Proceedings of the International MultiConference of Engineers and Computer Scientists 2013 Vol II,
IMECS 2013, March 13 - 15, 2013, Hong Kong

Optimal Condition-Based Maintenance Replacement based on Logical Analysis of Data (LAD)

Alireza Ghasemi, Sasan Esameili

***Abstract*— This paper develops equipment optimal condition based replacement model, using Logical Analysis of Data (LAD). LAD is a powerful classification method that does not relying on any statistical theory which enables LAD to overcome the usual problems concerning the statistical properties of the data. LAD profits from a straightforward procedure and self-explanatory results.**

In this paper, our objective is to develop an optimal replacement method by taking its working condition (condition monitoring data) into consideration using LAD. Using equipment's survival probability and associated costs of scheduled and non-scheduled replacements, an optimal replacement method is introduced.

The proposed method is applied on a hypothetical problem and its easy to understand approach and its high performance is shown. Analysis of performance of the proposed methods reveals that the methods provide self-explanatory results that are greatly beneficial to maintenance practitioners.

***Index Terms*— Optimal Replacement, Condition Based Maintenance (CBM), Logical Analysis of Data (LAD), Condition Monitoring**

I. Introduction

Condition Based Maintenance (CBM) [1] is a maintenance program considering the equipment's health condition while optimizing or improving the maintenance activities. The equipment's age and health condition are the indicators based on which CBM predicts a failure in equipment and optimizes its policy.

Logical Analysis of Data (LAD), first introduced in [2], is a Boolean logic based methodology for the analysis of data. LAD extracts knowledge hidden in a dataset in order to detect the sets of causes that would lead to certain outcomes. In the context of maintenance, a cause can be the equipment's age or any health condition indicator value, while an effect (outcome) can be the equipment's survival or failure during a defined period. Each cause is called an Attribute. A literal is either an attribute or its Negation. In This research, observations are categorized into two classes: observations that fail during the coming period, referred to as the *Positive Class*, and observations that survive at least until the end of the next period, referred to as the *Negative Class*. A Positive (Negative) Pattern is a set of literals that is reflected in one or more of the observations of the positive (negative) class while not reflected in any (many) of the observations of the negative (positive) class. A pattern cannot include an attribute and its negation.

A. Ghasemi is an Assistant Professor with Department of Industrial Engineering of Dalhousie University, Halifax, NS, Canada (alireza.ghasemi@dal.ca). S. Esmaeili is a graduated Master's student form Department of Industrial Engineering of Dalhousie University.

Since its introduction, LAD has been applied for the analysis of data in different fields such as medicine, biotechnology, economics, finance, politics, properties, oil exploration, manufacturing and maintenance ([2], [3], [4], [5], [6], [7], [8][9], and [10]). Recently LAD was used for diagnosis of equipment failure ([11],[12], [13], [14]). LAD has proved to be a promising technique that provides interpretable results that are comparable to most pioneer techniques in the field of diagnostics in CBM. [15] improved LAD methodology to predict equipment's chance of survival at each observation moment when new data on attributes of the equipment is available. It showed that LAD provides comprehensible results that are greatly beneficial to maintenance practitioners in prognosticating fault in machinery. In this work, we will introduce an optimal replacement model that minimizes the maintenance cost of equipment considering its condition monitoring data, using LAD.

II. Methodology

First, we will illustrate LAD's basic steps used in equipment's diagnostics [14] and prognostics [15]. Patterns, LAD's outcomes that characterize the failure and survival characteristics of equipment, will be generated. Then, we will introduce instructions to use the generated patterns to make optimal replacement decision. The optimal replacement model, which takes into account equipment's age, condition indicators and failure and replacement costs, will be constructed based on a given historical dataset, the Train Set. Quality of optimization model will be examined by applying it on another part of the historical dataset, called the Test Set.

A sample train set is shown in Table 1. The data consists of the monitored attributes at different observation moments, associated with different pieces of equipment. Each row identifies an observation. The first and the second columns show the equipment identification and the observation time. Third column shows the class of each observation. If the equipment has survived during the next observation period, it is "-"otherwise "+". Clearly, only last observation available for each piece of equipment will be "+". The forth and the fifth columns are the measurements of age (operating time) and condition of equipment. Similar to the approach of [15], we consider both age and condition of equipment as the equipment's health indicator, and use both as LAD attributes. This will allow us to build a prognostic model that will be used as the basis of the maintenance optimization model.

