Predictive maintenance using FMECA method and NHPP models

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Abstract: Most of predictive maintenance technologies are inaccessible to small scale and medium scale industries due to their demanding cost. This paper proposes a predictive maintenance policy using failure mode effect and criticality analysis (FMECA) and non-homogeneous Poisson process (NHPP) models which require minimal use of advanced monitoring technologies and sophisticated data acquisition systems. Most of the repairable systems show long term reliability degradation with repeated overhauls. Here, critical component of a system or machinery exhibiting sad (deteriorating) trend is used as an indicator to predict overall maintenance time of a system. Firstly, the component to be used as an indicator for predictive maintenance is chosen using FMECA method, in which the most critical component is chosen. Secondly, the failure data of the chosen component is analysed using NHPP models and based on analysis of the data, relevant NHPP model is selected and finally, the Mean Time Between Failure (MTBF) of the component is compared with the threshold mean time between failure [MTBF(Th)] of the component to decide the overall maintenance time for the system. The developed methodology is validated on an overhead crane in a steel manufacturing company.

Keywords: predictive maintenance; NHPP models; FMECA analysis.

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1 Introduction

It is evident that health of any operating system deteriorates with time and requires frequent maintenance. Maintenance can be defined as the set of activities performed in order to restore a system to its acceptable working condition (Ahmad and Kamaruddin, 2012; Dhillon, 2002). Maintenance can be classified under three main headings. Firstly, corrective maintenance, where the system is restored to its working condition after it has failed (Ahmad and Kamaruddin, 2012; Bevilacqua and Braglia, 2000). Secondly, the preventive maintenance, where periodic maintenance is performed to prevent breakdowns and thereby decreasing the likelihood of equipment failure and improving the availability of the system (Moghaddam and Usher, 2011; Joo and Min, 2013; Yeh et al., 2009; You et al., 2011; Zhao, 2003). Lastly the predictive maintenance, where the system is continuously monitored to determine the health of the system and the maintenance is done when the health of the system deteriorates to a predefined threshold level (Chu et al., 1998; Costa et al., 2012; Dieulle et al., 2001; Hsiao et al., 2013; Moya, 2004; Neves et al., 2011; Silva et al., 2012). There are several benefits associated with predictive maintenance over corrective and preventive maintenance such as, increased plant reliability, improved plant availability, reduced maintenance cost, better asset protection, reduced spare part inventory, reduced catastrophic and unexpected machine failures, better product quality, reduced energy consumption, increased personnel safety, reduced mean time between failure (MTBF) of plant equipment (Beltran and Lopez, 2000; Carnero, 2006; Christer et al., 1997; Hu et al., 2012; Kakkar, 1999; Lupinucci et al., 2000; Shahin et al., 2012; Tan and Raghavan, 2008; Villar et al., 2000).

Two major difficulties are practically encountered during implementation of predictive maintenance policy. Firstly, it is the absence of any concrete statistical model for predictive maintenance (Tan and Raghavan, 2008) and secondly, it is the demanding cost of advanced monitoring technology and sophisticated data acquisition systems which makes it a complex and costly affair (Wendai and Daescu, 2002). Most of the models developed for failure data analysis are followed by supposition that the failure data is homogeneous and identically distributed which is true in most of the cases where total renewal process takes place (Coetzee, 1997; Walls and Bendell, 1986). However in reality most of the repairable systems show long term reliability degradation with repeated overhaul and at times replacement of the degraded component of the system, failure data is found to be non-homogeneous exhibiting sad failure trend that is wear-out failures, in which the failure rate increases wit time(Coetzee, 1997; Battini et al., 2013). The proceeding section shows the framework of the proposed predictive maintenance policy for repairable systems. This paper proposes a predictive maintenance policy for system consisting of large number of components with assumption of minimal repair (Barlow and Hunter, 1960) and follows non-homogeneous failure trend with minimum use of advanced monitoring technologies and sophisticated data acquisition systems. Maintenance of the machine is based on the failure pattern of most critical component, where the criticality of the component is calculated using failure mode effect and criticality analysis (FMECA) method. The failure data of the most critical component is analysed using non-homogeneous Poisson process (NHPP) models. After analysis the most appropriate NHPP model is selected and the MTBF for the selected component is calculated which is compared with the threshold mean time between failure [MTBF(Th)] to predict the overall maintenance time of the system.

The following section of the paper, literature review on predictive maintenance policy is discussed. Subsequently, a predictive maintenance framework and methodology is proposed. Section 4, basically demonstrates how the proposed methodology is tested on overhead cranes in a steel manufacturing company. Finally, the general conclusion is presented in Section 5 of this research paper.

2 Literature survey

In past, various models have been proposed for predictive maintenance. Basically there are five classes of models developed so far. *Firstly*, there are probabilistic models based on assumptions that a system either undergoes a perfect renewal with a constant probability of *p* or minimal repair with a constant probability of (*1-p*) and on further enhancement of these probabilistic models a time varying probabilistic function was introduced to account the systems age and degradation (Caesarendra et al., 2011; Chu et al., 1998; Tan and Raghavan, 2008, 2010; Widodo and Yang, 2011; Zhao et al., 2010). *Secondly*, we have age-based models, where ageing factor plays a dominant role in deciding the maintenance times of the system (Fan et al., 2011; Yang and Liu, 1999; Zhou et al., 2007). *Thirdly*, is the cost-based models, where the maintenance times or component replacement of the system is dependent on the maintenance cost of the system (Bajracharya et al., 2009; Crowder and Lawless, 2007; Curcuru et al., 2010; Ekpenyong et al., 2012;Grall et al., 2002; Maillart and Pollock, 2002; Wu et al., 2007). *Fourthly*, there are technological models, where different technology such as vibration analysis, thermography, sensors, etc. are used for monitoring the identified machine parameters and when the parameter value falls below a predefined threshold level maintenance is performed (Bagavathiappan et al., 2013; Bogard et al., 2002; Chiementin et al., 2008, 2009; Hashemian, 2011; Hashemian and Bean, 2011; Orhan et al., 2006; Rodriguez and Perez, 2002; Schlangen et al., 2010; Taplak et al., 2013; Wilson et al., 2011; Younus and Yang, 2012). *Finally*, there are degradation models, where system undergoes degradation owing to different stress conditions and random shock events (Deloux et al., 2009; Grall et al., 2002; Fouladirad et al., 2008; Kaiser and Gebraeel, 2009; Ponchet et al., 2010; You et al., 2010a, 2010b) . Predictive maintenance models along with their classifications are shown in Table 1.

