A Simple Quantitative Model for Replacement of Medical Equipment Proposed to Developing Countries

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Abstract—Along the medical equipment life cycle, hospitals need to take decisions on medical equipment acquisition, maintenance, use and replacement on the basis of complete and reliable information. In this paper, the authors focus on the replacement criteria in developing countries where there is a lack of scientific, realistic and comprehensive assessment. In the proposed model, we use Fault Tree analysis (FTA) to model the replacement process using a set of indicators that impact directly or indirectly the replacement decision. We include the vendor support as a fundamental technical indicator in the analysis. This model considers the replacement decision as a final and undesirable event. Using probability theory, the medical equipment status is classified into 4 groups. According to the final event score, the replacement decision is approved or not. Neonatal Intensive Care Unit (NICU) equipment of 8 different types, along three years, are utilized to investigate the proposed model. Our model proposes a priority list of equipment that should be replaced. The type and number of equipment to be purchased is determined according to the available budget. The results show that 15% of equipment should be replaced, 33% need to be tested, 33% are under surveillance and 19% could be maintained.

I. INTRODUCTION

HEALTHCARE technology management (HTM) is one of the most important segments of the healthcare system according to the joint commission (JCAHO) environment of care standards because of its main role in the healthcare transformation.

The goal of HTM is to optimize the acquisition and utilization of technology to achieve maximum beneficial impact on health outcomes. Along the medical equipment life cycle, hospitals need to take decisions on medical equipment acquisition, maintenance, use and replacement. In developing countries, there is a lack of scientific, realistic and comprehensive assessment of medical equipment replacement decision. This is due to the fact that replacement decisions of medical equipment are mainly based on inadequate reliable information and poor analysis of relative costs, age and condition of equipment, utilization levels, expected future service provision and benefits from new technologies.

There are different criteria by which the medical equipment replacement decision should be considered. Firstly, the technical criteria; that include indicators such as useful life time ratio, utilization, downtime, technological change, vendor support, etc... Secondly, the financial criteria; that may include the service and operating costs, availability of backup, etc... Finally, the safety criteria; that include factors such as hazards/alerts and user/technician errors. According to these criteria, different criteria are developed for proposing medical equipment replacement. These techniques are either qualitative which employ combination of the previous factors to estimate the proper replacement decision or quantitative that exploit mathematical models to determine the replacement threshold.

One of qualitative approaches compiles a list of medical equipment with its basic data to calculate the cumulative cost of replacement then determine “cut off” line that depends upon the available budget [1]. Another method performs replacement prioritization according to a combination of the above criteria utilizing software program which produces relative replacement number (RRN) for each equipment [2]. A medical equipment replacement score system (MERS) is a similar automated technique that is designed based on technical, safety and mission critical rules, where higher scores propose higher priorities to replace [3]. An example of the last approach uses medical equipment inventory, work order and external factors, through an analysis program. This information is weighted then appropriate times for medical equipment replacement are prioritized [4].

Using Mathematical model, as a quantitative approach, provides better analysis; hence, an accurate decision for replacement could be taken. One technique is to model the optimal policies of machine replacement under technological change [5]. It develops a new analytical technique based on deriving a nonlinear equation for the variable optimal machine service life. However, this technique is complicated for medical equipment and lacks for other important factors such as safety and vendor support. Another model [6] uses neural network to classify the medical equipment life into three zones, depending on its service costs and age factors using software program; zone I: remove equipment, zone II: surveillance, zone III: maintain equipment.