In what follows, we first, describe a data binarization method. Then, we describe pattern generation method. Finally, we will describe method to use the generated patterns to calculate the survival probability of the

ISBN: 978-988-19252-6-8
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

equipment from which a new observation is collected. All these three methods will be the best of all the methods introduced by [15]. In this work we have adopted their example as well, to demonstrate our approach to optimally replace a piece of equipment.

Table 1. Sample Train Set [15]

Observations			Attributes	
Equipment ID.	Observation Time	Class	Age	Condition Indicator
1	0	-	0	14
1	1	-	1	16
1	2	-	2	20
1	3	-	3	18
1	4	+	4	20
2	0	-	0	12
2	1	-	1	18
2	2	+	2	22
3	0	-	0	16
3	1	-	1	18
3	2	-	2	20

III. PROGNOSTICS USING LAD

A. Data Binarization

In real life problems, the attribute values may or may not appear in numerical. However, LAD uses Boolean attribute values. The binarization procedure transforms each non-binary attribute value into a set of binary ones which is done by comparing attribute values to certain threshold Cut-Points. For each numerical attribute, a binary attribute is associated with every cut-point as following: [8]

$$b_{a,c} = \begin{cases} 1 & ;\text{if} \quad a \geq c \\ 0 & ;\text{if} \quad a < c \end{cases} \tag{1}$$

Where a is the numerical value of attribute, c is the cut-point value, and $b_{a,c}$ is the binary value of attribute, associated with a and c. As a result, each numerical attribute is converted to n binary attributes, where n is equal to the number of cut-points. We will employ Sensitive Discriminating method in which a cut-point is defined as average of two consecutive attribute values, each belonging to different classes [15]. The outcome cut-point represents a threshold, which is able to differentiate between positive and negative classes.

B. Pattern Generation

A pattern differentiates one or more of the observations of its class from all or most of the observations of the opposite class. Some heuristic methods have been introduced that require less computational effort than examining all combination of the literals, while providing equivalent performance. Amongst them, we will use Hybrid Greedy method that has been proved to be outperforming or equally efficient [15].

Hybrid greedy method is a heuristic algorithm that finds the optimal Prime pure patterns [8]. A pattern is prime pure if it does not cover any observation from the opposite class and removal of any of its literals results in coverage of observations from the opposite class. The restriction on the generation of pure patterns by allowing the algorithm to cover observations from the opposite class is relaxed. In this case, a pattern is defined as a combination of literals covering at least a minimum number of observations of the pattern's class, and at most a maximum number of observations of the opposite class. The numbers are called Coverage and Fuzziness parameters, respectively. The hybrid greedy method is composed of two phases: The bottom-up phase starts with only one literal then tries to add as many literals as required up to a point that the combination of literals forms a pattern. If any observation remains uncovered by the created patterns in the first phase, the top-down phase starts with an uncovered observation. An observation is definitely a pattern. Then it tries to remove as many literals as possible from the pattern (observation) up to a point where the removal of any more literal, will result in losing the pattern.

C. Prognostics Model Formulation

Up to author's knowledge, there are only two introduced methods to calculate the conditional survival probability of the equipment, based on the estimated survival functions using Kaplan-Meier (KM) estimation. In this research we will use the conditional survival probability calculation method that equally favours the baseline and the pattern survival probabilities as explained later [15].

Table 2 shows the positive and negative patterns along with their corresponding covered observations, based on the sample train set provided in the Table 1.

Table 2. List of Generated Positive and Negative Patterns based on the Sample Train Set [15]

Positive Patterns	Covered Observations
PP1	1-3 , 1-4 , 3-3
PP2	2-2 , 3-3
Negative Patterns	**Covered Observations**
NP1	1-0 , 1-1 , 1-2 , 2-0 , 2-1 , 2-2 , 3-0 , 3-1 , 3-2
NP2	1-0 , 1-1 , 1-3 , 2-0 , 2-1 , 3-0 , 3-1

