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Influence of imperfect prognostics on maintenance decisions

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Abstract: A comprehensive framework (from real-time prognostics to maintenance decisions) studying the influence of the imperfect prognostics information on maintenance decision is an underexplored area. Thus, we bridge the gap and propose a new comprehensive maintenance support system. First, a new sensor-based prognostics module was modelled employing the Weibull time-to-event recurrent neural network. In which, the prognostics competence was enhanced by predicting the parameters of failure distribution despite a single time-to-failure. In conjunction, new predictive maintenance (PdM) planning model was framed through a tradeoff between corrective maintenance and lost remaining life due to PdM. This optimises the time for maintenance via all gathered operational and maintenance cost parameters from the historical data. Its performance is highlighted with a case study on maintenance planning of cutting tools within a manufacturing facility. We provide systematic sensitivity analysis and discuss the impact of the imperfect prognostics information on maintenance decisions. Results show that uncertainty, regarding prediction, drops as time goes on; and as the uncertainty drops, the maintenance timing gets closer to the remaining useful life. This is expected as the risk of making the wrong decision decreases.

Keywords: *Prognostics, Predictive Replacement, Maintenance Planning, Recurrent Neural Network*

1. Introduction

Much of maintenance today is either corrective (replacing asset after it fails) or preventive (assuming a certain level of degradation, with no input from the asset itself, and maintaining asset on a fixed schedule whether required or not). Both situations are exceedingly inefficient. Thus, predictive maintenance (forecasting the asset remaining useful life and attaining maintenance decisions) gotten huge consideration in the literature throughout the most recent decade [1]. For instance, a novel integrated diagnostics and prognostics system using support vector machine was presented in [2]. In [3], many approaches to remaining useful life (RUL) assessment using physics and data-driven based methods are reviewed. It is observed that available approaches just spotlight on the prognostics step and don't think about the maintenance decisions, which are addressed independently. For instance, [4, 5] dealt to the post-prognostics issue but with assumption that the prognostics data of the asset is available. Nonetheless, both of the groups don’t give an extensive system (from real-time prognostics to maintenance decisions) researching the effect of the imperfect prognostics on maintenance decision. Consequently, this work put forward a new comprehensive maintenance support system.

First, a sensor-based real-time prognostics module is formulated employing Weibull time-to-event recurrent neural network (WTTE-RNN). It is innovatively modelled to project a detailed picture of the asset’s reliability via predicting a probability of failure distribution, in contrast to predicting time-to-failure. This is coupled with new predictive maintenance (PdM) planning model. Which, resourcefully creates a tradeoff between corrective maintenance (CM) cost and PdM cost. Facilitating the determination of the optimal time for maintenance that minimises the overall system maintenance cost. Also, we analysed how imperfect prognostic information influences maintenance decisions. Critical insights are underlined viz. uncertainty regarding prediction drops as time goes on; as the uncertainty drops, the maintenance timing gets closer to the RUL since the risk of making a wrong decision decreases. Based on this analysis, guidelines are offered for a manager that helps improve his chances of making the right maintenance decisions. This study acts as a proof of concept, showing the importance of utilising prognostics information in maintenance planning.

The novel contribution of this paper is in the conceptualisation of a comprehensive maintenance support system; satisfying the vital necessities: a) the real-time prognostics approach that can be extensively realized for several systems; b) the flexible maintenance decision model evaluating rapidly different operational and maintenance costs; c) considering the implications of imperfect prognostics on maintenance decisions to find the right moment for performing maintenance activities. Having such a comprehensive system, the supervisor can design the maintenance exercises all the more viably to diminish machine downtimes and improve the production stream. The added contribution lies in results. Performance of the framework is proven via a case study from a manufacturing environment and complimented with a systematic sensitivity analysis.