According to our investigation, there are two generic analytical methods: induction and deduction. Inductive method constitutes reasoning from individual cases to a general conclusion (bottom-up analysis). Failure mode and effect analysis (FMEA) is an example. Deductive method constitutes reasoning from the general to the specific (top-down analysis). In effect, FMEA identifies and prevents process problems before they occur. Deductive method
constitutes reasoning from the general to the specific (top-down analysis) and fault tree analysis (FTA) is an example [7]. For medical equipment replacement, FTA is more appropriate because it is a statistical analysis provides the decision marker with quantitative tools for the replacement process. Using FTA, the replacement action is taken as final decision marker with quantitative tools for the replacement appropriate because it is a statistical analysis provides the

For medical equipment replacement, FTA is more widely used criteria namely, service and operating costs and availability, call response and repair time in addition to many factors such as equipment type. In our proposed model, we consider some vendor support indicators such as; spare parts availability, call response and repair time in addition to widely used criteria namely, service and operating costs and useful life time.

II. METHODOLOGY

FTA attempts to model and analyze failure process of engineering and biological systems. An undesired effect is taken as the root “top event” of a tree of logic, there should be only one top event and all concerns must tree down from it [7]. Many different approaches are used to model FTA; the most common and popular way is summarized as follows:

- Definition of the Undesired Event (UE)
- Identification of events that cause UE
- Construction of the fault tree
- Evaluation of the fault tree

A. Definition of Undesired Event

This study aims to propose a mathematical model that can help the decision maker to replace medical equipment (UE) from inventory.

B. Identification of Events that Cause Replacement.

We propose four major events (criteria) for replacement:

- Hazards and Alerts (HA), it is a safety indicator which reflects the number of hazards and alerts from the manufacturer for a certain device because of troubles.
- The Useful Life ratio (UL), it is the ratio of utilized lifetime to expected lifetime of the medical equipment. It indicates how far the equipment is from its life end.
- The Cost, it can be characterized by the service and operating costs (SC) and unavailability (U). The SC means the total cost including maintenance, repair and operating costs. The U is the periodic intervals at which the equipment is out of service due to faults.
- Vendor Support, it is a very significant factor especially for developing countries. It reflects the complete support offered by the manufacturer to guarantee the performance of equipment during its life time. Various indicators are linked to this criterion such as availability of spare parts (SP), time consumed in repair compared to down time (RD), call response (CR), preventive maintenance quantification, training and users recommendations, availability of stocks and finally warranty and service contract.

In our proposed model, we focus on certain vendor support indicators; namely availability of spare parts (SP), call response (CR) and time-to-repair (RD).

C. Construction of Fault Tree Model

FTA is basically composed of logic diagrams that display the state of the system using a series of events lead to the occurrence of UE. It is constructed using graphical techniques as shown in Fig. 1.

Fig. 1. The proposed Fault Tree Model (FTA) for replacement of medical equipment considering vendor support.

Events in this model are a combination of intermediate and primary events which are connected together using logic gates. The intermediate event is a fault event which occurs because of one or more antecedent reasons acting through logic gates, whereas the primary event is an event which has not been further developed. The tree is usually written out using conventional logic gate symbols. A set of events that together cause the tree top UE event to occur is called a Cut Set (CS). The shortest credible way through the tree from fault to initiating event is called a Minimal Cut Set (MCS) [7]. As shown in Fig. 1, the medical equipment replacement will take place if one or more of the following occur:

- Hazards and alerts (HA), that can impact on the safe use of equipment
- The equipment age reaches to its end compared to its expected useful life time (UL)
- High service cost ratio (SC) and unavailability (U) events that together lead to high cost and less revenue.
- Long call response (CR), long repair time-to-downtime (RD) and unavailable spare parts (SP) events that together lead to poor vendor support.

To obtain a mathematical model, it is necessary to substitute the logical gates from up to down, by resolving the FT shown in Fig. 1 to evaluate the replacement R as follows:

\[ R = HA + UL + [SC \times U] + SP \times CR \times RD + w \times SP \]  \hspace{1cm} (1)

From Eq. 1, there are 8 cut sets which are (HA, UL, SC, U, CR, SP, RD and SP) where HA, UL and SP are the first order cut sets (minimal cut sets) but SC, U, CR, SP and RD are the second order cut sets. We consider w in Eq. (1) to weight the effect of spare parts unavailability. FTA is a
A qualitative model that can be evaluated quantitatively and often is. Once the CS and MCS are obtained, probability evaluations can be performed if quantitative results are desired. The quantitative evaluation is performed in a sequential manner; first the component failure probabilities are determined, then the system top event probability is evaluated [7]. If the sum of all these factors is greater than 1, it means that at least one factor has a great effect on equipment life and this equipment must be replaced. The probabilities can be calculated as follow:

1) Hazards and Alerts: based on the manufacturer recommendations and/or accidents, the probability can be expressed as 1 in case of existence; and 0 otherwise.

