Maintenance Planning with Prognostics for Systems Located In Various Places

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ABSTRACT

Predictive maintenance has been attracting researchers and industry in recent years, since maintenance and repair of assets is one of the most contributing factors of operating & support cost. Predictive maintenance proposes to maintain the assets only when necessary aiming to reduce the unnecessary repair and maintenance by monitoring the health of the assets. The expected time of the failure is estimated by analyzing the monitored signals and remaining useful life of the asset before failure is used to plan, get prepared and perform the maintenance. When one team is responsible for maintenance of systems that are located in various places, the travel time between these systems should also be incorporated in the maintenance planning. Off shore wind farms and railway switches are two examples of these systems. This paper presents formulation of the problem that incorporates travel times between systems and prognostics information obtained from each system.

1. INTRODUCTION

Predictive maintenance has been attracting researchers and industry in recent years, since maintenance and repair of assets is one of the most contributing factors of operating & support cost (Camci & Chinnam, 2010). Predictive maintenance, also called Condition Based Maintenance (CBM), proposes to maintain the assets only when necessary aiming to reduce the unnecessary repair and maintenance by monitoring the health of the assets. The term asset represents any system that is monitored for predictive maintenance.

In CBM, health of the asset is observed real time by analyzing signals collected from sensors embedded on the asset. Two main aspects of CBM are diagnostics and prognostics (Jardine et. al. 2006). Diagnostics is the process of detection of an existing incipient failure, whereas prognostics is the process of forecasting the time of the failure and identification of remaining useful life (RUL) of the asset before failure (Camci & Chinnam 2010a). Maintenance is scheduled immediately for an asset when a failure is diagnosed. On the other hand, when a failure is prognosed, the identified remaining useful life can be used for planning, preparation, and performing the maintenance. The asset is expected to perform its functionality maybe with less efficiency within the identified RUL.

In predictive maintenance research, RUL information may be given in different formats such as the real time (e.g., three months to failure), operational working period (e.g., 3000 miles of driving before failure), efficiency decrease (%95 efficiency), or probability of failure (0.20 probability to fail) (Camci & Chinnam 2010a). In most maintenance scheduling methods with RUL information, a threshold value is set to RUL (Barbera et. al. 1996, Marseguerra et. al. 2002, Sloan & Shanthikumar 2002, Yam et. al., 2001, Berenguer et. al. 2003). In these methods, maintenance is performed when the RUL reaches the threshold. Even if the threshold is optimized perfectly for an asset, the cost of travelling for maintenance will be a critical issue that cannot be incorporated easily in the static threshold optimization. An optimization model without threshold setting has been discussed in (Camci F. 2009), (Camci F. 2009a). However, the optimization model presented in these studies assumes that all the components or systems are located in the same place and do not incorporate travel time between systems.

Consider an off shore wind farm with many wind turbines located in the middle of the sea. Assume that one of the wind turbines is scheduled for maintenance next week, since the RUL is expected to reach to the threshold next week. A team of maintenance operators will be sent to the sea for maintenance. Consider that two wind turbines are located 10 miles and 20 miles away from the wind turbine scheduled for maintenance. The RUL of these wind turbines are identified to be two and three weeks, respectively. Maintenance scheduling based on only RUL thresholds will not always give the best maintenance scheduling. Thus, cost of travelling should also be incorporated within the maintenance scheduling. This paper presents the problem of incorporating the maintenance scheduling with RUL information for geographically distributed assets. Section 2 presents the problem modeling, and section 3 demonstrates the problem with small number of systems. Section 4 concludes the paper.

2. Problem Definition

Consider multiple systems that are located in various places and are within the responsibility of one maintenance team. The health of each asset is observed using condition monitoring techniques and forecasted by analyzing the signals obtained using prognostics techniques. Forecasted health (RUL information) is assumed in the format of probability of failure.

The problem aims to identify the most cost effective maintenance routing. The cost function to be minimized involves three major terms: expected failure cost, maintenance cost, and travel cost. All three terms are highly correlated with the time of the maintenance of each asset. Early maintenance reduces the failure risk more than late maintenance. The order of the locations to be visited for maintenance affects the time of maintenance in each location. For example, if maintenance is scheduled for an asset that requires long travelling time, then all other assets waiting for maintenance will be negatively affected from this decision. Fig. 1 illustrates the effect of early, late, and no maintenance on failure probability of a system for a given time frame.

