A methodology using health and usage monitoring system data for payload life prediction

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Abstract

This paper presents a methodology to monitor the fatigue life of aerospace structures and hence the remaining allowable fatigue life. In fatigue clearance, conservative load assumptions are made. However, in reality, a structure may see much lower loads and so would be usable for much longer. An example of this is air carried guided missiles. In the UK, missiles must be decommissioned after a period of carriage. The implementation of a system that can monitor the usage of a missile during its time in service is advantageous to the military customer and provides a competitive advantage for the missile manufacture in export markets where reduced through-life costs, longer in-service lives and increased safety are desired. The proposed methodology provides a means to monitor the service life of a missile. This paper describes how machine learning algorithms can be used with accelerometers to determine loads on a missile structure which would then be used to predict how long the missile has left in service.

1 Introduction

Current aircraft increasingly incorporate a Health and Usage Monitoring System (HUMS). HUMS is a data collection system that records inputs from the aircraft such as speed, other flight parameters, power and voltages of electrical systems [1]. Health and Usage Monitoring Systems (HUMS) come under the category of Damage Detection. The use of damage detection has become increasingly important for existing structures and mechanical systems. Existing structures such as bridges and systems such as aircraft have become more and more expensive to maintain. By introducing damage detection for structures and mechanical systems, it will be possible to extend their operational use beyond their designed service life [2] and prevent failure during service.

Distinguishing the two meanings behind health and usage monitoring is essential.

- Health Monitoring: the process of identifying aspects of data obtained through sensory measurement from a system over time and quantifying the extent of the damage.
- Usage Monitoring: the process of recording data during the structure's or system's operation. The data measured can include environmental variables such as temperature and moisture and operational variables such as speed and altitude [3].

The application of health and usage monitoring systems was first applied to rotary aircraft; however, it originated from the methodology of structural health monitoring (SHM) [2]. SHM is the process of damage detection for aerospace, civil and mechanical engineering infrastructure. In the aerospace industry, SHM has been predominant with rotor aircraft during early stages of HUMS development both in commercial and military sectors. The implementation of HUMS into aircraft has now been increasingly common practice since the 1990's. It has been proven to lead to both improved safety and provide economic benefits [4]. While safety aspects are an important issue and a reason to implement the HUMS, the cost was the deciding factor. The typical cost and upkeep for a helicopter can be broken down into five categories. 36% for depreciation, 29% to insurance, 24% to maintenance, 6% to the flight crew and 5% to fuel [4]. The drive behind implementing HUMS in helicopters was to reduce the cost of insurance and maintenance. The reasoning behind this was cost saving in areas of replacement parts. The HUMS data would be used to identify parts which are damaged or reached their safe-life. Therefore, there was a reduced number of spares used for unnecessary removals of healthy parts and an increased time of the helicopter in-service. However. Guided weapons are typically safe-life structures and as such detectable damage is unlikely to be permitted while in-service. Hence, in this case, Damage Detection is less applicable than Operational Monitoring techniques.

The use of machine learning in the aerospace industry has been researched by Homes et al. [5], who used Gaussian Process Regression (GPR) to predict the loading on the landing gears during landing, taxiing and take off using onboard data recording systems. Previous research has used machine learning for fault and damage detection such as Baskaya et al.[6] and Bondyra et al.[7] whom both used Support Vector Machine (SVM), a machine learning algorithm, on a small Unmanned Aerial Vehicles (UAV) for fault diagnosis. The notable benefit of using supervised machine learning is that it only requires two sets of data, the inputs and output. This eliminates the problem of prior knowledge of the model, in this case, the dimensions and structural properties of the missile. This makes the methodology versatile since the process can be applied to any aircraft to predict any characteristic, whether it is loads, flight manoeuvres or damage detection. However, the potential downside of this methodology is that a machine learning model must be created for every eventual scenario. For example, if an aircraft is carrying one missile on either end of the wing, data would have to be collected, and a machine learning model would have to be created for that scenario. If there were two missiles on either end of the wing, then new data would potentially have to be collected, and a new model would have to be produced. If the missile type was changed but used the same layout configuration then the process has to be repeated. Every change could potentially require a specific model for the prediction to reliable and accurate. This process may be cumbersome. However, the same process would have been used to test a non-machine learning methodology to validate the algorithms.

The machine learning approach in this article utilises Gaussian Process Regression (GPR) along with Neural Network (NN) and Support Vector Machine methodologies in order to predict loads in the attachments of an air-carried missile to the aircraft, or hangers. Machine learning is a computer-based program which uses mathematics to predict and identify outcomes based on the properties of data. The information from the data would later be used to predict future data. Machine Learning works because it can learn patterns from non-random data such as simulations, experiments and surveys. It learns these patterns by generalising the data. Generalising the data is a method for the program to understand the data. The first step when creating a machine learning algorithm is selecting the raw data which will be used for the inputs. This is known as the input space. Each set of inputs which makes up the input set is known as features. For example, if an input space had recordings from one temperature sensor, one accelerometer and two strain gauges, then the data set would have four features. The next stage is pairing the input space with the output data. The output data are target output which one is trying to predict. The input space and the target output form together the training data. The next step is selecting the classifier which is the machine learning algorithm that forms a predictive algorithm based on patterns between the known input space and known target output data [8]. This process is known as the training stage. This stage takes up the most computational time since it is going through many iterations to obtain the optimal prediction algorithm to fit the data. The training data can consist of any statistical data whether it is numerical or categorical. Testing is the final stage where the classifier is tested to try to predict unknown output data using unknown input space data which has not been used in the training stage. The classifier is using patterns learnt from the training stage to predict the unknown targets. This stage is used to test the performance of the predictions and optimise the parameters to improve accuracy.

