Intelligent Data Analysis to Calculate the Operational Reliability Coefficient

Zoila Esther Morales Tabares[1(✉)], Alcides Cabrera Campos[1], Efrén Vázquez Silva[2], and Roberto Antonio Infante Milanés[1]

[1] University of the Informatics Sciences, Havana City, Cuba
{zemorales, alcides, rainfantem}@uci.cu
[2] Salesian Polytechnic University, Cuenca City, Ecuador
evazquez@ups.edu.ec

Abstract. Nowadays the complexity that medical equipment has reached means that not all failure patterns can be easily managed through maintenance activities, carried out after their manufacture and commissioning. For this reason, experts in electromedicine consider that the analysis of failure patterns should be carried out with the tools of reliability engineering, since medical equipment is a technology that is not without risks. Failures in these devices are caused by risks associated mainly with operator malfunctions, impairment of the electrical fluid that causes the stopping of procedures in execution in an unexpected manner and others inherent to the technology. All these risks lead to a dynamic working behaviour of medical equipment, which passes through a finite number of states: running, faulty and broken. As part of the analysis of failure patterns in medical equipment, the CONFEM algorithm is proposed in this manuscript to determine the operational reliability coefficient.

Keywords: Medical equipment · Failure patterns · Risks
Operational reliability coefficient · Algorithm

1 Introduction

The maintenance management through automated systems allows the classification and characterization of the information according to the specific requirements of each user. In addition, it offers the possibility to analyze and make decisions based on globally defined indicators in important processes such as the planning of the demand for spare parts stock. The literature defines a wide range of indicators for assessing maintenance management. The value of these indicators is used as a comparative value or a reference level in order to take corrective, modifying and predictive actions as appropriate.

The most commonly used maintenance indicators in the management of production equipment or services are: mean time between failures (MTBF), mean repair time (MTTR), technical availability, maintenance frequency, failure frequency, operational reliability, among others [17–20]. Reliability has been analyzed for different environments or situations [1–13]. Operational reliability analysis is the fundamental basis of the continuous improvement process, which systematically incorporates advanced tools for diagnosing the current status and predicting the future performance of equipment,

Y. Hernández Heredia et al. (Eds.): IWAIPR 2018, LNCS 11047, pp. 68–76, 2018.
https://doi.org/10.1007/978-3-030-01132-1_8

systems or processes. Its study is carried out through the analysis of fault history or technical status data.

The health sector is one of the areas that must constantly be redirecting its resources to guarantee the operational reliability and technical availability of medical equipment, because medical technology is widely used for the prevention, diagnosis and treatment of various diseases and abnormal physical conditions. It is not without risks, due to the occurrence in clinical practice of failures caused by improper handling by the operator and others related to the technology [15], such as, for example, those related to quality standards; non-compliance with the procedures established by the manufacturers; poor calibration or others related to external causes. All these risks lead to a dynamic working behaviour of medical equipment, which passes through a finite number of states: running, faulty, broken. These states can be absorbent (running, faulty and broken) and non-absorbent (low technique), where when the latter are reached the monitoring process ends. Only absorbent states will be considered in the investigation [23].

This paper presents an algorithm (CONFEM) based on the intelligent analysis of data to obtain the operational reliability coefficient of medical equipment in a health unit, from which it will be possible to carry out adequate maintenance planning (corrective, preventive and predictive) according to the classification categories of medical equipment in order to obtain an adequate relationship between productivity and maintenance cost at the equipment level [14]. The manuscript is divided into two sections. In the first section: Materials and methods, the fundamental concepts used in the development of the algorithm are dealt with, explaining its operation step by step. On the other hand, in the section: Results and discussion, the Equipment Availability and Reliability Sub-module is presented as a practical contribution to the solution. Also, this section presents a detailed analysis of the algorithm's operation to show the reliability of the calculation of the operational reliability coefficient. Finally, Sect. 4 presents the conclusions and future projections made by the authors in relation to the calculation of the operational reliability coefficient.

