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Applying Fuzzy Approach in Medical Devices Maintenance System; a Case study in Jordan

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Abstract

For medical devices, maintenance policies are provided to reduce the incidence of system failure or to return a failed system to the operating state. Fuzzy approach has been applied to the area of medical devices maintenance systems (MDMS) in the last decade, in which a large number of expert systems were constructed to help reliable maintenance. In this paper, a fuzzy inference model was proposed to identify the device to be replaced in order to reduce expenditure in a hospital and to increase medical staff satisfaction. The result concerning this study can offer the service of reliable medical devices maintenance procedures.

Key words fuzzy inference system , Maintenance management.

Introduction

The competitiveness and performance of services companies depend on the availability, reliability and productivity of their production devices. This perception has led to a drastic change of perception on maintenance over the past decades maintenance policies are provided to reduce the incidence of system failure or to return a failed system to the operating state [1]. In order to ensure a good performance of the service plant, maintenance managers need a good overview of maintenance processes and achievements. This can be attained by a fuzzy approach based medical devices maintenance systems (MDMS).

The concept of fuzzy set theory, which was developed by Zadeh (1965), makes it possible to define inexact medical entities as fuzzy sets, it provides an excellent approach for approximating medical text. Furthermore, fuzzy logic provides reasoning methods for approximate inference [2]. In this way, maintenance performance measurement should be defined on all management levels (i.e. strategic, tactical and operational)[(3]. There are some papers investigating the maintenance policy in fuzzy environments. Su et al. [4] proposed an approach using fuzzy dynamic programming for the component commitment of a power system. Huang et al. [5] also discussed generator maintenance scheduling in power systems where multiple objectives and soft constraints were expressed by fuzzy sets. Huang [6] formulated a fuzzy system with respect to multiple objectives and soft constraints where genetic algorithms were applied to solve the proposed generator maintenance scheduling problem.

In this paper, a fuzzy inference model was proposed to identify the device to be replaced in order to reduce expenditure in a hospital and to increase medical staff satisfaction [7]. The model considered both linguistic and quantitative parameters, estimated in an objective way in order to include many of the factors that actually influence replacement decisions .

Then, the model was described from a theoretical perspective. After that, the results from the application of the model on 300 devices belonging to the King Hussein Hospital (KHH) in king Hussein medical city in Jordan were displayed. Eventually, summary and conclusions have been drawn.

The applied model

3.1 The Theoretical Part

The tendering procurement and replacement policy of medical devices plays a strategic role in hospital management since it significantly influences the efficiency of healthcare plants. In our model the replacement analysis is based both on technical deterioration and the medical staff satisfaction on medical devices state. The model structure which shown in figure 1 includes seven different input parameters and one output.

The technical deterioration of each device was influenced by the parameters related to the characteristics of the device itself and to the aging processes: mean downtime, maintenance costs and age of each device. Inputs of our model related to the above mentioned parameters were calculated by considering functioning devices and typical values mentioned in their catalogues as a benchmark.

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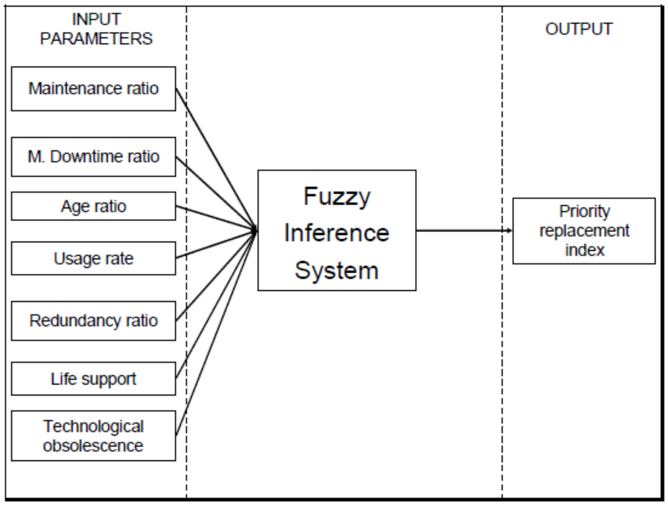

Figure 1: The model structure

The mean downtime of the kth device was compared with the average downtime (DTk) of the other similar n devices (DTi) belonging to the hospital structure. The formula used for the input parameter mean downtime ratio (MDT) is:

$$MDT_k = \frac{DT_k}{\frac{\sum_{i=1}^{n} DT_i}{n}} \qquad (1)$$

Where :
DTk: the average downtime
N: number of devices
MDT: mean downtime ratio

The data necessary to evaluate MDT were difficult to obtain, however, The presence of a Computerized Maintenance Management System (CMMS) facilitates the evaluation of MDT.

