Remaining Useful Life Prediction of Turbo Actuators for Predictive Maintenance of Diesel Engines

Devawrat Bhave[1], Deepa Tavargeri Adiga[2], Nilesh Powar[3], and Thomas Mckinley[4]

[1,2,3,4] *Cummins Inc.500 Jackson St Columbus, IN 47201U.S.A.*

devawrat.bhave@cummins.com
deepa.adiga@cummins.com
nilesh.powar@cummins.com
thomas.l.mckinley@cummins.com

ABSTRACT

Prognostics applications in the automotive industry are growing rapidly and customers have begun to expect this capability. Remaining useful life (RUL) models are an important aspect of a prognostic as they affect both how far in advance and with what confidence failures can be predicted. Model selection and design must include technical considerations such as mathematical complexity and training data availability, as well as business considerations such as implementation plans, constraints, and risks of inaccurate predictions.

This paper compares different RUL models that have been developed for turbo actuators on diesel engines, with the business objective of advising bus fleet customers on preventive maintenance intervals. The design, development, validation, and resulting prediction accuracy of each RUL model is detailed. A selection process is then applied to choose the model best suited to the intended purpose. In doing so, the paper sheds light on strengths and weaknesses of deep learning RUL models over statistical RUL models. The paper also focuses on the state-of-the-art deep learning network "Tabnet" and its results for useful life predictions. Among the different methods, Accelerated Weibull Failure Time model provides better predictions with a concordance of 0.94 and ~15% less error than any other model[1].

1. INTRODUCTION

Growing automotive product complexity and data availability have fueled significant research and innovation in the area of prognostics. Prognostics aims to predict future faults and failures of a system/subsystem, providing ample time to plan proactive Engine and After treatment system/subsystem maintenance; in turn improving uptime. Prognostics applied to critical and expensive components benefit the automobile industry manufacturers and their customers with the control over 1) recurring overhead cost of sudden component replacements and 2) extended component life with timely maintenance. Further, timely replacement of faulty emission control components helps the manufacturer to enhance its reputation with customers and in the market.

The concept of RUL prediction is applied to determine the life span of the component to avoid catastrophic failure during its service life. Although RUL prediction of components comes with uncertainty and has shown limited success, they include a powerful set of algorithms. Though these algorithms involve multiple set of approximations during implementation, if designed well with the backing of good data, they result in valuable RUL model. Validation and verification of such RUL models are key factors for successful implementation. Typically, there are three broad RUL based modelling techniques. First one uses a similarity models where historical run-to-failure data from similar components showing failure is modelled and one can estimate RUL based on those data profiles. Second one uses a degradation model based on a threshold of a condition indicator or feature. Depending on the present value of the condition indicator and the modelled threshold, one can estimate the RUL of the component. Last one uses a survival models where probability distribution of component failure times is used to estimate RUL from lifetime data of the component. This paper focuses on specific survival model based on Weibull estimation.

This paper discusses application of RUL models to a turbo actuator on a production diesel engine, including model design, model development, validation processes and their prediction outcomes. The work also highlights how the model was utilized to serve the needs of the business and its customers.

1.1. Turbo Actuator:

Variable geometry turbochargers (VGT) are in widespread use for on-highway diesel engines, due to several advantages they provide over fixed geometry and wastegate turbochargers. With a VGT, a nozzle ring or inlet guide vanes upstream of the turbine stage are positioned to vary the power extracted from the exhaust gas and delivered to the compressor stage. This allows continuous adjustment of engine air flow rate and exhaust gas recirculation rate to achieve optimal fuel economy within emissions constraints.

Moreover, VGT positioning can also be used to support special functions such as engine braking and exhaust temperature management, without the need for additional components such as intake throttles or exhaust throttles. Accurate VGT nozzle ring or inlet guide vane positioning is accomplished by a turbo actuator that includes an electric motor, a position sensor, and a circuit board. Because positioning can affect engine tailpipe emissions, actuator failures need to be monitored by on-board diagnostic algorithms. If a failure is detected, a dash lamp is illuminated and, in some cases, a Derating is triggered by on-board diagnostics (OBD) (Feneley, Pesiridis, Andwari (2017)).

Figure 1. Electric turbo actuator and actuation mechanism

While progress continues in developing more reliable and durable turbo actuators, there are reasons why an electric turbo actuator fails. To name a few – a) Limited temperature and vibration capability of the actuator's electric components compared to other engine components is a constraining factor, b) Expansion and contraction of board wire connectors could eventually lead to breakages and the failure of an electric actuator and c) Electric actuators may be more susceptible to water ingress owing to the position of the turbo in the engine compartment leading to rusting of the actuator. Such contaminated actuator results in incorrect signals and ultimately failure [2]. Electrical systems do require the addition of coolant pipes to avoid overheating that results in actuator failures [3]. Also, it is observed that most of the electric turbo actuator failures occur in the engine's late life (i.e., when engine has aged and run certain miles), due to solder cracks, capacitor depletions and hot shutdowns that result in thermal overstress.