2 Materials and Methods

Medical equipment requires high safety standards to ensure that the services offered are provided properly and that their operations are carried out in the most appropriate manner. For this reason, a reliability analysis of these medical technologies determines their functionality and availability characteristics, allowing the operator to estimate the deviation of any operating characteristic of a component that may consequently become a failure of the component itself and jeopardize the safety of the medical equipment as a system. Hence, it is defined as the study of reliability: "the probability that an element, device, equipment or system will perform a given function under the correct conditions in a given time" [16, 22]. The following describes the data management process for calculating the operational reliability coefficient of a medical equipment.

2.1 Data Management in the Process of Calculating the Operational Reliability Coefficient

The data used for the process of calculating the operational reliability coefficient came from two different sources: the Management System for Clinical and Electromedical Engineering (SIGICEM) database, which involves current data, and the Reportech software database, which involves historical data [25]. Both databases are available from the National Electromedical Center of Cuba. For this reason, the data were not standardized, so the need arose according to the domain of the problem, to extract the necessary data to locate them in a single source of information (Fig. 1). For this purpose, the extraction, transformation and loading (ETL) processes were performed from SQL statements, which were executed through a script in the MySQL Database Management System, without the need to use tools designed to perform ETL processes, due to the fact that a high degree of transformations, calculations and processing was not required.

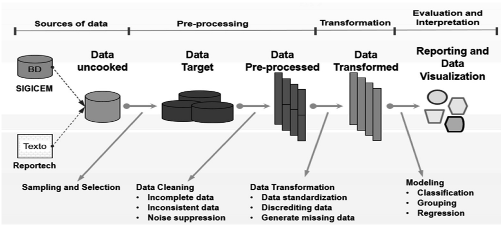

Fig. 1. Data management in the process of calculating the operational reliability coefficient.

Data cleaning was performed according to:

- Incomplete data in attributes of interest or summarized data (equipment_name).
- Existence of noise: errors in the data (equipment_model_attribute).
- Inconsistent data: there is a discrepancy in the values (annual_quantity attribute).

The extraction process consisted of collecting the relevant data from the source databases (SIGICEM and Reportech) to carry out the business component processes. The following transformation techniques were applied to these data:

- Normalize: to avoid data redundancy, data updating problems in the tables and protect their integrity.
- Discrete: transform a continuous value into a discrete one (Equipment states: Running, F; Faulty, D; Broken, R. This transformation allowed the construction of the sequence of absorbing states to obtain the quantitative indicators used in the calculation of the operational reliability coefficient. Another example is the one related to electromedical specialties, where each one was assigned a number in the range of 1 to 12).
- Generation of missing data: by the average of the class to which the object belongs.

After the necessary transformations to improve the quality of the data were carried out, they were loaded into the target database (BD_Stock), which were classified and grouped for better evaluation and interpretation. The population of medical equipment was grouped into non-overlapping and internally homogeneous subpopulations for the performance of the processes that integrate the business component with the use of cluster sampling techniques. To carry out the operational reliability process, the population of medical equipment was stratified into subpopulations by specialty, equipment designation, make and model. These subpopulations were then stratified according to their technical state into three groups of equipment: Running, Faulty and Broken. The classification and grouping of the data allowed the calculation of the operational reliability coefficient based on its evolution over time on continuous variables.

2.2 Process for Calculating the Operational Reliability Coefficient

In the operational field, the operational reliability coefficient (C_0) is calculated as a function of maintenance times:

$$C_o = \frac{MTBF}{MTBF + MTTR} \tag{1}$$

where,

Mean Time Between Failures (*MTBF*).

Mean Time to Repair (*MTTR*).

- *MTBF*: indicates the average time elapsed until the fault event arrives.
- *MTTR*: is the measure of the distribution of the repair time of an equipment or system. This indicator measures the effectiveness of restoring the unit to optimum operating conditions once the unit is out of service due to a failure within a given period of time.

To make up the chain (absorbent states of medical equipment), we rely on historical data from service orders made by the electromedicine specialists of the health units. The service orders contain a set of data related to the management of the equipment, including the technical status (Running, Faulty, Broken). Equipment is managed on the basis of four factors: Equipment Function, Physical Risk Associated with Clinical Application, Maintenance Requirements, and Equipment Trouble History. The first factor has a direct relationship with the equipment and the rest with its level of performance over time [14].

The status chain is constructed by stratifying equipment by specialty, name, brand and model to facilitate the search for reports associated with its operation over time.