The ultimate goal of this methodology is to provide a process which results in a system that can determine the fatigue damage and thus remaining life of a missile. The process begins with load prediction using GPR. With this loads data in principle, stress time histories could then be determined and fatigue damage calculated making use of Cycle Counting, S-N curve data, and the Palmgren-Miner rule. Over time, this process can be refined so that the cycle counting method and S-N curve data would not be longer be required and the system would only require the data from the HUMS and the machine learning algorithm to provide a prediction yielding the remaining life of a missile.

2 Theory - Overview of GP Regression

GP is a supervised machine learning algorithm which can solve complex datasets which traditional parametric methods may not be able to handle [9]. The algorithm used for this project was developed by Carl Rasmussen [10]. GP regression works by having a training dataset which contains the observed response data, in this project the strain, and the input vector data which are the accelerations. GP creates a prediction based on the dataset by forming a family of functions to fit the data and provides a predictive distribution as opposed to a single prediction [5]. What makes GP beneficial compared with other machine learning algorithms is its ability to show uncertainty estimates with predictions. It does not require cross-validation because the kernel and regulation parameters can be learned directly from the data. Also, feature selections can be used during the training stage [9]. Features are the input data used in prediction, such as acceleration, temperature and speed. Feature selection is an algorithm which removes features so that the optimal prediction algorithm can be created.

The Gaussian process is defined by two functions in the form of:

$$f(x) \sim GP(m(x), k(x, x')) \tag{1}$$

where

$$m(x) = \mathbb{E}[f(x)] \tag{2}$$

$$k(x, x') = \mathbb{E}[(f(x) - m(x))(f(x') - m(x'))] \tag{3}$$

The mean function, $m(x)$, represents the expected value of the function $f(x)$ at the input x. The mean function is generally set as zero because little is known about the input data when it is the first time training the prediction model. The covariance function, $k(x, x')$, determines the covariance of the two predictions at any two specific points and can be considered as a measure of the confidence level for $m(x)$.

The GP then forms the following algorithm:

$$y = f(x) + \eta \tag{4}$$

Where y represents the observed response, x represents an input vector, η represents the noise.

When it comes to deciding on which covariance function should be used, the most common one is the squared exponential. This is used as a standard when first using GP regression on new data. The general form is written as follows [10]:

$$k(x, x') = \sigma_f{}^2 exp\left(\frac{1}{2l^2}|x - x'|^2\right) + \sigma_n{}^2\delta_{pq} \tag{5}$$

Where $\sigma_f{}^2$ and $\sigma_n{}^2$ are signal and noise variances, respectively, and l is the characteristic length scale.

3 Missile Loads Testing Setup

The Structural Health and Usage Monitoring System (SHUMS) data was collected via a test rig to which a representative missile structure was mounted, via two of the hangers, by attachments providing simple support conditions. The structure was representative of an air carried complex weapon in terms of geometry, inertial characteristics and body bending stiffness. Excitation was provided by a shaker on which the test rig was mounted. To record the load acting on the hangers during the vibration test, two strain gauges were attached to each support, making four in all. The mean strain was calculated for each support giving two sets of axial strain recordings for the hangers. Seven tri-axial accelerometers were placed at specific positions along the length of the missile structure.

In this study, the dataset collected contained 810442 by 11 data points over a time of 100 seconds of excitation. Seven columns contained the acceleration data, and the last four contained the strain data.

4 Results

The following section shows the results predicting strains on the attachments under vibrational loads using Gaussian Process Regression, Neural Network and Support Vector Machine. Figure 1, Figure 2 and Figure 3 are the results from GPR predictions. Figure 1 is the overview of the full data between 0 and 100 seconds, Figure 2 is the view between 0 and 4.5 seconds and Figure 3 is the view between 80 and 80.5 seconds. Figure 4 shows the equivalent results for NN and SVM. Figure 5 shows the scatter plots for all three machine learning algorithms showing the actual strain against predicted strain. The last of the results is shown in Tables 1 and 2 which provide measures of the performance of the three algorithms.

All three machine learning algorithms were programmed to use 70 percent data training and 30 percent testing. Therefore after 70 seconds, the algorithms were predicting unseen data. In each Figure are two more graphs that represent the strain data from the two hangers, for example as shown in Figure 1. Figure 5 gives scatter graphs representing the actual strain against the predicted strain.

