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# OPTIMAL MAINTENANCE STRATEGY ON MEDICAL INSTRUMENTS USED FOR HAEMODIALYSIS PROCESS

# OPTYMALNA STRATEGIA KONSERWACJI URZĄDZEŃ MEDYCZNYCH WYKORZYSTYWANYCH W PROCESIE HEMODIALIZY

*Haemodialysis machines are one of the important medical equipment which is used to treat renal failures and minimum downtimes are thus essential. Uninterrupted and constant use of these machines in hospitals worldwide makes them vulnerable to failures if not maintained properly. Consequently, the maintenance cost for dialysis machine is high. A method to implement a cost effective maintenance strategy is demonstrated in this work. Root Cause Based Maintenance (RCBM) strategy is employed at the component level to optimize the Reliability Based Maintenance schedules derived from the existing maintenance and failure data. In order to minimize the average cost of maintenance for Haemodialysis machines and ensure their high operational availability, a Cost-Model is derived, and Genetic Algorithm is employed for optimization in this work. The application of RCBM strategy results in cost saving of about 60% of the cost incurred using current maintenance scheme. Statistical and optimization calculations are performed using Reliasoft's Weibull++ and MATLAB tools respectively.*

**Keywords**: *reliability-based maintenance, dialysis machines, genetic algorithm, reliability analysis, statistical distributions, operational availability.*

*Aparaty do hemodializy to ważne urządzenia medyczne wykorzystywane w leczeniu niewydolności nerek, dlatego ich przestoje muszą być jak najkrótsze. Ciągłe, nieprzerwane korzystanie z tych urządzeń w szpitalach na całym świecie sprawia, że, w przypadku braku właściwej konserwacji, są one podatne na awarie. W związku z tym koszty konserwacji aparatów do dializy są wysokie. W prezentowanej pracy przedstawiono metodę wdrażania ekonomicznej strategii konserwacji. Wykorzystano strategię konserwacji opartą na analizie przyczyn źródłowych uszkodzenia (RCBM). Zastosowano ją na poziomie części składowych w celu optymalizacji harmonogramów konserwacji opartej na niezawodności (RBM) tworzonych na podstawie istniejących danych dotyczących konserwacji i uszkodzeń. Aby móc zminimalizować średni koszt konserwacji aparatów do hemodializy i zapewnić ich wysoką gotowość operacyjną, opracowano model kosztowy, a optymalizację przeprowadzono za pomocą algorytmu genetycznego. Zastosowanie strategii RCBM daje około 60-procentową oszczędność kosztów, jakie ponosi się przy użyciu obecnie wykorzystywanego programu konserwacji. Obliczenia statystyczne i optymalizacyjne wykonano, odpowiednio, przy użyciu oprogramowania Weibull ++ i MATLAB firmy Reliasoft.*

**Słowa kluczowe**: *konserwacja oparta na niezawodności, aparaty do dializy, algorytm genetyczny, analiza niezawodności, rozkłady statystyczne, gotowość operacyjna.*

## Notations Used:

| | |
|---|---|
| $\eta$ | Scale parameter, or characteristic life (Weibull Distribution) |
| $\beta$ | Shape parameter (or slope) (Weibull Distribution) |
| $\gamma$ | Location parameter (or failure free life |
| $z$ | $\ln(t)-\mu$ |
| $e^{\mu}$ | Scale parameter (Gamma Distribution) |
| $k$ | Shape parameter (Gamma Distribution) |
| $t'$ | $\ln(t)\cdot$ t values are the times-to-failure |
| $\mu'$ | Mean of the natural logarithms of the times-to-failure |
| σ' | Standard deviation of the natural logarithms of times-of-failure |
| $P_i$ | Price of component $i$ |
| $T_{r,i}$ | Time of replacing work of component $i$ |
| $T_{fc,i}$ | Time of function check and rinse |
| $C_{mp}$ | Manpower cost per hour (250 $NTD$ / $hour$) |
| $T_s$ | Time interval that we want to calculate for the cost |
| $t_i$ | Replacement period of component $i$ |
| $k$ | Number of component |
| $C_{Ri}$ | The cost of replacing component $i^{\text{th}}$ time |

$t_{tk}$ Regular maintenance period (220 days)

$P_{tk}$ Price of tool kit(2600ntd)

$\left(T_{r,tk} + T_{fc,tk}\right)$ Time of repairing work plus function check and rinse (2 hours).

$C_{mp}$ Manpower cost per hour (250 $NTD$ / $hour$)

$C_{ex,i}$ Expected cost of component $i$

$C_{uex,i}$ Unexpected cost of component $i$

$C_{tk}$ Cost of tool kit maintenance

$C_{rp}$ The repeat calculated function check and rinse cost that occur when more than one component was repaired in a repair event.

$\lambda$ Failure rate.

## Abbreviations Used:

| | |
|---|---|
| RV | Relief Valve |
| TMP | Trans Membrane Pressure |
| NTB | Network Terminal Box |
| R Chamber | Rise Chamber |
| BLD | Blood Leak Detector |
| CCB | Carbon Cleaning Brush |
| PdM | Predictive Dialysis Maintenance |
| V39 | Valve 39 |

## 1. Introduction

Medical technology has witnessed rapid strides in the modern world which is a result of sophisticated and yet fascinating advancement in the medical methods and procedures. Highly advanced medical equipment has become an indispensable tool for modern medical procedures by virtue of which, most of the diagnosis and treatment are highly dependent on this equipment. The annual revenue for medical technology industry is worth half a trillion US dollars [13, 33] which shows the extensive use of medical equipment in modern medical facilities. Amongst few life-supporting medical equipment which are used in quick succession in hospitals and clinics, Haemodialysis is an important machine which works as an artificial kidney. In critical situations like renal failures, it is this Haemodialysis machine that removes the toxic waste products and restores the normal levels of body fluid volume and composition [3,18]. Hence, the availability requirement of this machine is high in order to treat the patients when need arises, and thus the number of such machine in a given hospital tend to be high.