Maintaining an electric actuator benefits the system in terms of rapid response time, more precise actuation of the moving elements and accurate minimum and maximum air flow (Feneley, Pesiridis & Andwari, (2017)). Unexpected disruption of vehicle operation due to actuator failure is clearly undesirable. The associated customer pain can be greatly alleviated by shifting reactive repairs to proactive replacements. There has been prior work in the area of predictive maintenance of diesel engines using artificial intelligence which helps in failure prediction of other after treatment components (Mckinley, Somwanshi, Bhave & Verma, (2020)). This prior work will form the basis for the RUL based approach described in this paper. Advanced analytics can support this transition through guiding the selection of preventive maintenance intervals. Development of a supporting analytics model for this purpose is described in the following sections.

In this paper, Section 2 describes the problem statement, followed by a detailed solution approach in section 3. Section 4 presents different models to predict RUL of turbo actuator, section 5 discusses the results and provides comparison on different RUL models. This is followed by a summary of the key conclusions of this effort and future work.

2. Problem Statement

Diesel engine efficiency, power, and emissions are sensitive to the ratio of air flow rate to fuel flow rate delivered to the cylinders. The air flow rate is largely determined by engine speed and pressurization of the air in the intake manifold which is completed by the turbocharger. As such, the turbocharger plays a leading role in both engine performance and engine emissions.

Variable geometry turbochargers allow closed loop control of air flow rate by varying turbine stage as mentioned above. This is accomplished by commanding the position of the turbo actuator. A position sensor on the actuator is used to compare actual and commanded position and to adjust actuator motor inputs accordingly.

Should the actuator be unable to accurately and promptly achieve its commanded position, tailpipe emissions could exceed regulatory limits. Many governmental agencies require that this be signaled to the operator using a dash lamp and the recording of 'fault codes' in the engine control module to advise service technicians that the actuator must be replaced. Unfortunately, under most circumstances the dash lamp is illuminated without prior warning. This leads to unplanned downtime, and in some cases to termination of the vehicle's mission.

The problem to be solved is to provide guidance on when an actuator should be proactively replaced to avoid the cost and inconvenience of an unexpected fault code and its impact of vehicle operation. As described in the following section, this can be accomplished by RUL modeling, supported by data recorded within the engine control module, historical records of past actuator failures, and subject matter expertise.

3. APPROACH

3.1. Definition of Data

Our analytics effort is focused on transit bus engines in the United States and Canada. Two main data sources were used: (a) Reliability data and (b) Engine snapshot data. Reliability data was originally collected for the purpose of warranty claim filing and payment (Lawless, Hu &Cao, (1995)). Reliability data provides particulars of the engine that experienced turbo actuator failure and when the failure occurred. Reliability data includes name of the bus fleet owner, engine details such as engine type, date of manufacture, serial number, service date, vehicle identification number, and all warranty claims for each engine such as date of repair, odometer reading at repair, type or repair, parts replaced, location of repair shop, repair explanation by the service technician.

Engine snapshot data was collected from the engine's electronic control module (ECM) during service events to assist the service technician in troubleshooting the fault code. Availability of these snapshots are subject to connecting the ECM device at an authorized workshop. The engine snapshot data includes a list of active and inactive fault codes and frequency of their trigger and the number of times the control system entered *engine protection* mode to name a few – high coolant temperature, high intake air temperature. Snapshot content also includes data used by the manufacturer to associate failures with duty cycle effects. Some of the duty cycle parameters available include histograms of engine speed – engine load combinations, metrics of vehicle speed, and similar.

We utilized duty cycle, engine age, and usage features in our study. These features are listed in our previous work (Mckinley, Somwanshi, Bhave &Verma (2020)). Some of the significant features considered are: Engine months since build, Fleet failure rate, Engine hours per month, Engine runtime hour, Average vehicle speed, Coolant temperature and Engine miles.

This study is interested in predicting turbo actuator failures in the engine's late life (i.e., when engine has aged and run certain miles), due to different wear out failure modes. Hence, we consider data from most recent engine snapshot till the first occurrence of the wear out failure, instead of random failure engine snapshots.

3.2. Analytics Model approach

Figure 2 depicts an overall approach taken to build an analytics model to find the useful life of the component – Turbo actuator. The approach illustrates 3 steps of modeling. They are:

Step 1. Capturing turbo actuator degradation conditions and identifying failure

Step 2. Building different RUL models capturing different details and variation in the data and identifying the model best suited to predict the life.

Step 3. Performing error analysis to choose the best model to predict the remaining life for the non-failures to help identify the failure time in miles for that component.