In each of Figures 1 to 3, there are three crucial pieces of information being shown, the predicted strain, true strain and confidence level. The predicted strain was calculated using the GP algorithm. The true strain is the recorded strain from the hangers. The confidence interval uses the 95 percent approach from a normal distribution.

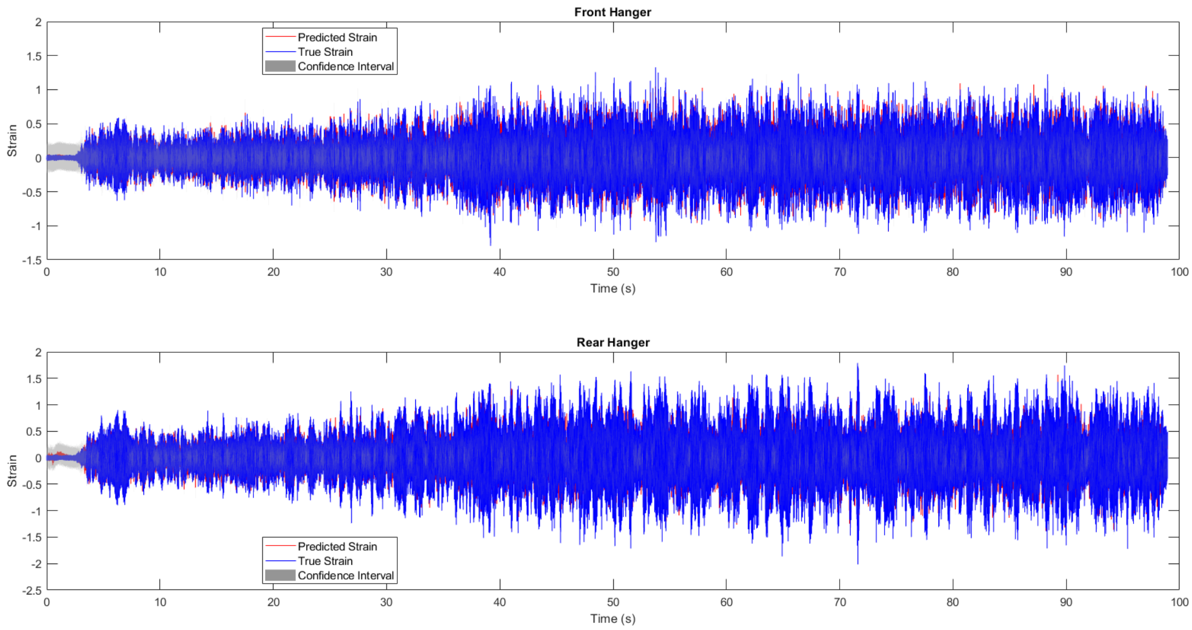


Figure 1: GP prediction graph for stains in the Front and Rear Hanger between 0 and 100 seconds.

A critical part of the load prediction is predicting peak loads, especially where these points are essential to extract data that will be important for later analysis such as Cycle Counting. Figure 2 and Figure 3 shows a magnified view of Figure 1. It is challenging to analyse large amounts of data, so the figures mentioned provide a small window of the load prediction. The purpose of showing the first 5 seconds was to demonstrate reconstruction during low loads and then higher loads. During flight, an aircraft will experience long hours of steady flight and the model would have to be capable of predicting these levels accurately.

It can be seen in Figure 2 during the first 3 seconds that the predicted strain deviates away from the true strain especially for the rear hanger between 0.2 and 2 seconds. This is corroborated by the confidence interval being much higher. This may be due to the acceleration data or the positions of the accelerometers. When it transitions to higher loads after 3 seconds the predictions become more accurate and the confidence interval shrinks which tells that the model recognises the data. The predictions for the testing data, shown in Figure 3, also shows accurate predictions. One of the problems that occurs with GPR is the predicted strain undershooting the true strain. For example, in Figure 3, the front hanger, at peak 80.32 seconds the predicted strain undershoots the true strain. There maybe a few undershoots in this graph but when the time increases these undershoots accumulate. As mentioned previously, undershooting is not ideal if the peaks are going to be used for Cycle Counting because it is safer if a missile has to be decommissioned early from service due to predictions overshooting rather than staying in service longer due to undershooting where the missile structure could be prone for failure.

