A framework for failure prediction models of medical electron linear accelerators

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***Abstract*—Among the available maintenance strategies, predictive maintenance seems to be the most promising for medical linear accelerators (linacs). Predictive maintenance predicts failures and allows timely reaction. Input data and model are important to implement predictive maintenance. The aim of this study is to provide a new framework including workflow, data and models that can be used for developing a predictive maintenance approach for medical linear accelerators. In this paper, 51 operational parameters and output performances data related to 15 systems of linacs, 8 environment data, processing data methods and 29 prediction models are identified. This work shows there is no standard failure prediction model apply to medical linacs.**

Keywords: data, failure, linear accelerator, maintenance model, prediction.

I. Introduction

In health care facilities, maintenance plays a critical role to increase reliability, lifetime and prevent unexpected failures of medical equipment. Maintenance costs of complex and sophisticated medical equipment are a major parts of the total operating costs. According to [1], in the USA in 2010 approximately 412 Million US dollars were assigned to medical equipment maintenance. The surveys of maintenance management effectiveness indicated that a part of maintenance cost is wasted [2]. The dominant reason for this ineffective management is due to the equipment maintenance strategies. Medical equipment maintenance approaches fall into three categories: reactive maintenance, preventive maintenance and predictive maintenance (PdM) [2] [4]. The philosophy of each strategy is summarized on Fig. 1.

Reactive maintenance (Fig. 1-a) is performed to maintain a machine only after a breakdown. However, this approach cannot be applied to medical linear accelerators (linacs) because unscheduled downtime can negatively impact the quality of life of the patients.

To prevent breakdowns, maintenance tasks are scheduled periodically to maintain or replace critical components regardless on its condition (Fig. 1-b). This strategy is called preventive maintenance. The drawback of this strategy is that component can still be in a usable condition when replacement is performed.

In contrast to preventive maintenance, with predictive maintenance (PdM) (Fig. 1-c), maintenance operation is performed when required by the condition of the system [5]. Predictive maintenance is intelligent health monitoring of equipment to avoid future equipment failure. Among these strategies, predictive maintenance seems to be the most promising for medical linacs.

For successful practical implementation, PdM is determined by two important factors: (i) the model used for failure prediction and (ii) the data used by failure prediction model [6]. Predictive maintenance has been the subject of a large amount of research work for various equipment in general. This paper proposes a general framework including workflow, data and models that can be used to develop a predictive maintenance strategy for medical linear accelerators.

The rest of this paper is organized as follows. In section II, we present the operation of medical linacs and some existing work for their predictive maintenance. Section III describes the possible data that can be used for prediction and how to preprocess them. Section IV presents prediction models identified. Finally, the conclusion is presented.

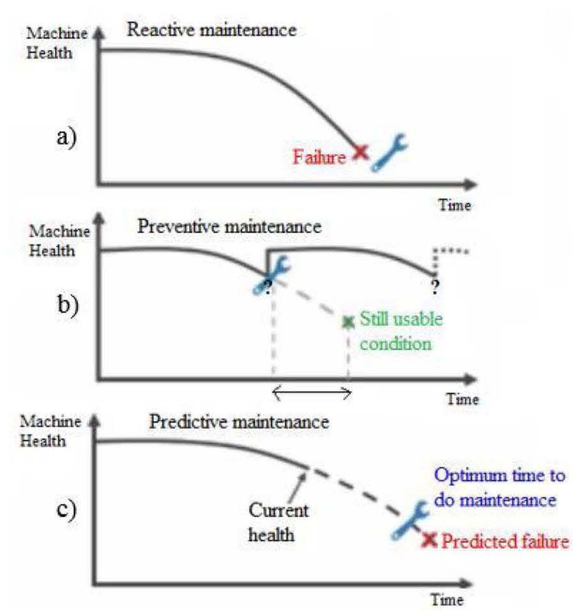

Fig 1. Different maintenance strategies

II. Maintenance of Medical Electron Linear Accelerators

Medical electron linacs are complex digital devices which accelerate electrons to kinetic energies between 4 and 25 It is used to treat and relieve patients suffering from cancer symptoms. The patient can be irradiated either with these electrons or with photons, situations that are referred to as electron and photon irradiation modes respectively [7]-[8]. The block diagram of a medical electron linacs is presented on Fig.2.

