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DEEP LEARNING PREDICTION MODEL OF REMAINING USEFUL LIFE OF A TURBOFAN ENGINE USING C-MAPPS DATA

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Abstract—In the period of sector 4.0, safety, effectiveness and trustability of sector equipment is an abecedarian concern in marketing sectors. The accurate remaining useful life (RUL) vaticination of an outfit in due time allows us to effectively plan the conservation operation and alleviate the time-out to raise the profit of business. In the once decade, data driven grounded RUL prognostic styles had gained a lot of interest among the experimenters. There live colorful deep literacy- grounded ways which have been used for accurate RUL estimation. One of the extensively used methods in this regard is the long short- term memory(LSTM) networks. To further enhance the vaticination delicacy of LSTM networks, our paper proposes a model in which efficacious pre-processing ways are collaborated with LSTM network. C-MAPSS turbofan machine declination dataset released by NASA is used to corroborate the performance of the proposed model.

Keywords— RUL, turbofan, C-MAPSS,LSTM.

I. INTRODUCTION

In our day-to-day life as we are using many accoutrements in every field we should maintain that equipment. Vaticination of outfit conservation conditions helps the businesses to plan conservation of outfit before the failure occurs. There are three types of maintenance techniques used in industries, reactive maintenance, preventive maintenance and predictive maintenance. There are two types of predictive maintenance, First one is the classification approach in which it predicts the possibility of failure in next n-steps and second one is Regression approach where it predicts the time left before the next failure. Currently detectors are fitted in outfit in manufactories and these detectors are landing huge quantum of data and it's being stored into large storehouse bias including pall waiters .the geste of the detector data contains useful information to decide what may lead to an outfit failure. For an aeroplane to move through the air, some kind of propulsion system should induce a thrust. utmost ultramodern air liners use turbofan machines for this.

II. RELATED WORK

This part briefly reviews the being literature on the turbofan machine RUL estimation. Traditional model- grounded ways generally employ algorithms like Kalman filter(KF), extended Kalman filter(EKF) and patches pollutants to come up with mathematical expression of machine grounded on multi detector time series sequence data. Classical Declination system such as Eyring model or Weibull distribution was enforced in. Salahshoor et al. used a unified frame of EKF grounded design for detector data emulsion algorithm to further enhanced the discovery and opinion of declination trends and system faults. Ordonez et al. enforced the auto-regressive integrated moving average (ARIMA) model and support vector machine (SVR) styles inclusively to estimate the RUL. The needed features can be created by assaying previous literacy about the declination models as presented in. In it is suggested that failure thresholds or declination state estimation is no longer needed in literacy-acquainted approach. Khelifetal. presented machine literacy grounded support vector regression(SVR) model to project the direct association between multivariate detector data or health indicator and the aircraft turbofan machine RUL. Across all these ways for turbofan machine RUL prognosis, deep neural network- grounded styles have gained vast fashionability. Zhang et introduced a multi objective evolutionary algorithm to expand and organized the deep belief network into multiple correspondent networks contemporaneously to negotiate the two condemning objects i.e. diversity and delicacy. These networks attained a fine RUL prognosis delicacy especially in case of complicated operations and in the presence of noise in input data. Saeidi et al., proposed a naive Bayesian category algorithm to measure the health indicator for turbofan machine. The pre-processing step takes the detector data as input and apply moving average clarifier for removing the noise. It further classifications the dataset into four different classifications on the base of time cycles i.e. time cycle values between 0 to 50 is labeled as critical case which need immediate conservation and farther categorization is also done in a analogous manner. Zheng et al.proposed LSTM network combined with piece wise direct function for RUL for estimating the declination trends. It achieves valid results by applying piece wise direct function and data normalization. Wei etal. proposed aBi-LSTM network which can learn high position features in both direction and it can run training pass from forward to backward and backward to further with back propagation algorithm. Wang etal. offered a mongrel network for turbofan machine in which trends and retired pattern in long sequence detector data is linked through LSTM network and short duration sequence was anatomized through time window system with gradient boosting regression(GBR). This system has two stages, offline stage to learn declination pattern with LSTM network and TW- GBR used in online stage for rooting short sequence data. It also executed standardization and detector selection criteria. Babu et al, proposed deep CNN retrogression network for RUL estimation. The network contain of two dimensional convolutional layers for point birth followed by a completely connected retrogression subcaste for vaticination.