Table 1 Classification of predictive maintenance models

Predictive maintenance models
1 Probabilistic models
• Chu et al. (1998) used Markov process and dynamic programming to develop a PdM model for single unit replacement.
• Practical PdM framework for multi-state systems using Markov chain analysis, universal generating function is developed (Tan and Raghavan, 2008).
• Tan and Raghavan (2010) developed a PdM model for multi state systems using Markov chain, universal generating function and restoration factor.
• Zhao et al. (2010) developed a PdM method using probabilistic fault prediction which reveals evolvement of the systems degradation for a gradually deteriorating system.
• Caesarendra et al. (2011) and Widodo and Yang (2011) used probability approach and support vector machine to predict machine health conditions.

Table 1 Classification of predictive maintenance models (continued)

	Predictive maintenance models
2	*Age-based models*
	• Yang and Liu (1999) simulated ageing failure mode of a DC motor using rotating speed as a state variable.
	• Zhou et al. (2007) developed a PdM programme based on hybrid hazard rate recursion rule using age reduction factor and hazard rate increase factor.
	• Fan et al. (2011) proposed a cooperative PdM model based upon hazard rate function and effective age of the system.
3	*Cost-based models*
	• Grall et al. (2002) to minimise the long run expected maintenance cost per unit time derived a mathematical model for the system.
	• Maillart and Pollock (2002) presented cost-minimising policies to determine the time and allocation of monitoring resources to multiple systems.
	• Wu et al. (2007) developed a cost-based PdM model using condition monitoring of rolling element bearing through vibration analysis, artificial neural network model and cost matrix.
	• Crowder and Lawless (2007) observed wear process over time and developed a PdM model based on degradation and monitoring cost using Gamma process, Weiner process and replacement cycle cost analysis.
	• Bajracharya et al. (2009) developed a framework to predict the health state of the equipment based on effects of different maintenance actions. The maintenance action is optimised using cost function.
	• Curcuru et al. (2010) proposed a procedure for the computation of the maintenance time that minimises the overall maintenance cost.
	• Ekpenyong et al. (2012) developed modified generator maintenance scheduling model by modifying classical generator scheduling model and formulated an economic cost objective function.
4	*Technological models*
	• Vibration analysis models: where system vibrations are sensed and used for PdM (Bogard et al., 2002; Chiementin et al., 2008, 2009; Orhan et al., 2006; Taplak et al., 2013).
	• Thermography-based models: where heat signatures are sensed and used for PdM (Younus and Yang, 2012; Bagavathiappan et al., 2013; Schlangen et al., 2010; Wilson et al., 2011).
	• Hashemian (2011), Hashemian and Bean (2011) and Rodriguez and Perez (2002) developed sensor-based models for predictive maintenance.
5	*Degradation models*
	• Grall et al. (2002) developed a PdM structure for a gradually deteriorating single unit system using mathematical modelling, replacement and renewal process.
	• Fouladirad et al. (2008) proposed an on-line change detection policy for non-stationary degradation process due to sudden changes.
	• Deloux et al. (2009) proposed a PdM policy using statistical process control and condition-based maintenance to inspect and replace the system in accordance with the observed deterioration level.

Table 1 Classification of predictive maintenance models (continued)

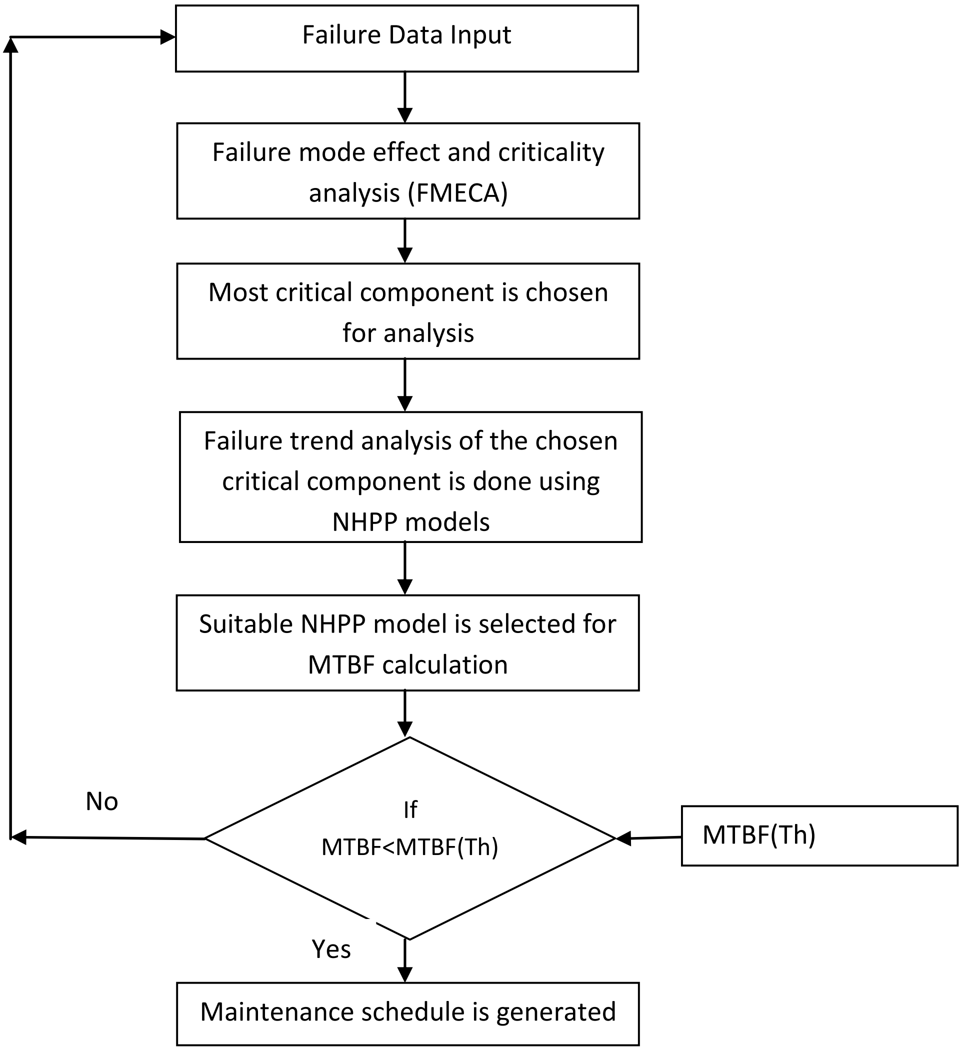
Predictive maintenance models
5 Degradation models
• Ponchet et al. (2010) developed a maintenance policy for stochastically deteriorating system using Markov process.
• You et al. (2010b) proposed an updated sequential PdM policy to decide a real time PdM schedule for a continuously monitored degrading system.
• You et al. (2010a) developed a statistically planned and individually improved PdM policy for degrading systems and compared it with typical degradation model showing higher availability in case of the developed PdM policy.
• Kaiser and Gebraeel (2009) proposed a maintenance policy which utilises contemporary degradation models with reliability and degradation characteristics of the component's population.

