Distributed Diagnostics, Prognostics and Maintenance Planning: Realizing Industry 4.0

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Abstract: In this paper, a novel distributed yet integrated approach for diagnostics and prognostics is presented. An experimental study is conducted to validate the performance. Results showed that distributed prognostics give better performance in leaser computational time. Also, the proposed approach helps in making the results of the machine learning techniques comprehensible and more accurate. These results will be handy in arriving at predictive maintenance schedule considering the criticality of the system, the dependency of the components, available maintenance resources and confidence level in the results of the prognostic.

Keywords: Industry 4.0, distributed approach, diagnostic, prognostic, predictive maintenance planning.

1. INTRODUCTION

Use of contemporary technologies for creating intelligent assets on manufacturing shop floor, is being widely explored by researchers for the realization of Industry 4.0. However, managing manufacturing operations of a shop floor, which consists of such advanced and intelligent assets, are still not aptly explored in the literature (Upasani et al. 2017). Maintenance is one such important operations planning aspects of any manufacturing shop floor. Maintenance is crucial in determining the overall efficiency of manufacturing operations as it contributes 3 to 12% in the overall manufacturing costs. The advent of current maintenance technology viz. condition-based maintenance plays an integral part in industry 4.0. It is based on online component monitoring, diagnostics, and prognostics of the physical assets. For example, Rastegari et al. (2017) highlighted Condition Based Maintenance (CBM) and its implementation in the manufacturing industries. Similarly, Zhang et al. (2016) proposed an approach for Tool Condition Monitoring (TCM) and Remaining Useful Life (RUL) prediction. A condition-based preventive maintenance approach integrated into a machine monitoring framework was presented in Mourtzis et al. (2016). Such approaches, though at the component level, make the maintenance planning more intelligent and capable. However, they fail to incorporate and utilize the typical characteristics of the overall intelligent manufacturing system. For instance, such approaches do not consider the machine to machine communication and autonomous decision making. Autonomous decision making is important for dynamic maintenance planning. Also, researchers have attempted to develop multi-sensor fusion-based approaches for effective diagnostics and prognostics (Jain and Lad 2016). However, such approaches mostly rely on centralized data collection and decision-making. As, data from all sensors are collected, stored, and computed using machine learning techniques, at the single processor. Distributed approaches like Palau et al. (2018) and Palau et al. (2019) exist, which involve deploying prognostics algorithms at the asset level. However, they rely on identifying similar assets within a fleet and subsequently sharing data within these assets. Such approach is very subjective to the operator's notion of similarity and boils down to centralised learning in an extreme case where all assets are deemed similar. Such a centralized system does not harness the typical characteristics of industry 4.0 viz., distributed intelligence, and autonomous decision making.

Apart from these, there are various peripheral issues with the conversational diagnostics and prognostics approaches. Conventionally researchers are focused on the improvement of the accuracy of the results of diagnostics and prognostics separately. For example, Jain et al. (2014) focused only on the prognostics of the high-speed milling cutter. Similarly, Wang et al. (2015) focused only on tool wear predictions. Jain and Lad (2019) presented an integrated TCM system where diagnostics and prognostics were considered jointly. However, the authors used a centralized framework for data collection and processing. Another issue is the black-box nature of the machine learning approaches used for diagnostics and prognostics. Such approaches give imperfect interpretations of the outcomes, resulting in a low level of confidence in the solutions and, consequently, reduced implementation rate. Holzinger (2016) highlighted the disadvantages of machine learning techniques and the requirement of interactive machine learning in order to include humans in the loop. Similarly, Biran and Kathleen (2017) proposed a novel machine learning approach that focuses on domain knowledge and human reasoning. However, such human-centric machine learning approaches are still at the exploratory stage. The use of such human-centric approaches for diagnostics, prognostics, and maintenance planning in manufacturing is missing. Subsequently, this paper attempts to present a novel system encompassing the above issues, especially, centralized framework for data collection and processing and black-box nature of machine learning based prognostics and diagnostics approaches, through distributed yet integrated diagnostics, prognostic, and maintenance planning approach.

