Smart Warning System for The Rotating Parts Based on Cloud Computing

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Abstract

New Smart Warning System (SWS) that use to send a warning level report about the machine components failure behavior via distance is proposed in this article. The data were collected from the experimental setup to enhance the maintenance strategies. The new warning system uses the collected data to build a Probability Hazard Model (PHM) that computes the warning level to give the decision- making team the advice about component replacement. The proposed system uses cloud computing technology to connect between the physical world and the remote main hub of SWS which receives the monitored signal to compute the warning level and warning level of the machine element. In this article, a novel SWS is built to reach the near-zero breaks down. Also, the system sends a warning alarm through E-mail to the decision-making team to follow the failure behavior of the monitored parts. In this article, the run to failure data of 8 identical belts is collected from an experimental setup that simulates the operation condition in the real factory. The proposed system gives the industrial processes the time to complete the required tasks with near-zero breaks down. This paper presents a simulation of a new smart monitoring system by using a new methodology in the context of Industry 4.0. Section building the SWS illustrates the schematics of the proposed system. Finally, current and future smart monitoring systems in Industry 4.0 are discussed.

Keywords
Smart Warning system, Proportional Hazard Model (PHM), CPS, and Industry 4.0.

1. Introduction

The prediction of when we need to make replacement action of machine parts to prevent sudden failure is nowadays showing a tremendous growth of interest within the new paradigm of Industry 4.0 (I 4.0). The maintenance costs constrain 60% to 70% of the total cost of the product lifecycle Dhillon (2006) and Venkataraman (2010). In the ordinary factory, the maintenance strategy depends on the experience of the operation team. Otherwise, the determination of the warning level becomes the main role of the maintenance team in the new smart factory. The statistical model generation is discussed in several articles and books which including Vlok et al. (2002) and Kalbfleisch and Prentice (2011). Mikhail et al. (2019) present an optimization model that depends on the machine learning field to find the optimal maintenance strategies which achieve the minimum downtime and allow the system to make autonomous decisions. El Houda et al. (2021) offers a new methodology based on risk analysis to select a better maintenance strategy to enhance the productivity, reduce of maintenance cost and improve the environmental protection.

In this article, we build a smart warning system to calculate and send the warning level to the decision-making teams to avoid the sudden shutdown of the rotating machine. Indeed, the new smart factories are built upon Cyber-Physical System (CPS) design in five levels (Lee et al.2015). The highest level of the CPS is self-configure for resilience and self-adjust for operation variation. Also, the prediction of the machine behavior is a major characteristic of the new manufacturing system built based on I 4.0 (Napoleone et al. 2020).

Based on the former literature survey, the originality of this paper arises from its aim to build an SWS based on cloud computing to predict the warning level of the monitored machine part. The proposed system builds by novel steps as shown in figure (1). The first step to build the proposed SWS is building an experimental setup to collect the run to failure data of the machine part in the normal operation condition, and then we transfer the collected vibration data to statistical features use to build the PHM. After that, we use the generated PHM to build the SWS that sends the warning level of the monitored part to the local operation team to allow the machine to complete its job with near-zero breaks down. This system uses to enhance the maintenance decision-making system. Also, the combining of survival modeling and Cloud computing brings the maintenance to the new age of industry which name I 4.0.