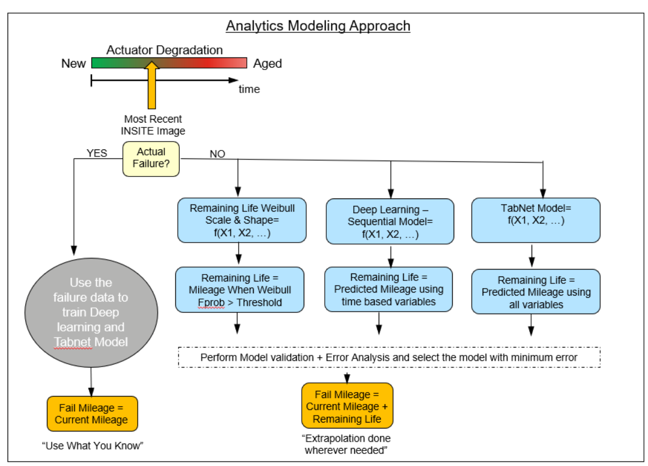


Figure 2. Analytics Modeling Approach

Capturing turbo actuator degradation conditions involve assessing the parameters such as Engine age, Engine operational hours, Average engine run per hours and Average miles per hour. As this study is interested in finding wear out failures due to engine age, we consider the data from most recent engine snapshot till the first occurrence of the wear out failure, instead of random failure engine snapshots. The first occurrence of wear out failure is identified by a look up in warranty claim data. Wear out failures are assumed to occur after a certain number of engine hours i.e., threshold engine hour, whereas random failures occur prior to the chosen threshold engine hour.

Once the failure data and records are identified, we continue with the Step 2 by building different models and executing tasks such as data exploration, feature creation, outlier treatment, model training and model validation. Three types of RUL models were trained on different parameters that capture variations in the data from the engine snapshot and reliability data. One of those models is a statistical model while the other two are deep learning architecture-based models. In this paper we call attention to the state-of-the-art deep learning model – "TabNet", a deep learning library by Google Research. Deep learning-based approaches use failure data to train the model and then predict the time of failure for all the non-failures whereas statistical model considers both failure and non-failure data and predict time of failures for the non-failures.

In Step 3, we undertake performance analysis of all the three developed models to select the one having the minimum error. That model was then applied to predict the remaining useful life in miles for the non-failure observations. To carry out the error analysis, we utilized the ground truth i.e. the failure data.

3.3. Feature Engineering

Feature engineering is a crucial and foundational step to machine learning and statistical studies to create ingenious features to assist the model building process by capturing variations using multiple variables and minimize information loss. Moreover, a good feature engineering process also helps us to reduce the model error. Following are the details of engineered and inventive features that were engineered before training the model.

We utilized the data sources (a) Reliability data and (b) Engine snapshot data defined in 3.1 to narrow down on the features.

Engineered Feature 1: Engine derating is the reduction of an engine's output due to less-than-ideal operating conditions. Derating sometimes is done intentionally when you want to prolong the engine's life and avoid substantial wear or damage. Due to less than ideal operating engine's output, Engine derating directly affects the engine, over a period. Also, it is observed that electrical turbo systems require additional coolant systems to avoid overheating for their smooth operations (Feneley, Pesiridis & Andwari (2017)). During exploration of the data we observed, effect of coolant temperature and Engine Derate on the turbo actuator failures and identified that there is a confounding effect between two explanatory variables – Coolant temperature and Engine Derate.

Low Engine Derate and high Coolant Temperature conditions contributed significantly to the turbo actuator failures. Figure 3 shows a multivariable (coolant temperature, Engine Derate and Failure and non-failure) scatter plot. The plot indicates that if we divide the interaction between these two variables by plotting two axes that will help us in differentiating failures and non-failures which are color coded in the plot. Quadrant 4 does have maximum failures occurring with specific range of Coolant temperature and Engine Derate. By applying a regular expression, we created a new variable – Coolant Derate, basis the interaction of these two variables.

Engineered Feature 2: We calculated the correlation coefficients of different duty cycle parameters to select most effective features, instead of dimensionality reduction techniques. This simple yet effective method was used to make feature creation and selection, more explainable. In Figure 4, we plotted the interaction plot that indicates the interaction of the three parameters – Climbing time, High speed time and light load time in identifying the failures. The highlighted areas indicate failures. This signifies that high highspeed time, low light load time and high climbing time had impact on the turbo actuator failures. The time mentioned in the below plot is the percent times the engine was at light load, high speed and climbing, out of the total trip time. These parameters correlation coefficients were calculated which is listed out in the Table 1.

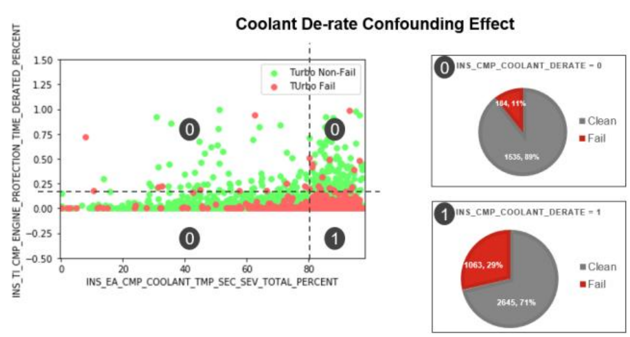


Figure 3. Feature Engineering 1 – Exploration of Coolant Temperature and Engine Derate parameters