FMECA is typically used as a technique for identifying critical failure modes, thus improving the reliability of products or component. There are quite a number of research papers addressing the application of FMECA. For example, a distributed computing system approach of FMECA for air traffic control is presented by Becker and Flick (1996). Braglia (2000) developed an integrated FMECA with economic considerations for failure investigation and tested it on an Italian refrigerator manufacturing company. Bertolini et al. (2006) applied FMECA methodology to traceability system analysis in food supply chain in order to locate critical points in traceability system and propose improvements. Bassetto et al. (2011) performed FMECA for risk analysis in order to assess risk involved in production ramp-up by semi-conductor manufacturers. Okayama et al. (2011) used FMECA and fuel cycle system (FCS) to assess system availability in a tritium plant. Vayrynen et al. (2011) performed FMECA on a remotely operated water hydraulic manipulator (WHMAN) for reliability improvements. Ahmad et al. (2012) integrated FMECA and failure time modelling (FTM) based on proportional hazard model (PHM) to obtain more reliable results in failure analysis. Jun and Huibin (2012) applied FMECA in an aircraft equipment in order to analyse its reliability and hence improving operational reliability of the product. Sawant and Christou (2012) used FMECA as a tool to identify the critical failure modes of the LEDs and its suitability for the target medical diagnostic applications. Kim and Jeong (2013) used FMECA to develop Reliability Centered Maintenance programme for wind turbines. Igba et al. (2013) studied braking system of railroad vehicles using FMECA in order to improve efficiency, reliability and safety of railroad maintenance task.

3 Methodology

In this research paper, we propose a hybrid technique of predictive maintenance policy by combining the benefits of FMECA methodology for identifying the critical modes and NHPP models for taking decision on times when the maintenance has to be scheduled. NHPP is a reliability engineering tool finding wide application in modelling failure process of repairable systems (Bae et al., 2013; Coetzee, 1997; Krivtsov, 2007; Louit et al., 2009; Weide and Pandey, 2011; Yue and Cao, 2001), software reliability (Hsu et al., 2011; Okamura et al., 2013; Zheng, 2009), warranty claims (Akbarov and Wu, 2012; Wu and Akbarov, 2012), etc. Here we assume that; the components of machine are repaired or replaced on failure, single component failure pattern could be used to predict the overall maintenance time of the machine and the machine degrades with time following increasing (sad) failure trend. Figure 1 depicts the proposed framework for predictive maintenance using FMECA method and NHPP models.

Figure 1 Framework for predictive maintenance



The proposed framework basically involves the following steps.

Step 1 As a first step of the proposed methodology failure data is generated from the downtime of the machine (Edward et al., 1998). The data contains all relevant information required for developing the maintenance policy, such as:

- type of failure
- reasons of failure

- component(s)/part(s) failed
- frequency of failure.

Step 2 Failure data generated in Step 1 is analysed using FMECA where the criticality for each failure mode and failed component is calculated. FMECA involves reviewing components, assemblies and sub-systems to identify failure modes, causes, effects and criticality of such failures. For each failure mode the failed component is identified, their effect on the rest of the system is noted down and classifies it into several categories based on their severity (shown in Table 2).

Table 2 Severity classification and its' probability value

Category	*Classification*	*Description*	*Probability value (f_s)*
I	Catastrophic	Significant system failure causing major damage such as loss of life, injury, etc.	1.00
II	Critical	Complete loss of system occurs	0.75
III	Marginal	System is degraded	0.50
IV	Negligible	Minor failure occurs	0.25

Criticality of failure modes are calculated for each of the component (Ebeling, 1997; O'Connor, 2010; Ahmad et al., 2012).

Table 3 FMECA worksheet

Component	*Failure mode*	*Failure cause and effect*	*Sevearity class, f_s*	*Parameters of criticality index*			
				Failure mode ratio $\alpha_i = f_i/f_t$	*Failure rate $\lambda_{pi} = f_i/t$*	*Operating time $\beta_i \times t$*	*Failure mode criticality $Cm = \beta_i \times \alpha_i \times \lambda_{pi} \times t$*

From the Table 3, the most critical component whose *Cm* value is largest is chosen for further analysis

Step 3 For the identified critical component, the failure data collected in Step 1 is used to develop the prediction model. It is quiet logical that the failure pattern of this component will perhaps dictate the maintenance policy of the whole machine or equipment. Here, we use NHPP models for fitting the failure data. The NHPP models used in this paper are chosen on the basis of, well established theoretical base, suitability for modelling data with a trend and minimal repair systems and models have been tested fairly well (Ascher and Feingold, 1969; Bassin, 1969, 1973; Bell and Mioduski, 1976; Crow, 1974, 1990; Durr, 1980; Thompson, 1981). Some of the popular NHPP model used for failure analysis are shown in Table 4. The NHPP model reflecting the highest coefficient of correlation (R^2) is selected as it is the best fit model.

