Prediction of Medical Equipment Failure Rate: A Case Study

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Abstract. Medical equipment is one of the important inputs required for the provision of efficient healthcare services. Following maintenance programs will make the equipment last longer, work more efficiently and reduces the likelihood of equipment failure during critical processing operations. Prediction of these failures affects the efficiency and enlarges the uptime of medical equipment, minimizes sudden failures and even can prevent it. Therefore, time series analysis using autoregressive model (AR) has been used to analyze failure rate data. AR model uses the past behavior of the system output to predict its behavior in the future. The mean squared error (MSE) between model output and real-life data was less than 0.1 %. Moreover, it succeeded to predict duration of next failures.

Keywords: Medical equipment maintenance · Time series analysis · AR model · Failure rate forecasting

1 Introduction

Medical equipment is designed to aid in the diagnosis, monitoring or treatment of medical conditions. Following the recommended maintenance program can reduce equipment failures [1]. Prediction of these failures affects the efficiency of health care delivery system, and enlarges the uptime of medical equipment to reach the optimal usage and minimizes sudden failures and even can prevent it. This can be achieved either by installing the necessary spare parts before the failure's occurrence, using a backup equipment or by purchasing new equipment in case the forecasting process predicts continuous failures that recommends equipment's retirement. As the core interest is patient safety, this will positively influenced by forecasting such failures that aid in decision making. The practical usage of equipment failure rate models is to find optimum equipment replacement policies, and to identify imperfect or hazardous repair, so that maintenance practice can be further investigated and enhanced.

Over the past few decades, failure rate prediction, also known as reliability prediction, of medical devices have been studied by many researchers at the design stage [2, 3]. But not many researchers dealt with the medical equipment's reliability prediction while they were used in hospitals. For example, the field data have been used to

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study the reliability prediction for Philips medical systems using power law and exponential law models. The aim was to model the failure patterns and to valuate models' prediction results. For some failure patterns; as each system has different failures number, the models couldn't fit individual systems that makes the predictive values lacking accuracy [4]. Similarly, medical imaging systems' field data have been utilized for failures prediction using non-homogeneous Poisson process and non-parametric Nelson-Aalen model [5]. Moreover, different failures type of a particular infusion pump could be classified to establish policies for analyzing field data at system and component levels [6]. The Cox proportional hazard model have been utilized to develop a model for failure events prediction based on a single event sequence collected from in-service equipment [7].

Failure rate models are also of intrinsic interest to mathematicians. Over the years, probability and operational researchers have published many papers on failure rates of repairable systems. Most work is concerned with formulating models of failure rate, as a function of system age t and the periods $t1\ldots t_n$ at which failures occur and repairs are carried out. Policies for system replacement (such as replacement at a specified age) are then evaluated under the model [8]. Time series analysis for prediction can be a very useful tool in the field of medical equipment failure to forecast and to study the behavior of failure along time. This creates the possibility to give early warnings of possible equipment malfunctioning [9]. Proper care should be taken to fit an adequate model to the underlying time series. It is obvious that a successful time series forecasting depends on an appropriate model fitting. Various important time series forecasting models have been evolved in [10].

The aim of this paper is to produce a rigorous model for failure data analysis leading to the estimation of optimal approach for failure rate forecasting to aid in replacement decision-making.

The rest of this paper is organized as follows: Method description is in the next section where data analysis and AR model were introduced. Section 3 reports results and discussion. While conclusion is illustrated in Sect. 4.

2 Material and Method

Observing the failure history of medical equipment in order to anticipate the future failures was the main interest. This is referred to as forecasting or prediction.

The analysis is applied to the COULTER MAX.M hematology equipment, Beckman Coulter, Inc. used in the clinical laboratory at Dar Al-Fouad hospital that is a private hospital in Egypt. Failures history occurred with the MAX.M have been observed and scheduled along three years. The differences between two failures have been calculated.