2. Methodology

2.1. Prognostics Module

In the recent technical literature, a large variety of prognostic applications estimating the time-to-failure have been reported [6]. In contrast to predicting time-to-failure, predicting probability distribution projects a detailed picture of the asset's reliability. Hence, in this paper, a new sensor-based real-time prognostics module is built employing the WTTE-RNN. Herein, we combine the survival theory with recurrent neural networks [7] to work out multivariate time-to-event estimation problem. For fulfilment, the relevant mathematics is given. One can refer [8] for more inside information. Herein, a log-likelihood loss function is offered that eases up training a RNN to predict the two governing parameters (shape parameter (θ) and scale parameter (η)) of a Weibull probability distribution of the time-to-failure. The prognostics module take a vector of sensor values as an input; representing the asset's current health condition at a given time, based on which the recurrent neural network (RNN) estimates (θ, η). The log-likelihood loss function to be maximized by the RNN is:

$$log(L) = \sum_{n=1}^{N} \sum_{t=0}^{T_n} log[\, Pr(\, Y_t^n = y_t^n | \, x_{o:t}^n)] \quad (1)$$

The prognostics module tries to maximise the probability of estimated time-to-failure (Y_t^n) being equivalent to the actual time-to-failure (y_t^n) for a available vector of sensor features (x). The summations ($\sum_{n=1}^{N} \sum_{t=0}^{Tn}.$) are made over every trajectories (N) and over every time-steps for every trajectory (T_n). The probabilities appearing in equation 1 are gotten via survival analysis. For a discrete event (failure) case, and where the time-to-failure follows Weibull distribution, the loss function can be shown as:

$$log(L_d) = \sum_{n=1}^{N} \sum_{t=0}^{T_n} \left(log \left\{ exp \left[\left(\frac{y_t^n + 1}{\eta_t^n} \right)^{\theta_t^n} - \left(\frac{y_t^n}{\eta_t^n} \right)^{\theta_t^n} \right] - 1 \right\} - \left(\frac{y_t^n + 1}{\eta_t^n} \right)^{\theta_t^n} \right) \quad (2)$$

where η_t^n and θ_t^n are the scale and shape parameters of the Weibull distribution respectively, and y_t^n is the time-to-failure at every time step t and trajectory n. In summary, the RNN tries to find the weights so that the $log(L_d)$ described in equation 2 is maximized. The output (failure probability distribution) of the prognostics module is coupled with PdM planning model.

2.2. Predictive Maintenance Planning Model

We consider an industrial facility; comprising of a single asset system with time-to-failure complying Weibull distribution. In this, failure is viewed as asset degradation (F_{AD}) because of wear and tear. It is assumed that whenever failure is observed, corrective replacement (CR) is carried out, leading to a CR cost. The unexpected failure of the asset due to degradation can increase the risk and safety hazards. Accordingly, predictive replacement (PdR) of the asset is actioned to bring down the probability of asset failure and reduce the risk of an unexpected failure. However, PdR brings additional time and funds. Therefore, PdR optimization is executed to trade-off the failure and PdR cost. To exhibit the benefits of PdM, a cost model is developed via capturing the various costs pertaining to the industrial operation; which are governed via failures and PdM planning. The economic objective is to minimize the expected total cost per unit time of carrying out predictive maintenance ($[ETC]_{(PdM)}$) by choosing the optimal time for PdR (O_{PdR}). Herein, $[ETC]_{(PdM)}$ is the proportion of the addition of the expected total cost of carrying CR due to asset degradation ($E[(C_{CR})_{F_{AD}}]$) and PdR ($E[C_{PdR}]$) to the planning period/evaluation time (E_T) for which the analysis is done. It is written as follows:

$$[ETC]_{(PdM)} = (E[(C_{CR})_{F_{AD}}] + E[C_{PdR}])/E_T \quad (3)$$

Theoretic and numerical models of constitutional costs in $[ETC]_{(PdM)}$ are detailed in following sub-sections.