The Maintenance Ratio (MR) was calculated by considering the total amount of maintenance costs of each device spent in the last three years divided by its purchase cost. In the maintenance expenditure the repair costs and the preventive maintenance costs should be included. We did includes the spare parts costs.

On the other hand, if the contract includes guarantees, the extra fee paid to the buyer should be considered in the maintenance expenditure but this was not considered in our research because the percentage of contracted devices was neglected.

The devices' Age Ratio (AR) was calculated by comparing the current age of each device with its expected life calculated as a mean of the life of other similar devices disposed by the hospital structure. In our research we referred to Mummolo et al, which consider 4, 6 and 12 years of expected life, respectively for laboratory, electrophysiology and radiology devices.

In order to simplify the application of our model in a real context, we have introduced a score system for the evaluation of the usage, as reported in table 1.

Table 1: The scoring system for the Usage rate (UR)

Usage frequency rate	Score
More than 8 hours per day	3
[0:8] hours per day	2
not daily use	1

In our model we have classified each device in 4 categories and we have assigned the scoring system reported in table 2.

Table 2: The scoring system for the Life support index

devices	Score
life support	3
Therapeutic	2
Diagnostic	1
other	0

The value of failure's consequence of a device depends on its redundancy level. In each hospital, the medical staff requires a determined level of device redundancy in order to assure a specific level of safety for the patients .

If the actual number of devices is less than the number fixed by the medical staff, a critical situation occurs and the correct functioning of each device is important for patient satisfaction and safety. The input parameter Redundancy Ratio (RR) for the kth device is defined as:

$$RR_k = \frac{(\text{actual redundancy level})_k}{(\text{the requested redundancy level})_k} \qquad (2)$$

Where:
RR: Redundancy Ratio

The last input parameter is the technological obsolescence (TO). This parameter plays a key role both for the patient and the medical staff satisfaction: the medical staff members using high technological devices improve the efficiency and the effectiveness of their performance with a considerable advantage for the patient satisfaction.

In our model, the score assigned to each device is 1 if the medical staff indicates the presence of a newer and a more technologically advanced device able to create advantages in the efficiency and in the effectiveness of the medical performances; 0 otherwise.

The output of the model is the priority replacement index (PRI) that provides a quantification of the urgency in the device replacement.

Each device has a score from 1 to 30. If the device has a score between 0 and 10 the priority of replacement is low. If the score is between 10 and 20 then the priority replacement index is medium and the device becomes “to be monitored”. Finally, if the device has a value between 20 and 30, the model suggests its immediate replacement.

3.2 **The fuzzy model**

The selected modeling approaches followed in order to develop an expert system able to predict the PRI index were three: we firstly used a Fuzzy Inference System (FIS) based on a pre-established set of rules, then we trained an artificial neural network on the same seven variables in order to compare their performances and we set up a neuro fuzzy system to find the most relevant features.

In our experiment we used a Mamdami Fuzzy model characterized by seven input variables and only one output being the coefficient that suggests if a certain machine should be changed.

After the Fuzzy Inference System has been completed the neural network model has been designed. Artificial neural networks had a great success in the scientific community due to their flexibility. A preliminary preprocessing stage has been carried out in order to normalize the data in the [0-1] range in order to optimize the matching between the data domains and transfer functions ones’. A seven input-one output architecture with logistic transfer functions has been designed as shown in figure 2.

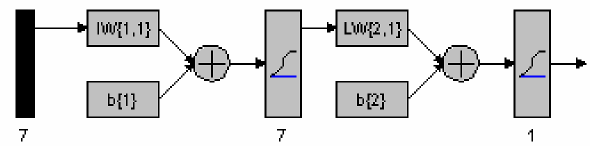

Figure 2: Neural network architecture

The neural network (ANN) has been trained using 70% of the whole available dataset using the conjugate gradient back propagation algorithm with Powell-Beale restarts (Powell, 1977).