A. PROBLEM STATEMENT :

The predictive maintenance ways is different from the reactive and preventative conservation ways in terms of safety, trustability, effectiveness and unwarranted time-out for aircraft turbofan machine(50). These styles insure dependable result managing the health of turbofan machine to reduce the time-out, which leads to significant loss in profit. Thus, failures in a turbofan machines can invoke catastrophic accidents due to its sensitive nature and it needs to be estimated previous in time so that we can give conservation services in order help any fatal incident.

In current script, due to the perpetration of cyber-physical system(CPS, that link the cyber world with a physical world, called smart manufacturing), the industrial sector similar as health care, nuclear power factory etc. generate enormous volume, speed, veracity and variety of data. thus, with the rise of AI and accessibility of tackle computing resources, data driven grounded artificial intelligence(AI) prophetic conservation models have a capability to reuse big quantity of real- world machines data with ease and prognosticate heath indicator of aircraft turbofan machine in time before failure to help unwanted breakdown.

III. DESCRIPTION OF C-MAPSS TURBOFAN ENGINE SIMULATION DATASET

C- MAPSS dataset released by NASA is developed in MATLAB atmosphere as a tool for simulation of turbofan machines. C- MAPSS dataset was published in 2008 for 1st International conference on PHM. This dataset was published some time agone but still it has been laboriously used in exploration for assessing the prophecies model with a focus on accurate estimation of RUL. This model have fourteen input parameters related to five rotating factors of machine to pretend different degree of fault and deterioration of the model. A aggregate of twenty one variables out of fifty eight different detector responses is considered from the model for prognosticating the RUL. The three operating parameters of C- MAPSS simulation model are given in table- 1 and the details of 21 detectors are given in table- 2. The legends of last column in table- 2 Trends indicates the declination pattern of detector data with respect to time, where ‘‘ ’’ represents irregular detector actions, I describe the parameter adding with time and finally, D is the variation of parameter that decreases with time.

TABLE 1. Operating parameters of C-MAPSS

Parameter	Operating Range
Mach Numbers	0 to 0.90
Altitude	Sea level to 40,000 feet
Sea-level temperature	-60 to 103° F

IV. Proposed methodology

This paper proposes LSTM grounded RUL vaticination model for turbofan machines, which proves to be additional robust than utmost of the being ideals obtainable in the literature.

TABLE 2. Output parameters C-MAPSS turbofan engine datasets.

Sensor	Parameter	Description with units	Trend
1	T2	Total Temperature in fan inlet (oR)	~
2	T24	Total Temperature at LPC outlet (oR)	I
3	T30	Total Temperature at HPC outlet (oR)	I
4	T50	Total Temperature at LPT outlet (oR)	I
5	P2	Pressure at fan inlet (psia)	~
6	P15	Total pressure in bypass-duct (psia)	~
7	P30	Total pressure at HPC outlet (psia)	D
8	Nf	Physical fan speed (rpm)	I
9	Nc	Physical core speed (rpm)	I
10	Epr	Engine pressure ratio (—)	~
11	Ps30	Static pressure at HPC outlet (psia)	I
12	Phi	Ratio of fuel flow to Ps30 (psi)	D
13	NRf	Corrected fan speed (rpm)	I
14	Nrc	Corrected core speed (rpm)	D
15	BPR	Bypass ratio (—)	I
16	farB	Burner fuel air ratio (—)	~
17	htBleed	Bleed enthalpy (—)	I
18	NF-dmd	Demanded fan speed (rpm)	~
19	PCNR-dmd	Demanded corrected fan speed (rpm)	~
20	W31	HPT coolant bleed (lbm/s)	D
21	W32	LPT coolant bleed (lbm/s)	D

A. CORRELATION ANALYSIS

Here, we must arrange our wellness-to-negligence data into an applicable form for perfecting the delicacy of the LSTM network for effective training operation. C-MAPSS dataset contains of three function settings and twenty one detector indicator of machines with apparatus life time expansion. These indicator are also given as an input to interconnection survey system to find out the applicability of features with RUL. The algorithm eliminate the detector values.

$$r = \frac{conv(x,y)}{s_x s_y} \quad (1)$$

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})(\sum_{i=1}^{n}(y_i - \bar{y}))}} \quad (2)$$

this correlation is further than 15% for stylish feasible case.