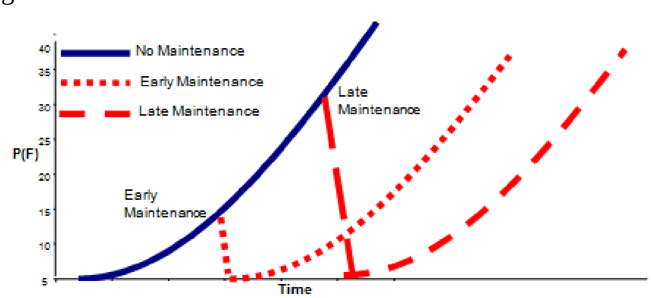

Fig.1 Illustration of reducing risk by maintenance

The problem aims to minimize the total cost that consists of failure, maintenance, and travel cost by finding the best maintenance schedule of n geographically distributed assets. The objective function is the sum of each asset cost.

In the simple case of the problem, it is assumed that every location is visited only once and the tour ends at the initial location. Thus, the maintenance cost will be constant assuming that one and only one maintenance will be performed at each location. Thus, only failure cost will be considered in the formulation, since total maintenance cost will be constant. Mathematically, the problem can be expressed as follows: find a permutation $(\pi_1\pi_2 \ldots \pi_n)$ of integers from 1 to n that minimizes the total cost of travelling, expected failure and maintenance cost of assets given a distance matrix $D = d_{i,j}$, where $d_{i,j}$ is the distance between locations *i* and *j*. This is the first objective function to be explored in this paper and shown in (1). Note that the distance information is actually considered as time-to-travel information. If it is given as real distance, it should be converted to time-to-travel, since the time information affects the expected failure cost, not the distance.

$$\sum_{i=1}^{n} f_{\pi_i}\left(\sum_{k=0}^{i} d_{\pi_k,\pi_{k+1}}\right) \tag{1}$$

π_i: Asset number scheduled for maintenance with i^{th} order (starting point when *i=0*)

f_{π_i}: Failure cost function for system located at π_i

Tm_{π_i}: Scheduled maintenance time for location π_i

$\sum_{k=0}^{i} d_{\pi_k,\pi_{k+1}}$: Time to travel to reach from π_k to π_{k+1}

Failure cost is the product of fixed failure cost and the cumulative failure probability ($CP_{i,T}$) of the asset as shown in (2). Effects of maintenance times should be considered in calculation of cumulative failure probability ($CP_{i,T}$) within the given period (*T*). The given period is divided into periods as before and after maintenance since only one maintenance in the given period is assumed. $CP_{i,T}$ is calculated as the union of failure probabilities in before and after maintenance periods ($P_{i,b}$, $P_{i,a}$ failure probabilities before maintenance, after maintenance respectively) since failure may occur either before or after maintenance in the given period. The formulation of $CP_{i,T}$ calculation is given in (3).

$$FR_i = CP_{i,T} \times F_i \tag{2}$$

$$CP_{i,T} = P_{i,b} + P_{i,a}\left(1 - P_{i,b}\right) \tag{3}$$

$P_{i,b}$: Cumulative failure probability starting time 0 till just before the maintenance

$P_{i,a}$: Cumulative failure probability starting from maintenance time till end of given period

Forecasted failure probabilities can be obtained in two ways: prognostics-based and reliability-based. In prognostics-based calculation, failure probabilities (*Pfo*) represent the specific failure probability of the asset under observation with CBM. This failure probability (*Pfo*) is used until the maintenance time of the system. Many prognostics methods to predict failure probabilities have been presented in the literature (Lu H. et. al.2001, Xu et. al., 2008, Xu et. al., 2009, Heng et. al. 2009, Sritavastava & Das 2009). After the maintenance, failure probabilities obtained from reliability-based calculation is used. Reliability based failure probability (*Pfw*) is obtained from the reliability analysis of past similar assets. Reliability based failure probability (*Pfw*) is not specific to the asset under observation. We do not use prognostics-based failure probability after maintenance because we do not know how the asset under observation will behave after maintenance (maintenance has not happened yet.)