2.1 Data Analysis

Consider the obtained data as a time series that is defined as a sequential set of data points, measured typically over successive times. The measurements taken during an event in a time series are arranged in a proper chronological order. The time series is represented here by the failure rate data. Failure rate is the time difference between two failures.

Time Series Stationary. Properties of stationary time series do not depend on the time at which the series is observed. A white noise series is stationary because it does not matter when it is being observed, it should look much the same at any period of time. Yet, some cases can be confusing, a time series with cyclic behavior (but not trend or seasonality) is stationary. That is because the cycles are not of fixed length, so we cannot assure where the peaks and troughs of the cycles will be before we observe the series [11]. Thereupon, the failure rate data are considered as a stationary time series.

In general, models for time series data can have many forms and represent different stochastic processes. One of the most widely used linear time series model in literature is Autoregressive (AR) [12] that is remarkably flexible at handling a wide range of different time series patterns [11] and appropriate when the time series is stationary. This Linear model has drawn much attention due to its relative simplicity in understanding and implementation [10]. Failure rate data analysis involves data preprocessing in which failure data were smoothed and interpolated before using the AR stochastic model for failure forecasting.

Data Preprocessing: Smoothing and Interpolation. Initially, data fitting has been utilized to find the curve which matches the failure rate data. Smoothing approach has been followed to overcome any abrupt changes in these data. One of the most widely used nonlinear correction techniques is the locally weighted scatterplot smoother (Lowess) technique that was first applied to microarray data [13, 14]. The Lowess is a data analysis technique for producing a smooth set of values from a time series that has been contaminated with noise that may causes missing or masking the true data value. This missing data can be found by linear interpolation [15]. Or, by way of explanation, the resulted smoothed data are non-uniformly space sampled that necessitates applying interpolation technique to achieve uniform sampled data. Compared to other non-parametric regression techniques, the Lowess is more robust in many types of scenarios [14]. Steps required to select the model structure are shown in Fig. 1.

This structure depends on two basic steps: (1) Model Order Selection; and (2) Parameters Estimation.

The model order and parameters were estimated so that to yield minimum mean squared error (MMSE) as in Eq. (1),

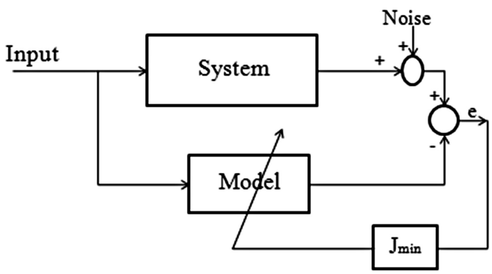

Fig. 1. Criterion for model structure selection

$$J_{min} = (\frac{1}{n}) \sum_{k=1}^{n} e_k^2 \tag{1}$$

Where:
J_{min}: MMSE;
n: No. of data points;
e: System to model error.

2.2 AR Model

AR model is a simple and effective method in time series modeling. It is a model which uses the past behavior of a variable to predict its behavior in the future. In other words, it is simply a linear regression of the current value of the series against one or more prior values of the series where the input is assumed to be white noise. It can easily handle messy data frequently seen in biological signals such as in heart rate variability studies [16]. Yet, in that instance, we have applied it to the smoothed, interpolated failure rate data. The most often seen form of the equation is a linear form as shown in Eq. (2):

$$Y_t = C + \sum_{k=1}^{p} \varphi_k Y_{t-k} + \varepsilon_t \tag{2}$$

Where:
Y_t: Dependent variable values at the moment t;
Y_{t-k} $(k = 1, 2, \ldots, p)$: Dependant variable values at the moment $(t - k)$;
p: Order of AR model and written as $AR(p)$;
$\varphi_1, \ldots\ldots \varphi_p$: Parameters or regression coefficients;
C is a constant; and ε_t is an error at moment t.