2. METHODOLOGY

2.1 Distributed yet Integrated Diagnostics and Prognostics Approach

Figure 1 represents the distributed architecture applied to one of the components of the manufacturing system viz. milling cutter. This component is connected with a number of Measuring and Computing Units (MCUs). An MCU is a sensor unit capable of collecting, storing, and computing the data. Such distribution of information collection and decision making is now possible and highly desirable in any Industry 4.0 system (Xu et al. 2018, Sodhro et al. 2019). Also, it helps in collecting big data in distributed manner and protecting against the failure of the central data server used in the case of conventional diagnostics and prognostics approaches. Three MCUs viz. force MCU (F MCU), vibration MCU (V MCU), acoustic emission MCU (AE MCU) are used in this work. Each of the MCUs is capable of processing the captured data, run diagnostics and prognostics algorithms and return health stage (i.e. current condition) or RUL estimates to the base station (where information about each components state obtained from all the MCUs is collected and processed). Initially, all the MCUs only predict the heath stage (elaborated in section "diagnostics module") of the component. As soon as any MCU predicts the component in stage II or III, a fault (fault means change in current condition) is triggered by MCU which initializes the prognostics module of that particular MCU. All such MCUs then predict RULs of the component and report to the base station. The base station decides the suitable RUL for further maintenance planning. Suitable RUL may be decided based on the criticality of the component and confidence in predicted RUL or health stages, as discussed in section 2.2. With time, MCU's performance is also analyzed, and the MCUs giving poor predictive performance are removed or are explored for better features and machine learning algorithms.

Experimental Platform: An experimental platform pertaining to milling machine is designed. It allows investigation of the degradation behaviour of cutting tools by running run-to-failure tests on 6 mm diameter high-speed steel milling cutters. The milling process used was face milling for generating a flat surface on a mild steel workpiece (165mmX100mm) at a fixed operating profile (feed=300mm/min, speed = 1000RPM, depth of cut = 0.25) in dry state. Mitutoyo TM-505 tool maker's microscopy system at 15x eyepiece magnification and resolution of 0.001mm, according to ISO/IEC 17025, was used to measure tool degradation (flank wear) of the tool. After every 1320 mm of machining, tool wear was measured and recorded manually. The average value of cutter flank wear from four cutting edges was considered to represent the failure of the cutting tool, with wear threshold being 0.746mm. Three types of sensor measurements viz. cutting force, vibration, and acoustic emission were used to monitor the cutting tool condition in real-time. Online time-domain signals were collected with distinct sampling frequency (1 KHz for force MCU and 2.5 KHz for vibration and acoustic emission for the entire life of the tools. This experiment was carried out on six identical cutting tools. Two different failure types were witnessed, namely worn-out and breakage.

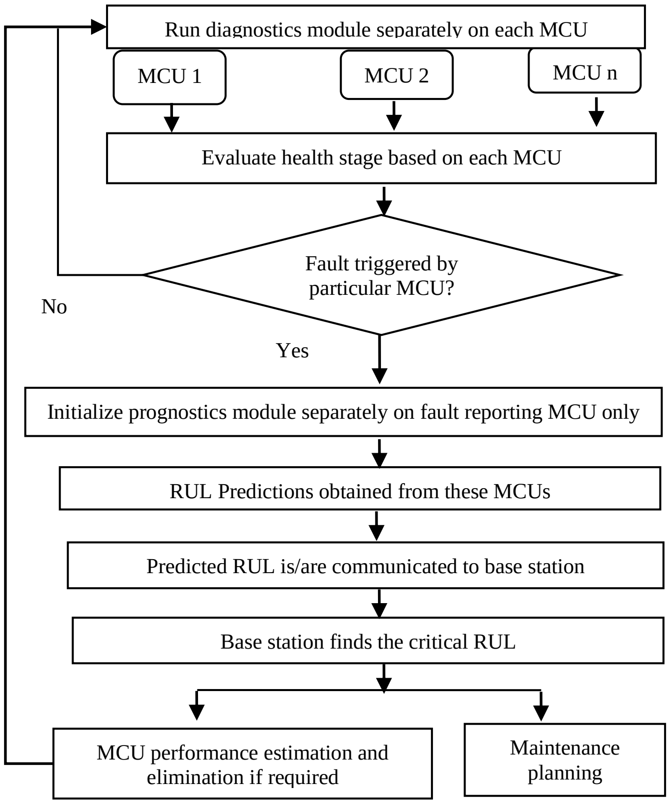


Fig. 1. Flow diagram of distributed diagnostics and prognostics.