However, the hospitals and medical facilities all around the world are presented with a challenge to maintain the Haemodialysis machine effectively, given the fact that it is being used continuously, one patient after another. The process of maintenance must be performed efficiently and effectively because improper maintenance and repairs can lead to unsafe conditions and reduced system performance and availability. Moreover, the cost-factor makes the maintenance strategy challenging because it is believed that 1/3rd of the overall maintenance cost is wasted either due to unnecessary or ineffective maintenance [24, 27], and given the large number of such machine, the waste can be significant. Therefore, there is an urge to develop a cost effective maintenance strategy.

Ever since the conception of Minimal repair model in 1960 [5], many optimal Maintenance strategies have been laid down in order to have minimum failures and maximum efficiency. The most common maintenance technique used is either preventive [5, 17] or corrective [7] in nature. Both these techniques have time and again been deemed as ineffective because Corrective Maintenance (CM)[2] inculcates large and unpredictable downtimes while Preventive Maintenance (PM) [21, 29] swings between extreme cases of 'more than necessary' and 'less than necessary' repairing frequency during infancy and aging periods respectively [34]. In particular, PM is carried out periodically on the basis of experience [41] or from the recommendation of the equipment manufacturers, and it does not account for unexpected failures because their failure mechanisms are time based [8]. PM and CM has been employed for general medical equipment [16, 19, 23, 25] but their implementation lacks simplicity and cost-effectiveness [21, 24].

Contrary to these maintenance strategies, Predictive Maintenance (PdM) [4, 40] is known to be more viable and effective method [6,26] which has been applied to various applications such as railway network [6], diode lasers [30], aircraft [36, 37], high yield etching process [10, 16, 38] etc. PdM technique is basically a condition-driven preventive maintenance scheme which takes into account the operational condition, efficacy and other health indicators that determine actual time needed for maintenance [22, 24, 25, 35, 36].

PdM technique has been applied for the evaluation of Haemodialysis machine's performance where their focusses were on the dialysis session performance and adequacy [10, 18]. However, these dialysis session performance and adequacy are dependent on the patients' condition rather than Haemodialysis machine, and thus their techniques cannot be applied to the machine maintenance.

To be more specific, the most common performance metrics for Haemodialysis machines is 'Kt/V' (dialyzer urea clearance K and dialysing time t per unit urea distribution volume V) or 'URR' (Urea Reduction Ratio) values [8, 5, 11] and they were considered as the health index for the application of PdM [19]. However, post and pre-dialytic urea concentration are required to evaluate URR, and urea clearance, dialysing time and distribution volume are required to calculate Kt/V. All these are dependent more on the patients' conditions rather than the Haemodialysis machine itself. Hence, it is not possible to determine the actual machine's health index or metrics for developing the maintenance strategy of the equipment. Therefore, the standard PdM strategy is not appropriate for the Haemodialysis system.

As the machine degradation depends on its components' degradation, reliability of the components will determine the reliability of the machine and its degradation, hence maintenance policy can also be developed at the components' level as well. The reliability of all the components can be calculated and thus optimal maintenance schedule can be planned accordingly. Such methodology is termed as the RCBM (Root Cause Based Maintenance) policy and has been developed by one of the author [35].

This work therefore implements RCBM strategy on Haemodialysis machines in Linkou Chang Gung Memorial Hospital, Taiwan. In particular, a method to evaluate specific time intervals to replace or maintain the individual components is demonstrated, in order to avoid unexpected failures and minimize the maintenance cost. The reliability data of each component is evaluated using Reliasoft software while the optimal maintenance time intervals are deduced using Genetic Algorithm which is implemented using MATLAB software. The maintenance cost reduced to approximately 40% of the original with the implementation of the RCBM strategy.

## 2. Haemodialysis description

4008S Haemodialysis Systems by Fresenius Medical Care stationed at one of the most reputed hospitals of Taiwan- Linkou Chang Gung Memorial Hospital are used for this work. There are 82 Haemodialysis machines in total installed at the hospital branch. Fig. 1 depicts the functional classification of the Haemodialysis system which comprises of several sub-parts or components under regular maintenance.