Based on the theoretical foundations on operational reliability described above, the sequence of states was constructed to select the dates on which the equipment moves from state F to state D or R until it reaches state F again. Later, the time in days of the occurrences $F \rightarrow (Do'R) \rightarrow F$ is counted, divided by the number of such occurrences present in the chain.

In this manner, the MTBF was calculated:

$$MTBF = \frac{CDías_{F \to (D\ o'R) \to F}}{Oc} \tag{2}$$

where,

$CDías$: number of days elapsed in the occurrence $F \to (Do'R) \to F$
Oc: number of occurrences.

The *MTTR* was calculated taking into account the number of days spent on the occurrences $D \to Fo'R \to F$, divided by the number of such occurrences present in the chain.

The numerical value obtained from the relationship between the mean time between faults with the addition of the mean repair time and the mean time between faults is multiplied by 100 for a better interpretation of the operational reliability coefficient in percentage.

2.3 CONFEM Algorithm

The calculation of the operational reliability coefficient shall be performed for n steps. The following describes the operation of the CONFEM algorithm and the MTTR and MTBF functions. It has as input parameters a list with the sequence of states through which a medical equipment passes during its useful life and the instant of time (number of months).

Algorithm 1 CONFEM

Input:

listEquipment: List of equipment reported in service orders
varLongEq: Equipment list length
varSequence: Sequence of states of a device
varLongSec: Sequence length
varMTBF: Mean Time Between Failures
varMTTR: Average repair time

Output:

varCo: Operational reliability

Begin:

```
For i=1 to i< varLongEq do
    varSequence = GenerateSequence (listEquipment[i])
    If varLongSec < > 0 do
        varMTBF = FunctionMTBF (varSequence)
        varMTTR = FunctionMTTR (varSequence)
        varCo = varMTBF/ (varMTBF+ varMTTR)
    If not
      "The selected equipment has not been installed"
    End if
End For
Return varCo
```

In the CONFEM algorithm (Algorithm 1), the methods MTBF Function and MTTTR Function are problem dependent methods, so the complexity of CONFEM was determined from the complexity of these functions. The complexity of MTBF Function is $O(n^2)$ and $O(nlogn)$ is that of MTBF Function. With the application of the summation rule it can be concluded that the complexity of the CONFEM algorithm is $O(n^2)$.

3 Results and Discussion

As a practical contribution of this work, a sub-module was implemented that bears the name Availability and reliability of the equipment, which is integrated with the Prediction and Stock Management Module of the Management System for Clinical Engineering and Electromedicine. This sub-module incorporates the DISTEM algorithm, because the operational reliability and technical availability coefficient is one of the variables considered in the multivariate model for the prediction of spare parts stock for medical equipment.

The CONFEM algorithm was incorporated into the business component of the MPREDSTOCK: Multivariate model for predicting spare parts stock for medical equipment [25]. For this reason, CONFEM receives the same parameters as the MPREDSTOCK as input for its execution. To validate the efficacy of the CONFEM algorithm the experimental method was used on the basis of having each piece independently.

A case database of 385 cases was also designed, which included the entire set of data from 30,843 reports on health center service orders in the national territory in the years 2003 to 2014 available in the Reportech System [26]. The 385 instances were divided into k = 10 training sets, so 356 instances were used for training and 39 for testing. However, only the results for 55 instances are shown in this manuscript because the result achieved with the rest of the instances is similar to the one obtained in Sect. 3.2.

Different combinations of the CONFEM algorithm were executed, such as the execution specified in Sect. 3.1. On the other hand, in Sect. 3.2 it was demonstrated by means of the nonparametric test of the Wilcoxon-signed ranges that the observed operational reliability coefficient does not statistically differ ($p\_value > 0.05$) from the operational reliability coefficient calculated from the theoretical assumptions specified in Sect. 2.3.

3.1 Execution of the CONFEM Algorithm

Medical Equipment

- Specialty: Electro-optical and laboratory
- Equipment designation: Blood gas analyzer
- Mark: ROCHE
- Model: COBAS b121
- Description of the piece: THB/SO2 Module

Sequence of states: FFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFDDDDDDDRRRRRRRRR

The sequence of states of the ROCHE COBAS 121b blood gas analyzer represents 0.17% of the 30, 843 reports made in the service orders of health centers in the national territory. From the sequence of states, the determination matrix of Table 1 and the transition graph between the absorbent states (Fig. 2) were defined with their initial probability vector represented by a 1*x*3 invariant row vector (π).