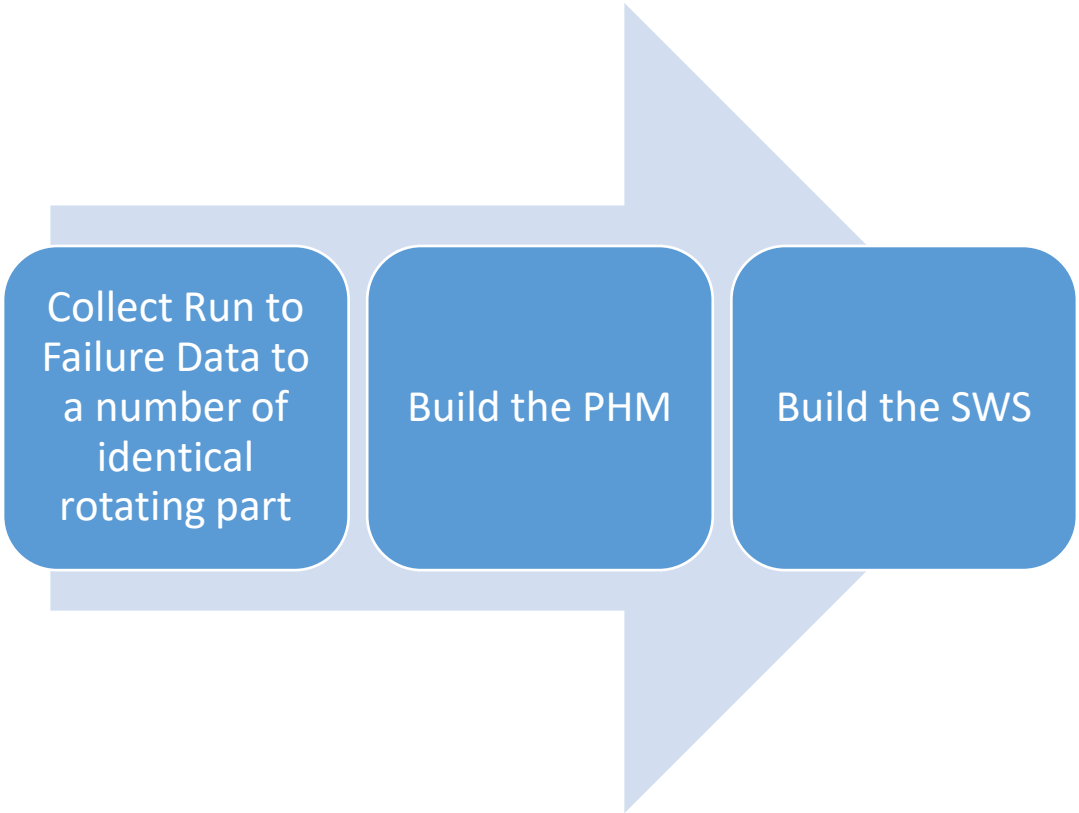


Figure (1) Steps to Build SWS

In the following section, the proposed Methodology of the SWS is introduced, while in section 3 the SWS architecture is proposed, whereas in section 5 the case study is presented. Finally, the discussion and conclusion of this article are exhibited.

2. Methodology

The proposed methodology to build the SWS adjustor to achieve near-zero breaks down. The first step in our study is to collect the Run to Failure data of a mechanical part. The monitored data is a vibration signal. In the following section, the analysis and feature extraction of data is presented. Three forms can be used to illustrate the vibration signal: time, frequency, and time-frequency domains respectively. Those forms can be used to diagnosis the failure states in the rotating system. However, in the three forms, there are a lot of hidden data that can be extracted to improve the accuracy of the diagnosis technique. The advantages of the hidden data extraction techniques and the disadvantages are studied in [Mortada et al. (2011) and Lakis (2007)]

After acquiring the vibration signals for operation conditions, a wide set of features is calculated from the vibration signals using statistics. The features used in our analysis are range; mean, standard divination, skewness, kurtosis, root mean square and crest factor features are illustrated in the table (1).

Table (1) Vibration signal feature formula:

Feature Name	Formula
Range	$Range = Max(y_i) - Min(y_i)$
Mean Value	$Mean = \frac{\sum_{i=1}^{N} y_i}{N}$
Standard Divination	$STDE = \sqrt{\frac{\sum (y_i - \bar{y})^2}{(N-1)}}$
Skewness	$Sk = \frac{n}{(n-1)(n-2)} \sum \left(\frac{y_i - \bar{y}}{STDED} \right)^3$
Kurtosis	$Ku = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{y_i - \bar{y}}{STDED} \right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)}$
Root Mean Square	$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^2}$
Crest Factor	$CF = \frac{Max(y_i)}{RMS}$

Where n is the sample size and s is the standard deviation. After extract the data from the collected vibration signal the second step is to build PHM. A run to failure experimental setup of the monitored machine part is defined as a test used to predict the failure model of a product or material by monitor the behavior of the monitored machine part under the operating condition such as temperate, speed, applied force, and voltage. In our study, the operation condition in our study is speed (v) and tension force (T) to generate the statistical failure model [Nelson (1980) and Viertl (1988)]. By using the experimental run to failure test output data the designers and engineers can make prognostications about the machine part service life and its maintenance intervals [Melnick et al. (2008)]. In a belt- drive, testing may be done at a high rotating speed, high tension force, and high temperature. The generated Cox PHM model is shown in the following equation (1).

$$F_{(t)} = 1 - \mathrm{e}\left\{ -\left(\frac{t}{\eta}\right)^{\beta} e^{r_n Z_n(t)} \right\} \tag{1}$$

Where $F_{(t)}$ is the Failure Probability function, β is the shape parameter; η is the scale parameter, r_n weight of parameter, $Z_{\_n}$ (t) parameter function with time.