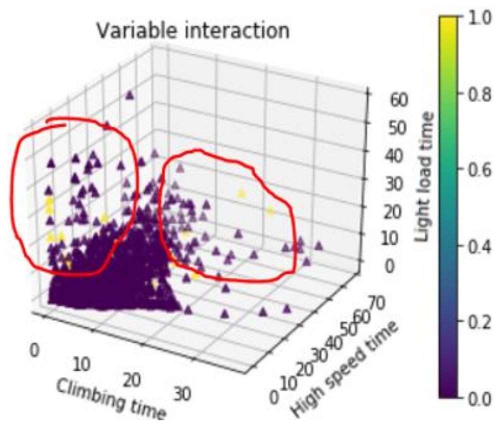


Figure 4. Feature Engineering 2 – Three-dimensional plot for Climbing time, High Speed time, Light load time

Table 1. Feature correlation matrix

Feature 1	Feature 2	Co-relation
Low speed time	Low speed medium torque	0.93
High speed time	High speed high torque	0.91
High speed time	Cruise mode time	0.70
Climbing time	High speed time	0.27
Climbing time	Low speed time	0.11

*High correlation- any one variable can represent
*Low correlation- can use both the variables

Post this assessment we chose the following features:

Low speed medium torque, Cruise mode time, Climbing time, Key switch cycles, Engine speed in miles per hour, Engine Age, Total Engine operational Hours, Fleet failure rate, Number of Days since occurrence of secondary fail code, Coolant temperature and Coolant Derate. Most of the features are operational features as they are the good indicator of a component's state at any given point in time

During the model-building phase, the analytical model learns failure probability of the component through the failure and latest engine snapshots with the help of captured/engineered feature values.

4. RUL MODELS

This section showcases three models that we developed to predict "Remaining Useful Life" of Turbo actuator. We present the details of these models in below subsections.

4.1. Deep Learning Model

Use of deep learning algorithms for remaining useful life (RUL) estimation based on telemetry data is very frequent. It has been proven that traditional multi-layer perceptron (MLP) approach for modeling the remaining useful life of a component based on the history is superior to the reliability-based approaches.

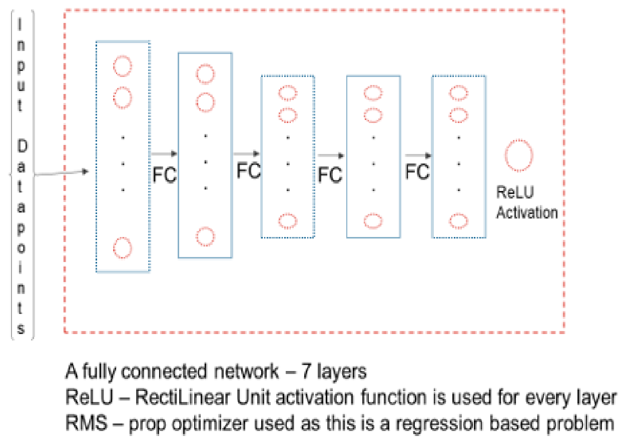


Figure 5. Fully connected network

Hence, we decided to use the deep learning architecture for prognostics that was already presented (Babu, Zhao and Li (2016), Yilmaz and Kaynar (2011)). Our data and the way it was spread across time, was the challenge to build deep learning-based solutions. Our data consisted of Engine image data where two images were not separated by constant time factor and it was sparse which was spanned across years. Most of the deep learning architectures work well when the data points are either separated by 1 second, 1 minute, 1 hour or 1 day. Hence we trained the deep learning model by converting our problem into more of regression based problem, where we knew the miles that unit had travelled before the failure. So, we built a model to predict the miles that the unit would travel before the failure of Turbo actuators. This was a challenging problem to solve as few data points were captured very close to the failure and few were captured distant from the failure. This resulted into high range of prediction which in turn induced extreme prediction error. Figure 6 depicts extreme predictions of deep learning model.

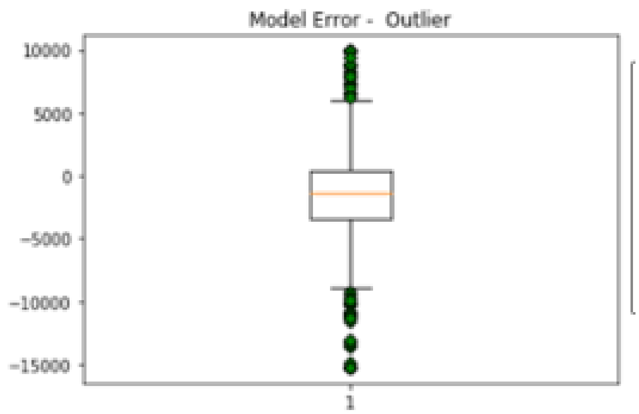


Figure 6. Prediction errors of deep learning model

Deep learning model was trained only on the failure data as the ground truth of only failure data points was known to us. This posed a limitation to train and build the model. Table 2 lists results of the model.