2.1.1. Corrective Replacement Cost

Assuming the system is stopped during the replacement. Taking $(C_{CR})_{F_{AD}}$as the cost of corrective replacement due to asset degradation letting in the downtime cost. Consequently, the expected cost of carrying corrective replacement owing to asset degradation ($E[(C_{CR})_{F_{AD}}]$) is taken as:

$$E[(C_{CR})_{F_{AD}}] = \{A_{CR} \times [P_r \times C_{lp} + C_L] + C_{FCR}\} \times F(E_T)_{\theta,\eta} \quad (4)$$

where, $A_{CR} \times [P_r \times C_{lp} + C_L]$ is the downtime cost owing to CR, A_{CR} is mean time to perform the corrective replacement (hours), P_r is the production rate (products/hours), C_{lp} is the cost of lost production (GBP), C_L is the cost of the labour (GBP/hours), C_{FCR} is a fixed cost of corrective replacement (letting in the cost of asset replacement) and $F(E_T)_{\theta,\eta}$ is the cumulative probability of failure owing to asset degradation for a given evaluation time as a function of given shape (θ) and scale (η) parameter.

2.1.2. Predictive Replacement Cost

In general, the cost per PdR of the asset is modelled to let in the downtime cost due to a replacement, labour, and asset cost. The replaced asset always has some useful remaining life; usually not looked at in PdR cost [9]. An comprehensive model, considering the effect of lost remaining life in overall PdR cost, will be increasingly critical. Therefore, in our model, the effect of asset lost remaining life is also modelled in PdR cost. This will prompt optimum utilization of the asset life. RUL is the residual life of the asset after a certain time. Here, the proposed model captures the real-time RUL information of the asset with the help of failure probability distribution acquired as an output from the prognostics module. Moreover, we take the cost of lost remaining life ($CLRUL_i$) relative to mean life cost. It is assumed that the asset cost is uniformly distributed over the lifetime of the asset [10]; the $CLRUL_i$ is given as:

$$CLRUL_i = (C_A/A_L) \times \eta_i \Gamma(1 + \frac{1}{\theta_i}) \tag{5}$$

where C_A is the cost of the asset (GBP), A_L is the mean life of the asset (hours).

The function $\eta_i \Gamma(1 + \frac{1}{\theta_i})$ gives the RUL of the asset in hours at a given point of time. Therefore, the total cost per predictive replacement is given as:

$$E\left[C_{PdR}\right] = \{A_{PdR} \times \left[P_r \times C_{lp} + C_L\right] + C_{FPdR} + CLRUL_i\} \tag{6}$$

where $A_{PdR} \times \left[P_r \times C_{lp} + C_L\right]$ is the downtime cost owing to PdR, A_{PdR} is mean time to perform predictive replacement (hours), C_{FPdR} is a fixed cost of predictive replacement (GBP) (letting in the cost of asset replacement).

For assessing the optimal time for predictive replacement (O_{PdR}), a balance is created between the cost of the lost remaining life of the asset with maintenance and failure costs. The addition of both the costs; $[ETC]_{(PdM)}$ is calculated for each time step of the operation to be made by the asset, and corresponding to minimum cost; optimal predictive replacement cost along with the optimal time for predictive replacement is obtained.

3. Real Life Case Study

In this section, the proposed methodology is verified on the cutting tool degradation data set from reliability and prognostics repository; provided by Industrial and Systems Engineering, IIT Indore, India. This data set is generated for the prognostics and health management studies [11]. This is yielded by a testing platform furnished with a CNC milling machine and sensors viz. dynamometer, etc. The primary objective was to provide real-life historical data at different operating conditions for a population of identical cutting tools with cutting force sensor data that characterise the degradation of tools along with their entire operational life. In the present study, the data considered comprises of six identical cutting tools operated at a fixed operating condition. Herein, cutting force signal in feed direction is measured for every 0.07 hours' of operation for each tool until complete failure. As the pre-processing step, a total of six statistical features like average cutting force, summary statistics organised by the group, root mean squared value, signal power, and maximum force level are extracted from cutting force signals for every time steps (0.07 hours') to represent the degradation of the tools.