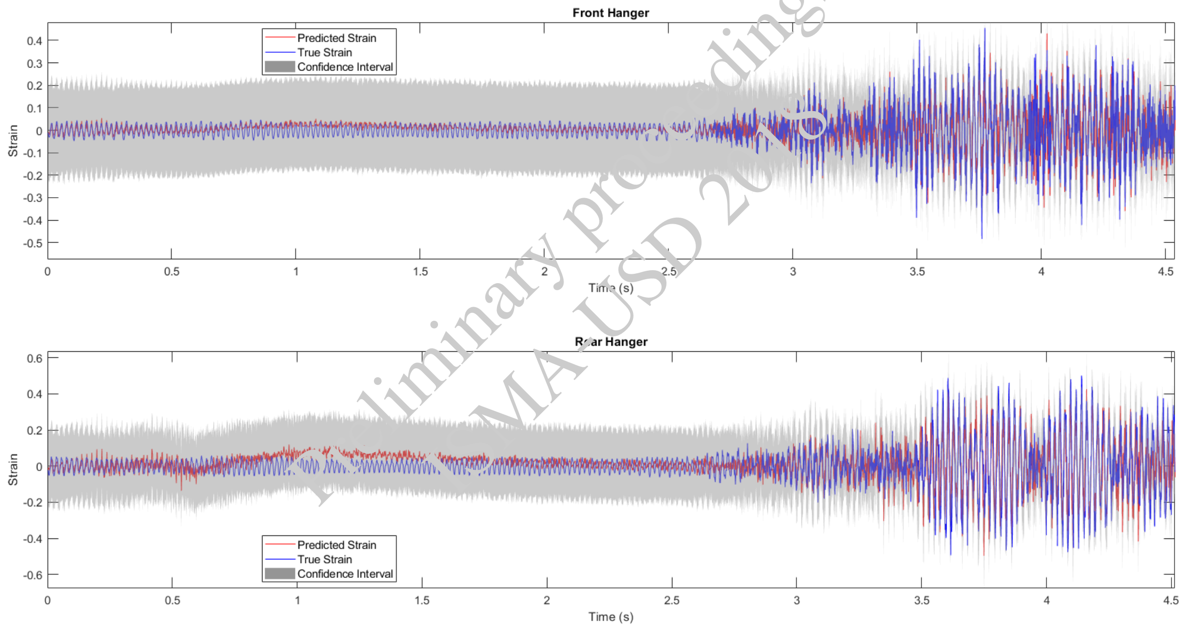


Figure 2: GP prediction for stains in the Front and Rear Hanger between 0 and 4.5 seconds.

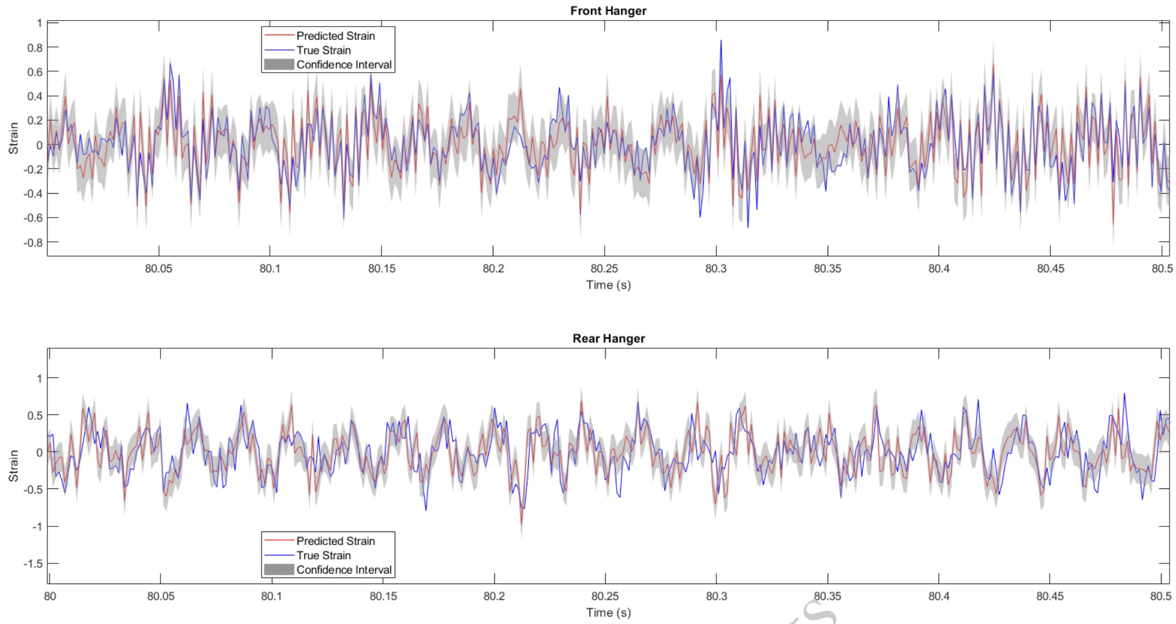
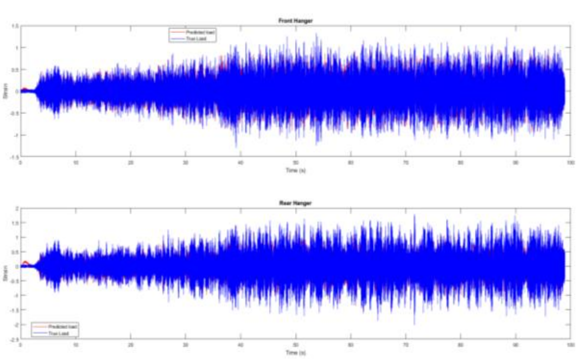
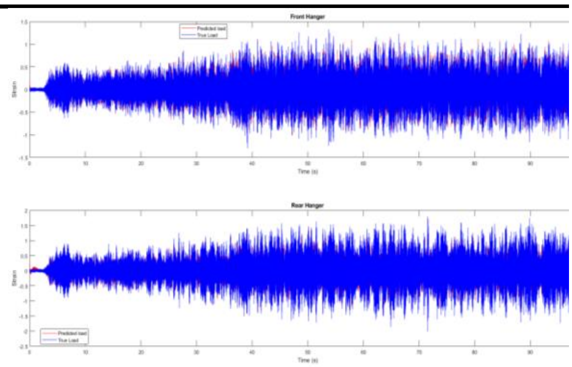