Feature Selection: Pre-processing of data was performed by converting raw signals into more informative features or parameters. In specific, 31 statistical features were extracted by each MCU. The feature screening followed this. In this work, Pearson correlation methodology was applied for feature screening, to help identify highly correlated features and thus remove redundant features. A correlation value near -1 and 1 was considered as strongly correlated and value near to 0 was considered as unrelated features. Therefore, it helps in eliminating redundant features. In this way, 18 features for force MCU, 16 features for vibration MCU and 11 features for acoustic emission MCU were retained for further analysis. Three methods viz. logistic regression, random forest classifier, and decision tree classifier are applied for identifying the most relevant features. The accuracy of the results was calculated for each method (refer to table1). The top 5 features based on the most accurate method (highlighted in bold in table 1) for a particular MCU are then used for further diagnostics and prognostics. These features are listed in table 2.

Diagnostic Module: This predicts the current health state by assessing the information provided by the features selected for each MCU. During machining process a new tool progressively move to greater levels of wear and eventually breakage. This paper uses a multi-stage categorization for tool wear. The tool is categorized in one of the following three stages: Stage I: Slight wear zone; Stage II: Moderate wear zone; and Stage III: Critical or worn out zone. The threshold for classification of the health stages is determined based on historical degradation information of the component. The tool is classified into one of the three health stages, as shown in figure 2. A similar classification is used by Jain and Lad (2017).

An experimental dataset of 237 data points generated by six cutters was used for developing and validating the classification models. 60% of data are used for training while remaining data are used for testing. Features mentioned in table 2 for respective MCUs are used for the classification models. Six wear classification models are tested in terms of accuracy. A 10-fold cross-validation technique is employed on the test set in the python environment. The implementation results are given in table 3. Based on the accuracy, the Gaussian NB classifier, logistic regression classifier, and random forest classifier were selected for diagnostics based on force, vibration, and acoustic emission MCU, respectively. For each classifier, the precision and sensitivity index is calculated for all stages for the most accurate methods. The results are shown in table 4. In the confusion matrix, we observed that there were only a few cases where the classifier predicts stage III; when compared with actual values, it was found that most of the cases tool breaks down in stage II before reaching the fully worn-out stage. This implies that the tool can unexpectedly fail at any time after stage II. Consequently, the threshold for triggering prognostics is set as stage I to initiate appropriate maintenance actions.

Prognostics Module: As soon as the diagnostics module of any of the MCU predicts stage II or III, the corresponding prognostics module is initiated. The prognostics module predicts the RUL of the cutting tool. In this approach, the prognostics module predicts the RUL of the tool by assessing the information provided by the features selected for each MCU. A deep learning-based technique viz. Long Short-Term Memory (LSTM) is employed by each MCU to predict RUL. The LSTM is an artificial recurrent neural network architecture and has feedback connections (Palau et al. 2018). The LSTM model was optimized by running the model in the loop having a defined range of hyperparameters and Root Mean Square Error (RSME) was calculated; a combination of hyperparameters showing minimum RMSE was selected for the final model. The optimized set of hyperparameters for LSTM and calculated RMSE for each MCU is shown in table 5. The model was cross-validated with the test set. Scatter plots in figure 3 show the predicted RUL through LSTM against the actual RUL values for the test dataset. It was observed that all points fall approximately on a straight line inclined at 45 degrees, which is highly desirable for the predictive models. Moreover, data scatterings are very less, which confirms the precision of prognostic models. One of the reasons for better predictive performance is the integration of diagnostics and prognostics. In the present approach, prognostics start only after the triggering of a fault by diagnostics modules of corresponding MCUs. This, in turn, removes the higher prediction error during the initial life of the component. Also, the integration reduces the computation load as diagnostics models are computationally less complex than prognostics models. The predicted RULs are communicated to the base station by each MCU for further analysis. One can select RUL obtained by any of the MCUs. For example, RUL prediction from the MCU showing minimum RUL may be selected in case failure is very critical. Alternatively, one can give different importance to different MCUs' prediction, based on the past performance of the MCUs, and obtain a weighted RUL for further use. Preferences may be dynamically updated, and MCU, which is not contributing significantly in estimation of the RUL of the component may be removed. This helps in removing redundant or less critical sensors, making the prognostics system lean and effective.

Comparison of Centralized and Distributed Prognostics: In this section, the performance of the distributed diagnostics and prognostics approach is compared with that of the centralized approach. For this, the minimum value of the predicted RULs from different MCUs is used in the case of the distributed approach. Table 6 shows the working of both the methods for cutter 5 data. For the diagnostics module, a centralized approach triggers the faults (stage II) at cut number 21, while the same is triggered at the 27th cut by a distributed approach. From the actual wear data, it was observed that the actual transition to stage II happened at the 28th cut. Thus the distributed diagnostics show better capability in identifying the fault, thereby reducing the false alarm. For comparison of prognostics performance, RSME is used. The same are shown in Table 7 for both cutter 5 and 6. Also, computation time is also estimated. It was observed that distributed prognostics give better performance in leaser computational time.