Table 4 NHPP models

Model		*Parameter estimation*
1	*Power law* $W(T) = \lambda\beta T^{\beta-1}$ for $\lambda > 0, \beta > 0, T \geq 0$ (Crow, 1974; Duane, 1964)	$\beta = \frac{n\sum_{i=1}^{n}(\log W \times \log T) - \sum_{i=1}^{n}\log W \times \sum_{i=1}^{n}\log T}{n\sum_{i=1}^{n}(\log T)^2 - \left(\sum_{i=1}^{n}\log T^2\right)} + 1$ $\lambda = e\frac{1}{n}\left(\sum_{i=1}^{n}\log W - \left(\frac{n\sum_{i=1}^{n}(\log W \times \log T) - \sum_{i=1}^{n}\log W \times \sum_{i=1}^{n}\log T}{n\sum_{i=1}^{n}(\log T)^2 - \left(\sum_{i=1}^{n}\log T^2\right)}\right) \times \sum_{i=1}^{n}\log T\right) - \log\left(\frac{n\sum_{i=1}^{n}(\log W \times \log T) - \sum_{i=1}^{n}\log W \times \sum_{i=1}^{n}\log T}{n\sum_{i=1}^{n}(\log T)^2 - \left(\sum_{i=1}^{n}\log T^2\right)} + 1\right)$ *Coefficient of correlation* $R^2 = \frac{SSR}{SST}$ where $SSR = \sum_{i=1}^{n}\left\{(\beta - 1) \times (\log T - \left(\left(\sum_{i=1}^{n}\log T\right) \div n\right)\right\}^2$ $SST = \sum_{i=1}^{n}\left\{\log W - \left(\sum_{i=n}(\log\lambda + \log\beta + (\beta - 1)\log T)\right) \div n\right\}^2$ *MTBF calculation* $MTBF(T_b, T_{b-1}) = \frac{T_b - T_{b-1}}{\lambda\beta T_b^{\beta-1}}$ for $\lambda > 0, \beta > 0, T_b \geq T_{b-1} \geq 0$
2	*The linear model* $W(T) = \lambda(1 + \alpha T)$ for $\lambda > 0, T \geq 0$ (Vesely, 1991; Atwood, 1992)	*Parameter estimation* $\lambda = \frac{1}{n}\left\{\sum_{i=1}^{n}W - \left(\frac{n\sum_{i=1}^{n}(\log W \times \log T) - \sum_{i=1}^{n}\log W \times \sum_{i=1}^{n}\log T}{n\sum_{i=1}^{n}(\log T)^2 - (\sum_{i=1}^{n}\log T)^2}\right) \times \sum_{i=1}^{n}T\right\}$ $\alpha = \frac{n\sum_{i=1}^{n}(\log W \times \log T) - \sum_{i=1}^{n}\log W \times \sum_{i=1}^{n}\log T}{n\sum_{i=1}^{n}(\log T)^2 - \left(\sum_{i=1}^{n}\log T^2\right)} \times \left[\frac{1}{n}\left\{\sum_{i=1}^{n}\log W - \left(\frac{n\sum_{i=1}^{n}(\log W \times \log T) - \sum_{i=1}^{n}\log W \times \sum_{i=1}^{n}\log T}{n\sum_{i=1}^{n}(\log T)^2 - \left(\sum_{i=1}^{n}\log T^2\right)}\right) \times \sum_{i=1}^{n}T\right\}\right]^{-1}$

Table 4 NHPP models (continued)

Model		Coefficient of correlation
2	*The linear model*	$R^2 = \frac{SSR}{SST}$ where $SSR = \sum_{i=1}^{n}\left\{\lambda(1+\alpha T) - \left(\sum_{i=1}^{n} W\right) \div n\right\}^2$ $SST = \sum_{i=1}^{n}\left\{W - \left(\sum_{i=1}^{n} W\right) \div n\right\}^2$ *MTBF calculation* $MTBF(T_b, T_{b-1}) = \frac{T_b - T_{b-1}}{\lambda(1+\alpha T_b)}$ for $\lambda > 0$, $T_b \geq T_{b-1} \geq 0$
3	*The log-linear model* $W(T) = e^{(\alpha+\beta T)}$ for $-\infty < \alpha, \beta < \infty, T \geq 0$ (Cox and Lewis, 1966)	*Parameter estimation* $\beta = \frac{n\sum_{i=1}^{n}(\ln W \times T) - \sum_{i=1}^{n}\ln W \times \sum_{i=1}^{n} T}{n\sum_{i=1}^{n}(T)^2 - \left(\sum_{i=1}^{n} T^2\right)}$ $\alpha = \frac{1}{n}\left\{\sum_{i=1}^{n}\ln W - \left(\frac{n\sum_{i=1}^{n}(\ln W \times T) - \sum_{i=1}^{n}\ln W \times \sum_{i=1}^{n} T}{n\sum_{i=1}^{n}(T)^2 - \left(\sum_{i=1}^{n} T^2\right)}\right) \times \sum_{i=1}^{n} T\right\}$ *Coefficient of correlation* $R^2 = \frac{SSR}{SST}$ where $SSR = \sum_{i=1}^{n}\left\{(\alpha + \beta T) - \left(\sum_{i=1}^{n}\ln W\right) \div n\right\}^2$ $SST = \sum_{i=1}^{n}\left\{\ln W - \left(\sum_{i=1}^{n}(\alpha + \beta T)\right) \div n\right\}^2$ *MTBF calculation* $MTBF(T_b, T_{b-1}) = \frac{(T_b - T_{b-1})}{e^{(\alpha+\beta T_b)}}$ for $-\infty < \alpha, \beta < \infty$, $T_b \geq T_{b-1} \geq 0$

Step 4 For the NHPP model as selected in Step 3, the calculated MTBF is compared with MTBF(Th). MTBF(Th) is derived by equating weekly machine maintenance cost with overall machine maintenance cost.

System maintenance cost is the total maintenance cost incurred during a week which includes the replacement cost of the critical component, labour cost for maintenance of critical component, downtime cost and other cost. Here, downtime cost is the cost incurred due to loss of production during machine breakdowns and other cost includes the maintenance cost of other non-critical components of the system. Thus the derivation of MTBF(Th) is given as:

$$C = W_{Th} \times C_o + (C_l \times T_l) + (C_d \times T_d) + C_m$$

Or

$$W_{Th} = \frac{(C - (C_d \times T_d) - C_m - (C_l \times T_l))}{C_o}$$

We know that,

$$MTBF(Th) = \frac{1}{W_{Th}}$$

So, we get,

$$MTBF(Th) = \frac{C_o}{C - (C_d \times T_d) - C_m - (C_l \times T_l)}$$

On comparison if MTBF is found more than MTBF(Th) the system is in acceptance level of performance and does not require maintenance. It is obvious that the MTBF will remain same till the occurrence of next component failure. On occurrence of next component failure the whole process from Step 1 is repeated again and in case MTBF becomes less than MTBF(Th) then the maintenance schedule is generated and the machine maintenance is performed.

4 Application of model – a case example

Here we consider a case example of a steel manufacturing company in India, where we tried to develop a maintenance policy of a newly bought overhead crane. An overhead crane, also called as a bridge crane consists of parallel runways with a travelling bridge spanning the gap. The overhead crane is a heavy duty crane with 100 ton capacity. The crane is used in a steel warehouse which handles loads averaging 55% of the rated capacity. It operates with an average lifts of 10 to 15 per hour to an average height of 15 feet. Presently, the overall maintenance of the overhead crane is only performed in every 16th week. Components associated with several failure mode shows varying severity effecting production rate.

Step 1 Twelve week failure data of the overhead crane was collected. The collected data contain all relevant information such as:

- type of failure
- reasons of failure
- component(s)/part(s) failed
- frequency of failure.

Step 2 Failure data generated in step 1 is analysed using FMECA method as shown in Table 5.