B. DATA NORMALIZATION

The scope of detector affair after examine from the graphs is from knockouts to thousands and if we utilize these raw values for guide the gride also delicacy will release remarkably.

Z-Score regularize is used in this paper which initial calculate the mean (μ) and standard deviation (σ) of each point vector and also apply the following working on each detector affair.

$$y_n = \frac{x_c - \mu_n}{\sigma_n} \quad (4)$$

C. IMPROVED PIECEWISE LINEAR DEGRADATION MODEL

It's detect that RUL is direct dwindling task with esteemed to time as the effectiveness of the arrangement humiliation. Still, as the arrangement begin their functioning, there's no declination offer in the detector readings. In this paper, we've mounted an advanced interpretation of the self moving slice wise candid task for affair RUL labeling.

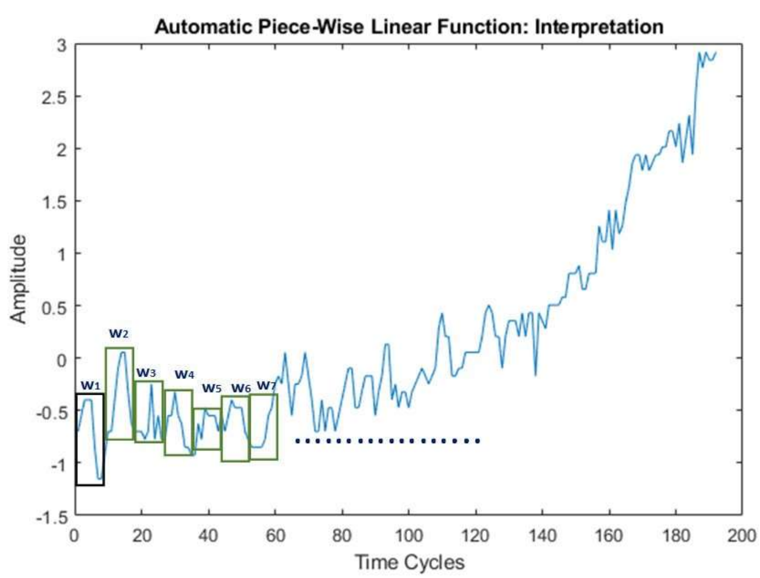

Figure 1: degradation process represented in the form of windows of time cycle

Algorithm 1 Bettered piece-wise Linear task for original RUL computation for all machine
1: **Inputs**: Time cycle values (*tc*) and detector data after filtering and normalization
2: **Parameters**: w = window length, g = total number of windows, $w1$, $w2. . .wg$ = posterior windows,
  Th=threshold
3: **Output**: Initial RUL label (*irul*)
4: e = Excerpt detectors values from the given windows(w_1, $w_2 \ldots w_g$)
5: m = Calculate the centroid of each window by calculating the mean for each window
6: **for** i (2 *to* g 1) **do**
7: s = Subtract the mean of two windows (w_1, w_i)
8: sq = square (s)
9: **if** $sq >= Th$ **then**
10: $irul = tc - w * i$
11: **else**
12: $i = i + 1$
End

D. LSTM MODEL DEVELOPMENT

The data from the formalize phase with modernize RUL markers from the declination prototype is used to teach a deep LSTM grid. Our proposed LSTM prototype contain of LSTM subcaste, powerhouse subcaste, completely combined subcaste and the retrogression subcaste. Our proposed prototype contains of four subcaste attach in a
successional method with various number of invisible units and a powerhouse subcaste is also join in between the LSTM for intensify the concept of grid to prevent over befitting.