Decision Rule

In this section we present the important question in maintenance which is "when we need to replace the tool?" [Shaban et al. 2014]. To answer this question, we monitor the component behavior at discrete time interval. The following equation illustrates the optimal stopping rule.

$$T_d^* = \inf\{t \geq 0: Kh(t, Z(t)) \geq d^*\}$$

Where K is the difference between the cost of failure replacement C+K and the preventive replacement cost C.
From this equation we get:

$$Kh(t, Z(t)) \geq d^*$$

$$\left(\frac{\beta}{\eta}\right)\left(\frac{t}{\eta}\right)^{\beta-1} e^{\gamma Z} \geq \frac{d^*}{K}$$

$$e^{\gamma Z} \geq \frac{d^* \eta^{\beta} t^{-(\beta-1)}}{K\beta}$$

$$\gamma Z \geq ln\frac{d^* \eta^{\beta}}{K\beta} - (\beta - 1)\ln t$$

$$Z^c(t) \geq g(t)$$

The function $g(t)$ can be used to illustrate the warning level applied to covariate vale $Z^c(t)$.
After that, we use the generated PHM to predict the failure probability to avoid a sudden breakdown. In the following section, the architecture of the proposed SWS is presented.

SWS Architecture.

The proposed smart warning system is a system that uses the PHM to compute the hazard rate which illustrates in the previous section. The novelty of this article is not only building PHM to predict the behavior of failure of the monitored machine part but also the combining of the generated model and the cloud computing to build a smart system in the context of Industry 4.0. The proposed system has three major layers; the following figure (2) illustrates the layers of the warning system.

(1) Physical Layer: is the real factory consists of (N) of Rotating machine parts with embedded sensors which collect the working data of the parts. This senor has the capability for wireless communication that enables data transfer via the internet to other layers. Also, the decision-making team that receives the warning report to take the necessary action to avoid sudden breaks down.
(2) Transport network: this layer consists of distributed files for each machine part that can be used to enhance the modeling of PHM. Also, this layer connects between the physical world and the remote prediction hub. Also, it has the role of sending the warning report to the local maintenance team.
(3) Remote Prediction Hub: this layer is consisting of the main hub software that analysis and computes the warning level depends on the generated PHM in the previous section.