Each of the functions defined in Fig. 1 is performed by several sub-parts or components out of which 19 components are of utmost interest due to regular failures observed in a span of about 8 years,

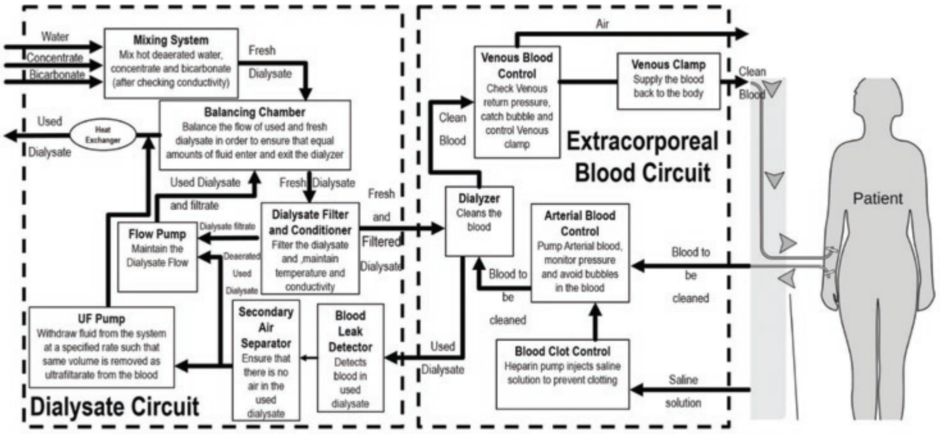


*Fig. 1. Functional classification of 4008S Haemodialysis machine used for PdM strategy [9].*

even though they are regularly maintained by the hospital. Table I shows a list of these 19 components.

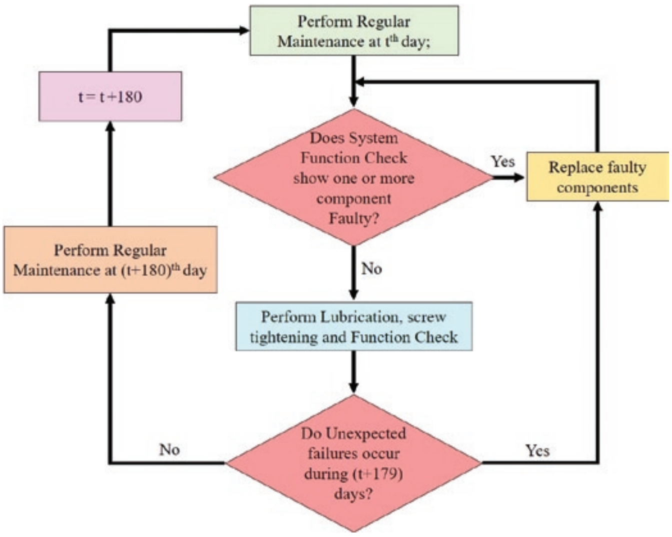


*Fig. 2. Current practice of 180-day regular maintenance for the Haemodialysis machines at the Hospital.*

The maintenance strategy used at the Hospital has been preventive in nature wherein the maintenance staff carries out regular maintenance every 180 days suggested by the manufacturer as shown in Fig. 2. If any faulty components are detected during the regular maintenance, they are replaced by a new component. Any failure in between regular maintenance cycle of 180 days will cause a suspension of that particular machine for a day or two, and a spare machine will be used in replacement while the faulty machine is diagnosed with necessary remedial action taken.

Such a maintenance scheme has the following drawbacks:

1. Not all the components have similar failure rates, and they also vary differently over the age of the components and machine. Hence, there are possibilities where not all components require maintenance every 180 days, some may be less and some may be more.
2. The downtime and maintenance cost is high particularly for unexpected failures which are not taken into consideration with the current practices with regards to maintenance at the Hospital.

In a need for improvement in the maintenance strategy where unexpected failures and various components' failure rates are to be taken into consideration, methodology for the application of PdM strategy on the 4008S Haemodialysis machine is developed in this work as will be discussed in the subsequent sections.

## 3. Methodology of RCBM strategy

The methodology for the application of RCBM strategy (a version of PdM) consists of formulation a 'Maintenance Policy' based on the Reliability analysis of components from maintenance records and the evaluation of a 'Cost Model' (described in subsequent sub-sections), in order to achieve a cost effective maintenance. This is followed by optimization of maintenance schedules for each component, in order to minimize the overall cost of maintenance.

The aforementioned methodology incorporates following assumptions:

*Table I. Components of interest for application of PdM*

| S. No | Name of Components | No. of failures in a span of 3060 days | Abbreviation used for the component | S. No | Name of Components | No. of failures in a span of 3060 days | Abbreviation used for the component |
|---|---|---|---|---|---|---|---|
| 1 | Motor 29 | 141 | M29 | 11 | Carbon Cleaning Brush | 5 | CCB |
| 2 | Valve 39 | 20 | V39 | 12 | Silicone Tube | 10 | ST |
| 3 | Relief Valve | 38 | RV | 13 | AK O-Ring | 14 | AKOR |
| 4 | Trans Membrane Pressure | 33 | TMP | 14 | #65 Regulator | 12 | 65R |
| 5 | Network Terminal Box | 6 | NTB | 15 | Flow Current | 7 | FC |
| 6 | Blood Leak Detector | 61 | BLD | 16 | Power Supply | 23 | PS |
| 7 | Gear 29 | 71 | G29 | 17 | CAL Pressure | 4 | CP |
| 8 | Filter 210 | 28 | F210 | 18 | Heparin Pump | 8 | HP |
| 9 | Motor 21 | 76 | M21 | 19 | AK Tube | 8 | AKT |
| 10 | Rise Chamber | 7 | RCh | | | | |

a) If a component is replaced during regular maintenance or unexpected failures, the reliability of the component will be restored to 100% after replacement.
b) The time window for cost calculation of the developed maintenance strategy is based on the existing life cycle of the machine (which is 3060 days) for fair comparison.
c) The failure mechanism of one component does not interact or influence that of other components for the sake of simplicity in analysis.