Table 5 FMECA of overhead crane data

Component	*Failure mode*	*Failure cause and effect*	*Sevearity class, f_s*	*Parameters of criticality index*			
				Failure mode ratio $\alpha_i = f_i/f_t$	*Failure rate $\lambda_{pi} = f_i/t$*	*Operating time $\beta_i \times t$*	*Failure mode criticality $Cm = \beta_i \times \alpha_i \times \lambda_{pi} \times t$*
A/H Brake	A/H brake loose	Wear and tear; loss of control	IV, 0.25	1.00	0.0402	168	6.75
Gearbox coupling bolt	loose	wear and tear; increased noise and power consumption	IV, 0.25	1.00	0.064	168	10.75
LT wheel coupling bolt	loose	wear and tear; increased noise and power consumption	IV, 0.25	1.00	0.0714	168	12.00
O-ring	*Failed*	*Wear and tear; increased noise, power consumption and vibrations*	*III, 0.50*	*1.00*	*0.0804*	*336*	*27.01*
Motor	M/H brake loose	Wear and tear; loss of control	IV, 0.25	0.45	0.0268	75.6	2.06
	coupling bolt loose	wear and tear; increased noise and power consumption	IV, 0.25	0.30	0.0179 0	50.4	0.92
	base bolt loose	Wear and tear; loss of control and increased noise	IV, 0.25	0.25	0.0149	42	0.63

From Table 5, we observe that O-ring is the most critical component and hence it is chosen for further analysis.

Step 3 Failure data as obtained in Step 1 of critical component O-ring is analysed using NHPP models. O-ring failure data is shown in Table 6, where number of failures is shown for a particular week.

Table 6 O-ring failure data

Week no.	*Number of failures*
1	1
2	1
3	2
4	2
5	3
6	4
7	5
8	5
9	6
10	7
11	9
12	11

The data in Table 6 is fitted in NHPP models and coefficient of correlation for each model is calculated as shown in Table 7.

Table 7 NHPP model analysis

NHPP model	*Coefficient of correlation*
The power law model	0.965
The linear model	0.940
The log-linear model	0.983

From Table 7, we observe that the log-linear model has the highest coefficient of correlation and hence is the best fit model. So, the log-linear model is used for further analysis.

Step 4 Here the MTBF calculated using NHPP model selected in Step 3 is compared with MTBF(Th). MTBF(Th) is calculated using the following data:

As per the data obtained from company log books:

C_o = Rs 650/- C_l = Rs 350/- C_d = Rs 500/- C_m = Rs 6,500/-

T_l = 0.6 hours T_d = 9.6 hours C = Rs 18,000/-

(Note: Here Rs stands for Rupees and 1 US$ = Rs 59.8)

We get;

$MTBF(Th) = 0.1002$

The MTBF(Th) so calculated is compared with the MTBF calculated using NHPP model selected in Step 3. If MTBF calculated is more than MTBF(Th) the system is in acceptance level of performance and does not require maintenance. It is obvious that the MTBF will remain same till the occurrence of next component failure. On occurrence of next component failure the whole process from Step 1 is repeated again and in case

MTBF becomes less than MTBF(Th) the maintenance schedule is generated and the machine maintenance is performed.

Table 8 Comparison of MTBF and MTBF(Th)

Week no.	*MTBF (log-linear model)*	*MTBF(Th)*	*Action performed*
1	0.9259	0.1002	None
2	0.7407	0.1002	None
3	0.5952	0.1002	None
4	0.4761	0.1002	None
5	0.3831	0.1002	None
6	0.3076	0.1002	None
7	0.2469	0.1002	None
8	0.1980	0.1002	None
9	0.1589	0.1002	None
10	0.1274	0.1002	None
11	0.1001	0.1002	Overall maintenance schedule generated
12	0.0821	0.1002	Overall maintenance schedule generated

From Table 8, we observe that the crane requires maintenance in 11th week of operation instead of 16th week, as the company perform scheduled maintenance every 16th week. Since company did not performed maintenance in 11th week, the methodology generated maintenance schedule for 12th week also.

Further, we calculated the, extra expenditures incurred during operation of the overhead crane from 12th to 16th week, as given in Table 9.

Table 9 Maintenance expenditure incurred

Week no.	*Maintenance expenditure (Me) in Rupees*	*Extra expenditure incurred (Me – 18,000) in Rupees*
12	20533.56	2533.56
13	23950.50	5950.50
14	28224.36	10224.36
15	33270.43	15270.44
16	40349.78	22349.78
Total		56328.64

Note: 1 US$ = Rs 59.8

From Table 9, it can be seen that the extra expenditure incurred during 12th to 16th week of operation amounts to Rupees 56328.64 every 16 weeks. Thus expenditure on maintenance increases if the overall maintenance is delayed beyond 11th week. The proposed methodology hence seems economical and provides better control over machine failures.

5 Conclusions

This paper proposes a new methodology for developing predictive maintenance policy using FMECA method and NHPP models. This methodology avoids costly technology for continuous monitoring of conditions of machine and moreover it is very simpler to adopt in practical cases. Through FMECA we identify the critical component and subsequently through NHPP model we find the MTBF and is compared with the predetermined value, MTBF(Th). This methodology is applied in a real life case situation for deciding maintenance policy of an overhead crane in a steel manufacturing company in India. The analysis of the case shows the need of machine maintenance in 11th week instead of 16th week as is the policy of the company. On further analysis we observe that on applying the proposed model, a savings of Rupees 168985.92 per annum can be made. This model can also be applied in other industries and on other machines also.

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References

Ahmad, R. and Kamaruddin, S. (2012) 'An overview of time-based and condition-based maintenance in industrial application', *Computers & Industrial Engineering*, Vol. 63, No. 1, pp.135–149.

Ahmad, R., Kamaruddin, S.., Azid, A.I. and Almanar, I.P. (2012) 'Failure analysis of machinery component by considering external factors and multiple failure modes – a case study in the processing industry', *Engineering Failure Analysis*, Vol. 25, pp.182–192.

Akbarov, A. and Wu, S. (2012) 'Forecasting warranty claims considering dynamic over dispersion', *International Journal of Production Economics*, Vol. 139, No. 2, pp.615–622.

Ascher, H.E. and Feingold, H. (1969) 'Bad as old analysis of system failure data', *Annals of Assurance Sciences,* Gordon and Breach, New York, pp.49–62.

Atwood, C.L. (1992) 'Parametric estimation of time-dependent failure rates for probabilistic risk assessment', *Reliability Engineering and System Safety*, Vol. 37, No. 3, pp. 181–194.

Bae, S.J., Mun, B.M. and Kim, K.Y. (2013) 'Change-point detection in failure intensity: A case study with repairable artillery systems', *Computers and Industrial Engineering*, Vol. 64, No. 1, pp.11–18.

Bagavathiappan, S., Lahiri, B.B., Saravanan, T., Philip, J. and Jayakumar, T. (2013) 'Infrared thermography for condition monitoring- A review', *Infrared Physics & Technology*, Vol. 60, pp.35–55.

Bajracharya, G., Koltunowicz, T., Negenborn, R.R., Papp, Z., Djairam, D., Schutter, B.D. and Smit, J.J. (2009) 'Optimization of maintenance for power system equipment using a predictive health model', *IEEE Bucharest Power Tech Conference*, Bucharest, Romania, pp.1–6.