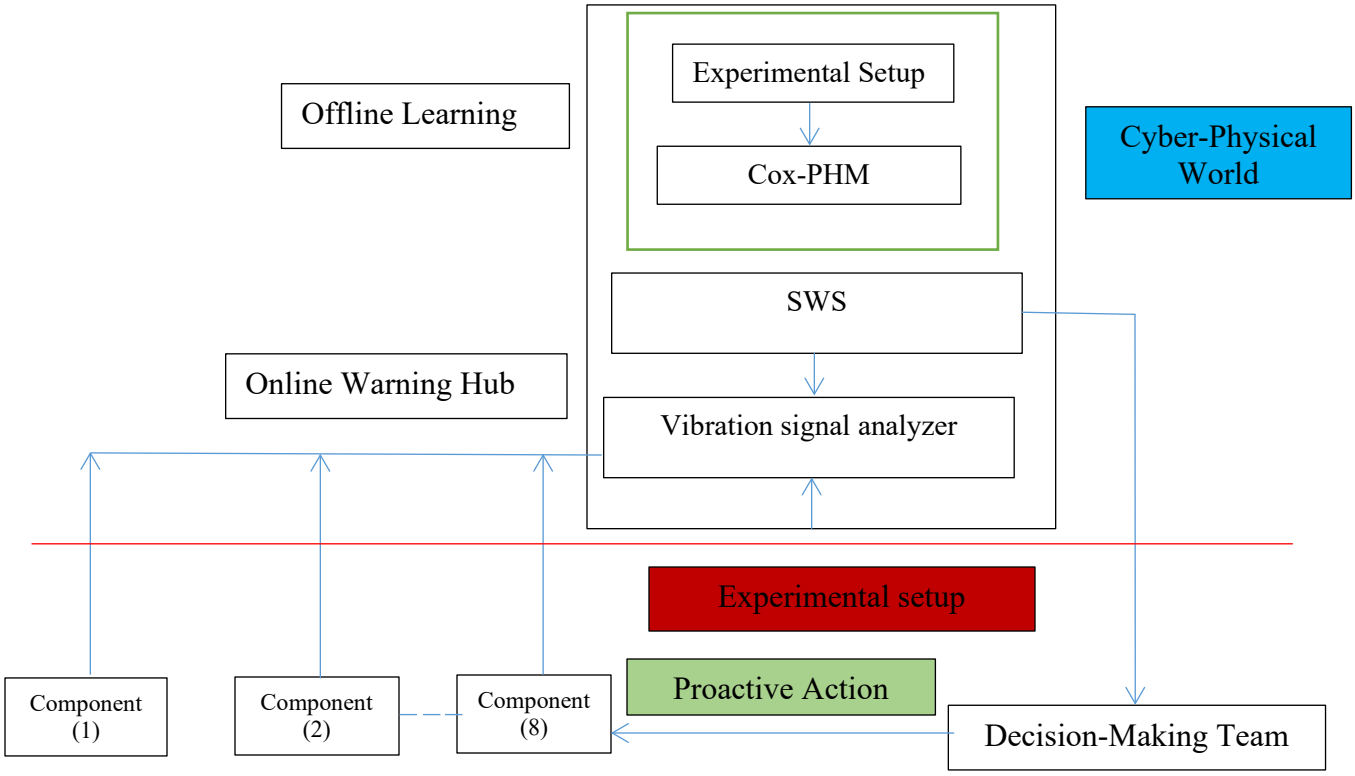


Figure (2) Proposed Smart Warning System Architecture

Based on the proposed SWS architecture present in this section we select a belt drive as a case study. We select the belt drive as it's widely used in the industrial field. The following section explains the experimental setup. We use eight identical belts (n=8) to collect run to failure vibration signal data. The operation condition used in this test rig simulates a real case in the manufacturing process.

Description of the Experimental Work:-

To test the proposed methodology, the following section shows the case study on a V-belt drive and we use an actual controllable variable which is rotating speed (4000 rpm) on the faster pulley and tension force (70 N)and the other pulley speed is 2000 rpm. Figure (3) shows a photo of the G.U.N.T. machinery diagnostic system (PT 500) and analysis setup located in the Vibration and Dynamics Laboratory of the Faculty of Engineering –Mattaria (Helwan University).

Two accelerometers (IMI 603C01) are mounted Via Studs to the belt drive which is used to measure vibration signals in the horizontal and vertical directions. The measurement and analysis setup also includes a G.U.N.T. measuring amplifier, a USB bmcm data acquisition box, and a Laptop for data analysis and archiving. Frist a healthy belt is erect on the belt drive with the selected tension force which is measured by using the device shown in figure (4) are measured and the fault belt is measured.
We measure the run to failure data of (8) identical belts. The technical data of the V-belt drive is as follows.

V-belt Technical data

- Large pulley Diameter = 125 mm
- Small pulley Diameter =63 mm
- Type of Belt = V-belt 9.5 mm Wide *925 mm Length
-