### 3.1. Reliability based 'Maintenance Policy'

In order to develop a new maintenance policy, the maintenance records from the hospital, for a duration of about 8 years is studied. The current maintenance policy is a fixed period preventive maintenance of 180 days wherein faults are diagnosed during regular maintenance or unexpected failures and rectified by replacing the faulty component. Fig. 3 shows the stick-diagram for the existing maintenance strategy of a component presented as a Network Terminal Box (NTB) for illustration. The solid thick sticks represent 180-day regular maintenance and the thin-smaller sticks represent the actual failures that happened in-between regular maintenance cycles.

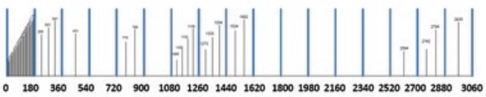


*Fig. 3. Stick-diagram for the existing maintenance strategy of a component presented as Network Terminal Box, for illustration*

Fig. 3 highlights two major issues associated with the existing maintenance strategy. *Firstly*, the initial failures (within the first 180 days) are large in number which was not detected earlier before our analysis, and *secondly*, unexpected failures occur quite often, in-between regular maintenance period. All these lower the operational availability of the equipment and increases the maintenance cost due to unexpected maintenance and the need of spare machines in order to maintain high availability. The first issue can be detected through standard data logging. However, the second issue requires the study of the reliability of each component.

In order to improve the existing maintenance strategy, the maintenance record for each of the 19 components mentioned in Table I is analysed using Weibull++ v10 by Reliasoft. The failure times and reliability of each component (excluding initial failures) are estimated

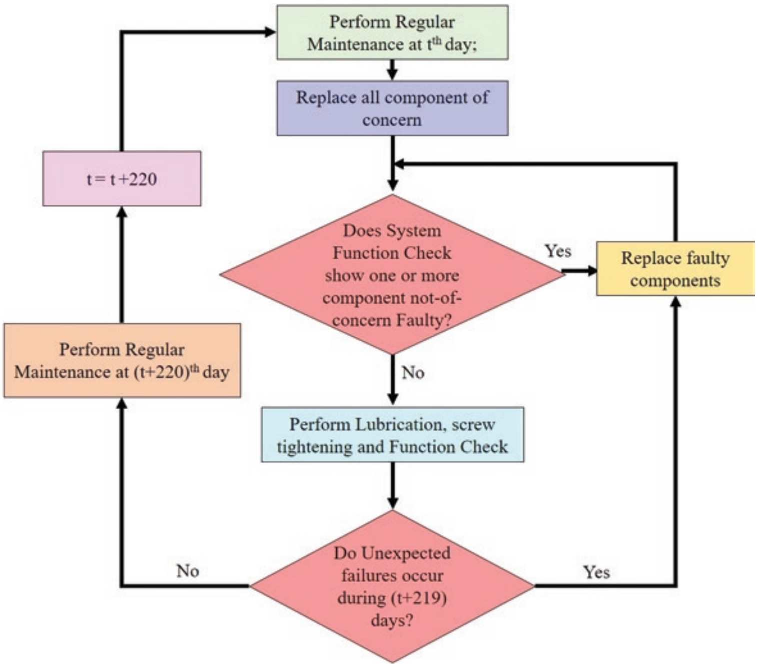


*Fig. 4. Suggested 220-day maintenance policy*

*Table II. 220-Day Maintenance Scheduling based on Reliability Data (without considering the initial failures)*

| S. No | Component | Associated Statistical Distribution | Distribution Parameters |
|---|---|---|---|
| 1 | M29 | 2P-Weibull | Beta: 2.49, Eta (Day): 971.02 |
| 2 | V39 | 3P-Weibull | Beta: 1.32, Eta (Day): 5345.53, Gamma (Day): 89.06 |
| 3 | RV | 2P-Weibull | Beta: 2.30, Eta (Day): 2612.57 |
| 4 | TMP | 2P-Weibull | Beta: 2.10, Eta (Day): 3736.00 |
| 5 | NTB | 2P-Weibull | Beta: 2.08, Eta (Day): 2743.23 |
| 6 | BLD | 3P-Weibull | Beta: 0.74, Eta (Day): 4050.97, Gamma (Day): 196.61 |
| 7 | G29 | Lognormal | Log-Mean (Day): 7.34, Log-Std: 0.70 |
| 8 | F210 | Gamma | Mu (Day): 7.77, K: 1.78 |
| 9 | M21 | 3P-Weibull | Beta: 1.93, Eta (Day): 1833.00, Gamma (Day): 4.19 |
| 10 | RCh | 2P-Weibull | Beta: 1.55, Eta (Day): 9503.80 |
| 11 | CCB | 3P-Weibull | Beta: 0.89, Eta (Day): 21327.93, Gamma (Day): 351.63 |
| 12 | ST | Lognormal | Log-Mean (Day): 7.99, Log-Std: 0.15 |
| 13 | AKOR | Lognormal | Log-Mean (Day): 8.46, Log-Std: 0.76 |
| 14 | 65R | 3P-Weibull | Beta: 2.24, Eta (Day): 3711.45, Gamma (Day): 375.00 |
| 15 | FC | Gamma | Mu (Day): 8.24, Gamma (Day): 1.82 |
| 16 | PS | 2P-Weibull | Beta: 2.08, Eta (Day): 3579.83 |
| 17 | CP | 2P-Weibull | Beta: 1.47, Eta (Day): 12556.33 |
| 18 | HP | Lognormal | Log-Mean (Day): 8.70, Log-Std: 0.70 |
| 19 | AKT | Lognormal | Log-Mean (Day): 7.96, Log-Std: 0.37 |