Table 1. Parameters used in the experimental analysis.

	Running (F)	Faulty (D)	Broken (R)	Totals
Running (F)	39	1	0	40
Faulty (D)	0	6	1	7
Broken (R)	0	0	8	8
Totals	**39**	**7**	**9**	**55**

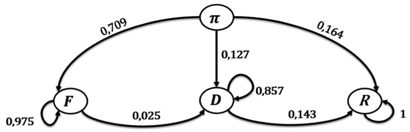

Fig. 2. Transition graph between states of the blood gas analyzing medical equipment.

For a 12-month period, the operational reliability coefficient was 71%, with a technical availability of 52%.

3.2 Application of the Non-parametric Wilcoxon-Signed Range Test

Measurement

- Operational reliability coefficient observed.
- Estimated operational reliability coefficient.

Wilcoxon test hypothesis

$\boldsymbol{H}_0$: There is no difference between the median of the observed and estimated operational reliability coefficient.
$\boldsymbol{H}_1$: There are differences between the median of the observed and estimated operational reliability coefficient.
Decision rule: if $p\_value > 0.05$ is not rejected H_0.
Tools used in the analysis: SPSS 13.0 and Weka 3.5.2.

Table 2. Statistics of related samples.

	Median	*N*	*Z*	*p_value*
Coefficient observed	0.7722	55	−0.537	0.592
Estimated coefficient	0.7522			

The experimental results in Table 2 show a $p\_value > 0.05$, so H_0 is not rejected, indicating that there is no statistically significant difference between the median of the observed operational reliability coefficient and the estimated one.

4 Conclusions and Future Projections

The CONFEM algorithm starts from the analysis of the failure patterns of medical equipment for the calculation of the operational reliability coefficient, for which it allows the sequence of states to be extended without altering the adopted model or the temporal complexity of its execution. The results and discussion show that it is satisfactory that the algorithm is based on the distillation of information collected, classified, organized and integrated into the SIGICEM database, and that new information and an appropriate representation of the data for use by the computer system developed is derived. However, the group of authors recommends, in order to achieve greater accuracy in the calculation of the operational reliability coefficient, measuring external effects and states that are not directly visible in the functioning of medical equipment, using more complex methods based on learning, such as the Markov's Hidden Models.

References

1. Yin, H., Wang, K., Qin, Y., Hua, Q., Jiang, Q.: Reliability analysis of subway vehicles based on the data of operational failures. EURASIP J. Wirel. Commun. Netw. (2017). https://doi.org/10.1186/s13638-017-0996-y
2. Pas, J., Rosiński, A.: Selected issues regarding the reliability-operational assessment of electronic transport systems with regard to electromagnetic interference. Eksploat. Niezawodn. Maint. Reliab. **19**(3), 375–381 (2017)
3. Sun, C., He, Z., Cao, H., Zhang, Z., Chen, X., Zuo, M.J.: A non-probabilistic metric derived from condition information for operational reliability assessment of aero-engines. IEEE Trans. Reliab. **64**(1), 167–181 (2015)
4. Carroll, J., McDonald, A., McMillan, D.: Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. University of Strathclyde Glasgow. Wind Energy (2015). https://strathprints.strath.ac.uk/54141/. ISSN 1095-4244
5. Qin, W., Song, J., Han, X., Wang, P.: Operational reliability assessment of power systems based on bus voltage. IET Digit. Libr. **9**(5), 475–482 (2015). https://doi.org/10.1049/iet-gtd.2014.0198. ISSN 1751-8695
6. Garipova, J., Georgiev, A., Papanchev, T., Nikolov, N., Zlatev, D.: Operational reliability assessment of systems containing electronic elements. In: Abraham, A., Kovalev, S., Tarassov, V., Snasel, V., Vasileva, M., Sukhanov, A. (eds.) Proceedings of the Second International Scientific Conference "Intelligent Information Technologies for Industry". Advances in Intelligent Systems and Computing, vol. 68, pp. 340–348. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-68324-9_37