Probability of failure in each section bases on the maintenance time and corresponds the failure probability value at the time the maintenance will be performed as shown in (4) and (5). Note that (*Pfw*) and (*Pfo*) are received as input in the problem.

$$P_{i,b} = Pfo_{tm} \tag{4}$$

$$P_{i,a} = Pfw_{T-tm} \tag{5}$$

The second objective function involves failure and travel costs as shown in (6). Travel cost simply is calculated as product of traveling cost one unit distance and total travel to reach location π_i.

$$\sum_{i=1}^{n} f_{\pi_i}\left(\sum_{k=0}^{i} d_{\pi_k,\pi_{k+1}}\right) + g\sum_{i=0}^{n} d_{\pi_i,\pi_{i+1}} \tag{6}$$

$g\sum_{i=0}^{n} d_{\pi_i,\pi_{i+1}}$: Cost of travelling from π_0 to π_n

The third objective function involves maintenance cost as well as failure and travel cost as shown in (7). This is important when systems at various locations may be maintained in different number of times in the given period and they are different with different maintenance costs (M_{π_i}).

$$\sum_{i=1}^{n} f_{\pi_i}\left(\sum_{k=0}^{i} d_{\pi_k,\pi_{k+1}}\right) + g\sum_{i=0}^{n} d_{\pi_i,\pi_{i+1}} + \sum_{i=0}^{n} M_{\pi_i} \tag{7}$$

3. DEMONSTRATION OF THE PROBLEM

In this section, the problem is demonstrated with a simple case study. In this case study, there are four locations to perform maintenance, and a starting point π_0. Distances between locations are shown in Table 1.

Table 1 Distance matrix

Locations	0	1	2	3	4
0	0	4	11	6	2
1	4	0	8	10	6
2	11	8	0	13	10
3	6	10	13	0	4
4	2	6	10	4	0

Fixed failure and maintenance costs for the systems at these four customers are indicated in Table 2.

Table 2 General Parameters of first example

Locations	1	2	3	4
Failure Cost ($)	3500	3200	300	5100
Maintenance Cost ($)	450	230	400	150

Table 3: Results of the case study

Visiting Order				Time	Total Cost		
π_1	π_2	π_3	π_4		OF1 in Eq. 1	OF2 in Eq. 6	OF3 in Eq. 7
4	3	2	1	31	2809.85	**5909.85**	**7139.85**
4	3	1	2	35	2863.45	6363.45	7593.45
4	2	3	1	39	2990.04	6890.04	8120.04
4	2	1	3	36	2878.36	6478.36	7708.36
4	1	2	3	35	2869.59	6369.59	7599.59
4	1	3	2	42	3049.07	7249.07	8479.07
3	**4**	**2**	**1**	**32**	**2785.23**	5985.23	7215.23
3	4	1	2	35	2811.33	6311.33	7541.33
3	2	4	1	39	2945.77	6845.77	8075.77
3	2	1	4	35	2901.21	6401.21	7631.21
3	1	2	4	36	2910.32	6510.32	7740.32
3	1	4	2	43	2961.12	7261.12	8491.12
2	3	4	1	38	2926.14	6726.14	7956.14
2	3	1	4	42	3080.28	7280.28	8510.28
2	4	3	1	39	2917.07	6817.07	8047.07
2	4	1	3	43	2951.86	7251.86	8481.86
2	1	4	3	35	2819.3	6319.3	7549.3
2	1	3	4	35	2884.5	6384.5	7614.5
1	3	2	4	39	3021.5	6921.5	8151.5
1	3	4	2	39	2915.29	6815.29	8045.29
1	2	3	4	31	2823.15	5923.15	7153.15
1	2	4	3	32	2786.4	5986.4	7216.4
1	4	2	3	39	2921.64	6821.64	8051.64
1	4	3	2	38	2910.35	6710.35	7940.35

To simplify the problem, it is assumed that each location will be visited at least and at most once. This limits the total number of possible visit alternatives to 24. In Table 3, total costs for all these alternatives are shown. First four columns in Table 3 show the visiting order of locations. Fifth column is the total travelled distance. Sixth column gives the total cost obtained from the first objective function in (1). The seventh column displays the second objective function given in (6). The last column is the third objective function in (7).