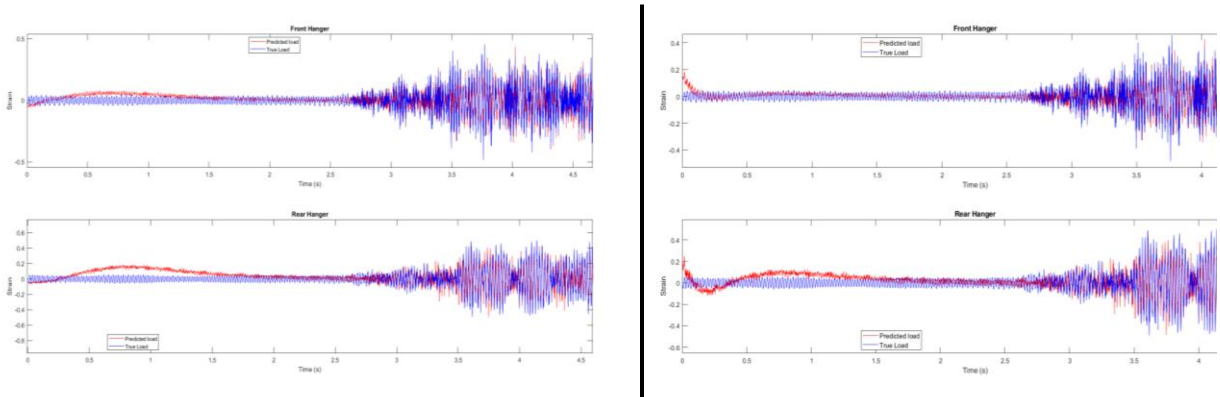
Figure 3: GP prediction for stains in the Front and Rear Hanger between 80 and 80.5 seconds.

Neural Network and Support Vector Machine approaches have a disadvantage, and that is that the model cannot show the extent to which it recognises the data through the confidence interval [11], as shown when using GPR. There are other methods to compensate for this by improving accuracy such as cross-validation and training with more data. What is noticeable in Figure 4 (c) is the first 2 seconds. The predicted strain forms a 'bump' in the line plot. This is greater than that seen in the GPR Figure 2. This prediction error may be due more to the acceleration data than the model itself. For the test data results, shown in Figure 4 (d), they are very similar to the GPR. The NN scatter plot in Figure 5 (a) and (b) show similar shape to GP scatter plot.

Figure 4 (b), (d) and (f) show the load predictions using SVM. This model shows almost identical results to GP and NN. However, for the front hanger, there is a difference during the first 2 seconds where the prediction begins with a strain value higher than the true strain, and then it normalises after 0.2 seconds. This does not occur with the rear hanger where the predicted strain undershoots and then overshoots before normalising at 2 seconds. Since these discrepancies occur during the first 2.5 seconds for the three models, the cause may be due to the recorded data rather than the model setup.

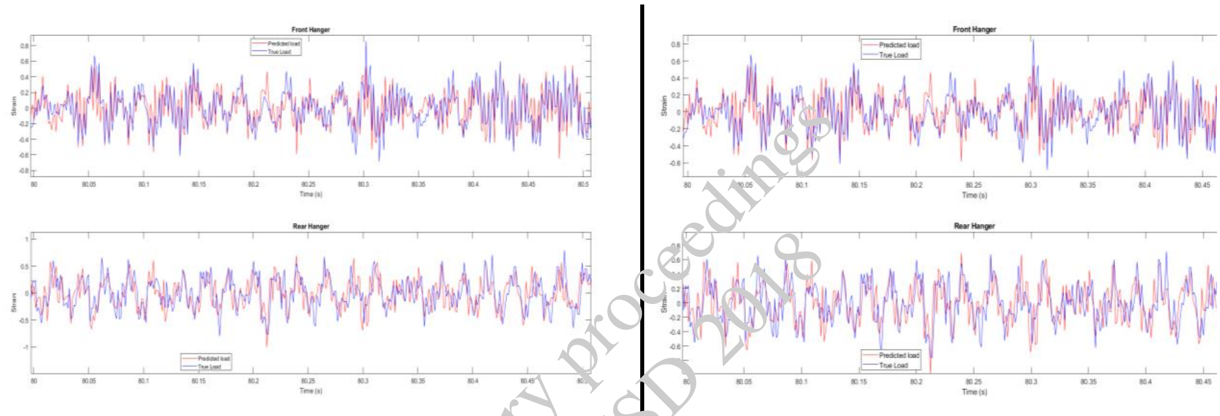
Neural Network	**Support Vector Machine**
	
(a)	(b)

Front and Rear Hanger between 0 and 100 seconds



(c) (d)

Front and Rear Hanger between 0 and 4.5 seconds.