Barlow, R.E. and Hunter, L. (1960) 'Optimum preventive maintenance policies', *Operations Research*, 1960, Vol.8, No. 1, pp.90–100.

Bassetto, S., Siadat, A. and Tollenaere, M. (2011) 'The management of process control deployment using interactions in risks analyses', *Journal of Loss Prevention in the Process Industries*', Vol. 24, No. 4, pp.458–465.

Bassin, W.M. (1969) 'Increasing hazard functions and overhaul policy', *ARMS, IEEE-69*, C8-R, pp.173–180.

Bassin, W.M. (1973) 'A Bayesian overhaul interval model for Weibull restoration process', *Journal of the American Statistical Society*, Vol. 68, No. 343, pp.575–578.

Battini, D., Faccio, M., Persona, A. and Regattieri, A. (2013) 'Buffer design for availability: a new simulative study in case of infant and random failures', *Int. J. of Services and Operations Management*, Vol. 14, No. 2, pp.157–174.

Becker, J.C. and Flick, G. (1996) 'A practical approach to failure mode, effects and criticality analysis (FMECA) for computing systems', *High-Assurance System Engineering Workshop, IEEE*, Niagara on the Lake, Ontario, Canada, pp.228–236.

Bell, R. and Mioduski, R. (1976) 'Extension of life of US Army trucks', *ARMS, IEEE-76*, CHO-1004-7 RQC, pp.200–205.

Beltran, P. and Lopez, A. (2000) 'Predictive Maintenance in air-generators', *Proceedings Fourth Spanish Maintenance Congress*, AEM, Barcelona, pp.377–385.

Bertolini, M., Bevilacqua, M. and Massini, R. (2006) 'FMECA approach to product traceability in the food industry', *Food Control*, Vol. 17, No. 2, pp.137–145.

Bevilacqua, M. and Braglia, M. (2000) 'The analytic hierarchy process applied to maintenance strategy selection', *Reliability Engineering and System Safety*, Vol. 70, No. 1, pp.71–83.

Bogard, F., Debray, K. and Guo, Y.Q. (2002) 'Determination of sensor positions for predictive maintenance of revolving machines', *International Journal of Solids and Structures*, Vol. 39, No. 12, pp.3159–3173.

Braglia, M. (2000) 'MAFMA: multi-attribute failure mode analysis', *International Journal of Quality & Reliability Management*, Vol. 17, No. 9, pp.1017–1033.

Caesarendra, W., Widodo, A. and Yanga, B.S. (2011), 'Combination of probability approach and support vector machine towards machine health prognostics', *Probabilistic Engineering Mechanics*, Vol. 26, No. 2, pp.165–173.

Carnero, M.C. (2006) 'An evaluation system of the setting up of predictive maintenance programmes', *Reliability Engineering and System Safety*, Vol. 91, No. 8, pp.945–963.

Chiementin, X., Bolaers, F., Rasolofondraibe, L. and Dron, J.P. (2008) 'Localization and quantification of vibratory sources: application to the predictive maintenance of rolling bearings', *Journal of Sound and Vibration*, Vol. 316, No. 1, pp.331–347.

Chiementin, X., Bolaers, F., Rasolofondraibe, L. and Dron, J.P. (2009) 'Restoration of a temporal indicator specific to each vibratory sources for a predictive maintenance', *Mechanical Systems and Signal Processing*, Vol. 23, No. 6, pp.1909–1919.

Christer, A.H., Wang, W. and Sharp, J.M. (1997) 'A state space condition monitoring model for furnace erosion prediction and replacement', *European Journal of Operation Research*, Vol. 101, No. 1, pp.1–14..

Chu, C., Proth, J.M. and Wolff, P. (1998) 'Predictive maintenance: the one-unit replacement model', *International Journal of Production Economics*, Vol. 54, No. 3, pp.285–295.

Coetzee, J.L. (1997) 'The role of NHPP models in the practical analysis of maintenance failure data', *Reliability Engineering and System Safety,* Vol. 56, No. 2, pp.161–168.

Costa, C.A.B., Carnero, M.C. and Oliveira, M.D. (2012) 'A multi-criteria model for auditing a Predictive Maintenance Programme', *European Journal of Operational Research*, Vol. 217, No. 2, pp.381–393.

Cox, D.R. and Lewis, P.A. (1996) *The Statistical Analysis of Series of Events*, Methuen, London.

Crow, L.H. (1974) 'Reliability analysis for complex repairable systems', in F. Proschan and R.J. Serfling (Eds.): *Reliability and Biometry*, SIAM, Philadelphia, pp.379–410.

Crow, L.H. (1990) 'Evaluating the reliability of repairable systems', *Proceedings of the Annual Reliability and Maintainability Symposium*, *IEEE*, Los Angeles, pp.275–279.

Crowder, M. and Lawless, J. (2007) 'On a scheme for predictive maintenance', *European Journal of Operational Research*, Vol. 176, No. 3, pp.1713–1722.

Curcuru, G., Galante, G. and Lombardo, A. (2010) 'A predictive maintenance policy with imperfect monitoring', *Reliability Engineering and System Safety*, Vol. 95, No. 9, pp.989–997.

Deloux, E., Castanier, B. and Be´renguer, C. (2009) 'Predictive maintenance policy for a gradually deteriorating system subject to stress, stochastic modeling', *Reliability Engineering and System Safety*, Vol. 94, No. 2, pp.418–431.

Dhillon, B.S. (2002) *Engineering Maintenance – A Modern Approach*, CRC Press, Florida.

Dieulle, L., Berenguer, C, Grall, A. and Roussignol, M. (2001) 'Continuous time predictive maintenance scheduling for a deteriorating system', *Annual Reliability and Maintainability Symposium*, pp.150–155.

Duane, J.T. (1964) 'Learning curve approach to reliability monitoring', *IEEE Transactions on Aerospace,* Vol. 2, No. 2, pp.563–566.

Durr, A.C. (1980) 'Operational repairable equipments and the duane model', *Proceedings of the International Conference on Reliability and Maintainability*, Centre de Fiabilite, CNET, Lannion, France, pp.189-193.

Ebeling, C.E. (1997) *Reliability and Maintainability Engineering*, McGraw-Hill Companies, Inc., USA.

Edward, D.J., Holt, G.D. and Harris, F.C. (1998) 'Predictive maintenance techniques and their relevance to construction plant', *Journal of Quality in Maintenance Engineering*, Vol. 4, No. 1, pp.25–37.

Ekpenyong, U.E., Zhang, J. and Xia, X. (2012) 'An improved robust model for generator maintenance scheduling', *Electric Power Systems Research*, Vol. 92, pp.29–36.