Changes in the visit order changes the time of the visit for each location. Thus, the failure probability for the system at each location for a different visit order becomes different leading to different failure costs, which cause variations in the values of the first objective function. The best result for the first objective function is obtained from the visit order (3-4-2-1) given in the 7[th] row with $2785.23.

The calculation of the second objective function involves the cost of travel in addition to failure cost. It is assumed that traveling one unit distance-time costs 100$. The best routing is given in the first permutation (i.e., 4- 3- 2- 1) with minimum cost of $5909.85. It is shown in this example that the travel cost affects the decision of the maintenance order.

The third objective function includes the maintenance costs as well as failure and travel cost. This example was simplified with the assumption of visiting each location at least and at most once. Thus, the maintenance cost for each permutation will be the same. Even though maintenance times are different, systems at all locations will be maintained once. Thus, the ranking of results of the second and third objective function are the same. If this assumption is removed, then some of the locations may be visited multiple times or some are not visited at all. Table 4 gives an example of costs for a given visit order without any visit limits.

Table 4: Result example without visit limit

Visiting Order				Time	Total Cost			
π_1	π_2	π_3	π_4		OF1 in Eq. 1	OF2 in Eq. 6	OF3 in Eq. 7	Main`t Cost
4	3	2	1	31	2809.85	5909.85	7139.85	1230
4	1	2	4	28	2016.56	4816.56	**5646.56**	830

As seen from the table, not visiting location three reduces the failure cost because the failure consequence of the system in location three is very low compared to the system in location four ($300 in location 3, $5100 in location 4). Thus, replacing maintenance in location three with location four reduces the total failure cost. In addition, maintenance cost in location four is lower compared to location three. Total travel time is also low if location three is not visited at all. Note that this example is selected to demonstrate the nature of the problem, not fully demonstrate a real system.

4. Conclusion

The cost reduction pressure on industry has increased research on condition based maintenance. Maintenance schedule now bases on detection and forecasting of failures. This paper presents a problem formulation to be used in maintenance planning that incorporates prognostics output with distances between systems located in various places. Formulation and numerical example are presented in the paper. As future work, it is recommended to develop heuristic or meta-heuristics algorithms for the given problem formulation with large number of locations.

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Fatih Camci has been a faculty member at the IVHM Centre at Cranfield University, UK since 2010. He works on development of diagnostics, prognostics and maintenance planning technologies for electro-mechanical systems. Previously, Dr. Camci worked as an Assistant Professor at Fatih University in Turkey and as senior project engineer at Impact Technologies, in Rochester NY before joining Cranfield University. Dr. Camci received his BSc and MSc degrees in Computer Engineering at Istanbul and Fatih University in Turkey. He received his PhD in Industrial Engineering from Wayne State University, USA.

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Musa Karakas is an MSc student at Computer Engineering Department at Fatih University, Istanbul Turkey. He worked part-time in a research project aiming to develop maintenance planning systems for railway turnouts.

Ian Jennions Ian's career spans over 30 years, working mostly for a variety of gas turbine companies. He has a Mechanical Engineering degree and a PhD in CFD both from Imperial College, London. He has worked for Rolls-Royce (twice), General Electric and Alstom in a number of technical roles, gaining experience in aerodynamics, heat transfer, fluid systems, mechanical design, combustion, services and IVHM. He moved to Cranfield in July 2008 as Professor and Director of the newly formed IVHM Centre. The Centre is funded by a number of industrial companies, including Boeing, BAe Systems, Rolls-Royce, Thales, Meggitt, MOD and Alstom Transport. He has led the development and growth of the Centre, in research and education, over the last three years. The Centre offers a short course in IVHM and the world's first IVHM MSc, begun in 2011.

Ian is on the editorial Board for the International Journal of Condition Monitoring, a Director of the PHM Society, contributing member of the SAE IVHM Steering Group and HM-1 IVHM committee, a Fellow of IMechE, RAeS and ASME. He is the editor of the recent SAE book: IVHM – Perspectives on an Emerging Field.