*Table III. 220-Day Maintenance Scheduling based on Reliability Data*

| Maintenance Cycle | Components of-concern to be maintained in | | | Total No. of Components to be maintained |
|---|---|---|---|---|
| | 220 days | 440 days | 1100 days | |
| 1st cycle on 220th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | - | - | 10 |
| 2nd cycle on 440th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | CCB, ST, AKOR, 65R, FC, PS, CP | - | 17 |
| 3rd cycle on 660th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | - | - | 10 |
| 4th cycle on 880th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | CCB, ST, AKOR, 65R, FC, PS, CP | - | 17 |
| 5th cycle on 1100th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | - | HP, AKT | 12 |
| 6th cycle on 1320th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | CCB, ST, AKOR, 65R, FC, PS, CP | - | 17 |
| 7th cycle on 1540th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | - | - | 10 |
| 8th cycle on 1760th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | CCB, ST, AKOR, 65R, FC, PS, CP | - | 17 |
| 9th cycle on 1980th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | - | - | 10 |
| 10th cycle on 2200th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | CCB, ST, AKOR, 65R, FC, PS, CP | HP, AKT | 19 |
| 11th cycle on 2420th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | - | - | 10 |
| 12th cycle on 2640th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | CCB, ST, AKOR, 65R, FC, PS, CP | - | 17 |
| 13th cycle on 2860th day | M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh | - | - | 10 |
| 14th cycle on 3080th day | M21, RCh | - | - | 2 |

using the Cumulative Distribution Function (CDF) based on specific statistical distribution associated with the specific components as shown in Table II.

Assuming the reliability of each component must be above 0.97, which implies that the chance of the failure of each component is less than 0.03, we can derive a suitable maintenance cycle for each component as shown in Table III.

From our reliability analysis of the components, we found that their reliabilities are adequately high, apart from their early failure, and thus 180-days maintenance cycle is too conservative. Also, Table III shows that not all the 19 components need to be maintained during the regular maintenance. In a life cycle period of 3060 days, 10 components including M29, V39, RV, TMP, NTB, BLD, G29, F210, M21, RCh are to be maintained every 220 days, 7 components including CCB, ST, AKOR, 65R, FC, PS, CP are to be maintained every 440 days, 2 components including HP, AKT are to be maintained every 1100 days. The 14th cycle has an exception of only 2 components (M21 and RCh) instead of 10 in 220-day cycle. Fig. 4 shows the suggested 220-day maintenance strategy.

In comparing the current 180-days maintenance policy with the suggested 220-days maintenance policy, one can obtain the following major advantages:

- Number of maintenance cycles reduce to 14 cycles from 17 in a life cycle period of 3060 days.
- The regular maintenance cost reduces by 18.18%. This results in a total saving of 18,279 Unit Dollar (Unit$) per year per machine (excluding initial and unexpected failures' consideration)

The value of 0.97 reliability criteria is arbitrary, and it could be too stringent or too loss to assure cost effective maintenance with respect to lower unexpected failure and high availability. Thus, a systematic method is needed to determine the reliability criteria for each component, and a Cost-Model for a RCBM maintenance policy is required. The development of the Cost-Model will be discussed in the next sub-section.

One needs to note that the initial failures are not included in the cost saving calculations because these can be avoided by considering better quality components or by considering a different vendor.

## 3.2. The Cost model

The 'Cost Model' is formulated in order to evaluate the cost-saving from the suggested maintenance strategy including both expected and unexpected failures as well as for optimization of maintenance strategy. Assuming there are k components and the replacement period of component $i$ to be $t_i$, then the total cost of maintenance can be given by equation (1):

$$\mathrm{Totalcost}\left(t_1,t_2,t_3,\ldots,t_k\right)=\sum_{i=1}^{k}C_{ex,i}+C_{tk}+\sum_{i=1}^{k}C_{uex,i}-C_{rp} \quad (1)$$

where $C_{ex,i}$ is expected cost of replacement for $i^{th}$ component, $C_{uex,i}$ is expected cost of replacement for $i^{th}$ component, $C_{tk}$ is toolkit cost and $C_{rp}$ is calculated function check and rinse cost (repeated).

With this equation, we can develop optimal RCBM policy to minimize the total cost of maintenance as follows, where Cm is the minimum total cost of maintenance:

$$Cm=min\left(Total\ cost\left(t_1,\ t_2,\ t_3,\ \ldots,t_k\right)\right) \quad (2)$$

The detailed calculations of the 4 terms in equation (1) are deduced below.

### 3.2.1. Expected cost of replacement ($\sum_{i=1}^{k}C_{ex,i}$)

As replacement of components are bound to happen, the expected cost of replacement ($\sum_{i=1}^{k}C_{ex,i}$) for k components is the summation of expected cost of replacement $C_{ex,i}$ for $i^{th}$ component which can be computed as the sum of the price of the component $P_i$ and the related manpower cost as given below:

$$C_{R,i}=\ P_i+\left(T_{r,i}\ +\ T_{fc,i}\right)\times\ C_{mp} \quad (3)$$

where $C_{Ri}$ is the cost of replacing component $i$ th time, $T_{r,i}$ and $T_{fc,i}$ are the man-hour for replacing and performing function check-rinse respectively, and $C_{mp}$ is the manpower cost per hour.