We associate to each pattern P, set of Pattern Conditional Survival Probabilities $SP_P(i)$; $i = 1,2,\ldots$, which represent the pattern's survival estimation of a piece of equipment for at least i periods, when the equipment's observation is covered by the pattern. KM estimation of pattern conditional survival probability is defined as the proportion of the number of observations covered by pattern P whose corresponding pieces of equipment survived at least i periods after being covered by the pattern, to the total number of observations covered by pattern P.

$$SP_P(i) = \frac{\#(P \cap S; \tau > \tau_0 + i\Delta)}{\#(P \cap S; \tau > \tau_0)} \tag{2}$$

S is the set of observations in the train set, and $P \cap S$ represents the subset of observations in the train set S that are covered by the pattern P. Function #(N) counts the number of members of a set N. τ is the actual failure time of the corresponding equipment, and τ_0 is the current age of the corresponding equipment at the observation moment when it is covered by pattern P. Δ is the observation period length.

Table 3 shows KM estimation of conditional survival probability of the patterns in the Table 2, based on their corresponding covered observations.

Table 3. KM Estimation of Conditional Survival Probability of Generated Patterns

$i\Delta$	1	2	3	4
PP1	0.333	0	0	0
PP2	0	0	0	0
NP1	0.889	0.667	0.333	0.111
NP2	1	0.714	0.428	0.143

Baseline Conditional Survival Probability indicates survival function by considering the age only, regardless of the equipment's condition. KM estimation of baseline conditional survival probability is calculated as the proportion of the number of pieces of equipment that survived at least *i* periods, to the number of all the pieces of equipment in train set.

$$SP_b(i) = \frac{\#(E;\tau>i\Delta)}{\#(E)} \tag{3}$$

E is the set of all pieces of equipment in the train set. Table 4 shows KM estimation of baseline conditional survival probability based on all the observations in Table 1.

Table 4. KM Estimation of Baseline Conditional Survival Probability

$i\Delta$	1	2	3	4
$SP_b(i)$	1	1	0.667	0.333

Table 5 shows a sample test set along with the list of patterns that cover each observation.

Table 5. Sample Test Set

Observations		Attributes		Covering Patterns
Equipment ID.	Observation Time	Age	Condition Indicator	
1	0	0	14	NP1 , NP2
1	1	1	16	NP1 , NP2
1	2	2	20	NP1
1	3	3	22	PP1 , PP2

To calculate equipment's survival probability we give more weight to the latest observation than older observation and consider equal weight for Pattern and Baseline Conditional Survival Probabilities. The conditional survival probability of the equipment at current observation moment is calculated as follows: [15]

$$SP(i) = \begin{cases} \dfrac{\frac{\sum_{p=1}^{n} SP_p(i)}{n} + SP_b(i)}{2} & ;if \quad t = 0 \\ \dfrac{\frac{\sum_{p=1}^{n} SP_p(i) + SP_{former}(i+1)}{n+1} + SP_b(i)}{2} & ;if \quad t > 0 \end{cases} \tag{4}$$

The conditional survival probabilities of the equipment at different observation moments are shown in Table 6.

Table 6. Conditional Survival Probability of Sample Test Equipment at Different Observation Moments

Obs.	Covering Patterns	SP (t)				
		1	2	3	4	>4
1-0	NP1,NP2	0.9	0.85	0.5	0.	0
1-1	NP1,NP2	0.9	0.65	0.3	0.	0
1-2	NP1	0.7	0.42	0.0	0.	0
1-3	PP1,PP2	0.3	0.02	0	0	0

IV. Optimal Replacement Policy

Condition Based Maintenance (CBM) or predictive maintenance is based on observing the state of equipment and on collecting information concerning its condition, in order to prevent its failure and to determine the optimal maintenance actions. This optimization is done by taking into account costs of failure and predictive replacements. The difference between classical preventive maintenance and CBM is that while the former is based on modeling the aging process and/or on using the manufacturer given information for setting maintenance plans, the latter is based on observing the condition of the equipment, measured by one or more indicators such as the vibration level, the level of metal particles in the lubricant, or the equipment's temperature, and taking maintenance actions based on the values of these indicators.