The constant term can be omitted for simplicity if the dependent variable Y_t has zero mean value. The Eq. (2) will become as in Eq. (3),

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \ldots + \varphi_p Y_{t-p} + \varepsilon_t \tag{3}$$

Accordingly, the observed failure rate data have been normalized (i.e. having zero mean and unit variance) before being used to omit the constant term in the model representing equation.

Some constraints are necessary on the values of the parameters of this model in order that the model remains stationary. For example, processes in the first-order autoregression model $AR(1)$ with $|\varphi 1| > 1$ is not stable. Generally, $|\varphi p|$ should be less than one to assure the stability of the model [17]. Therefore, it is important to use a stability test that is a fast and reliable numerical method based on calculating the reflection coefficients [18].

Reflection coefficients are the partial autocorrelation coefficients scaled by–1. They indicate the time dependence between Y_t and Y_{t-p} after subtracting the prediction based on the intervening $p - 1$ time steps [19].

Another constraint is that AR model's default input data are white noise (Gaussian distribution). Figure 2 shows the flowchart of the AR model estimation.

Selecting the Model Order. There is no straightforward way to determine the correct model order. As one increases the order, the mean square error generally decreases

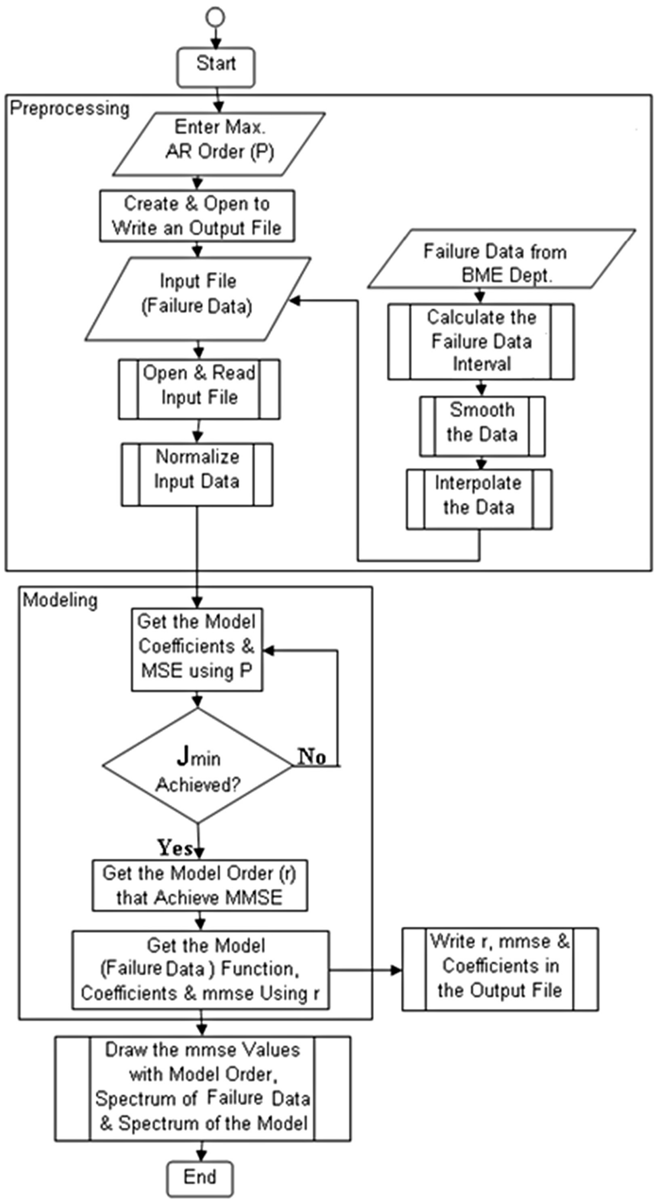

Fig. 2. AR model estimation flowchart

quickly up to some order and then become more slowly. An order just after the point at which the mean square error flattens out is usually an appropriate order [20].