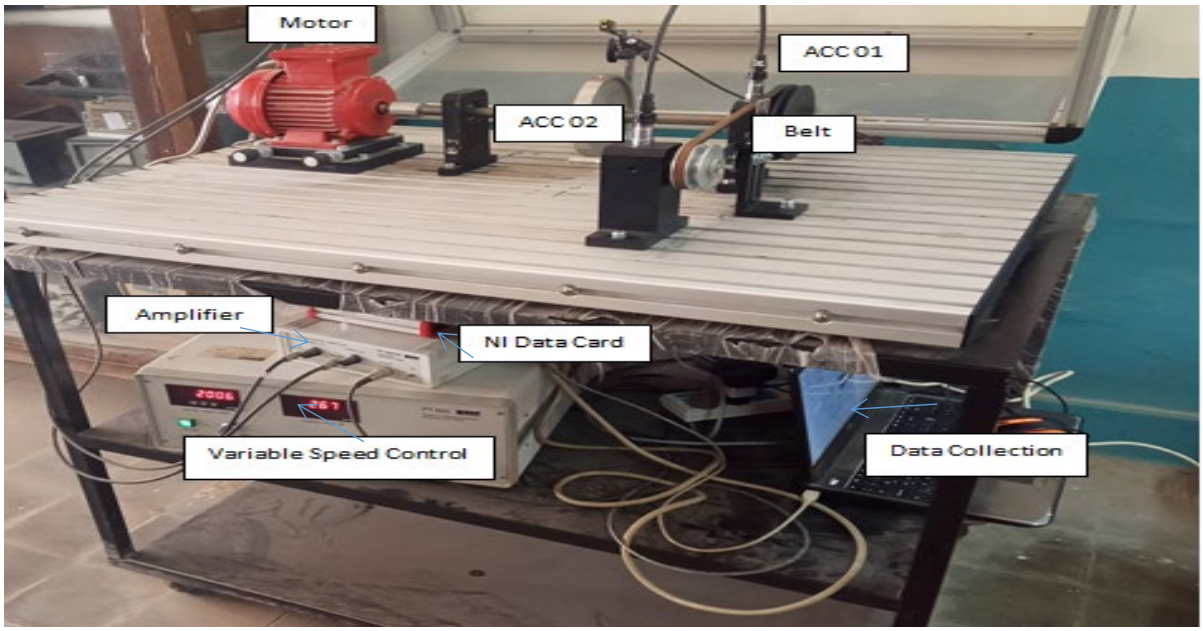


Figure (3) Photo of experiment

Continuous monitoring of belt drive till a failure is accorded. The failure is defined as a crake with a depth of 3 mm in the belt which is shown in figure (5). The continuous monitor vibration signal is saved on the cloud storage drive. In our case study, we use the Dropbox application as a storage hub. The signal is saved every 100 sec in the storage hub. After the crake occurs the file transfer to converter the vibration signal to statistical features to use in the PHM generation. A sample of the statistical feature which is extracted from the collected run to failure data is shown in table (2). Also, the Time to occur the pre-specific failure is presented in table (3) for all eight identical belts.

Figure (4) V-Belt Tension Gauge

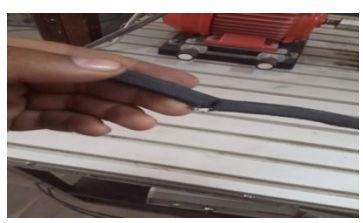


Figure (5) Belt with crake 3mm

Table (2) Start, and end feature extracted for each belt

			Accelerometer 1 Hanging on Large Pulley							Accelerometer 2 Hanging on Small Pulley						
b. no	Time (Sec)	No.	range1	mean1	st1	Skew1	Kurt1	RMS1	Crest Factor1	range2	mean2	st2	Skew2	Kurt2	RMS2	Crest Factor2
1-1	100	1	2.01718	0.0216	0.2204	0.0104	0.046	0.2215	4.04450	4.183906	0.00541	0.36584	-0.096	0.6260	0.3658	3.844499
1-1	11800	118	2.03343	0.0214	0.2496	0.0226	0.091	0.2506	3.7771	4.269688	0.01274	0.40883	-0.098	0.2684	0.4090	3.926719
1-2	100	1	4.67812	0.0161	0.6991	0.0131	0.247	0.6990	3.40517	3.487344	0.01284	0.48701	0.1490	0.0962	0.4869	3.944290
1-2	6000	60	9.03187	0.0172	0.9590	-0.141	0.618	0.9591	3.99141	5.444375	0.00996	0.76656	0.3263	0.3788	0.7665	3.892029
1-3	100	1	2.5725	0.0147	0.2523	0.1077	1.596	0.2525	4.80635	2.465625	0.02389	0.32325	0.0735	0.3841	0.3239	4.130757
1-3	9300	93	2.73218	0.0272	0.264	-0.022	0.721	0.2660	4.21311	4.118125	0.00466	0.42447	-0.121	0.4869	0.4244	4.185659
1-4	100	1	18.2321	0.0018	1.77	-0.085	1.048	1.7714	4.51164	5.821563	0.00180	0.73156	0.0316	0.0363	0.7315	4.033272
1-4	11900	119	18.2003	0.0217	1.8283	-0.008	0.208	1.8284	5.31415	6.559219	0.02101	0.84659	-0.083	0.2555	0.8468	3.623143
1-5	100	1	16.6668	0.0399	2.5586	0.0315	-0.21	2.5588	3.29493	8.461407	0.01278	0.95675	-0.099	0.1015	0.9567	3.934032
1-5	7100	71	20.4590	0.0219	2.0417	-0.001	0.564	2.0417	5.00499	9.175313	0.00703	1.10570	0.0016	0.2956	1.107	4.177591
1-6	100	1	19.3815	0.0166	2.4033	0.0693	0.006	2.4032	4.25211	8.634376	0.01033	0.91965	-0.012	0.2688	0.9196	4.614765
1-6	10600	106	16.2156	0.0104	1.9706	-0.044	0.374	1.9705	4.23296	8.317343	0.02388	0.97509	-0.018	0.2725	0.9753	4.241006
1-7	100	1	19.5228	0.0453	2.6504	0.0467	-0.28	2.6507	3.85519	8.825625	0.00250	1.01482	-0.086	0.2041	1.0147	4.177468
1-7	18700	187	12.4240	0.0462	1.4309	-0.053	1.016	1.4315	4.14138	10.23922	0.00729	1.34932	-0.073	0.1041	1.3492	3.794054
1-8	100	1	18.575	0.0020	3.4544	-0.206	-0.97	3.4543	2.51805	9.548437	0.00911	1.25659	-0.081	0.3416	1.2565	3.648078
1-8	8700	87	14.475	0.0596	1.356	-0.002	0.934	1.3582	4.69893	9.916406	0.01799	1.33049	-0.039	0.1585	1.3305	3.604816