In this work, we assume that, if a failure occurs, it is immediately recognized and the only possible action is Failure Replacement (FR). Otherwise, at any inspection point, we can decide whether to perform Preventive Replacement (PR) or to Do-Nothing (DN). The FR and the PR renew the system and return it to new or like new, and the age is reset to zero. The cost for the PR is *C*, while a FR costs *C+K, C, K>0*. Both actions, FR and PR, are instantaneous. We assume that failures happen shortly after observation moments. This assumption is supported by holding small enough observation period intervals.

A. Dynamic Programing Formulation

Let $f\left(k, SP^k(t); t=1,2,...\right)$ denote the minimum average cost of replacement per observation period of current replacement period, calculated at time *k* (*k*-th observation point), where the updated Survival Probability $SP^k(t)$ is the survival probability of the equipment calculated at this moment as explained in previous section.

$$f\left(k, SP^k(t)\right) = \min \begin{cases} \dfrac{C}{k} \\ SP^k(1) f\left(k+1, SP^{k+1}(t)\right) + \left(1 - SP^k(1)\right)\dfrac{(C+K)}{k} \end{cases} \tag{5}$$

C/k indicates the average cost of replacement per observation period, if we decide to replace the equipment at current observation moment, *k*. This is true because the only cost occurring is the replacement cost, *C*. However, if we decide to leave the equipment to work until next observation period, there is $SP^k(1)$ chance of survival for one more period. This will result in an optimal future cost of $f\left(k+1, SP^{k+1}(t)\right)$.

In case if a failure happens during next observation period, cost $(C+K)$ will occur. Assuming that failure happens shortly after the current observation period, the average cost of replacement is $(C+K)/k$. This cost happens with a chance of $\left(1-SP^k(1)\right)$.

At each observation moment, the optimal decision is the one that will result in smaller average cost, as shown in equation (5).

In calculation of future cost of replacement, in case of survival until next observation moment $f\left(k+1,SP^{k+1}(t)\right)$, the value of $SP^{k+1}(1)$ is required. $SP^{k+1}(1)$ is the updated conditional survival probability of equipment that has survived until k+1 observation moment for one more period. This probability can be best estimated by $SP^{k}(2)/SP^{k}(1)$. In Table 6, $SP^{1}(t)$, is 0.97, 0.85, 0.53, 0.23 and 0 for *t =1,2,…,5*. At this age (*k=1*) with associated attributes values, the equipment has 97% chance of survival until next observation moment. Also, 85% chance of survival until two next observation moments. This means that only 88% (=0.85/0.97) of equipment survived during next observation period will survival a second observation period too.

Table 7. Updated conditional survival probability, average cost of replacement and optimal decision

Obs.	$SP^{k+i}(1)$					AVG. COST			
1	*i=0*	*i=1*	*i=2*	*i=3*	*i=4*	*R*	*L*	*Min*	
k=1	0.97	0.88	0.62	0.43	0.00	1.00	0.42	0.42	*L*
k=2	0.96	0.68	0.51	0.12	0.00	0.50	0.35	0.35	*L*
k=3	0.72	0.58	0.21	0.33	0.00	0.33	0.32	0.32	*L*
k=4	0.38	0.05	0.00			0.25	0.31	0.25	***R***

Considering *C = 1* and *K = 0.5*, the results of the optimal replacement criteria of the example are shown in Table 7. The approach suggests to replace (R) the equipment at 4th observation moment.

Different *C/K* ratios will result in different optimal decision on the same set of observations. The higher the failure costs *K*, an earlier replacement will be advised.

Table 8, depicts that when *C = 1*, if *K* increases to 1, the equipment will be advised to be replaced at 3rd observation moment (and after) with same hypothetical data as before. At a very high *K*, like *k = 9*, same readings from the equipment results in a replacement decision as early as second observation moment.

Table 8 average cost of replacement and optimal decision for K=2 and K=9

Obs.	AVG COST FOR K=2				AVG. COST FOR K=9			
1	R	L	Min	L	R	L	Min	
k=1	1.00	0.46	0.46	L	1.00	0.79	0.79	L
k=2	0.50	0.36	0.36	L	0.50	0.52	0.50	**R**
k=3	0.33	0.37	0.33	**R**	0.33	1.11	0.33	**R**
k=4	0.25	0.39	0.25	**R**	0.25	1.63	0.25	**R**