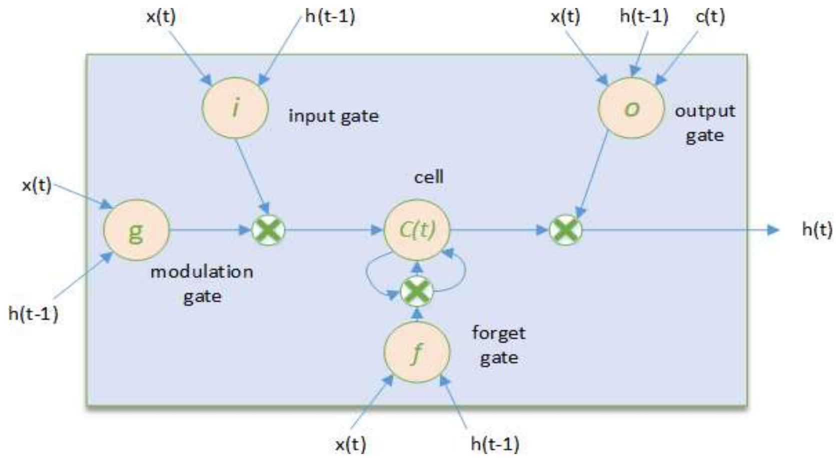

Figure 2: Structure of a LSTM cell.

E. POWERHOUSE SUBCASTE

The powerhouse subcaste is join to prevent the over befitting which innately do while guide to the deep neural grid. The regularization subcaste is join in between the completely combined subcaste and LSTM subcaste to enlarge the conception of the whole algorithm to more track the prognosticated RUL with high delicacy.

F. COMPLETELY COMBINED SUBCASTE

The completely combined subcaste gets the data from the last blend of LSTM and powerhouse subcaste, so that the quality remove from LSTM subcaste are used to induced the output. Due to it's completely combined nature between all the neuron show in the grid, it has a huge number of heavy criterion which want to be reckoned by coaching the grid. Completely combine subcaste along with a powerhouse subcaste is followed by unique retrogression subcaste for prognosticating the RUL. These criterion consists of literacy cost, group volume, number of subcaste, number of neurons in each subcaste, advance and the coaching ages.

G. EVALUATED METRIX

After grid progress, coaching of LSTM grid is sent out and choosing of excitable criterion is make on the base of root mean square error (RMSE) between factual RUL and prognostication RUL for each machine of the turbofan dataset.

Table 3: ranges/types of hyper parameter in LSTM model training

Hyper parameter	Range
Learning Rate	*0.01 to 0.05*
Mini-Batch Size	*10 to 30*
Max Epoch	*10 to 300*
No. of LSTM layers	*2 to 8*
No. of neurons in each LSTM layer	*30 to 100*
Dropout probability	*0.1 to 0.5*
Optimizer	*Adam, Stochastic Gradient Descent, RMSProp*

RESULTS AND DISCUSSION

In this part we can see the examination on RUL prognostication results by our proposed model. There are many Parameters that affects the model's delicacy. We have two types of parameters that is first is the parameters related to the initial RUL value, these includes window size and threshold values Second ones are LSTM hyper parameters. By combining these two parameters It will give us a large set of parameters

Table 4 . select LSTM model with hyper parameter values.

LSTM Models	Hyper-parameters						
	Learning Rate	Mini-Batch	Max Epoch	No. of LSTM Layers	No. of Neurons in each LSTM Layer	Dropout Probability	Optimizer
Model 1	0.01	10	20	2	30	0.1	Adam
Model 2	0.02	15	150	4	60	0.1	Adam
Model 3	0.001	20	250	6	90	0.1	Adam
Model 4	0.001	25	300	8	100	0.1	Adam

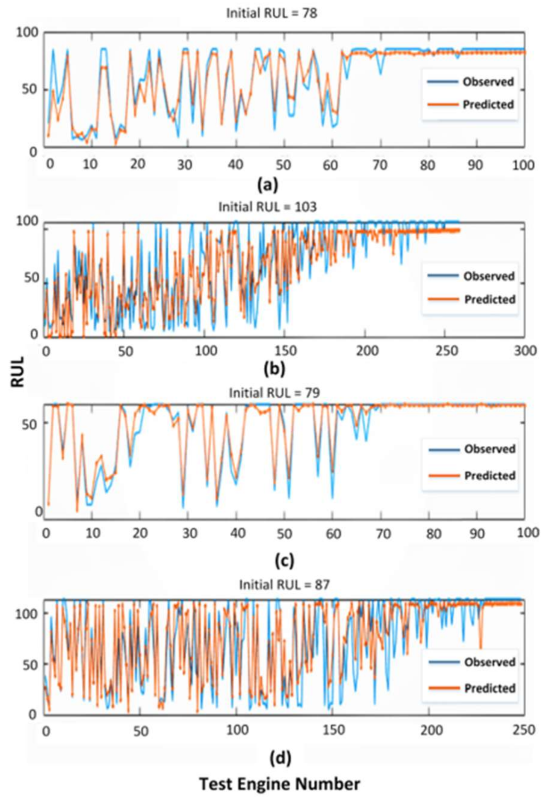

FIGURE 5. RUL Prediction on Test Set, (a) FD001 (b) FD002, (c) FD003, (d) FD004.