The remaining 30% has been used as follows: 15% as testing (used for testing generalization capabilities of the network on-line, in order to stop training when over fitting phenomena start to occur) and 15% as validation (in order to obtain an estimate on the predictive capabilities of the ANN on unseen data). Stopping criterion was set to SSE equal to 1e-3.

After these two approaches have been completed a hybrid neuro-fuzzy strategy has been faced using the ANFIS interface provided by MATLAB (v. 7.4.0). ANFIS is a adaptive neuro-fuzzy inference system that, using a given iput/output data set, constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone or in combination with a least squares type of method. This adjustment allows fuzzy systems to learn from the data they are modeling. The neuro-adaptive learning method works similarly to that of neural networks. Then, the Fuzzy Logic component computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data.

3.3 The Jordanian Case Study

In Jordan, the need to reduce health expenditure has made it necessary to define new management criteria based on a more efficient and rational use of health resources. In particular, one of the major problems affecting the national health system is the obsolescence of device in Jordanian hospitals and clinics.

The study was carried out through various medical devices still in use in a total of 8 military hospital structures. The device typologies analyzed are radiology diagnostic systems, such as x-ray machines, mammography devices, and ultrasound machines.

An example is that of device for radiological diagnosis which in 80% of cases exceeded 15 years, followed by mammography machines (50%). Moreover the geographic data shows that in the south of Jordan the obsolescence is greater than in the centre and in the north. The research also confirmed the seriousness of the phenomenon of aging diagnostic device in military healthcare structures.

Of particular concern were the data about device used for more than 15 years but still in use in public hospitals. In general the jordanian statistics show a considerable aging of technological devices in almost all device.

Retaining obsolete devices can have extremely negative consequences, among which, the increasing deterioration of the device (with resulting maintenance costs and risk of accidents due to devices that are out of order), an increase in operational costs and finally performance which is not in line with current technological standards.

The proposed model was applied to the devices of the Hospital King Hussein Medical City (KHMC) in Amman, Jordan. The hospital has the status of scientific institute for hospitalization an treatment of national importance in Jordan. Therefore, KHMC has extremely complex technological device both in qualitative terms (large devices for bioimages, innovative tools both for research and routine clinical analysis) as well as quantitatively, with more than 8000 devices.

This device is characterized by both a high level of economic renewal and a high level of integration with the technical resources of the hospital, such as IT systems, the management of these devices is the responsibility of the clinic engineering department within the hospital.

The task was to guarantee the safe, suitable and cost efficient use of technological device. This department was essential in acquiring the data necessary to apply the model analyzed here.

The hospital database contains data concerning the downtime of each device the age of device and it is continuously released by the clinical engineering department .

The model was applied to 200 devices belonging to the three groups of operating theatre. The sample selected is representative of the heterogeneity of the devices placed in the hospital structure.

The data collected for each device, according to the information needs of the proposed model was provided by the Clinical engineering Department. These data indicate that only few devices are critical (15% of the total number of devices) and have to be replaced. Other devices have are equally distributed between a medium level RPI (36%) and a low level of RPI (49%).

In particular we carried out two different analysis using a FIS and a Supervised Neural Network in order to assess the accuracy of FIS model. Results returned by Fuzzy Inference System and Artificial Neural Network resulted to be highly overlapping with a K-Statistic equal to 0.90.

After having verified the accuracy levels reached by both the systems we carried out a sensitivity analysis in order to find most predictive values. The results obtained by this analysis put in evidence that higher perturbation in “Maintenance ratio” values led to higher instability in output predictions.

Conclusions

Replacement analysis is one of the key issues in hospital management. A formal process for appraising medical device replacement is needed in order to avoid any risk for patient safety.

In this paper, a ranking procedure of medical device replacement based on Fuzzy Inference Systems (FIS) is proposed in order to include both quantitative and qualitative parameters influencing replacement decisions in a unique and simple process. The model is designed in order to be applied even in hospitals where there is a lack of available data. Moreover, the capability of the model could increase significantly if it is integrated with a computer management system.

To assess the accuracy of the proposed FIS we tried to validate it by using a supervised neural network and to estimate the parameters relevance we implemented a Neuro Fuzzy (ANFIS) approach.

The model, tested on a full case study, proves its effectiveness in the identification of the more critical devices that should be replaced. Obtained results have shown that previously neglected variable such as usage rate and patient safety are relevant for replacement decisions. Future research will focus on a more extensive campaign ofexperiments in order to improve the fuzzy model performance.

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