V. Conclusion

In this paper, we developed an equipment condition based replacement model by employing the Logical Analysis of Data (LAD). We used LAD methodology to predict equipment's chance of survival at each observation moment, when new data on the equipment health condition indicators is collected. Then, we introduced a dynamic programing approach to estimate the future costs of the replacement system, if the only possible actions are, Replace now (R) or Leave until the next observation moment (L). An optimal decision, based on readings from the condition monitoring system at each observation moment and previous ones, can be made. LAD optimal replacement model provides comprehensible results that are greatly beneficial to maintenance practitioners. LAD model has the advantage of not relying on any statistical theory, which enables it to overcome the conventional problems concerning the statistical properties of the datasets. Its main advantage is the straightforward process and self-explanatory results, which are greatly beneficial to maintenance practitioners.

Since the proposed LAD model is at its beginning phase, further research is required to improve the performance of the model. Due to the fact that the performances of the proposed calculation methods are highly sensitive to the defined survival function, a future research direction is to improve the survival function to reflect equipment's probable failure better. Also, the optimal replacement model has to be tested on real and simulated data to further investigate its performance.

References

[1] A. K. S. Jardine, D. Lin and D. Banjevic. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing 20(7), pp. 1483-1510. 2006.

[2] Y. Crama, P. L. Hammer and T. Ibaraki. Cause-effect relationships and partially defined boolean functions. Annals of Operations Research 16(1), pp. 299-326. 1988.

[3] G. Alexe, S. Alexe, D. E. Axelrod, T. O. Bonates, I. Lozina, M. Reiss and P. L. Hammer. Breast cancer prognosis by combinatorial analysis of gene expression data. Breast Cancer Research 8(4), pp. R41. 2006.

[4] S. Alexe, E. Blackstone, P. L. Hammer, H. Ishwaran, M. S. Lauer and C. E. Pothier S. Coronary risk prediction by logical analysis of data. Annals of Operations Research 119(1), pp. 15-42. 2003.

[5] M. S. Lauer, S. Alexe, P. Snader Claire E., E. H. Blackstone, H. Ishwaran and P. L. Hammer. Use of the logical analysis of data method for assessing long-term mortality risk after exercise electrocardiography. Circulation 106(6), pp. 685-690. 2002.

[6] G. Alexe, S. Alexe, P. L. Hammer and A. Kogan. Comprehensive vs. comprehensible classifiers in logical analysis of data. Discrete Applied Mathematics 156(6), pp. 870-882. 2008.

[7] A. B. Hammer, P. L. Hammer and I. Muchnik. Logical analysis of chinese labor productivity patterns. Annals of Operations Research 87(0), pp. 165-176. 1999.

[8] E. Boros, P. L. Hammer, T. Ibaraki, A. Kogan, E. Mayoraz and I. Muchnik. An implementation of logical analysis of data. Knowledge and Data Engineering, IEEE Transactions on 12(2), pp. 292-306. 2000.

[9] P. L. Hammer, Y. Liu, B. Simeone and S. Szedmak. Saturated systems of homogeneous boxes and the logical analysis of numerical data. Discrete Applied Mathematics 144(1-2), pp. 103-109. 2004.

[10] K. Kim and H. S. Ryoo. A LAD-based method for selecting short oligo probes for genotyping applications. OR-Spectrum 30(2), pp. 249-268. 2008.

[11] S. Yacout. Fault detection and diagnosis for condition based maintenance using the logical analysis of data. Presented at Computers and Industrial Engineering (CIE), 2010 40th International Conference on. 2010.

[12] A. Bennane and S. Yacout. LAD-CBM; new data processing tool for diagnosis and prognosis in condition-based maintenance. Journal of Intelligent Manufacturing 23(2), pp. 265-275. 2012.

[13] M. A. Mortada, S. Yacout and A. Lakis. Diagnosis of rotor bearings using logical analysis of data. Journal of Quality in Maintenance Engineering 17(4), pp. 371-397. 2011.

[14] M. A. Mortada, T. Carroll, S. Yacout and A. Lakis. Rogue components: Their effect and control using logical analysis of data. Journal of Intelligent Manufacturing 23(2), pp. 289-302. 2012.

[15] A. Ghasemi,; S. Esmaeili; S. Yacout, , "Equipment diagnostics using Logical Analysis of Data (LAD)", APMS 2012 International Conference, Greece 24-26 September 2012.