Fitting Models. Models in general, after choosing the order (p), are fitted by least square regression to find the parameters' values which minimize the error term. The autoregressive model parameters can be estimated by minimizing the sum of squares residual with respect to each parameter. The aim is to find the smallest values of p which provides an acceptable fit to the data [21].

3 Results and Discussion

3.1 Best Fit Model

Model identification is one of the most challenging and distressing issues in AR modeling. As shown in Fig. 3, Starting with AR (20) to estimate the variation of MMSE values relative to the AR model order, there is no significant improvement in MMSE with increasing model order. The MMSE value is decreased then stabilized at order 2. Consequently, AR (2) has been used and the result is illustrated in Fig. 4.

Table 1 compares the accuracy of different model order selections. The absolute value of the reflection coefficient for AR (2) is almost equals 1. To avoid model instability, a higher model order AR (3) has been used. The output is depicted in Fig. 5.

Figures 3, 4 and 5 show the identification of the spectral density of the original failure data with the spectral density of the AR (20), AR (2), and AR (3) models, respectively. This is because MMSE values between different models' output and real-life data were less than 0.1 %, as illustrated in Table 1.

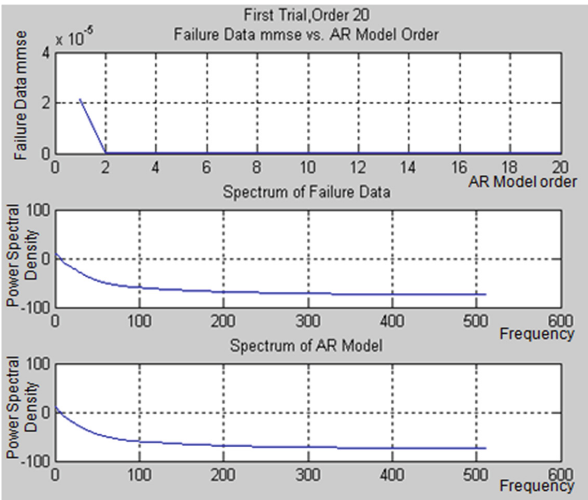

Fig. 3. Results of failure data applied to AR (20) model

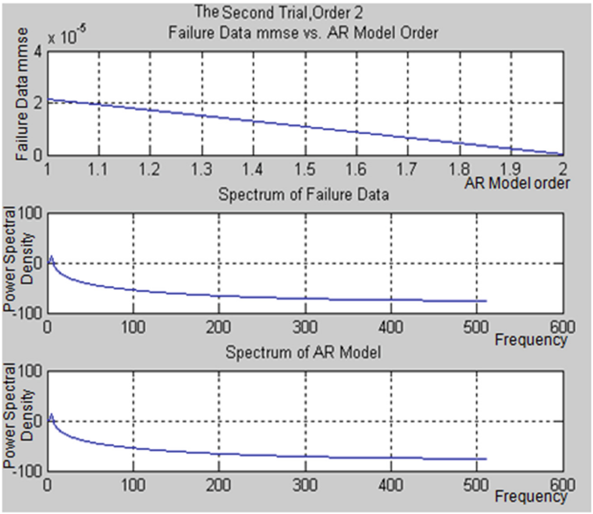

Fig. 4. Results of failure data applied to AR (2) model

Table 1. Influence of model order on MMSE

	1st trial	2nd trial	Last trial
Model order	20	2	3
MMSE	0.00060878	0.00067152	0.00067033
AR model reflection coefficient	−0.03315649	−0.9938938	−0.06470016