Hence, the expected cost of replacement for k components is given by equation (4):

$$\sum_{i=1}^{k}C_{ex,i}=\sum_{i=1}^{k}int\left[\frac{T_s}{t_i}\right]\times\ C_{R,i} \quad (4)$$

where $C_{ex,i}$ is expected cost of replacement for $i^{th}$ component, $int\left[\frac{Ts}{ti}\right]$ represents the expected number of replacements within a specific time interval of $T_s$.

### 3.2.2. Regular maintenance cost ($C_{tk}$)

The regular maintenance involves basic function check-rinse and repairing using a tool kit which costs $P_{tk}$ . Thus, the regular maintenance cost is given by equation (5):

$$C_{tk}=int\left[\frac{T_s}{t_{tk}}\right]\times\left(P_{tk}+\left(T_{r,tk}\ +\ T_{fc,tk}\right)\times\ C_{mp}\right) \quad (5)$$

where $C_{tk}$ is toollkit cost, $t_{tk}$ is the regular maintenance period, $\left(T_{r,tk}+T_{fc,tk}\right)$is the time of repairing work and function check and rinse (about 2 hours) and $C_{mp}$ is the manpower cost per hour.

### 3.2.3. Unexpected cost of replacement ($\sum_{i=1}^{k}C_{uex,i}$)

Unexpected failure can happen in-between designated maintenance cycles. In order to calculate the unexpected cost of replacement, number of unexpected failures is to be determined using the Non-Homogeneous Poisson's (NHP) process [2, 15, 16, 31], as the failure rate of all the components are time-dependent.

To apply NHP process (Fig. 5), one needs to determine the time interval so that the failure rate can be treated as a constant within the interval. Too large the time interval will produce error as the variation in the failure rate will be too high to be considered as approximately

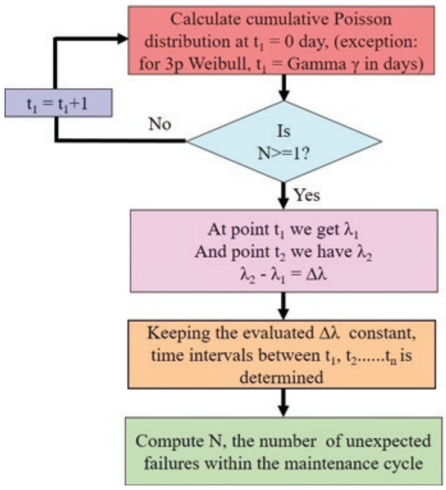


*Fig. 5. Procedure to calculate number of unexpected failures*

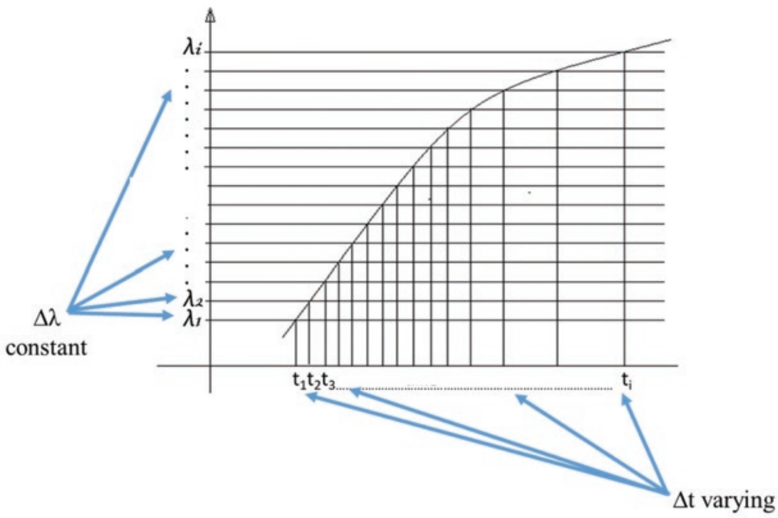


*Fig. 6. 'Plot-Division' to determine Δt based on constant Δλ*

constant. Too small the interval will also produce error as the number of failure will be zero.

Fig. 6 shows an example of the failure rate vs time curve as derived from the reliability function [12] of a component given as:

$$h(t) = (dF/dt)/(1-F(t)) \quad (6)$$

where F(t) is the cumulative density function given as F(t)=1-R(t).

In Fig. 6, the failure curve is divided into time intervals in such a way that Δt will be varied according to the curve while Δλ will be constant. Table IV shows an example for the calculation of *N* in case of a component- *Motor 29*, for a time period of 25 days, which is its replacement period.

*Table IV. An example of calculation of N in case of a component- Motor 29, for a time period of 25 days*

| N | Time | lambda | Reliability | Poisson Distribution, $P_N$ | Cumulative Poisson Distribution | $N*P_N$ |
|---|---|---|---|---|---|---|
| 0 | 25 | 0.000619 | 0.984644123 | 0.993829119 | 0.9938291 | 0 |
| 1 | 25 | 0.000619 | 0.984644123 | 0.006151802 | 0.9999809 | 0.006151802 |
| 2 | 25 | 0.000619 | 0.984644123 | 1.90398E-05 | 1 | ~0 |
| 3 | 25 | 0.000619 | 0.984644123 | 3.92855E-08 | 1 | ~0 |

From Table IV, unexpected failure cost for Motor 29 for a time period of 25 days can be calculated as:

$$Component\,Cost \times (N \times P_N) = 9291.97\,Unit\$ \times (1 \times 0.006151802) = 57.514319\ Unit\$$$

In general, the equation for Unexpected Cost calculation can be expressed as shown below:

$$\sum_{i=1}^{k} C_{uex,i} = \sum_{i=1}^{k} \left( \left( int\left[\frac{T_s}{t_i}\right] \times E\left[N_f(i,t_i)\right] + E\left[N_f(i,t_{irm})\right] \right) \times C_{R,i} \right) \quad (7)$$

where $E\left[N_f(i,t_i)\right]$ is the expected value of the number of unexpected failures within $t_i$ for component i, $t_{irm} = T_s - int\left[\frac{T_s}{t_i}\right] \times t_i$ is the remaining time before the $T_s\,(here\,T_s = 3060\,days)$ ends and after the last replacement of component $i$, and $C_{R,i}$ is the replacement cost of the $i^{th}$ component as shown in equation (3).