3.1. Performance Assessment of the Prognostics Module

An exhaustive performance investigation of the prognostics module is executed to distinguish the robustness and applicability in a real industrial environment. Consequently, we divided the data into two subsets: training data (4 tools) and testing data (2 tools). All four trajectories in training data correspond to the same failure type (Breakage) and operating conditions. The trajectories are all of the different lengths and comprise the same number of sensor features. Moreover, the noise associated with the sensor values are random and can be filtered using a moving average. Therefore, the trajectories are cleaned (rolling average with window size 10), and the values are normalised. Finally, we get a training dataset of 4 run-to-failures with six features corresponding to each time step.

We demonstrate training WTTE-RNN, with one long short-term memory (LSTM) layer. The architecture for the RNN is 15*10*20*10*5 with the 15 neuron layer being the LSTM layer. Two sets of experiments (for two assets from testing data; test ID I and II) were performed to analyse the performance. This is evaluated by plotting each output performance of the prognostics module, as appeared in Fig. 1 and 2. The perception from this figure shows that each actual and predicted RUL are near to one another. Showcasing that the prognostics module is robust in prognosticating the RUL of the asset. To further compare and gauge the performance, mean absolute error (MAE) is computed. In this, MAE measures how the module makes close RUL predictions to the actual RUL. The MAE value of 1.14 and 0.41 from prognostics module displays predicted RUL is close to the actual RUL, demonstrating the applicability of the module in a real-life. This guarantee of a proficient predictive maintenance framework dependent on a timely cautioning of upcoming failures.

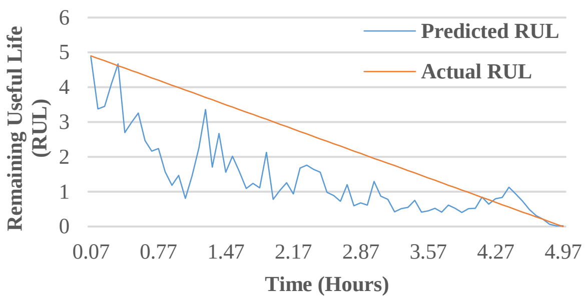


Fig. 1. Results for test ID I

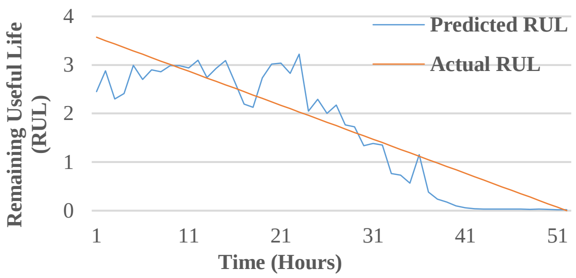


Fig. 2. Results for test ID II

3.2. Predictive Maintenance Framework

We consider a production facility representing of the cutting tool as a single component machine producing mild steel plates. All gathered operational cost parameters from the historical data are mentioned in Table 1. The cost of the cutting tool (C_A) utilized in the process is 3000 GBP. The mean life of the tool is computed by historical failure data, and given as 3.90 hours. As per maintenance history, the mean time to carry out corrective (A_{CR}) and predictive (A_{PdR}) replacement tasks are 0.6 hours respectively. The fixed cost of corrective (C_{FCR}) and predictive (C_{FPdR}) replacement is 3000 GBP separately.

Parameter	Production rate P_r (Product/h)	Cost of lost production C_{lp} (GBP/product)	Cost of the labour C_L (GBP/h)
Value	8	60	100

Table 1. Parameters utilised in the case study

3.2.1. Implications of Imperfect Prognostics Information on Maintenance Decisions

To analyse the implications of imperfect prognostics information on maintenance decisions, we evaluate the $[ETC]_{(PdM)}$ at every 10th time step of the test assets. Herein, for each test asset ID; we run the prognostics module at a different time step ($T_1, T_2 \ldots T_n$) and predict the probability distribution (θ and η) and estimate the variance. These parameters (θ and η) are feed to the predictive maintenance planning model to obtain the optimal time for predictive replacement (O_{PdR}). Table 2 presents the detailed results for both the test assets.