2.2 Conceptualization of a Novel Maintenance Planning System

In general, condition-based maintenance is considered on-time maintenance (Zhang et al. 2016). However, in a system consisting of many components and machines and having limited maintenance resources, on-time maintenance may not be possible. The predicted condition may still be subjected to allowable scheduled maintenance. The results obtained from the above-distributed diagnostics and prognostics approach will be handy in arriving at such predictive maintenance schedule considering the criticality of the components/system, the dependency of the components, available maintenance resources, confidence level in the results of the prognostic, etc. The distributed yet integrated diagnostics and prognostics approach presented in the previous section for one of the components of a machining system when applied to all the critical components of a machine tool is depicted in figure 4. The same can be extended to a shop floor. The base station continuously receives the RULs from MCUs of critical stage components from various machines in a system. Additionally, the base station can be modelled as a maintenance agent having information about the stochastic, economic and structural dependencies of the components within a machine or among various machines in a multi-machine system. Multiple estimates of RUL are obtained from a distributed approach to provide confidence bound on the prediction; it helps the maintenance mangers in making more informed maintenance planning decisions. For example, if the component is not very critical, the maintenance manager may use a lesser conservative prediction (highest RUL out of predictions from various MCUs) to take advantage of group maintenance. Similarly, multiple estimates of the RUL will provide more flexibility in integrating the maintenance planning with other shop floor operations planning like production scheduling. Also, different MCUs measuring and computing different aspects of a component make the results easy to interpret and use in deciding further maintenance actions. Thus, the proposed distributed diagnostics and prognostics approach is more human-centric rather than a black-box approach.

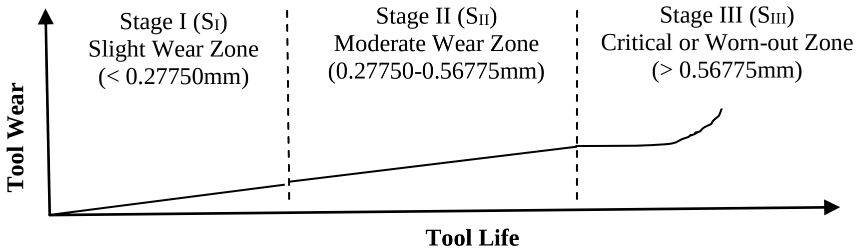


Fig. 2. Tool health stages (Jain and Lad 2019).

Table 1. Accuracy predicted for all MCUs

	Force MCU	Vibration MCU	Acoustic Emission MCU
Logistic Regression	83.33%	**88.60%**	86.82%
Random Forest Classifier	84.39%	81.40%	84.08%
Decision Tree Classifier	**89.65%**	79.82%	**89.55%**

Table 2. Selected features

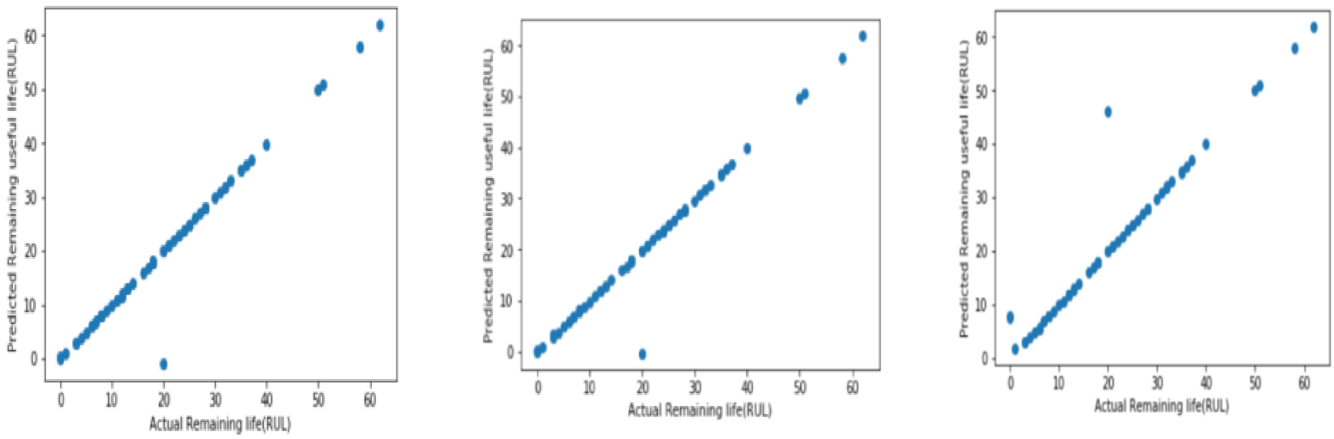
Force MCU	Vibration MCU	Acoustic Emission MCU
Mean	Crest Factor	Kurtosis
Median	Skewness	Crest Factor
RMS	Range of Values	Coefficient of Variance
Entropy	K-factor	Energy Operator
Kurtosis	Mode	Residual Kurtosis