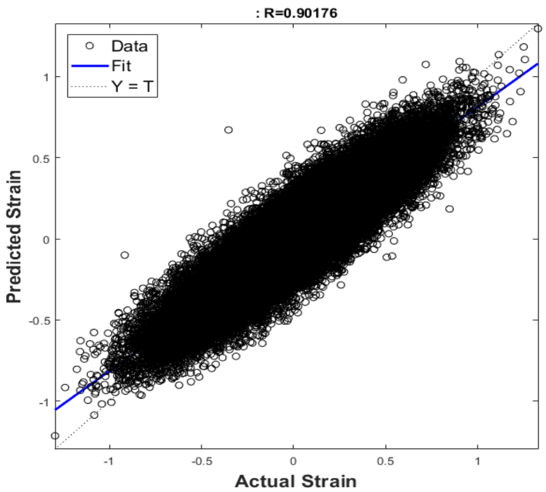


(e) (f)

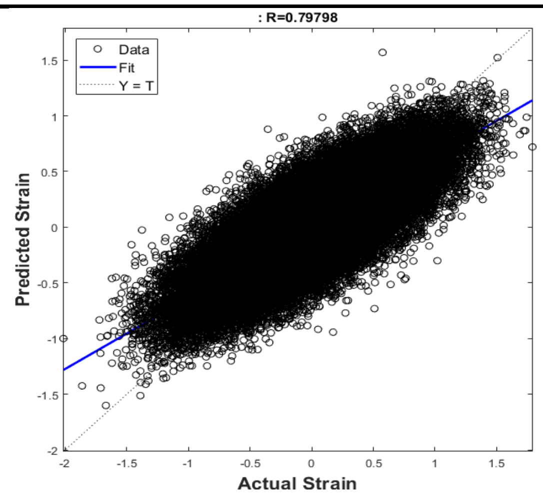
Front and Rear Hanger between 80 and 80.5 seconds

Figure 4: NN and SVM prediction graph for stains in the Front and Rear Hanger.

Front Hanger	**Rear Hanger**

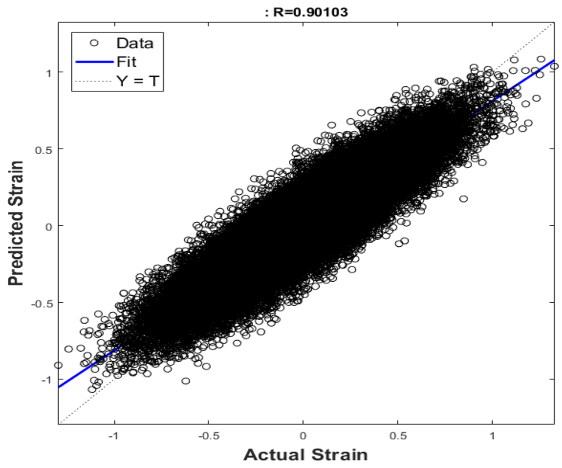


(a)

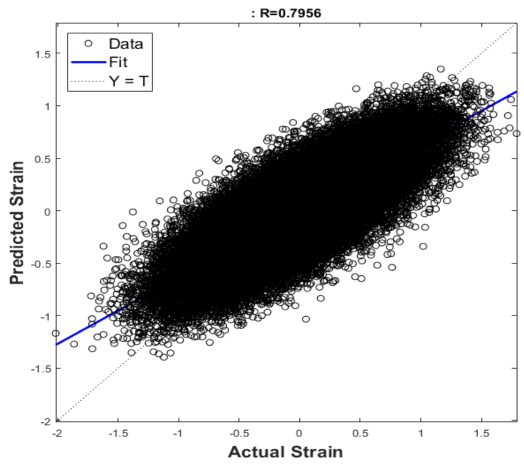


(b)

GPR scatter plots of Actual Strain against Predicted Strain

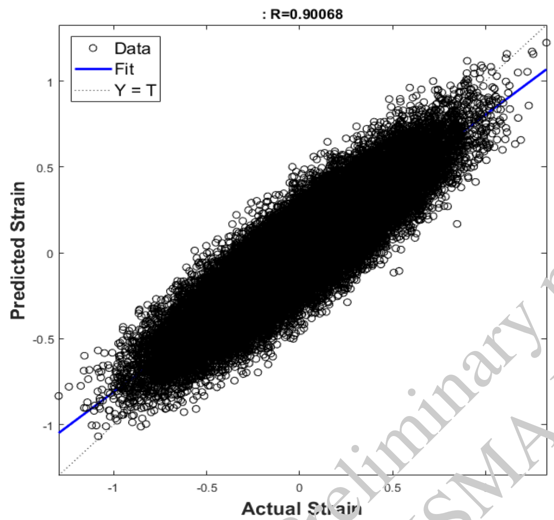


(c)