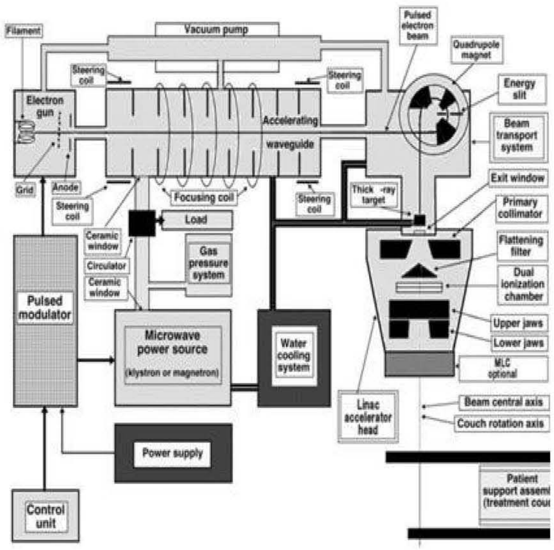

Fig 2. Medical linac block diagram [12]

The main systems of a medical linacs are presented in table I.

TABLE I. MEDICAL ELECTRON LINACS IMAIN SYSTEMS

System index	Systems
S1	Control console
S2	Patient support assembly
S3	Power supply
S4	Electron Injection/Electron gun
S5	RF power generation/Klystron or Magnetron
S6	RF power transmission
S7	Accelerating/Accelerator guide
S8	Electron beam transport
S9	Beam production and monitoring/Linac head
S10	Vacuum pumping
S11	Water cooling
S12	Gas pressure
S13	Interlock
S14	Motion control
S15	Automatic frequency control

For better detailing the functional diagram of medical electron linacs by taking into account the majority of links between its different systems, we transcribed the functional diagram presented in [9] [13] into functional matrix form showed in the table II. The 1 indicates that there is a connection between the system Si (i=1 to 15) on matrix line and the system Sj (j=1 to 15) on the column, otherwise it is 0 .

TABLE II. FUNCTIONAL MATRIX OF MEDICAL LINACS

	S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8	S 9	S 10	S 11	S 12	S 13	S 14	S 15
S1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S2	1	1	0	0	0	0	0	0	0	0	0	0	1	1	0
S3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S4	1	0	0	1	0	0	1	0	0	0	0	0	1	0	0
S5	1	0	0	0	1	1	0	0	0	0	1	0	1	0	0
S6	1	0	0	0	0	1	1	0	0	0	0	0	1	0	1
S7	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0
S8	1	0	0	0	0	0	0	1	1	0	0	0	1	0	0
S9	1	0	0	0	0	0	0	0	1	0	0	0	1	1	0
S 10	1	0	0	1	0	0	1	1	0	1	0	0	1	0	0
S 11	1	0	0	0	1	0	1	0	1	0	1	0	1	0	0
S 12	1	0	0	0	0	1	0	0	0	0	0	1	1	0	0
S 13	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0
S 14	1	1	0	0	0	0	0	0	1	0	0	0	1	1	0
S 15	1	0	0	0	1	0	0	0	0	0	0	0	1	0	1

As we can see through tables I and II, medical electron accelerators employ a wide variety sophisticated mechanical, electrical and electronic systems. While the manufacturing and design of medical electron accelerators has improved the reliability of operation, system dysfunction and failure still occur [8]. Then, an effective maintenance that predicts medical linacs component failure or system dysfunction is essential to exploit fully the capabilities of linacs.

The most closed works related to this topic are presented in [8] and [14]. However the works exposed in [14] are limited only to one component of the beam production and monitoring system which is Multi Leaf Collimator (MLC).

In contrast with the situation in [8] which takes into account the failure of a large number of systems, they are also limited to the data used for failure prediction of medical linacs components on one hand, and the workflow for developing the failure prediction algorithm is not presented on the other hand.

These three aspects are the main contributions of this work.

The main steps of medical electron linacs failure prediction workflow is presented on Fig 3. The details of each step are presented in the following sections.

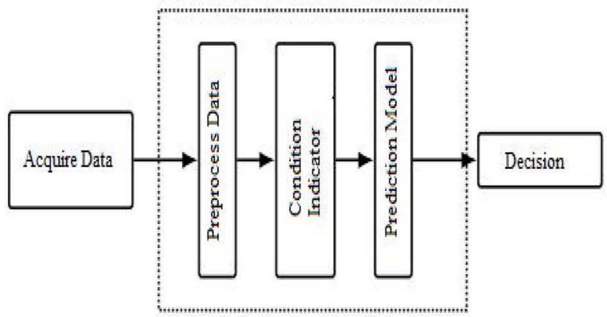

Fig 3. Architecture of framework for medical linacs failure prediction.

