epochs	987	985	995	997	926

The parameters are not chosen arbitrarily. Firstly, the number of neurons varied in the hidden layer, as a way to verify the influence of this parameter on the ANN. Then, it was concluded that this parameter has no direct influence for the problem. For instance, the first column on the Table 3 shows an arrangement 119-33-25, what means 119 input variables, 33 neurons in hidden layer, and 25 output variables.

The increase of neurons in the hidden layer neither increased nor decreased the error rate. It remained constant. Therefore for this problem, the simplest network arrangement can be used.

6. Conclusions

The present paper proposes a new approach to the failure pattern recognition in a dataset. The literature has other similar works to extract meaningful information with specialized systems, but most of them deal with quantitative data, what makes easier to model a neural network. Considering the present problem when text files are used, the proposed approach is very promising.

Conceptually the model has demonstrated reliable performance, yielding approximately 93% accuracy. This represents a step forward in this area, because in normal circumstances such analysis is performed manually (hand calculated). This work can be used in practical terms as a tool to help decision making process, but when the model is analyzed in terms of individual variables a considerable amount of error rate is observed. This constraint should be considered in a future research in furthering this technology solidifying its practicality and sustained benefits as a robust maintenance program for the aviation industry and the like. Currently, the tool can be used as an extra decision making tool to help airlines keep their fleets in optimal operational conditions and airworthiness.

Acknowledgements

The authors would like to thank the Brazilian agencies of CNPq and FAPEMIG for the support they gave this work.

References

1. Wang, W.M.; Cheung, C.F., Lee, W.B., and Kwok, S.K., 2008, “Mining knowledge from natural language texts using fuzzy associated concept mapping.” Information Processing and Management, 44, 1707-1719.
2. Bineid, M., and Fielding, J.P., 2003, “Development of a civil aircraft dispatch reliability prediction methodology.” Aircraft Engineering and Aerospace Technology, 75, 588-594.
3. Kurien, K.C., Sekhon, G.S., and Chawla, O.P., 1993, “Analysis of Aircraft Reliability Using Monte Carlo Simulation.” International Journal of Quality & Reliability Management, 10(2).

4. Farrero, J.M.C., Tarrés, L.G., and Losilla, C.B., 2002, "Optimization of replacement stocks using a maintenance programme derived from reliability studies of production systems." Industrial Management & Data Systems, 102(4), 188-196.
5. Knotts, R. M.H., 1999, "Civil aircraft maintenance and support - Fault diagnosis from a business perspective." Journal of Quality in Maintenance Engineering, 5(4), 335-347.
6. Sekhon, G.S., Rajpal, P.S., and Shishodia, K.S., 2005, "An artificial neural network for modeling reliability, availability, and maintainability of a repairable system." Reliability Engineering and System Safety, 87, 809-819.
7. Hansson, J., Backlund, F., and Lycke, L., 2003, "Managing commitment: increasing the odds for successful implementation of TQM, TPM or RCM." International Journal of Quality & Reliability Management, 20(9), 993-1008.
8. Fernandez, O., Walmsley, R., and Petty, D.J., 2003, "A decision support maintenance system – Development and Implementation." International Journal of Quality & Reliability Management, 20(8), 965-979.
9. Sarac, A., 2000, Daily operational aircraft maintenance routing problem. PhD. Dissertation. University of Buffalo at New York, NY.
10. Madu, C.N., 2000, "Competing through maintenance strategies." International Journal of Quality & Reliability Management, 17(9), 937-948.
11. Chen, T., and Popova, E., 2002, "Maintenance Policies with Two-Dimensional Warranty." Reliability Engineering & System Safety, 77, 61-69.
12. Kumar, U.D., 1999, "New trends in aircraft reliability and maintenance measures." Journal of Quality in Maintenance Engineering, 5(4), 287-295.
13. Air Transport Association of America – ATA., 2009, iSpec 2000 – Chapter 11 - Integrated Data Processing Materials Management, Washington, DC, USA
14. BTS - US Bureau of Transportation – Statistics about delays - http://www.bts.gov/. Accessed 01 August 2009.
15. ANAC – National Civil Aviation Agency (2009). Delay statistics in Brazil. http://www.anac.gov.br/. Accessed 01/10/2009.
16. Luxhøj, J.T., 1999, "Trending of equipment inoperability for commercial aircraft." Reliability Engineering and System Safety, 76, 365-381.
17. Prado, H.A., and Ferneda, E., 2008, Emerging technologies of text mining – techniques and applications. Hershey, PA: Information Science Reference – IGI Global, 1st. ed., p358.
18. Tan, S., 2008, "An improved centroid classifier for text categorization." Expert Systems with Applications, 35, 279-285.
19. Leitner, F., and Valencia, A., 2008, "A text-mining perspective on the requirements for electronically annotated abstracts." Federation of European Biochemical Societies, 582, 1178-1181.
20. Batyrshin, I.Z., and Sheremetov, L.B., 2008, "Perception-based approach to time series data mining." Applied Soft Computing, 8, 1211-1221.
21. Manning, C. D., & Schütze, H., 2002, Foundations of statistical natural language processing (5th printing). Cambridge, MA: MIT Press.
22. Bishop, C.M., 1995, Neural Networks for Pattern Recognition. New York: Oxford University Press, 1st ed., p477.
23. Chiang, D., Keh, H., Huang, H., and Chyr, D., 2008, "The Chinese text categorization system with association rule and category priority." Expert Systems with Applications, 35, 102-110.
24. Tsay, R., 2005, Analysis of Financial Time Series, 2nd ed., Wiley-Interscience.
25. Balestrassi, P.P., Popova, E., Paiva, A.P., and Marangon Lima, J.W., 2009, "Design of experiments on neural network's training for nonlinear time series forecasting." Neurocomputing, 72, 1160-1178.
26. Shankar, G., and Sahani, V., 2003, Reliability analysis of a maintenance network with repair and preventive maintenance. International Journal of Quality & Reliability Management. 20(2), 268-280.
27. Orengo, V., and Huyck, C., 2001, "A Stemming Algorithm for the Portuguese Language." 8th Symposium on String Processing and Information Retrieval, Spire, p186.
28. Söderholm, P., 2005, "A system view of the No Fault Found (NFF) phenomenon." Reliability Engineering and System Safety, 92, 1-14.
29. Haykin, S., 1999, Neural networks – a comprehensive foundation. Ontario, Canada: Prentice Hall International, 2nd ed., 842.