Fan, H., Hu, C., Chen, M. and Zhou, D. (2011) 'Cooperative predictive maintenance of repairable systems with dependent failure modes and resource constraint', *IEEE Transactions on Reliability*, Vol. 60, No. 1, pp.144–157.

Fouladirad, M., Grall, A. and Dieulle, L. (2008) 'On the use of on-line detection for maintenance of gradually deteriorating systems', *Reliability Engineering and System Safety*, Vol. 93, No. 12, pp.1814–1820.

Grall, A., Berenguer, C. and Dieulle, L. (2002) 'A condition-based maintenance policy for stochastically deteriorating systems', *Reliability Engineering and System Safety*, Vol. 76, No. 2, pp.167–180.

Hashemian, H.M. (2011) 'Wireless sensors for predictive maintenance of rotating equipment in research reactors', *Annals of Nuclear Energy*, Vol. 38, No. 2, pp.665–680.

Hashemian, H.M. and Bean, W.C. (2011) 'State-of-the-art predictive maintenance techniques', *IEEE Transactions on Instrumentation and Measurement*, Vol. 60, No. 10.

Hsiao, Y.L., Drury, C., Wu, C. and Paquet, V. (2013) 'Predictive models of safety based on audit findings: Part 1: Model development and reliability, *Applied Ergonomics*, Vol. 44, No. 2, pp.261–273.

Hsu, C.J., Huang, C.Y. and Chang, J.R. (2011) 'Enhancing software reliability modeling and prediction through the introduction of time-variable fault reduction factor', *Applied Mathematical Modelling*, Vol. 35, No. 1, pp.506–521.

Hu, J., Zhang, L. and Liang, W. (2012) 'Opportunistic predictive maintenance for complex multi-component systems based on DBN-HAZOP model', *Process Safety and Environmental Protection*, Vol. 90, No. 5, pp.376–388.

Igba, J., Alemzadeh, K., Ebo, I.A., Gibbons, P. and Friis J. (2013) 'A systems approach towards reliability-centred maintenance (RCM) of wind turbines', *Procedia Computer Science*, Vol. 16, pp.814–823.

Joo, S.J. and Min, H. (2013) 'A multiple objective approach to scheduling the preventive maintenance of modular aircraft components', *Int. J. of Services and Operations Management*, Vol. 9, No. 1, pp.18–31.

Jun, L. and Huibin, X. (2012) 'Reliability analysis of aircraft equipment based on FMECA method', *Physics Procedia*, Vol. 25, pp.1816–1822.

Kaiser, K.A. and Gebraeel, N.Z. (2009) 'Predictive maintenance management using sensor-based degradation models', *IEEE Transactions on Systems, Man and Cybernetics – Part A: Systems and Humans*, Vol. 39, No. 4, pp.840–849.

Kakkar, V. (1999) 'Ontario power generation's Nanticoke power plant', Orbit, Bently Nevada, Vol. 20, No. 4, pp.14–16.

Kim, J. and Jeong, H.Y. (2013) 'Evaluation of the adequacy of maintenance tasks using the failure consequences of railroad vehicles', *Reliability Engineering and System Safety*, Vol. 117, pp.30–39.

Krivtsov, V.V. (2007) 'Practical extensions to NHPP application in repairable system reliability analysis', *Reliability Engineering and System Safety*, Vol. 92, No. 5, pp.560–562.

Louit, D.M., Pascual, R. and Jardine, A.K.S. (2009) 'A practical procedure for the selection of time-to-failure models based on the assessment of trends in maintenance data', *Reliability Engineering and System Safety*, Vol. 94, No. 10, pp.1618–1628.

Lupinucci, M., Perez, J., Davila, G. and Tiseyra, L. (2000) 'Improving sheet metal quality and product throughput with Bently's machinery management system', Orbit, Bently Nevada, Vol. 21, No. 3, pp.37–41.

Maillart, L.M. and Pollock, S.M. (2002) 'Cost-optimal condition-monitoring for predictive maintenance of 2-phase systems', *IEEE Transactions on Reliability*, Vol. 51, No. 3, pp.322–330.

Moghaddam, K.S. and Usher, J.S. (2011) 'Sensitivity analysis and comparison of algorithms in preventive maintenance and replacement scheduling optimization models', *Computers & Industrial Engineering*, Vol. 61, No. 1, pp.64–75.

Moya, C.C. (2004) 'The control of the setting up of a predictive maintenance program using a system of indicators', *International Journal of Management Science*, pp.57–75.

Neves, M.L., Santiago, L.P. and Maia, C.A. (2011) 'A condition-based maintenance policy and input parameters estimation for deteriorating systems under periodic inspection', *Computers & Industrial Engineering*, Vol. 61, No. 3, pp.503–511.

O'Connor, P.D.T. (2010) *Practical Reliability Engineering*, 4th ed., John Wiley India (P.) Ltd., ISBN: 978-81-265-1642-1.

Okamura, H., Dohi, T. and Osaki, S. (2013) 'Software reliability growth models with normal failure time distributions', *Reliability Engineering and System Safety*, Vol. 116, pp.135–141.

Okayama, K., Houtte, D., Sagot, F. and Maruyama, S. (2011) 'RAMI analysis for ITER fuel cycle system', *Fusion Engineering and Design*, Vol. 86, No. 6, pp.598–601.

Orhan, S., Akturk, N. and Celik, V. (2006) 'Vibration monitoring for defect diagnosis of rolling element bearings as a predictive maintenance tool: Comprehensive case studies', *NDT&E International*, Vol. 39, No. 4, pp.293–298.

Ponchet, A., Fouladirad, M. and Grall, A. (2010) 'Assessment of a maintenance model for a multi-deteriorating mode system', *Reliability Engineering and System Safety*, Vol. 95, No. 11, pp.1244–1254.

Rodriguez, J.P. and Perez, C.R. (2002) 'Advanced sensor for optimal orientation and predictive maintenance of high power wind generators', *IECON, IEEE 28th Annual Conference*, Vol. 3, pp.2167–2172.

Sawant, M. and Christou, A. (2012) 'Failure modes and effects criticality analysis and accelerated life testing of LEDs for medical applications', *Solid-State Electronics*, Vol. 78, pp.39–45.

Schlangen, R., Deslandes, H., Lundquist, T., Schmidt, C., Altmann, F., Yu, K., Andreasyan, A. and Li, S. (2010) 'Dynamic lock-in thermography for operation mode-dependent thermally active fault localization', *Microelectronics Reliability*, Vol. 50, No. 9, pp.1454–1458.