III. DATA ANALYSIS

A. Data Acquiring

As data is the key to build prediction model, the first step of predictive maintenance is to collect a large valuable set of data representing healthy and faulty operation of medical linac with sensor. Referring to [6] and [15], these data are generally obtained by two techniques: the existing sensor based data and the test sensor based data.

In our case, the existing sensor based data includes: operational parameters of linacs and output performance data of linacs. These data are accumulated in the accelerator system as log file. The table III presents 51 existing sensor based data useful to predict failures of critical components of a linac. These parameters and performance data are stored in text log file and trajectory log file on linacs. In the table, the data are grouped by system of linacs

TABLE III. OPERATIONAL PARAMETERS AND PERFORMANCES OF MEDICAL ELECTRON LINACS

N°	System	Parameter
1	Patient support assembly	Couch Longitudinal position
2	Patient support assembly	Couch Lateral position
3	Patient support assembly	Couch Vertical position
4	Patient support assembly	Couch Angle
5	Power supply	Node Power Supply Voltage
6	Power supply	PFN Actual Voltage (KV)
7	Power supply	Positive 3V dc
8	Power supply	Positive 5V
9	Power supply	Positive 24V
10	Power supply	Analog Negative 5V dc
11	Power supply	Analog Positive 5V dc
12	Power supply	Negative 12V dc
13	Injection/Electron gun	Gun Current
14	Injection/Electron gun	Gun High Voltage
15	Injection/Electron gun	Gun Grid Voltage
16	Injection/Electron gun	Gun Filament Step Voltage
17	Injection/Electron gun	Gun Filament Voltage
18	RF power generation/ Klystron	Klystron Solenoid Current
19	RF power generation/ Klystron	RF Forward Power
20	RF power generation/ Klystron	RF Driver Voltage
21	RF power generation/ Klystron	Trim current
22	Accelerating/Accelerator guide	Accelerator Solenoid Current
23	Electron beam transport	Buncher Radial Current
24	Electron beam transport	Buncher Transverse Current
25	Electron beam transport	Position Radial Current
26	Electron beam transport	Position Transverse Current
27	Electron beam transport	Bend Magnet Current
28	Electron beam transport	Bend Magnet Voltage
29	Electron beam transport	Angle Transverse Current
30	Electron beam transport	Angle Radial Current
31	Beam production and monitoring/Linac head	Monitor Units 1
32	Beam production and monitoring/Linac head	Monitor Units 2
33	Beam production and monitoring/Linac head	Radial Symmetry
34	Beam production and monitoring/Linac head	Transverse Symmetry
35	Beam production and monitoring/Linac head	Dose rate
36	Beam production and monitoring/Linac head	Jaw X1- position
37	Beam production and monitoring/Linac head	Jaw X2- position
38	Beam production and monitoring/Linac head	Jaw Y1- position
39	Beam production and monitoring/Linac head	Jaw Y2- position
40	Beam production and monitoring/Linac head	Carriage A- position
41	Beam production and monitoring/Linac head	Carriage B- position
42	Beam production and monitoring/Linac head	MLC Bank A each leaf position
43	Beam production and monitoring/Linac head	MLC Bank B each leaf position
44	Beam production and monitoring/Linac head	MLC Bank A each speed
45	Beam production and monitoring/Linac head	MLC Bank B each leaf speed
46	Vacuum pumping	Accelerator vacion current
47	Water cooling	Water level
48	Water cooling	Hospital water temperature
49	Water cooling	Internal water supply temperature
50	Gas pressure	Gas pressure
51	Automatic Frequency Control (AFC)	Automatic Frequency Control (AFC) Error

Apart from these data, we can also get from accelerators system: console logs file, error sequences logs file, event log file, failure event sequence data [16] [19].

The test sensor based data can be obtained using: non-destructive testing, acoustic emission, infrared thermography, shock pulse method, radiographic inspection, strain monitoring, ultrasonic sensor data, technique, vibration data, lubrication oil parameters, bending moment and partial discharge. These types of data are interesting to monitor the following part of medical linacs: gantry, klystron oil tank, water tank and all fluid conduits.

Considering the fig. 4 which illustrates the generic model of the interactions between medical device and the environment, patient, user and accessories/ consumables, we cannot limit our work to the only two types of data evoked by [6] and [15]. For this reason, we take into account for model others data such as: historical data, inventory data (equipment manufacturer information, serial number, and linac type), maintenance data, service data, user data, patient data and environment data. Let underline that in Africa, medical equipment operates in challenging environments conditions. Then we consider the following eight (08) environment parameters: ambient air temperature, ambient air pressure, relative humidity, noise, vibration, pollution level, local information and power supply [20] [23].