Table (3) Time to Failure Collected Data

Belt No.	TTF (Sec)	Amb. Temp
1	11800	22
2	6000	19
3	9300	17
4	11900	14
5	7100	16
6	10600	18
7	18700	18
8	8700	16

3. Model development

The time to failure of any machine part is a random variable. The degradation of the pre-specific performance of the machine part is a stochastic process that depends on the operating condition (Mazzuchi et al. 1989). In our case study, the operation condition is rotating speed (v rpm) and tension force (T N). The generated Cox PHM model is shown in the following equation. (Yasser et al. 2016).

$$F_{(t)} = 1 - \mathrm{e}\left\{-\left(\frac{t}{\eta}\right)^{\beta} e^{r_n Z_n(t)}\right\}$$

Where **F** $_{(t)}$ is the Hazard function, β is the shape parameter; **η** is the scale parameter, $Z_n(t)$ are the covariates that represent the operating conditions and function with time, and r_n are the coefficients or weight of these covariates. The modeling of rotating part failure by using the Weibull distribution model as a baseline function is explained in (Tail et al.2010), (Mazzuchi and soyer 1989), and (Makis1995). By using **EXAKT** software (Banjevic et al. 2001), we generated the Cox PHM (Tang et al. 2013) model from the generated data as follows. Firstly we use all covariates to find the best significant covariate effect on the failure. In the following table (4) the summary of estimated parameters is shown.

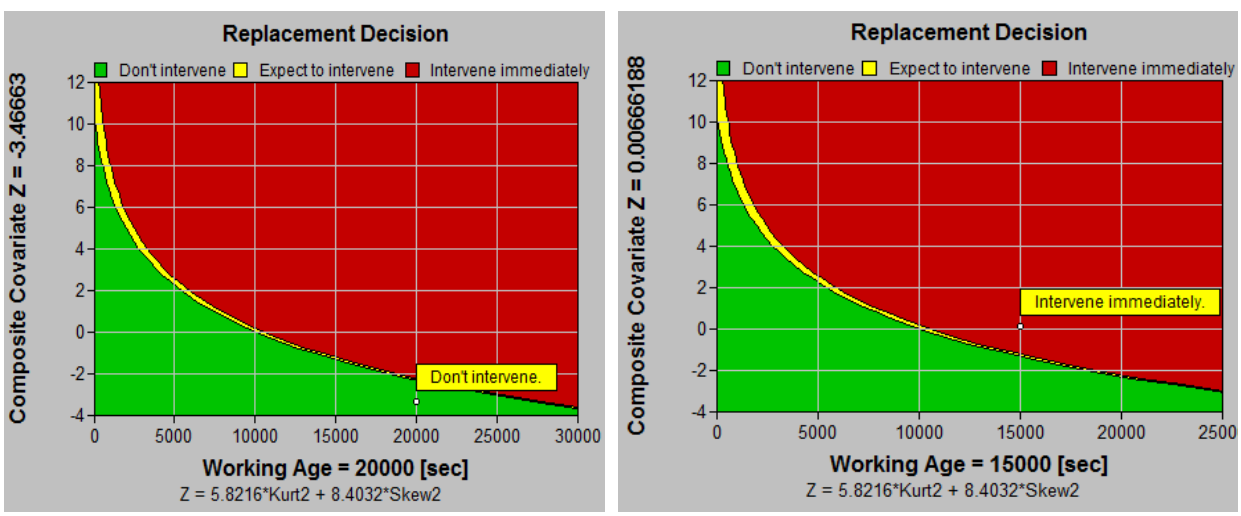
Table (4) summary of the estimated parameters (based on ML method)