The variance of the distribution give details about the uncertainty in prediction (higher variance means higher prediction uncertainty). At the initial stage of the operation when there is very less information about the health condition of the asset, the variance will be higher; implying higher uncertainty in prediction. Though, as time goes on, and we have more information about the asset health, the variance will reduce; implying lower uncertainty in prediction. In that line, figure 3 shows the probability density function (PDF) for test asset ID I at first and second time steps. It can be observed that at T_1, the PDF is very wide, with the variance being 1.90. This is because the predicted θ and η at time step T_1 having high uncertainty. As it's the first point of prediction and there is lack of information in terms of asset condition. However, as time goes on and we obtain more information about asset condition, the uncertainty in predicted θ and η gets reduced. It is evident as the PDF at T_2 gets squeezed; with 80.53% lesser variance than time step T_1; displaying the uncertainty drop. This become further clearer from figure 4 and 5; which shows the PDF for all time steps for test asset ID I and II. This implies that the uncertainty regarding prediction, drops as time goes on. On the other hand, figure 6 and 7 shows the predicted RUL and optimal time for replacement (O_{PdR}). It can be observed that at time step T_1 the optimal time for PdR is far from the predicted RUL. Though, at time step T_5 the optimal time for PdR is very close to the predicted RUL. This is again because of the uncertainty drop in the prediction. This implies that as the uncertainty drops the maintenance timing gets closer to the remaining useful life; since the risk of making a wrong decision decreases. Accordingly, the guideline for operational planner from this is to not to stick to the initial optimal maintenance plan but dynamically update the predictive maintenance plan as time goes on. So as to make the maintenance decision at the right time.