Table 2. Deep learning model outcomes

Training Error	
MAE	12200 Miles
RMSE	12600 Miles
Testing Error	
MAE	14000 Miles
RMSE	14500 Miles

4.2. TabNet

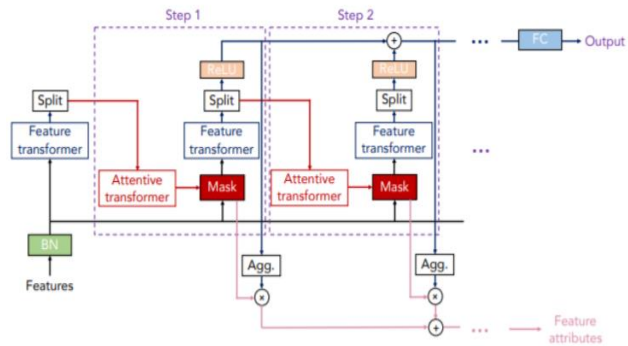
We implemented degradation model to predict remaining useful life of turbo actuator using TabNet(Arik and Pfister (2019), Xu, Yu, Yan & Xu (2020)). TabNet is a high-performance and interpretable canonical deep tabular data learning architecture. The TabNet uses sequential attention to choose features at every decision step, enabling more efficient learning for the salient features too. Relevant features are selected by using multiplicative sparse masks on inputs. Our dataset consisted of sparse features indicating indirect implication of other components failure or days before the engine was in service before Turbo actuator failure, etc. which we wanted the model to consider as salient features. The TabNet proved to be suitable choice for the implementation as in TabNet, its attention module is trained to select feature amongst vast normalized vector of input features and in later stage, the feature transformer consumes the selected features for overall embedding. Although the architecture is empirically motivated it was worth a try to compare it with other methods.

TabNet architecture has three major components as shown in the figure 7.

1. Attentive Transformer – It explains how much each feature has contributed before the current decision step.

2. Mask – It obtains global feature importance by performing feature aggregation

3. Feature transformer – It transforms the features basis their interactions. Step1 is encodes the features and Step2 decodes.



(a) TabNet architecture

Figure 7. TabNet Architecture

To make use of TabNet regressor that is built on a deep learning framework we did modify our problem statement. We created a TabNet multi-regressor class and modified the problem into a regression problem. Remaining useful life parameter was our target variable and all set of complete input features were independent variables. The regressor was only trained on failures and then the model was applied to predict failed miles for non-failures. Hyperparameters of TabNet regressor were tuned on the failure data basis 2 metrics - a validation score and root mean squared error. A validation score is defined as mean percentage deviation of all the data points.

Validation Score = Mean (sum (abs (Predicted - True))/ sum(true))

Out of the total dataset we had 25% failure data points to train the model. Those points were again divided into training and validation. Where 20 percent points were kept aside for validation. Figure 8, 9 and Table 3 present results of TabNet regressor.

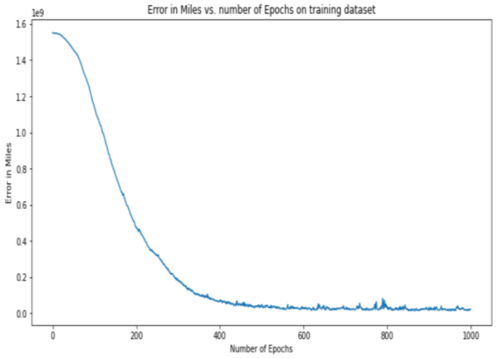


Figure 8. Convergence of the TabNet Model

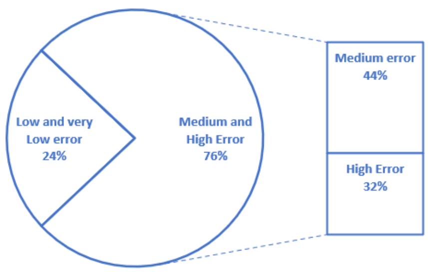


Figure 9. Error distribution of the TabNet Model- Actual values are masked and error buckets are considered instead

Table 3. TabNet model outcomes

Training Error	
MAE	10000 Miles
RMSE	10500 Miles
Testing Error	
MAE	12000 Miles
RMSE	12500 Miles

4.3. Accelerated Weibull Failure Time (AWFT) Model

Warranty terms and conditions are generally based upon calculated risks of failure. Many companies and design engineers utilize a statistical tool called life data analysis otherwise known as Weibull Analysis to determine component failure. By determining the risk of a product or component failure, the manufacturer can better estimate warranty costs over time and assign a corresponding warranty period. Weibull Analysis is a methodology used for performing life data analysis. Life data is the result of measurements of a product's life. Depending upon the product or industry, product life data is calculated in hours, miles, number of cycles or other metrics used to establish a measure of successful function of a product.