7. González, R., García, R.: Methods and tools for the operational reliability optimization of large-scale industrial wind turbines. In: Xu, J., Nickel, S., Machado, V., Hajiyev, A. (eds.) Proceedings of the Ninth International Conference on Management Science and Engineering Managemen. Advances in Intelligent Systems and Computing, vol. 362, pp. 1175–1188. Springer, Heidelberg (2015). https://doi.org/10.1007/978-3-662-47241-5_99
8. Jacob, J.: Fire safety concerns and operational reliability of automatic sprinkler systems. Int. J. Adv. Eng. **1**(9), 658–660 (2015). ISSN 2394-9279
9. Brusa, E., Stigliani, C., Ferretto, D., Pessa, C.: A model based approach to design for reliability and safety of critical aeronautic systems. In: Proceedings of INCOSE Conference on System Engineering. CIISE, Turin, Italy (2016)
10. Wen, L., Miao-na, C., Xu, J.: Research on comprehensive evaluation model for chemical equipment operation reliability. China Saf. Sci. J. **25**, 139–144 (2015)
11. Díaz, A., Romero, J.A., Cabrera, J., Viego, N.: Operational reliability study to support aeronautical maintenance in Cuba. Engineering **18**(66) (2015). International Microwave Power Institute
12. Zambrano, S., Tarantino, R., Aranguren, S., Agudelo, C.: Critical failure identification methodology in industrial processes based on operational reliability techniques. Colomb. Mag. Adv. Technol. **2**(20), 119–126 (2012). ISSN 1692-7257
13. Guevara, W., Valera Cárdenas, A., Gómez Camperos, J.A.: Metodología para evaluar el factor confiabilidad en la gestión de proyectos de diseño de equipos industriales. Revista Tecnura, 19, 129–141 (2015). https://doi.org/10.14483/udistrital.jour.tecnura.2015.se1.a11
14. World Health Organization (OMS): Introduction to the medical equipment maintenance program. World Health Organization Technical Paper Series on Medical Devices, pp. 47–50. (2012). http://www.who.int/about/licensing/copyright_form/en/index.html
15. Hernández, D.J.: SLD238-SIGICEM: management system for clinical engineering and electromedicine. In: VIII International Congress on Health Informatics. II Congreso Moodle Salud, pp. 1–9 (2011)
16. Espinosa, F.: Operational reliability of equipment: methodologies and tools. University of Talca (2011)
17. Amendola, L.: Human reliability model in asset management. Engineering Management, PMM Institute for Learning, Polytechnic University of Valencia, Spain (2004). www.pmmlearning.com
18. Christensen, H.C.: Maintenance indicators. Maint. Club Mag. **6**(18), 8–9 (2007)
19. Godoy, M.C.: Reliability element interaction model and safety inventory of equipment parts and spare parts through multivariate analysis. M.Sc. thesis, University of Zulia, Maracaibo, Venezuela (2008)
20. Melo, R., Lara, C., Jacobo, F.: Reliability-availability-maintainability estimation by Monte Carlo simulation of a bitter gas compression system during the engineering stage. Tec. Cien. Ed. (IMIQ), vol. 24, no. 2 (2009)
21. Castillo, A.M, Brito, M.L., Fraga, E.: Analysis of criticity personalized. Mech. Eng. J. **12**(3), 1–12 (2009). Redalyc.org. E-ISSN 1815-5944
22. de León, F.C.G.: Industrial Maintenance Technology. University of Murcia, Murcia (1998)
23. Morales, Z.E., Vázquez, E.: Algorithm for prediction of the technical availability of medical equipment. Appl. Math. Sci. **9**(135), 6735–6746 (2015)
24. Morales, Z.E., Vázquez, E., Caballero, Y.: Optimization of spare parts stock for medical equipment. Cuba J. Comput. Sci. **9**, 99–114 (2015)
25. Morales, Z.E., Cabrera, A., Vazquez, E., Caballero, Y.: MPREDSTOCK: multivariate model of spare parts stock prediction for medical equipment. Cuba J. Comput. Sci. **10**(3), 88–104 (2016). ISSN 2227-1899
26. Cabrera, O.: Reportech: medical technology management. In: VII Congress of the Cuban Society of Bioengineering, Havana (2007)