2) Useful Life ratio: it compares the age of the equipment to the expected useful life time (in hours or years).

\[ UL = \frac{A}{EL} \]  

\( UL \): useful life time ratio,
\( A \): age from purchasing year to the point of evaluations,
\( EL \): the expected life time, according to manufacturers’ recommendations, local experience, and international data.

3) Cost: it can be measured by two ratios, the service and operating costs to acquisition cost (SC) ratio, which is widely reported and standardized, and the unavailability (U) ratio. The SC can be formulated as

\[ SC = \frac{TC}{AC} \]  

\( SC \): service and operating costs ratio,
\( TC \): total cost includes operating, maintenance and repair,
\( AC \): acquisition cost.

The service cost-to-acquisition cost ratio is accepted worldwide in the range of 2.3-12% [8].

The unavailability can be calculated as a ratio of the downtime intervals to periodic interval:

\[ U = \frac{\sum D_i}{T} ; i = 1,2,...,n \]

\( U \): unavailability ratio,
\( D_i \): downtime in interval \( i \) in days,
\( T \): total interval (1095 days),
\( n \): number of periodic intervals (3 years in our case)

4) Vendor Support: this term can be quantified through three indicators; the availability of spare parts (SP), the call response (CR) ratio and repair time-to-downtime (RD) ratio.

The SP indicator reflects the discontinuation of any medical equipment where the availability of spare parts can maximize the usage of medical equipment. In this model, SP probability is taken as 1 in case of availability and 0 in case of unavailability. The unavailability of spare parts in some cases does not lead to replacement because of existence of equivalent spare parts that can do the same functions.

The CR ratio reflects the response of the vendor to maintain and repair the medical equipment when it is needed, the shortest response time the better the call response and better vendor support. It can be formulated as

\[ CR = \frac{\sum T_{Si}}{D_i} ; i = 1,2,...,n \]

\( CR \): call response ratio

\( T_{Si} \): average response time in interval \( i \) in days,
\( D_i \): downtime in interval \( i \) in days,
\( n \): number of periodic intervals (3 years)

The RD ratio is the time consumed in repair with respect to downtime, the shortest RD ratio the better vendor support. It can be formulated as

\[ RD = \frac{\sum T_{Ri}}{D_i} ; i = 1,2,...,n \]  

\( RD \): repair time-to-downtime ratio
\( T_{Ri} \): average repair time in interval \( i \) in days,
\( D_i \): downtime in interval \( i \) in days,
\( n \): number of periodic intervals (3 years)

By substituting Eq. (2) to Eq. (6) in Eq. (1), we get:

\[ R = HA + \frac{A}{EL} + \left( \frac{TC}{AC} \times \frac{\sum D_i}{T} \right) \times \left( \frac{SP \times \frac{\sum T_{Si}}{D_i} \times \frac{\sum T_{Ri}}{D_i}}{wSP} \right) \]

The weighting factor \( w \) is considered to reflect the effect of unavailability of spare parts on the possibility of repair and maintenance for different equipment types, e.g., blood gas analyzer, \( w \approx 1.0 \), ventilators, \( w \approx 0.8 \), and others, \( w \approx 0.5 \).