Table 3. Accuracy comparison of different diagnostics classifier models applied on three MCUs

Model	Force MCU	Vibration MCU	Acoustic Emission MCU
Logistic Regression	89.30%	**88.60%**	80.88%
Random forest Classifier	85.26%	80.18%	**82.11%**
Support Vector Machine	62.64%	79.76%	61.32%
Decision Tree Classifier	80.18%	74.21%	67.54%
K-Neighbors Classifier	84.56%	76.14%	76.84%
Gaussian NB Classifier	**90.70%**	85.79%	59.82%

Table 4. Performance measurement of selected classifiers using the confusion matrix

Index	Force MCU			Vibration MCU			Acoustic Emission MCU		
	Stage I	Stage II	Stage III	Stage I	Stage II	Stage III	Stage I	Stage II	Stage III
Precision	0.95	0.64	0.43	1	0.67	0	0.89	0.52	0
Sensitivity	0.87	0.70	1	0.78	0.71	0	0.84	0.54	0



Force MCU Vibration MCU Acoustic Emission MCU

Fig. 3. Scatter plot drawn between actual and predicted remaining useful life

Table 5. Hyperparameters combination for the LSTM model of each sensor and the RMSE

S. No	MCU	Optimal Parameters Value			RMSE
		LSTM_nodes	batch_size	epochs	
1	Force	5	1	1040	2.658
2	Vibration	5	1	1040	2.599