Most companies in business today monitor warranty costs and product failure rates. The goal is to reduce warranty costs and possible loss of brand equity. In addition, information gathered using a Weibull Analysis allows the manufacturer to plan for any known costs or set the proper warranty terms. Weibull Analysis is an effective method of determining reliability characteristics and trends of a population using a relatively small sample size of field or laboratory test data (Zhang (2016)). Life data is the result of measurements of a product's life. Weibull analysis has two important parameters – a**)** The "scale parameter". It is called the scale parameter because in the Weibull age reliability relationship it scales the value of age, t. That is, it stretches or contracts the failure distribution along the age axis. Its value and unit are determined by the unit of age, t, (e.g. hours, miles, fuel consumed, rounds fired, etc.). and b) The "shape parameter"**,** is also known as the Weibull slope. This is because the value is equal to the slope of the line in probability plot. Different values of the shape parameter can have marked effects on the behaviour of the distribution. In fact, some values of the shape parameter will cause the distribution equations to reduce to those of other distributions. For example, when slope = 1, the *probability distribution function* of the three-parameter Weibull reduces to that of the two-parameter exponential distribution. The slope parameter is a pure number (i.e., it is dimensionless).

We model the failure rate in Weibull analysis through a hazard function (Conditional density given that the event in question has not yet occurred prior to time t.) which can be a function of component age in years, in miles, operational hours etc. Our survival variable is Miles.

4.3.1 Hazard function for Weibull Shape and Scale regression model

The basic structure of the Weibull regression model has distribution of time to event, T, as a function of multiple covariates. This is also called the accelerated failure-time model because the effect of the covariate is multiplicative on time scale and it is said to "accelerate" survival time. In contrast, the effect of covariate is multiplicative on hazard scale in the proportional hazard model. Weibull regression model can be written in both accelerated and proportional forms, allowing for simultaneous description of treatment effect in terms of HR and relative change in survival time (event time ratio) (Lin (2018)). **Accelerated Failure Time model** (**AFT model**) is a parametric model that provides an alternative to the commonly used proportional hazards models. Whereas a proportional hazards model assumes that the effect of a covariate is to multiply the hazard by some constant, an AFT model assumes that the effect of a covariate is to accelerate or decelerate the life course of a disease by some constant. This is especially appealing in a technical context where the 'disease' is a result of some mechanical process with a known sequence of intermediary stages. The main assumption of an AFT model is that survival time accelerates by a constant factor when comparing different levels of covariates (Saikia & Pratim (2017)).

To assess the model performance, we used different metrics such as MSE, RMSE and Concordance. Although MSE and RMSE and MAPE are used in most of the regression problems we used Concordance as our main model performance indicator during this study.

Concordance is like accuracy as a metric, but it is more of a ratio. Concordance explains the variance of the model that we develop. For example, if we have several features, out of which feature-pairs on interaction that add value to the model either for detecting fail/non-fail correctly these number of feature pairs / total number of feature pairs is calculated as concordance. Usually the MAPE and RMSE values are expected to be lower for a model to be a good fit but the concordance value is expected to be higher. Table 4 showcases the features used and their significance Figure 10 shows the predicted vs. actual graph with median prediction considered to calculate the error.

Table 4. Feature importance – The actual importance values are masked but the significance was obtained using pvalues

Features	Significance
Engine hours per month	Very High
Coolant Derate	Very High
High Speed Low torque	High
Average Vehicle speed	High
Engine load	Medium
Idle fuel used	Medium

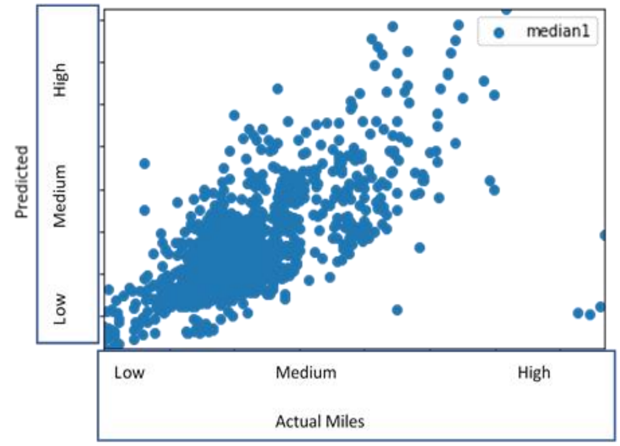


Figure 10. predicted vs. actual graph[2]

Figure 11 and Table 5 provide error distribution of the WFT model. If we look at the error distribution, then 34% error is in the low and very low bucket. This error is calculated basis the failures only. Here are the values of other metrics.

Table 5. Error distribution of WFT model

Training Error	
MAE	9000 Miles
RMSE	9500 Miles
Testing Error	
MAE	12000 Miles
RMSE	12500 Miles

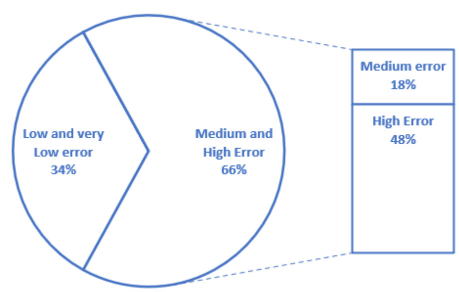


Figure 11. Error distribution of the WFT model – Actual Values are masked, and error buckets are considered instead

[2] Due to the organization's confidentiality rules, actual values could not be presented in the papers. Instead, representative terminologies such as low, medium and high have been used, wherever applicable.