D. Evaluation of the Fault Tree Model

To prove the validity of the proposed model, Neonate Intensive Care Unit (NICU) equipment in a University hospital is taken as data sample. We consider only three years interval (2007-2009) for investigation. The data include equipment name; purchasing date; expected life time [9]; operating costs; maintenance and repair costs, spare parts availability, failure rate and downtime. Then, a statistical analysis of the factors affecting the model is performed to investigate whether the data followed statistic behavior according to any cumulative distribution or probabilistic density functions. Those factors include: age-to-expected lifetime ratio, service costs-to-acquisition cost ratio, unavailability ratio, spare parts availability, call response ratio, repair time ratio and the replacement as a function of all factors.

III. Results

We apply the proposed model on 30 NICU equipment data of 8 different types. Due to limited access to trustable data along equipment life cycle; the model is focused on NICU equipment only for now. Table I shows sample data of various types of the investigated equipment along with the replacement values. As a result of using paper-based equipment information system, the equipment included in the data sample is relatively new; only 3 years after warranty. The statistical analysis is performed using MATLAB program. HA factor is taken 0 for all equipment as no hazards or alerts are reported. The weighting factor \( w \) is taken 1.0 for blood gas analyzer (BGA), 0.8 for ventilators and 0.5 for the other equipment.

Based on this analysis, the equipment life status can be classified into four groups. The equipment in group I must be replaced if the final event sum is greater than 1. In group II, the equipment should be tested if the score in the range...
0.8 to 1. Group III contains the equipment that should be under surveillance and it should be tested in the next year if the score is within range 0.5 to 0.8. Finally group IV contains the equipment that could be kept with no need for test if the score is less than 0.5.

<table>
<thead>
<tr>
<th>Equipment name</th>
<th>UL</th>
<th>SC</th>
<th>U</th>
<th>SP</th>
<th>CR</th>
<th>RD</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>BGA (Roche)</td>
<td>0.25</td>
<td>0.72</td>
<td>0.03</td>
<td>1</td>
<td>0.4</td>
<td>0.5</td>
<td>0.47</td>
</tr>
<tr>
<td>Incubator (Caleo)</td>
<td>0.9</td>
<td>0.29</td>
<td>0.28</td>
<td>1</td>
<td>0.66</td>
<td>0.2</td>
<td>0.7</td>
</tr>
<tr>
<td>(Bear Cub 750 VS)</td>
<td>0.9</td>
<td>0.29</td>
<td>0.39</td>
<td>0</td>
<td>0.01</td>
<td>0.9</td>
<td>1.8</td>
</tr>
<tr>
<td>CPAP (Arabella)</td>
<td>0.4</td>
<td>0.16</td>
<td>0.21</td>
<td>1</td>
<td>0.75</td>
<td>0.004</td>
<td>0.4</td>
</tr>
</tbody>
</table>

**TABLE I**
SAMPLE DATA OF INVESTIGATED EQUIPMENT FOR REPLACEMENT

BGA data are available for only two years of (2008-2009). The proposed model is applied for BGA with high rate of samples (more than 30 sample/day).

Our proposed model assures the fact that the age and cost factors have a direct impact on replacement decision as shown in Fig. 3. The result states that when the equipment reaches its useful time end, replacement should be considered and when the service costs increases, it is alarming for disposal.

**IV. CONCLUSION**

We propose a mathematical model that classifies the equipment life status into 4 groups according to reliable quantitative measures based on FTA. It provides the decision makers with the necessary tools that help in monitoring medical equipment status and remove/replace it from inventory at the right time.

Our proposed model includes, for the first time, the vendor support effect to enhance the medical equipment replacement decision. We consider the unavailability of spare parts that has a great effect on the replacement decision. It is taken into consideration with suitable weight according to the medical equipment type.

The mathematical model admits the correlation between the useful life and cost factors and the replacement decision. The analysis highlights the importance of existence of detailed and updated hospital documentations that significantly affect the disposal decision.

**ACKNOWLEDGMENT**

The authors would like to thank Eng. Ahmed Awadalh and Eng. Ahmed Fouad for their assistance and contribution in data collection and analysis.

**REFERENCES**