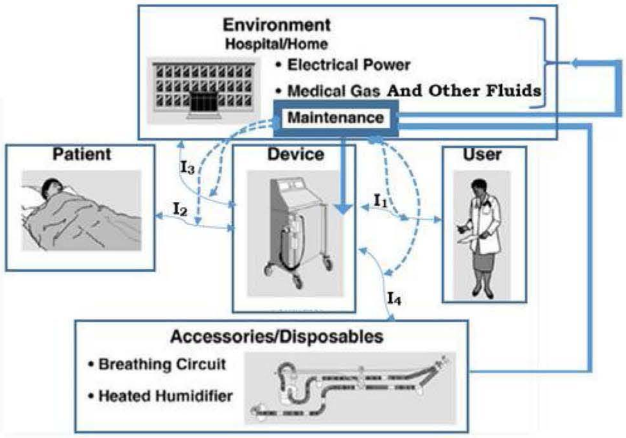

Fig 4. Illustration of the interfaces of a medical device in the medico-clinical context

B. Data Preprocess

Acquired data from the first step is unfiltered data which contains many quality problems related to completeness, consistency, timeliness and accuracy of the data.

Once we have these data, the next step is to remove the noise by using filtering methods. Filtering methods will improve quality of raw data collected from various sources such as

[18], Laplace test [24]. It is also necessary to reduce the dimension of operational parameter using t-statistic [3] as possible.

C. Condition indicator

The analysis of filtered data obtaining from the second step could be difficult to use to differentiate faulty and healthy operation. Then, it is recommended to use time domain analysis (mean, standard deviation, skewness, root mean square, Kurtosis), Frequencies domain analysis (Fast Fourier Transform, Short Term Fourier Transform, mean frequency, peak values, peak frequencies, harmonies, etc.) and times-frequencies domain (spectral kurtosis, amplitude demodulation, and spectral entropy).

IV. Prediction Model

As shown on fig. 3, the output of prediction model is decision. The decision may depend on the prediction model: detection of anomalies, identification of fault type, alarms, warning, failure time, linacs health condition, and remaining useful life of a critical component of linacs.

Referring to [6], prediction models can be classified into four categories such as: Category I (analytical model based on process data), Category II (analytical model based on failure data), Category III (statistical model based on data process), Category IV (statistical model based on failure data).

In this study, we identified twenty nine (29) non-exhaustive list of models that can be used for failure prediction of medical linacs. This is among other things: (1) Ada Boost M1 algorithm, (2) auto regressive averaging model, (3) Bayesian method, (4) Cox proportional hazard model [16], (5) decision trees, (6) double exponential smoothing (DES), (7) expert system [25], (8) exponential law models [24], (9) gradient boosting machines, (10) Hidden Markov models, (11) Hidden Semi-Markov models (HSMM), (12) LibSVM algorithm, (13) linear regression [24], (14) logistic regression, (15) mining and distribution estimation, (16) moving average model, (17) multiple-instance learning, (18) Nelson-Aalen estimator, (19) Neural Networks, (20) order analysis, (21) principal component analysis [26], (22) Random Forest algorithm, (23) Recurrent Neural Network, (24) Rough Set Theory [27], (25) statistical pattern recognition, (26) statistical process control [8], (27) support vector machine (SVM) [28], (28) trend analysis and (29) XGBoost algorithm.

One of the limitations of this work is that we have not been able to categorize the identified models referred to four categories proposed by [6].

V. Conclusion

This work has been done for developing a predictive maintenance strategy for medical accelerators which will be very soon installed in Republic of Benin. In this paper we proposed all data and models related to failure prediction of medical electron accelerators. It allowed us to draw out from existing scientific works on failure prediction for medical complex equipment system the models useable for Linacs. The effectiveness of predictive maintenance strategy depends on prediction model, techniques and methods used for data collection. Considering the number of models and data found, there is no standard model or data type for the practical implementation of this maintenance strategy till now.

In future work, we are planning to study extensively the appropriate model for the prediction of failures of critical medical accelerators systems. Nevertheless, depending on the importance of predictive maintenance, the model, which output would be the remaining useful life time of a critical component of medical electron linacs seems more appropriate. But it remains to be confirmed or refuted according to its feasibility.

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