Shahin, S., Shirouyehzad, H. and Pourjavad, E. (2012) 'Optimum maintenance strategy: a case study in the mining industry', *Int. J. of Services and Operations Management*, Vol. 12, No. 3, pp.368–386.

Silva, P.R.N., Negrao, M.M.L.C., Junior, P.V. and Bobi, M.A.S. (2012) 'A new methodology of fault location for predictive maintenance of transmission lines', *Electrical Power and Energy Systems*, Vol. 42, No. 1, pp.568–574.

Tan, C.M. and Raghavan, N. (2008) 'A framework to practical predictive maintenance modeling for multi-state systems', *Reliability Engineering and System Safety*, Vol. 93, No. 8, pp.1138–1150.

Tan, C.M. and Raghavan, N. (2010) 'Imperfect predictive maintenance model for multi-state systems with multiple failure modes and element failure dependency', *2010 Prognostics & System Health Management Conference*, Macau, pp.27–38.

Taplak, H., Erkaya, S. and Uzmay, I. (2013) 'Experimental analysis on fault detection for a direct coupled rotor-bearing system', *Measurement*, Vol. 46, No. 1, pp.336–344.

Thompson, W.A. Jr. (1981) 'On the foundations of reliability', *Technometrics*, Vol. 23, No. 1, pp.1–13.

Vayrynen, J., Mattila, J., Vilenius, M., Ali, M., Valkama, P., Siuko, M. and Semeraro, L. (2011) 'Predicting the runtime reliability of ITER remote handling maintenance equipment', *Fusion Engineering and Design*, Vol. 86, No. 9, pp.2012–2015.

Vesely, W.E. (1991) 'Incorporating aging effects into probabilistic risk analysis using a Taylor expansion approach', *Reliability Engineering and System Safety*, Vol. 32, No. 3, pp.315–337.

Villar, J.M, Masson, L.O. and Games, J.A. (2000) 'Proactive maintenance- a successful history', *Orbit*, Bently Nevada, Vol. 21, No. 3, pp.33–41.

Walls, L.A. and Bendell, A. (1986) 'The structure and exploration of reliability field data: what to look for and how to analyse it', *Reliability Engineering*, Vol. 15, No. 2, pp.115–143.

Weide, J.A.M. and Pandey, M.D. (2011) 'Stochastic analysis of shock process and modeling of condition-based maintenance', *Reliability Engineering and System Safety*, Vol. 96, No. 6, pp.619–626.

Wendai, W. and Daescu, D.D. (2002) 'Reliability quantification of induction motors- accelerated degradation testing approach', *Annual Reliability and Maintainability Symposium*, pp.325–331.

Widodo, A. and Yang, B.S. (2011) 'Machine health prognostics using survival probability and support vector machine', *Expert Systems with Applications*, Vol. 38, No. 7, pp.8430–8437.

Wilson, J., Tian, G., Mukriz, I. and Almond, D. (2011) 'PEC thermography for imaging multiple cracks from rolling contact fatigue', *NDT&E International*, Vol. 44, No. 6, pp.505–512.

Wu, S. and Akbarov, A. (2012) 'Forecasting warranty claims for recently launched products', *Reliability Engineering and System Safety*, Vol. 106, pp.160–164.

Wu, S., Gebraeel, N. and Lawley M.A. (2007) 'A neural network integrated decision support system for condition-based optimal predictive maintenance policy', *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, Vol. 37, No. 2, pp.226–236.

Yang, S.K. and Liu, T.S. (1999) 'State estimation for predictive maintenance using Kalman filter', *Reliability Engineering and System Safety,* Vol. 66, No. 1, pp.29–39.

Yeh, R.H., Kao, K-C. and Chang, W.L. (2009) 'Optimal preventive maintenance policy for leased equipment using failure rate reduction', *Computers & Industrial Engineering*, Vol. 57, No. 1, pp.304–309.

You, M., Liu, F., Wang, W. and Meng, G. (2010a) 'Statistically planned and individually improved predictive maintenance management for continuously monitored degrading systems', *IEEE Transactions on Reliability*, Vol. 59, No. 4, pp.744–753.

You, M.Y., Li, H. and Meng, G. (2011) 'Control-limit preventive maintenance policies for components subject to imperfect preventive maintenance and variable operational conditions', *Reliability Engineering and System Safety*, Vol. 96, No. 5, pp.590–598.

You, M.Y., Li, L., Meng, G. and Ni, J. (2010b) 'Cost-effective updated sequential predictive maintenance policy for continuously monitored degrading systems', *IEEE Transactions on Automation Science and Engineering*, Vol. 7, No. 2, pp.257–265.

Younus, A.M. and Yang, B.S. (2012) 'Intelligent fault diagnosis of rotating machinery using infrared thermal image', *Expert Systems with Applications*, Vol. 39, No. 2, pp.2082–2091.

Yue, D. and Cao, J. (2001) 'Some results on successive failure times of a system with minimal instantaneous repairs', *Operations Research Letters*, Vol. 29, No. 4, pp.193–197.

Zhao, Y.X. (2003) 'On preventive maintenance policy of a critical reliability level for system subject to degradation', *Reliability Engineering and System Safety*, Vol. 79, No. 3, pp.301–308.

Zhao, Z., Wang, F.L., Jia, M. and Wang, S. (2010) 'Predictive maintenance policy based on process data', *Chemometrics and Intelligent Laboratory Systems*, Vol. 103, No. 2, pp.137–143.

Zheng, J. (2009) 'Predicting software reliability with neural network ensembles', *Expert Systems with Applications*', Vol. 36, No. 2, pp.2116–2122.

Zhou, X., Xi, L. and Lee, J. (2007) 'Reliability-centered predictive maintenance scheduling for a continuously monitored system subject to degradation', *Reliability Engineering and System Safety,* Vol. 92, No. 4, pp.530–534.

Notations

$W(T)$ = Failure rate (ROCOF)	f_t = Total number of failure used in the analysis
β = Parameter of NHPP model	λ = Parameter of NHPP model
$R(T)$ = Reliability function	α = Parameter of NHPP model
$N(t)$ = Random variable of special interest	$N(T)$ = Number of failures in (0, T)
n = Number of observed failures	MTBF = Mean time between failures
SST = Total sum of squares	R^2 = Coefficient of determination
SSE = Error sum of squares component	SSR = Regression sum of squares
C_l = Cost of labour	W_{Th} = Threshold failure rate of critical
Tw=Total operating time per day function	T_l = Labour hours employed
α_i = Failure mode ratio	β_i = Conditional probability of loss of
C_o = Cost of critical component	λ_{pi} = Part failure rate
C_d = Downtime cost per hour	T_d = Total downtime
C = Overall maintenance cost classification	C_m = Other costs
f_i = Number of failure of component i for a particular failure mode	f_s = Probability value of severity