Scale	Shape	SKEW2	Kurt2
15151.7	4.45255	8.40321	5.82156

The resulting Probability of Failure function is given as follows.

$$F_{(t)} = 1 - \mathrm{e}\left\{-\left(\frac{t}{15151.7}\right)^{4.45255} e^{8.4Skew2(t)+5.822Kurt2(t)}\right\}$$

In the following figure (6) the optimal replacement age according to the decision rule illustrate in previous section.



(A) (B)

Figure (6) optimal replacement age examples resulting from EXAKT

Figure (6) illustrate two cases in our study in the first case the system send to the decision making team the report and advice not to the replacement action. Also, in case (B) the recommendation is to make the replacement immediately

4. Model Validation

The objective of this section is to present the validation method that uses to validate the use of the PHM in modeling the failure degradation of the rotating part. We use the Kolmogorov-Smirnov test for goodness of fit in the validation of the generated model (Massey et al. 1951). The following Table (5) presents the summary of the goodness of fit test results.

Table (5) Model validation result

Test	Observed Value	p-Value	PHM Fits Data
Kolmogorov-Smirnov	0.21616	0.798582	Not rejected

5. Building the SWS:

The generated PHM uses to compute the failure probability and builds the cyber-physical warning system code. The generated model illustrates the effect of the skewness and kurtosis of the small and fast pulley in the prediction of the warning level and the proactive action of the belt drive. Now, the proposed SWS are presented in figure (7) by using the generated PHM in the previous step.