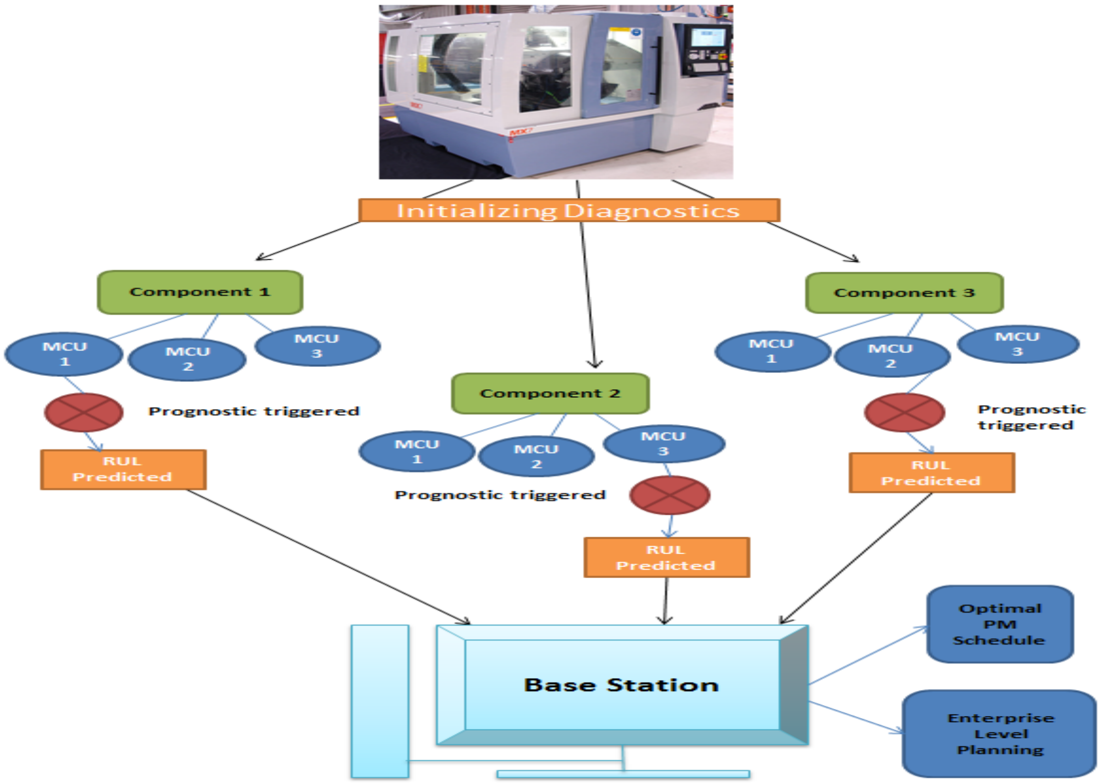


Fig. 4. Diagrammatic representation of distributed health management paradigm

Table 6. Distributed Vs. centralized approach (results are for tool 5)

Tool Cut	Centralized Approach				Distributed Approach							
	Diagnostics (Predicted Wear Stage)	Prognostic Triggering MCU	**Predicted RUL**	**Actual RUL**	Diagnostics (Wear Class Prediction)			Prognostics Triggering MCU	Prognostics (Predicted RUL)			**Selected RUL**
					F MCU	VMCU	AE MCU		F MCU	V MCU	AE MCU	
1 . . 20	I . . I				I . . I	I . . I	I . . I					
21	II	ALL	17.8	19	I	I	I					
22	II	ALL	17.1	18	I	I	I					
23	II	ALL	15.9	17	I	I	I					
24	II	ALL	15	16	I	I	I					
25	II	ALL	14	15	I	I	I					
26	II	ALL	13	14	I	I	I					
27	II	ALL	12.5	13	I	I	II	AE			11.5	11.5
28	II	ALL	11.0	12	I	I	II	AE			10.7	10.7
29	II	ALL	9.8	11	II	I	II	AE,F	10		9.9	9.9
30	II	ALL	9.1	10	II	I	II	AE,F	9		8.9	8.9
31	II	ALL	7.9	9	II	I	II	AE,F	8		7.8	7.8
32	III	ALL	6.3	8	III	I	II	AE,F	7		6.8	6.8
33	II	ALL	5.8	7	II	I	II	AE,F	6		5.8	5.8
34	II	ALL	5	6	II	I	II	AE,F	5		4.8	4.8
35	II	ALL	4	5	II	I	II	AE,F	4		4.3	4
36	II	ALL	3.0	4	II	I	II	AE,F	3		3.3	3
37	III	ALL	4.8	3	III	II	II	AE,F,V	2	2.5	1.8	1.8

38	II	ALL	5.7	2	II	II	II	AE,F,V	1	1.6	0.8	0.8
39	III	ALL	0	1	III	II	II	AE,F,V	0	0.4	24.2	0
40	III	ALL	0	0	III	II	II	AE,F,V	20	0.0	63.4	0.0

Table 7. Comparison between distributed prognostics and centralized prognostics

	Distributed	Centralized
RMSE(Cutter 5)	1.077034641	1.343944525
RMSE(Cutter 6)	0.845888785	1.345163151
Average RMSE	0.961461713	1.344553838
Computational Time	10 mins	17 mins

3. CONCLUSIONS

In this paper, a novel integrated yet distributed diagnostics, prognostics, and maintenance planning approach is developed. Each sensor works like an edge device performing local level diagnostic and prognostic. The different sensors measuring and computing different aspects of a component helps in providing more insight in the confidence bound obtained on the prediction thus it makes the results easy to interpret and use in deciding further maintenance actions. Thus, the proposed distributed diagnostics and prognostics approach is more human-centric rather than a black-box approach. Thus multiple estimates of RUL are obtained from each sensor; it helps the maintenance mangers in taking more informed maintenance planning decisions. A comprehensive analytical investigation is conducted via a case study to validate the model. The implementation results showed that integrated yet distributed diagnostics and prognostics approach give better performance in leaser computational time. The superiority of the proposed approach over the centralized approach is demonstrated in terms of accuracy and time. Also, the proposed approach helps in making the results of the machine learning techniques comprehensible and more accurate. A novel maintenance planning system is conceptualized. Herein, integrated yet distributed results will be handy in arriving at a predictive maintenance schedule considering the criticality of the system, the dependency of the components, available maintenance resources, confidence level in the results of the prognostic, etc. In essence, the proposed approach is more human-centric and expected to emerge as a promising solution for maintenance planning under the concept of Industry 4.0.

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