5. Comparison of the Models

This subsection we discuss comparison of all three models we developed and explain the process of validation. Figure 12 depicts validation graph of Deep learning, TabNet and WFT models.

The objective of our model is to predict the remaining useful life for a predictive maintenance interval selection. But this interval will be selected according to a bus fleet. The failure rate for every bus fleet can be different and hence the maintenance interval can be different too. Hence it is important to validate the model on fleet level. The X axis of the graph shows the miles and Y axis of the graph shows failure probability. Failure probability indicates how many percentage units for a particular fleet will fail by certain number of miles

Now if we look at all the models built, WFT gives the best prediction at on or before between low to medium miles. The failure percentage curve is closer to the actuals than any other model's prediction. We extrapolated the actual curves due to unavailability of quality data post warranty period and hence a two-point extrapolation method is used to identify the failure curve, post warranty period. WFT model regresses well with the extrapolated curve till medium miles and at 50% failure rate. For us 50% failure rate is high enough to identify or schedule a maintenance interval. The slope of the two-point extrapolated curve is high because of the high failures between last few miles of warranty period and hence it shows an aggressive failure percent estimation stating every unit would fail till high miles. So, we selected the model which is closer to the actual data at the end of warranty period miles. WFT outperforms the other two models at the selected point miles and hence it is our selected model.

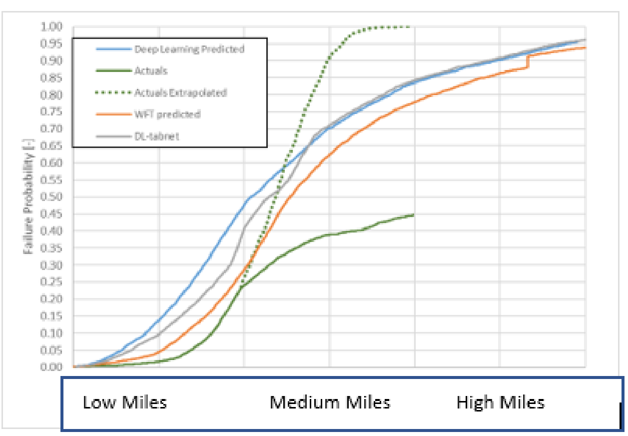


Figure 12. Validation graph of Deep learning, TabNET and WFT models

Table 6. - Summary of comparison of WFT, TabNet and RNN

	WFT	TabNet	RNN
Training data	All data points	Only Failures	Only failures
Performance at high failure rate	Satisfactory	Good	Good
Performance at low failure rate	Better than TabNet and RNN	Satisfactory	Satisfactory
Performance on new data	Good	Satisfactory	Satisfactory
Out of time validation	Low RMSE	Relatively high RMSE	High RMSE
Dependencies	Low	High	High
Feature importance	Feature significance can be obtained based on p values	Feature importance extraction is difficult	Feature importance extraction is difficult

6. Conclusion

The objective of this study was to demonstrate that Turbo actuator life in miles during the warranty period could be predicted with an acceptable error using available data. The results will allow preventive replacement of sensors using generic fleet specific maintenance intervals.

The study also compared the simple generic model (AWFT) with other deep learning models like TabNet and Recurrent Neural Networks (RNN). We had also established a hypothesis that the AWFT model will perform better than Deep learning technique due to nature of the available data. The results that we got prove this assumption right.

The results mentioned in the study show that this has been accomplished, setting the stage for preventive replacement of sensors using either unit specific life prediction or fleet specific maintenance intervals basis the predicted life failure probability curve. This was a challenging task, since Turbo Actuators have multiple failure modes, some of which are due to random events. Keys to success include Minimizing the influence of random failures, which comprise about 10% of all failures during the warranty period, by screening out failures occurring prior to an acceptable threshold engine hours. This allowed model training to focus on prediction of life basis more predictable wear-out failure modes. Using exploratory analysis in conjunction with subject matter expertise to rapidly accelerate feature engineering and the screening of features to be included in the model. Including system interactions through the consideration of prior failures (warranty claim fail codes and fault codes). Next steps also include preparing the model for production so that business benefits can be achieved through a precise estimate of developed remaining useful life model. The prediction of failure timing in miles can be improved by tuning the model by getting more data and identifying more failures. The techniques developed and proven here will also be reapplied to other key engine components.

7. ACKNOWLEDGEMENT

We are especially appreciative of technical insight and guidance provided over the course of this project by Dr. Nilesh Powar from Cummins. Mrs. Subhalakshmi Behera provided us key guidance on planning all the activities and helping us understand business requirements. Mr. Sandeep Verma, Mr. Virendra Parte and Mrs. Vidya Jasud provided us key insights regarding data extraction and storage. Mr. David Hall provided us necessary technical and engineering guidance on Turbo Actuator sensor failure. All these colleagues were key contributors to this effort. Finally, the authors thank Cummins, Inc for the opportunity to publish this work.