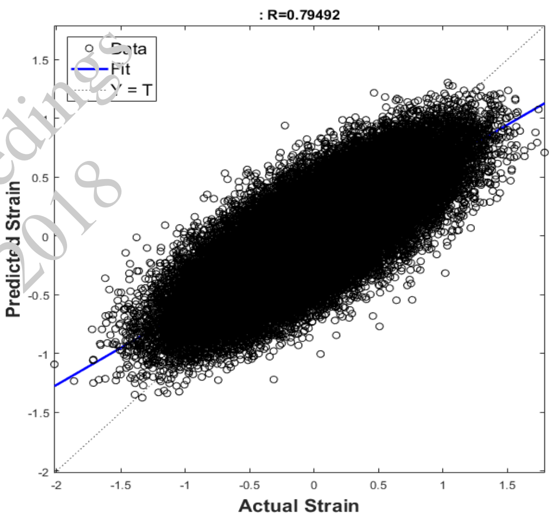


(d)

NN scatter plots of Actual Strain against Predicted Strain



(e)



(f)

SVM scatter plots of Actual Strain against Predicted Strain

Figure 5: GPR, NN and SVM scatter plots of Actual Strain against Predicted Strain.

Scatter plots of actual strain against predicted strain for the overall GPR used on both hangers are shown in Figure 5 (a) and (b). The closer a data point is to the Actual Strain versus Predicted Strain line the more accurate the prediction.

An overall evaluation of the performance of the models is given in Table 1 and Table 2 for the front and rear hangers respectively. In each table there are three evaluation columns: mean absolute error (MAE), root mean squared error (RMSE) and Pearson correlation coefficient (R). Furthermore, evaluation data for training, testing and overall is provided with a comparison of prediction when the model is shown seen and unseen data. The evaluation equations used to measure the performance of the classifiers for MAE, RMSE and R are as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \bar{f_i}| \tag{6}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \bar{f_i}\right)^2} \tag{7}$$

$$R = \frac{\sum_{i=1}^{N}(y_i - \bar{y})\left(\bar{f_i} - \bar{\bar{f}}\right)}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2\left(\bar{f_i} - \bar{\bar{f}}\right)^2}} \tag{8}$$

where

$$\bar{y} = \sqrt{\frac{1}{N}}\sum_{i=1}^{N} y_i \text{ and } \bar{\bar{f}} = \sqrt{\frac{1}{N}}\sum_{i=1}^{N} \bar{f_i} \tag{9}$$

where N represents the size of the dataset, y_i is the target output and $\bar{f_i}$ is the predicted output of the GPR prediction model.

In Figure 1, is the overall strain prediction using GPR. One of the noticeable discrepancies is in the performance values between front and rear hangers, as shown in Table 1 and Table 2. For example, the R value for the front hanger was 0.90176, and the rear hanger was 0.79798. This same difference can also be observed with the other two models. It would have been expected that these values would have been roughly the same since they were using the same model and inputs dataset. The only difference is the strain targets values and the position of the strain gauges. This may be the reason why the rear hanger performance value is not as good as the front hanger value. The current position and the number of the accelerometers may not be ideal for the rear hanger. Therefore, changing the accelerometer locations may influence the results of the predictions.

Front	**Training (70%)**			**Testing (30%)**			**Overall**		
Model	MAE	RMSE	R	MAE	RMSE	R	MAE	RMSE	R
GPR	0.0924	0.1227	0.90179	0.1200	0.1507	0.90171	0.1007	0.1317	0.90176
NN	0.0939	0.1243	0.899	0.1188	0.1489	0.90416	0.1014	0.1322	0.90103
SVM	0.0935	0.1243	0.89917	0.1195	0.1497	0.90301	0.1013	0.1324	0.90068

Table 1: Performance comparison of GPR, NN and SVM for the Front Hanger.

Rear	**Training (70%)**			**Testing (30%)**			**Overall**		
Model	MAE	RMSE	R	MAE	RMSE	R	MAE	RMSE	R
GPR	0.1926	0.2539	0.80319	0.2551	0.3196	0.78981	0.2113	0.2752	0.79798
NN	0.1961	0.2575	0.79683	0.2529	0.3170	0.79371	0.2131	0.2767	0.7956
SVM	0.1954	0.2575	0.79675	0.2540	0.3181	0.79206	0.2130	0.2771	0.79492

Table 2: Performance comparison of GPR, NN and SVM for the Rear Hanger.

5 Discussion

One of the limitations in using GP is that it is necessary to invert a large N by N matrix, where N is the number of data points in the training dataset. For this study, the total dataset contained 8914862 data points. The ability to do this is affected by a computer's hardware due to the size of the RAM. The larger the matrix, the more RAM and computational processing time are required. To reduce the demand on the RAM sub-sampling of every 11th data point from the dataset was implemented. One of the problems in using this approach is the likely chance of losing critical data especially at the peaks where strain is at maximum or minimum. While this approach was not ideal, it was necessary to overcome hardware limitations. However, there are ways to circumvent these problems. New studies in handling big data sets have emerged with regards to GP [12], [13]. The benefit of machine learning is once the classifier has been trained, the prediction process or testing stage is not limited by matrix size and computational time is greatly reduced to a few minutes.