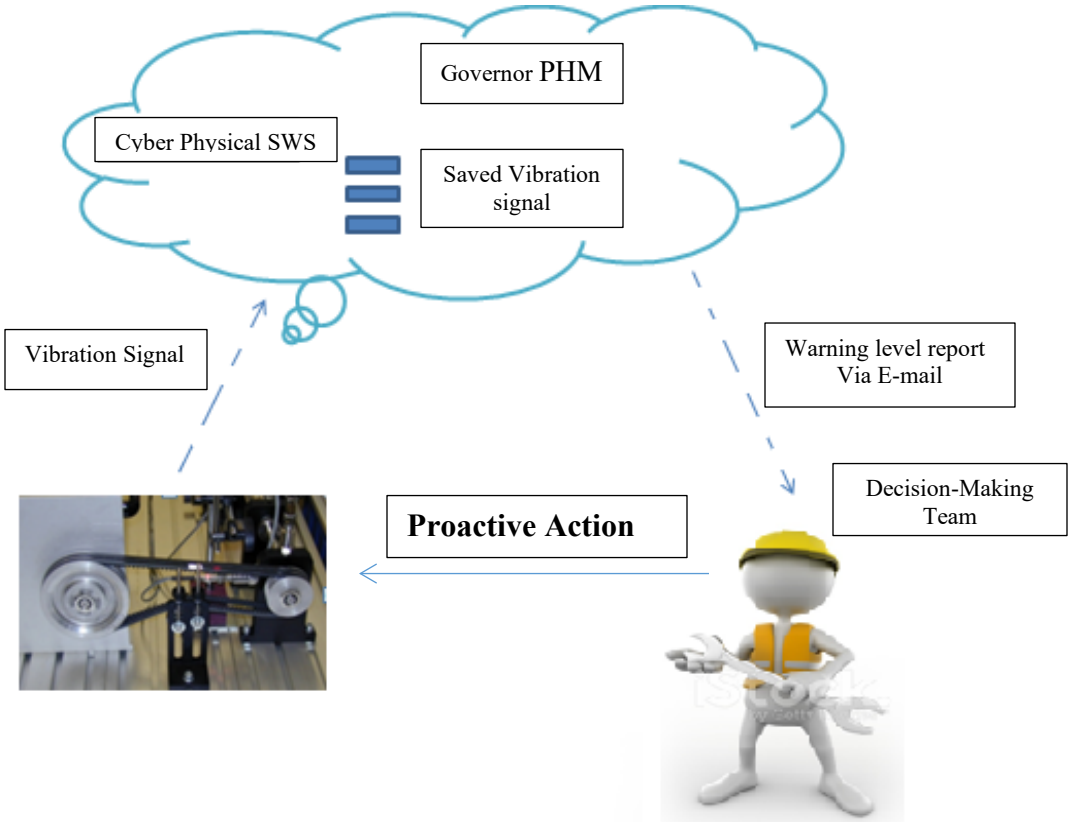


Figure (7) Proposed SWS

The vibration signal is sent from the data set file to the cloud file via the internet in the Dropbox application. It consists of two centers: the physical center, which includes the monitored machines having sensors with the ability to send the generated signal to the virtual world. Also on this side the decision-making team makes the proactive action that avoids the sudden breaks down occurrence. The cyber-physical virtual side, on the other hand, receives the data coming from the physical system converting it to useful information to monitor and control the physical world without the need for a human interface. The system should also be able to allow the local decision-making team to see a live view of the running machine to interact if required. In the displayed case study, the run to failure data set illustrated in the table (2) is used. Additionally, **MATLAB** was used to build the cyber-physical system code.

In our study, part(1) is the belt drive vibration signal data sets that were sent to the Cloud file in the Dropbox application via part (2) as infrastructure as a service (IaaS). That is the gateway used to send and receive the signals and the generated warning level from the cyber-physical center via the internet as an email to the decision-making team to give a clear view about the failure probability of the monitored belt drive. The function of Cloud computing is to be the bridge between the monitored machine part and the cyber-physical SWS and between the SWS and the decision-making team. It supports communication protocols like Wi-Fi or Bluetooth. For this case study, we used a Wi-Fi gateway. The benefits of using this gateway are: high scalability, lower costs, reduced telecommunication cost, and mitigate risks. The built governing code runs every certain time to analyze the received data and compute the warning level of the monitored component. For this case study, the software works every 100 seconds, and the period can be adjusted according to the application. In our case study, the failure probability automatically sends an alarm report by secured E-mail to the decision-making team. The generated decision is sent back to the machine controller via the gateway carrier. The historical data is then stored in the Dropbox file to improve the offline governor patterns generation accuracy. The generated report, which is sent to the decision-making team, is provided with a better understandable failure probability as a result of the proposed methodology. The proposed system limitation, is the dependence on the internet service that make the communication as a heart of the system, the delaying due to data transfer decrease the SWS possibility of the real-time, continuous monitoring of the vibration signal of the rotating machine components that can cause a time delay and data loss due to big data. On a different note, the anti-hacking and security of data technologies are important in the communication field to avoid any unwanted interface. Also, the automatic update of the software by using the stored historical data without an unwanted offline update is an important limitation

6. Conclusion

In this paper, a novel smart warning system is proposed to achieve near-zero breaks down. The proposed system computes the failure probability of the machine part. This work transforms the traditional machine to the I 4.0 age. Our system is based on using the run to failure data of the machine part to build the PHM which is used to predicate the warning level of the part. The warning level calculation saves the machine from running without sudden breaks down.

The wide use of belt drive pushes us to use the proposed methodology to find its governed equation that explains the behavior of its failure model. The proposed methodology is applied on the v-belt drive in G.U.N.T. machinery diagnostic system (PT 500). The study starts with the collect accelerated run to failure of eight belts. After that, we collect the time to failure data used to build the Cox model as shown in the modeling developing section. After that, we use the generated PHM to build the Smart warning system which consists of three layers as shown in the Smart warning system. The proposed SWS simulation is illustrated in the building SWS section. Figure (7) illustrate an example for the SWS results. The SWS gives the operating team a clear view about the failure behavior of the rotating machine parts. Also, the limitation of the proposed system is illustrated.

For future research, we work on enhancing the proposed methodology to work with controllable variables such as rotating speed and tension force. Also, the applying of multi-machine parts monitoring is the future of the proposed methodology. Also, build a prototype of the proposed system will be our task to deal with the real-time complications.

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