8. NOMENCLATURE

Table 7. Nomenclature

Sr.NO	Abbreviation	Definition
1	XGBoost	eXtreme Gradient Boosting
2	WFT	Weibull Failure Time
3	RNN	Recurrent Neural Network
4	AFT	Accelerated Failure time
5	WAFT	Weibull Accelerated Failure Time
6	HR	Hazard Rate
7	OBD	On-board diagnostics
8	MAE	Mean Absolute Error
9	RMSE	Root Mean Squared Error
10	MAPE	Mean Absolute Percentage Error
11	DL	Deep Learning
12	RUL	Remaining Useful Life
13	MLP	Multilayer Perceptron
14	ReLU	Recti Linear Unit

9. REFERENCES

[1] Feneley, A. J., Pesiridis, A., & Andwari, A. M. (2017). Variable geometry turbocharger technologies for exhaust energy recovery and boosting-A Review. *Renewable and sustainable energy reviews*, *71*, 959-975.

[2] https://www.recoturbo.co.uk/electronic-actuator-failure-repair

[3]https://x-engineer.org/automotive-engineering/internal-combustion-engines/ice-components-systems/variable-geometry-turbocharger-vgt/

[4] Mckinley, T., Somwanshi, M., Bhave, D., & Verma, S. (2020, July). Identifying NOx Sensor Failure for Predictive Maintenance of Diesel Engines using Explainable AI. *In PHM Society European Conference (Vol. 5, No. 1, pp. 11-11).*

[5] Lawless, J., Hu, J., & Cao, J. (1995). Methods for the estimation of failure distributions and rates from automobile warranty data. *Lifetime Data Analysis*, *1*(3), 227-240.

[6] Babu, G. S., Zhao, P., & Li, X. L. (2016, April). Deep convolutional neural network based regression approach for estimation of remaining useful life. In *International conference on database systems for advanced applications* (pp. 214-228). Springer, Cham.

[7] Yilmaz, I., & Kaynar, O. (2011). Multiple regression, ANN (RBF, MLP) and ANFIS models for prediction of swell potential of clayey soils. *Expert systems with applications*, *38*(5), 5958-5966.

[8] Arik, S. O., & Pfister, T. (2019). Tabnet: Attentive interpretable tabular learning. *arXiv preprint arXiv:1908.07442*.

[9] Xu, T., Yu, Y., Yan, J., & Xu, H. (2020). Long-term rainfall forecast model based on the TabNet and LightGbm algorithm.

[10] Liu, E. (2018). Using Weibull accelerated failure time regression model to predict survival time and life expectancy. *BioRxiv*, 362186.

[11] Saikia, R., & Barman, M. P. (2017). A review on accelerated failure time models. *International Journal of Statistics and Systems*, *12*(2), 311-322.

[12] Zhang, Z. (2016). Parametric regression model for survival data: Weibull regression model as an example. *Annals of translational medicine*, *4*(24).

10. BIOGRAPHIES

Devawrat Bhave, born in India, is a Data Science professional working in Cummins and holds a master's degree in data science from Praxis Business School. He is working the field of data science for last 8 years. His main area of interest is the study of various machine learning algorithms and their implementations in various domains. His work experience includes working for domains like Life sciences, Finance and Manufacturing domains.

Deepa Tavargeri Adiga, is a Principal Data Scientist, working in Cummins. She has a rich experience of 20 years spanned across research, industry and academia. Her past research work enabled her to develop expertise in Natural Language Processing and currently working on analytical solutions for automotive industry. Her contributions have been in the domains of Requirements Engineering, Behavioral Sciences, Cognitive Sciences and Manufacturing utilizing machine learning, deep learning, data science methodologies. In her free time, Deepa enjoys reading, painting, gardening and long walks.

Nilesh Powar is the Advanced Analytics Director at Cummins. He holds bachelor in electronics engineering from University of Bombay, India, M.S in Computer Engineering from Wright State University and a doctoral degree in Electrical and Computer Engineering from University of Dayton, Ohio. He has over 20+ years' experience in field of image processing, machine learning, statistical pattern recognition and system integration. He had worked in the US as Distinguished Research Scientist for University of Dayton Research Institute, Dayton, OH, USA. Recent efforts involve data analytics for die casting, predictive analysis for supply chain management and video summarization using deep learning.

Thomas L. McKinley is the Corporate Director of Engineering Analytics at Cummins, Inc. He holds bachelor and master's degrees in mechanical engineering from Purdue University at West Lafayette and a doctoral degree in Mechanical Engineering from the University of Illinois at Urbana-Champaign. His multi-decade career has included engine combustion and emissions modeling, product development, problem solving, physics-based product validation methods, and engineering analysis of a wide range of diesel engine emissions control systems. He has authored 18 technical publications, including six journal articles. In recognition of this expertise, he has been elected as a Fellow in the Society of Automotive Engineers (SAE) and served as an associate editor for the SAE International Journal of Engines. Current research interests include prognostics for critical engine components.