### 3.2.4. Repetitive cost of function check and rinse $(C_{rp})$

During a repair event, if there are more than one components that have to be replaced or, if this repair event coincides with the regular maintenance event, the function check and rinse will only be performed once. In order to compensate the repetitive calculation of the cost of function check and rinse $(C_{rp})$ as evident from equations (3) and (5), the term $C_{rp}$ is subtracted in equation (1). Assume there are $w$ repair event in an interval $T_s$, repetitive cost of function check and rinse is given by equation (8):

$$C_{rp} = \sum_{j=1}^{w} C_{rp,j} = \sum_{j=1}^{w} (m_j - 1) T_{fc} \times C_{mp} \quad (8)$$

where $m_j$ is the number of the components that have to be repaired in the repair event $j$.

### 3.2.5. Optimal failure criteria for minimization of total maintenance cost

In our previous example, we assume the reliability criteria of each component to be 0.97. Such high reliability criteria can reduce the number of unexpected failures within a maintenance cycle, but it will also shorten the maintenance period and thus increases the expected cost of maintenance. Fig. 7 shows the plot of Total Maintenance Cost for one of the components- Motor 21 (M21) with respect to the varying failure criteria as computed using Equations (4)-(8).

From Fig. 7, one can see that the minimum total maintenance cost occurs when the failure probability is chosen to be 0.3, neither too high nor too low. However, the plot in Figure 7 is specific to only one component. Every other component will have similar curve with different failure criteria for minimum value of Total Maintenance Cost. Therefore, there is a need for optimization of the maintenance periods in order to cater for different failure criteria and minimization of Total Maintenance Cost.

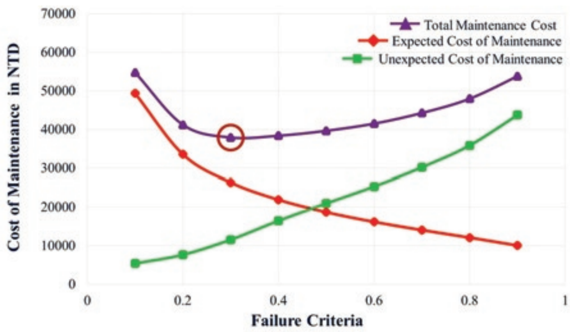


*Fig. 7. Cost of Maintenance vs Failure Criteria chosen for replacement period and regular maintenance of Motor 21; red solid circle shows the point of lowest total cost of maintenance for Motor 21*

## 4. Optimization of RCBM policy

In order to select an appropriate optimization technique for the proposed RCBM policy, we studied different optimization algorithms [20, 28] and Genetic Algorithm (GA)[32, 38] is selected because of the following reasons:

1. GA has a capability to be implemented as a 'universal optimizer' that could be used for optimizing any type of problem belonging to different fields [38,39].
2. Simplicity and ease of implementation of GA.

The basic principal of genetic algorithm is inspired by Charles Darwin's theory of natural evolution and Gene theory. Genetic algorithm optimizes the output in five phases[14] which in this case study can be understood as:

1. *Population Definition:* It defines target maintenance schedule (individuals in Gene theory) set.
2. *Fitness Function Analysis*: It determines how fit a maintenance schedule (individual in Gene theory) is by assigning a fitness score. The fitness function in this case is the cost model.

3. *Selection*: The idea is to select the fittest maintenance schedule (individuals in Gene theory) based on the fitness score.
4. *Crossover*: It is the most significant phase in a Genetic Algorithm. For each pair of maintenance schedules (parents in Gene theory) to be interacted (mated in Gene theory), a crossover point is chosen at random from within the prior set of information (Genes in Gene theory).
5. *Mutation*: In certain new maintenance schedules (offspring in Gene theory) formed, some of their information (Genes in Gene theory) can be subjected to a variation (Mutation in Gene theory) with a low random probability.

In this work, Genetic Algorithm function is implemented in MATLAB optimization toolbox using the 'Cost Model' derived in the previous section, so as to find the best periodic replacement schedule for each component. The key elements for implementation of GA is shown below:

1. In order to find the $min\left(Total\ cost\left(t_1, t_2, t_3, \ldots, t_k\right)\right)$, the replacement period of each component $t_i$ is encoded as the GA's population. Here the replacement period $t_i$ is considered in month. The population size is taken as 20 times the total number of components.
2. The constraints considered is with respect to the replacement period $t_i$.

$$Constraint \Rightarrow 1(month) \le t_i \le T_s$$

3. where $T_s$ is 3060 days in this case-study
4. The fitness function is according to the deduced 'Cost Model'.
5. The stop criteria for the iterations in GA is as follows:
   - Limit of generation = Infinity
   - Stall generations = 300
   - Function tolerance = 1e-7

Genetic Algorithm often needs large execution times to obtain the approximate optimized solution. Therefore, a computer with 20 core parallel computing is employed for the execution of Genetic Algorithm on an Intel® Xeon® CPU E5-2650 v3 @2.30GHz, which takes about 36 hours for the solution to converge.