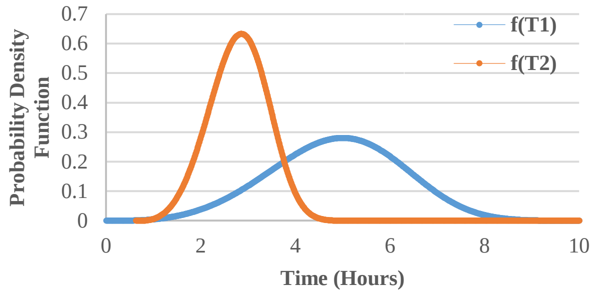


Fig. 3. PDF plot at T_1 and T_2 for ID I

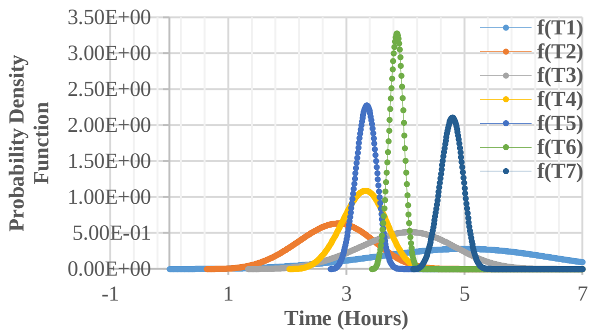


Fig. 4. PDF plot for T_1 to T_7 for ID I

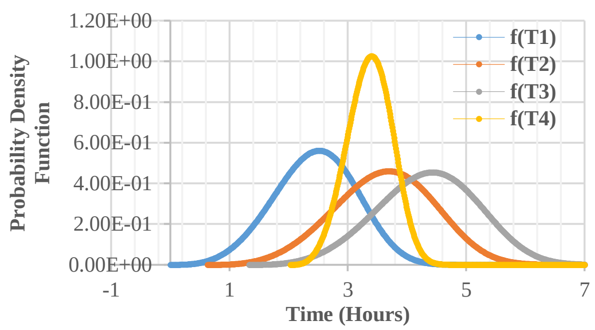


Fig. 5. PDF plot for T_1 to T_4 for ID II

3.2.2. Sensitivity Analysis

In exercise, the approximation of appropriate process and cost parameters subject to inaccuracies. So, it is vital to distinguish the influence of errors on the quality of the output attained. Accordingly, a systematic sensitivity analysis utilising essential model parameters is carried out, see table 3. The base level utilised is same as in the case study, and four other levels of these parameters at ± 10 and ± 20% of the base value. The range of the optimal parameter and obtained cost are presented in table 3 and 4. Fig. 8 shows that $[ETC]_{(PdM)}$ is more sensitive to the fixed cost of predictive replacement; and less susceptible to the mean time to perform predictive replacement, etc. Thus, the estimation of the fixed cost of a predictive replacement should be done accurately.

	Time (T_i) h	Predicted $\boldsymbol{\eta}$ (h)	Predicted $\boldsymbol{\theta}$	Variance	RUL (h)	Optimal time for replacement O_{PdR} (h)
Test Asset ID I	$T_1 = 0.07$	5.38	3.96	1.90	4.87	4.08
	$T_2 = 0.70$	2.40	3.98	0.37	2.17	1.36
	$T_3 = 1.40$	2.95	3.98	0.57	2.67	1.65
	$T_4 = 2.10$	1.39	3.97	0.13	1.26	0.41
	$T_5 = 2.80$	0.66	3.95	0.03	0.60	0.17
	$T_6 = 3.50$	0.46	3.93	0.01	0.41	0.15
	$T_7 = 4.20$	0.72	3.96	0.03	0.65	0.17
	$T_8 = 4.90$	0.02	1.65	0.00	0.02	0
Test Asset ID II	$T_1 = 0.07$	2.70	3.98	0.48	2.45	1.72
	$T_2 = 0.70$	3.29	3.98	0.71	2.98	2.04
	$T_3 = 1.40$	3.33	3.98	0.73	3.02	2.04
	$T_4 = 2.10$	1.48	3.97	0.14	1.34	0.63
	$T_5 = 2.80$	0.11	3.50	0.00	0.10	0.01
	$T_6 = 3.50$	0.03	1.97	0.00	0.02	0

Table 2. Implementation results for both test assets

Parameter	Base Level	-20%	-10%	+10%	+20%	Expected total cost per unit time of carrying out predictive maintenance ($[ETC]_{(PdM)}$)					Range
						Base Level	-20%	-10%	+10%	+20%	
A_{PdR}	0.6	0.48	0.54	0.66	0.72	1008.86	994.57	1001.71	1016.00	1023.52	994.57-1023.52
C_{lp}	60	48	54	66	72	1008.86	993.69	1001.28	1016.38	1023.90	993.69-1023.90
C_L	100	80	90	110	120	1008.86	1005.73	1007.28	1010.42	1011.99	1005.73-1011.99
C_{FPdR}	3000	2400	2700	3300	3600	1008.86	885.64	947.25	1070.46	1132.06	885.64-1132.06
C_A	3000	2400	2700	3300	3600	1008.86	975.52	994.91	1020.00	1026.06	975.52-1026.06
A_{CR}	0.6	0.48	0.54	0.66	0.72	1008.86	1004.87	1006.89	1010.85	1012.76	1004.87-1012.76
C_{FCR}	3000	2400	2700	3300	3600	1008.86	965.61	990.01	1024.54	1038.05	965.61-1038.05