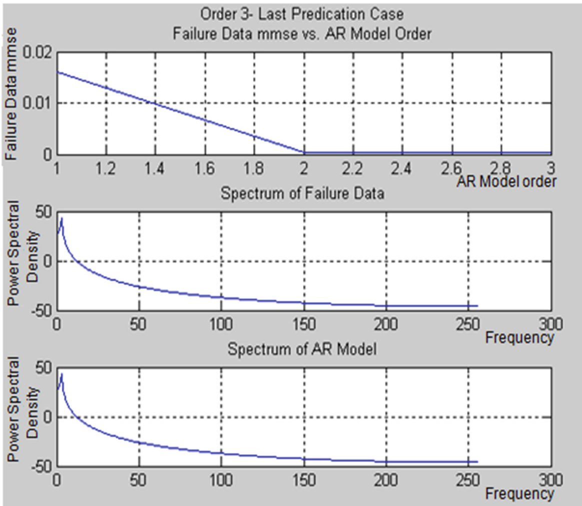

Fig. 5. Results of failure data applied to AR (3) model

It is clear that higher-order structures needs more computations especially for testing its stability which needs the determination of a polynomial roots of order 20; and consequently, the effect of its parameterization is much more difficult to generalize. The results for the AR (3) model showed that its parameter values could imply the same spectral pattern and smaller number of parameters represent an adequate fit for those data. Therefore, AR (3) model has been chosen to be used for failure rate forecasting.

3.2 Failure Rate Forecasting

Based on the main objective of this research is to forecast the period of next failure, whereas the prediction accuracy depends on the available set of failure rate data (n). These data have been evaluated over an interval from (n + 1) to (n + m) using AR (3). The results of prediction are illustrated in Fig. 6. It is noticed from this figure that failures will occur almost every two days.

This result can be considered in the replacement decision-making process as an alarm to put a plan for the equipment replacement as soon as possible.

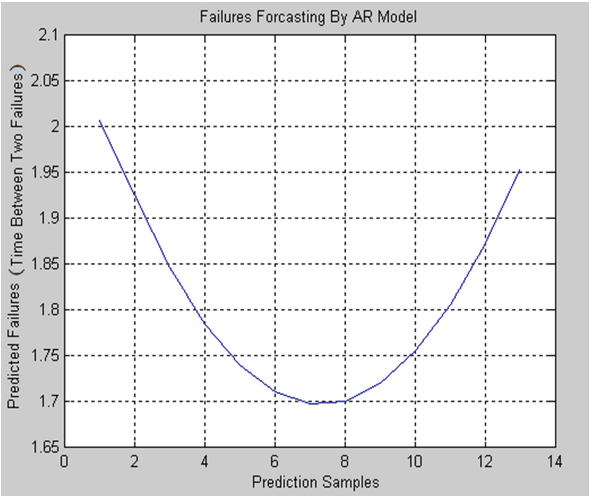

Fig. 6. The forecasted failure data

4 Conclusion

Observing the failure history of medical equipment in order to anticipate the future failures is referred to as forecasting. This can affect the medical equipment efficiency and minimize sudden failures. Time series analysis for prediction is a vital tool in the field of medical equipment failure to forecast and to study the behavior of failures along time. This creates the possibility to give early warnings of possible equipment malfunctioning and help in medical equipment replacement decision-making process.

Considering our model compared to others; both failures prediction models in [4] have given wrong predications for future failures when a failure pattern of 900 days has been used due to limited number of failures. Yet, in our model, we applied interpolation to the smoothed failure data to overcome this problem by reaching large number, uniform sampled data to achieve accurate prediction results.

Moreover, a failure prediction model based on Cox model could be implemented in [7]. However, recent publications suggest a growing interest in the quality of Cox applications [22]. On the other hand, the AR model is remarkably flexible at handling a wide range of different time series patterns [11], and it has drawn much attention due to its relative simplicity in understanding and implementation [10]. As well, it could define a highly rigorous failure forecasting model with MMSE less than 0.1 % and succeeded to represent failure rate data of Max.M equipment. The model could predict the failure rate occurrence every two days that persuades decision-making of equipment replacement.

In future, time series analysis using different stochastic models such as MA, ARMA, and GARCH should be applied to the failure rate data and the outcome of each model should be compared so that to achieve the best model that well represent the failure rate data. Furthermore, the finest failure forecasting model should be applied to the field data of different types of medical equipment to assess its contribution as a generalized failure forecasting model.

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