## 5. Results and discussions

### 5.1. Optimal maintenance schedules

The optimal maintenance schedule obtained from the Genetic Algorithm execution is summarized in Table V. It corresponds to minimized total maintenance cost value of 359,102 Unit$ for the entire life cycle of 3060 days for the Haemodialysis machine studied in this work.

### 5.2. Comparison of Average Cost of Maintenance

The average cost of maintenance of one machine (ACoM) is calculated as follows:

$$ACoM = \left(\sum_{j=1}^{r} \frac{TC_j}{T_j}\right) \div r, \quad (cost / day) \tag{9}$$

where r is the number of machines, $TC_j$ is the total cost of maintenance of machine 'j' and $T_j$ is the age of machine 'j' in days. All the machines are divided into four groups (on the basis of age) in order to draw a fair comparison between the actual maintenance cost and the corresponding optimized value.

Fig. 8 shows the comparison of the ACoM for all the four groups associated with the current and optimal maintenance strategy.

Using the optimal RCBM strategy, huge cost saving is exhibited with respect to the ACoM as shown in Fig. 8. The Average Cost of Maintenance of a machine which follows the current 180-day regular maintenance strategy is 128.91 Unit$/day. This value decreases to 78.83 Unit$/day in case of Reliability based 220-day maintenance strategy. The ACoM for the optimized RCBM strategy reduces further to 49.84 Unit$/day, accounting for almost 60% of the total cost saving.

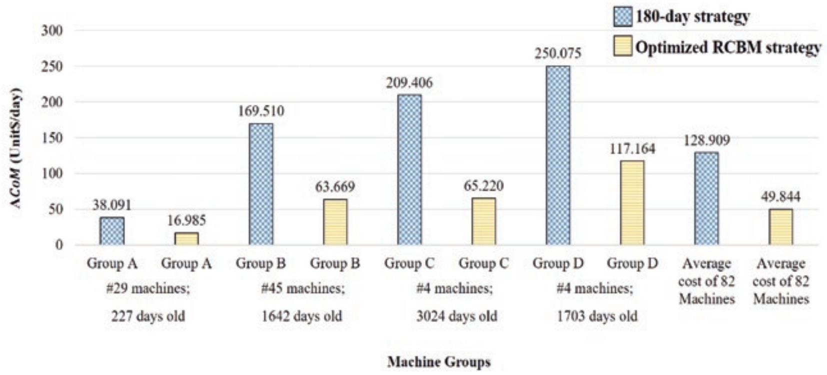


*Fig. 8. Comparison of ACoM between the machine groups with existing 180-day policy and optimized RCBM strategy*

*Table V. Optimised Maintenance Schedules deduced from GA*

| S. No | Component | Optimal Maintenance Schedule (in Days) |
|---|---|---|
| 1 | Motor-29 | 780 |
| 2 | Valve-39 | 1950 |
| 3 | Relief-Valve | 1830 |
| 4 | Trans-Membrane Pressure | 1890 |
| 5 | Network-Terminal Box | 1860 |
| 6 | Blood-Leak Detector | 3090 |
| 7 | Gear-29 | 1860 |
| 8 | Filter-210 | 2040 |
| 9 | Motor-21 | 1830 |
| 10 | Rise-Chamber | 1890 |
| 11 | Carbon-Cleaning Brush | 2880 |
| 12 | Silicone-Tube | 2340 |
| 13 | AK-O-Ring | 780 |
| 14 | #65-Regulator | 1890 |
| 15 | Flow-Current | 630 |
| 16 | Power-Supply | 1710 |
| 17 | CAL-Pressure | 630 |
| 18 | Heparin-Pump | 3090 |
| 19 | AK-Tube | 780 |

Table VI. Comparison of Operational Availability for 180-day maintenance policy and optimized RCBM policy

| Maintenance Policy | MTBF (in days) | MDT (in days) | OpAv |
|---|---|---|---|
| 180-day Regular Maintenance | 622.02 | 3.0200 | 0.99517 |
| Optimized RCBM | 742.82 | 0.0384 | 0.99995 |

### 5.3. Comparison of Operational Availability

The operational availability (OpAv) [1, 21,22] for a given system is defined as the fraction of average availability over a period of time and is expressed by equation (10):

$$OpAv = \frac{MTBF}{MTBF + MDT} \tag{10}$$

where MTBF is the Mean Time Between Failures and MDT is the Mean Down-time.

Table VI shows a comparison of MTBFs, MDTs and OpAVs of the current 180-day maintenance policy and optimal RCBM policy.

The operational availability (OpAv) calculated for the optimal RCBM is much higher than the same for 180-day regular maintenance practice.

## 6. Conclusion and future work

Haemodialysis machines at a reputed hospital are investigated in this work. The existing maintenance strategy is analyzed which is preventive in nature. Root Cause Based Maintenance (RCBM) strategy is implemented for reducing the cost of maintenance. Optimization of the maintenance schedules using Genetic Algorithm results in improving the operational availability and cost saving of about 60% of the current practice.

Spare part analysis and interaction of components degradation are important future works which can enable complex scenario to be included in the maintenance optimization.

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