Methods	Year	Pre-Processing Steps	FD001		FD002		FD003		FD004	
			RMSE	Score	RMSE	Score	RMSE	Score	RMSE	Score
CNN [41]	2016	Data normalization, RUL target function	18.44	$1.29x10^3$	30.29	$1.36x10^4$	19.81	$1.60x10^3$	29.15	$7.89x10^3$
LSTM [38]	2017	Data normalization, RUL target function	16.14	$3.38x10^2$	24.49	$4.45x10^3$	16.18	$8.52x10^2$	28.17	$5.55x10^3$
BiLSTM [62]	2018	Feature selection, Data normalization, RUL target function	13.65	$2.95x10^2$	23.18	$4.13x10^3$	13.74	$3.17x10^2$	24.86	$5.43x10^3$
DAG [63]	2019	Feature selection, Data normalization, Piece-wise function	11.96	$2.29x10^2$	20.34	$2.73x10^3$	12.46	$5.35x10^2$	22.43	$3.37x10^3$
CNN+LSTM [64]	2019	Variance threshold, Data normalization, Health indicator	16.16	$3.03x10^2$	20.44	$3.44x10^3$	17.12	$1.42x10^3$	23.25	$4.63x10^3$
Multi-head CNN+LSTM [45]	2020	Feature selection, RUL target function	12.19	$2.59x10^2$	19.93	$4.35x10^3$	12.85	$3.43x10^2$	22.89	$4.34x10^3$
CNN+LSTM+ BiLSTM [44]	2020	Correlation analysis, Min-max scaling, RUL target function	10.41	—	—	—	—	—	—	—
AGCNN [65]	2020	Feature selection, Data normalization, RUL target function	12.42	$2.25x10^2$	19.43	$1.49x10^3$	13.39	$2.27x10^2$	21.50	$3.39x10^3$
LSTM+ FCLCNN [66]	2021	Feature selection, Data normalization, RUL target function	11.17	$2.04x10^2$	—	—	9.99	$2.34x10^2$	—	—
Hybrid model [67]	2021	Feature selection, Data normalization, Piece-wise RUL	15.68	—	22.26	—	16.89	—	22.32	—
BLS + TCN [68]	2022	Feature selection, Data normalization, Piece-wise RUL	12.08	$2.43x10^2$	16.87	$1.60x10^3$	11.43	$2.44x10^2$	18.12	$2.09x10^3$
Bi-LSTM based Attention method [69]	2022	RUL target function	13.78	$2.55x10^2$	**15.94**	$\mathbf{1.28x10^3}$	14.36	$4.38x10^2$	**16.96**	$\mathbf{1.65x10^3}$
Proposed (without automatic piece-wise linear RUL function)	2022	Correlation analysis, Median filter, Data normalization,	13.5	$2.38x10^2$	23.37	$2.6x10^3$	13.54	$4.11x10^2$	23.36	$3.97x10^3$
Proposed	2022	Correlation analysis, Median filter, Data normalization, Automatic piece-wise linear RUL function	**7.78**	$\mathbf{1.00x10^2}$	17.64	$1.44x10^3$	**8.03**	$\mathbf{1.04x10^2}$	17.63	$2.39x10^3$

Table 5 : Comparision of RMSE and score with other method

CONCLUSION

This project is based on LSTM model for predict the RUL of turbo fan engine When the LSTM model combined effectively error-checking steps results highly accurate RUL predictions. The most common error-checking steps like feature selection, filtering and normalization. The prediction of initial value of RUL, we introduce improved piece-wise linear degradation model. The threshold value and window size are two important parameters in the degradation model. The LSTM network model consists of combination of multiple LSTM layers, dropout layers, regression layers and these layers will helps to find the hyper parameter to achieve the best results. The LSTM model will tested on C-MAPSS are the specialized tools. The prediction of accuracy of turbo fan engine is depends on some parameters such as calculation of initial value of RUL and hyper parameters for LSTM mode

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