Table 3. Systematic sensitivity analysis

Design Parameter	Optimal Time for Replacement O_{PdR} *(h)*
Range	3.59-4.86

Table 4. Range of optimal design parameter acquired through sensitivity analysis

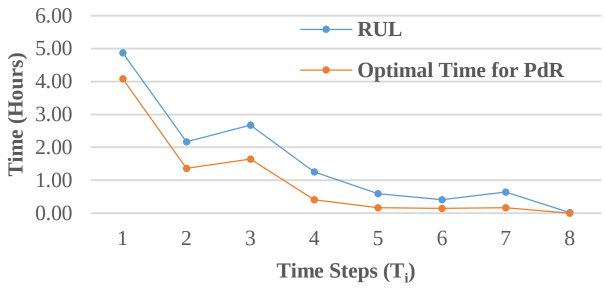


Fig. 6. RUL Vs optimal time for PdR for T_1 to T_8 for ID I

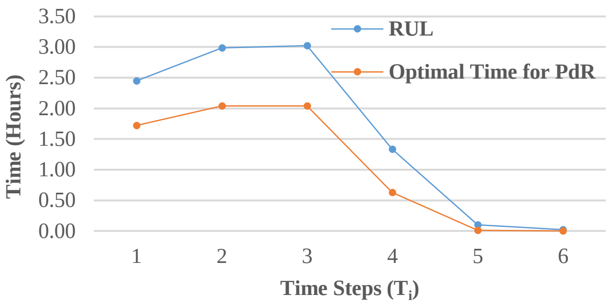
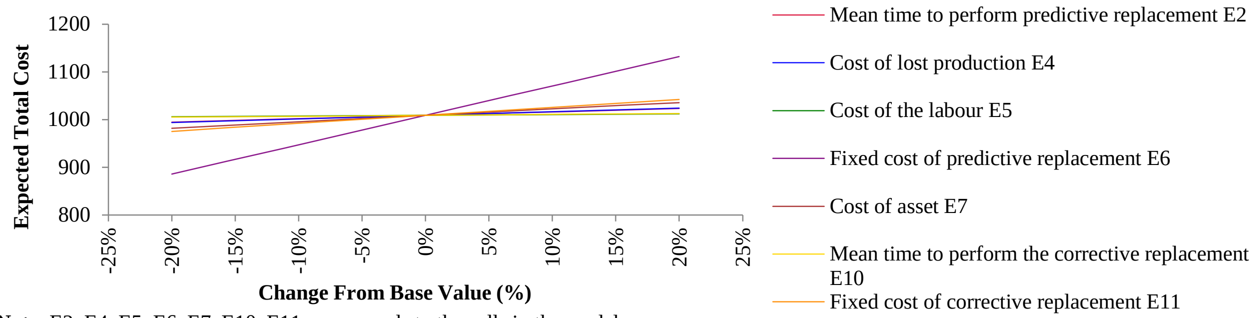


Fig. 7. RUL Vs optimal time for PdR for T_1 to T_6 for ID II



Note: E2, E4, E5, E6, E7, E10, E11 corresponds to the cells in the model.

Fig. 8. Expected total cost Vs percentage change of the model parameters

Conclusion

This paper formulates, a comprehensive framework from real-time prognostics to maintenance decisions. The intention was to render manufactures with a complete maintenance support system to instantaneously prevent asset performance degradation and unexpected failures. The key offerings of this paper are underlined here after:

a) For the prognostics phase, a new sensor-based prognostics module was modelled employing the WTTE-RNN. In which, the prognostics competence was enhanced by predicting the parameters of failure distribution despite a single time-to-failure, and therefore, the offered approach delivers a superior response to real-world requirements.

b) For the post-prognostics phase, a new predictive maintenance planning model was framed through a trade-off between corrective maintenance and lost remaining life due to predictive maintenance. Allowing rapid optimisation of time for maintenance via all gathered operational and maintenance cost parameters.

c) Its performance is highlighted via a case study from a manufacturing environment; complimented with systematic sensitivity analysis. The influence of the imperfect prognostics information on maintenance decisions is debated. Showcasing interesting insights viz. the uncertainty regarding prediction drops as time goes on; and as the uncertainty drops the maintenance timing gets closer to the remaining useful life; since the risk of making a wrong decision decreases.

In essence, it is an entire cognitive operation from carrying out the prognostics to making maintenance decisions. Such complete models integrating monitoring characteristics, prognostics, and maintenance assessment can give rise to fruitful discussions.

Acknowledgement

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