Overall, the results show promising predictions when using machine learning for load predictions. All three models provided accurate prediction. For the rear hanger improvements to the hanger positions and the number of accelerometers will be researched to improve the performance of the methodologies. As for which was the best model for load predictions, GPR did yield the highest correlation coefficient for both hangers but only by a small amount. Deciding which is the best machine learning model is not only decided by which provides the best results. As shown in the tables all three models showed similar results. What decides which model is the best is how much resources are needed to get a good prediction such as computational power and time to process and how much data is required. Also by what form of assurances can be provided to obtain the optimal predictive model, such as cross-validation and the confidence interval. Each model has its advantages and disadvantages. One of the issues which occur with machine learning is overfitting and underfitting. Overfitting occurs when the prediction results are identical to the actual results. This may be ideal; however, if unknown data is introduced, then the predictive model would be unable to produce accurate results, as found in [5]. Underfitting is the opposite to overfitting where the predictive results are poor and are not close to the actual results. There has to be a balance between the two and the confidence interval provides information as to whether the predictive model is balanced and optimal.

When using the GPR and SVM both had problems dealing with large datasets, the computational time was 8 and 6 hours for training, respectively, when using supercomputers. The GPR required 192 GB of RAM to complete training. However, NN was able to complete the training in 1 hour. NN can handle large datasets while GPR and SVM cannot. What makes GPR advantageous is its prediction of the confidence interval, its accessibility to different variations of covariance functions that can influence the prediction and the ability to modify the model to suit the problem. NN is accessible however it is a complex system in comparison with GPR.

The paper presented has focused on the use of machine learning algorithms for the load predictions of a missile supported by two hangers. It is common for missiles to be supported by two hangers, but some missiles require three hangers. It is necessary that GPR be capable of predicting loads for three hangers. During the development of GPR for two hanger load predictions, the three hanger problem was also tested using data obtained from a Finite Element Analysis (FEA) model which generated response data for given input loads. The purpose of using such FEA software rather than using experimental data was to test the capability of GPR and identify any potential problems before proceeding to an experimental setup which requires money, resources, time and validation data to confirm that the missile is setup correctly. After training the model to predict three loads through the hangers and then testing, the results were promising; the prediction resembled the results from the presented two hanger load predictions. A problem that load predictions has for a three hanger missile is it being ill-posed which was identified in research by Vishwakarma et al [14]. Using the pseudo-inverse method for load predictions, he proposed that to overcome the ill-posedness problem, regularisation was required. However, for GPR it appears that based on the initial results regularisation was not required.

6 Conclusion

The purpose of the paper was to show the potential application of Gaussian Process Regression to extend the life of an air-carried missile. Load predictions using GPR is part of the process for extending the life by monitoring the usage of a missile during its time in service. Using machine learning for monitoring the usage of a missile means that it does not rely on the use of a model which may have limitations. The only necessary data are the inputs and output, in this project, the acceleration and strain data, respectively. The machine learning algorithm forms a predictive model based on these two sets of data without requiring any knowledge of the structure. The disadvantage of this process is that it is computationally expensive in time and resources and requires a large dataset to obtain the optimal prediction model. Also, there may have to be multiple predictive models for every structural change to the missile and aircraft. However, once the predictive model has been obtained, it is capable of calculating prediction results rapidly, and the process is not limited by the data size and computational power available.

Using GPR has its advantages and disadvantages, it is computationally more expensive than NN due to the large inverse matrix which is required to process the data. However, there has been research into how to enable GPR to handle large data better. The important feature which GPR has is the confidence interval which provides information on the accuracy of the prediction. NN and SVM do not have this feature.

As for the GPR used in this missile load prediction study, it is necessary to implement improvements to the model and the training dataset, especially for the rear hanger. While the front hanger predictions were better, the peaks were not always well predicted. Further research is required to remove or reduce the noise to improve the accuracy of the prediction. It may only require the number and the position of the accelerometers to be changed to improve the results. Another possibility is that it requires the model's covariance function to be changed.

NN and SVM were used as a comparison for GPR. NN and SVM have proven to be more than capable for load prediction and making them possible alternatives. If there were no prospect to enable the use of GPR to handle large data without the requirement for large computational resources and NN had the ability recognise that the model is making inaccurate predictions, then NN would have been the ideal choice. However, GPR has accessibility to the code which makes it versatile for modification to suit the user requirements.

Using GPR is only one part of the system to predict Payload Life. Once this part has been optimised to perform to the user requirements, it can be implemented with standard methods for usage monitoring such as Cycle Counting Analysis. More research is required for HUMS since it has a wide range of accessible data to exploit other than accelerations, but GPR has shown it is capable of predict loads on a missile.To enable GPR to handle large data and reduce computer resources without changing the current GPR algorithm, one approach might be to create a logical method whereby the HUMS is only activated during manoeuvres where loads would be large. During flights where the aircraft will be flying straight and steady these can be classified as benign flight conditions, and fatigue damage could be assumed to accumulate at some pre-determined rate. Another algorithm or secondary machine learning algorithm can identify manoeuvres that go over a pre-determined threshold and filter out the benign flights which are only used for the load predictions training process.

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