Student Paper ☒

Transfer Learning for Flight Loads Estimation

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Abstract

Developments in flight test data systems have led to an abundance of data which can be harnessed via machine learning for flight load estimations. Main measurements used for the load estimations are strains. However, the transition from strains to loads requires load equations obtained from calibration load tests. Estimated loads obtained by strain data are used for several purposes, from predictive maintenance to development projects. The fidelity of the obtained loads highly affects these activities. Prior research showed that higher accuracy could be achieved with artificial neural network models instead of classical regression analysis. However, the models provided some inaccurate results for some load components during the transition to predicting flight data, and further development is required to improve the flight loads predictions.

Using the idea that calibration test data consists of the knowledge of the loads, our aim is to pass on this knowledge to the flight domain to increase the fidelity of the estimated loads. This is possible with machine learning algorithms classified under transfer learning. Transfer learning deals with the transfer of knowledge obtained in one domain to another domain. A load model developed using the calibration test data as a source for training artificial neural networks can be fine-tuned using flight test data, which also includes additional information to increase the accuracy. The research in this paper focuses on applying transfer learning to convey the knowledge in the calibration domain to the flight domain and shows the potential to overcome the poor generalisation in transition to flight in order to achieve high fidelity loads outputs when using such a method.

Keywords: flight loads prediction, flight test, load calibration test, transfer learning

Introduction

Load calibration and flight load tests are used for validation and verification of the loads calculated in aircraft design. They also assure the aircraft structural integrity under severe and repeated load cases over its life. Loads cannot be directly measured by strain gauges installed on aircraft. To obtain the loads under different conditions, strain gauges are installed in several locations on the aircraft to observe the behaviour of the related aircraft component under shear, bending and torsional loads. Load calibration tests provide the data to establish relationships between measurements from strain gauges and the applied loads. These relationships are given as inputs to calculate the loads during subsequent flight tests.

As the next step in the load estimation process, flight tests need to be performed. During the flight test, the aircraft performs different manoeuvres, which causes different types of loads over the aircraft structure. In addition, shear, bending moment and torsional loads are also related to each other. Measurements are taken from the flight test instrumentation (strain gauges) and the loads are calculated with the relationships obtained in load calibration tests. These relationships are usually obtained by multiple linear regression techniques.

Although multiple linear regression techniques can be used to derive these relationships, the application of novel mathematical approaches should be investigated to evolve the models for flight load prediction [1]. By using artificial neural networks, it is possible to obtain the relationship between the strain gauge measurements and applied loads during the calibration test more accurately [2]. By considering how fast-growing the improvements in Artificial Neural Networks (ANNs) are, the potential for impact using this field of analysis could be significant.

The study in [1] shows that although ANNs can provide superior results in terms of the calibration test, there was no consistent improvement in the load measurements during the fight test. The results from the flight test data comparison show that ANNs obtained by the calibration data generalise poorly for the flight test measurements. This brings into question the suitability of calibration based ANN models, suggesting this is not enough to estimate the loads in the flight phases.

This study aims to investigate the performance of a machine learning approach, transfer learning, in aircraft flight loads predictions. In this paper, processing time and generalisation ability of the transfer learning method are explored. The transfer learning system is compared first with a traditional learning system using flight data and second as the transition to the flight problem defined in prior research [1]. The results show that the transfer learning system provides less error and reduces the analysis time to 75% of that required for a traditional learning system trained with flight data. In addition, it shows the potential to overcome the poor generalisation in transition to the flight domain, since the results show 90% less error with a supervised transfer learning system that transfers the knowledge in calibration domain to the flight domain. In the following sections, transfer learning is explained further, and its application in aircrafts load analysis and the results of the analysis are discussed.

Transfer Learning

There are two domains in the transfer learning process: source domain and target domain. The source domain contains some knowledge that can aid in learning in the target domain and improve performance in target domain results. The idea of transfer learning is driven by the fact that people can solve any problem by using their previous knowledge and quickly get better solutions [3]. Transfer learning aims to improve the target learners' performance in the target domain by transferring the knowledge obtained from the related source domain [4].

A very good categorisation for different transfer learning settings is given in [3] according to inductive, transductive transfer learning settings and labelled and unlabelled data on the source and target domains. In inductive transfer learning, the target task can be different from the source task because the reasoning in the training process is achieved by obtaining the general rules. On the other hand, transductive learning tasks should be the same because the reasoning in the training process is achieved for specific test cases. It is also possible that an unsupervised transfer learning setting with fully unlabelled data in both source and targets could be used.

As discussed, both labelled and unlabelled data can be used in different settings in transfer learning. In transfer learning, the data distributions are taken separately for the source and the target domains, and data in the source domain is used to learn generalisable representations.

As a transductive transfer learning category, domain adaptation deals with a typical case where plentiful labelled data out of the domain and a small number of labelled data in the domain are available. This is an example of semi-supervised learning [5]. As such, it is possible to achieve good performance with minimal effort by fine-tuning with out-of-domain data in domain adaptation.

For different settings, instance transfer, feature-representation transfer, parameter transfer and relational knowledge transfer approaches are used in problem-solving [3]. The instance transfer approach re-weighs some labelled data in the source domain to use in the target domain. Feature representation transfer aims to minimise the error between source and target domains by finding a good feature representation. In the parameter transfer approach, shared parameters or priors between the source and target domain are found. Finally, in relational knowledge transfer, statistical relational learning techniques are used to transfer the relationship among data from a source domain to a target domain.

Transfer learning is an active field of research with applications in different fields, such as medical, bioinformatics, transport, and recommender systems [3]. Although there is no application in aircraft loads analysis, it can be said that knowledge from one domain can be used for estimating the loads in different domains with a transfer learning setting in this field. This may be the transfer of knowledge from one type of aircraft to another aircraft or the transfer of knowledge in the calibration domain to the flight domain. In this paper, the advantages of knowledge transfer from the calibration domain to the flight domain are investigated.

Transfer Learning in Aircraft Load Analysis

Different from the traditional learning setting, two different domains are used in the transfer learning setting: source domain and target domain. In this research, the source domain is set as load calibration data, and the target domain is flight test data. A learning system obtained using basic knowledge of load calibration data can be improved by fine-tuning with the data from flight load tests. The relevant knowledge from the source domain is promoted, and the effect of the irrelevant knowledge is reduced. The general setting of the problem is shown in Fig. 1.

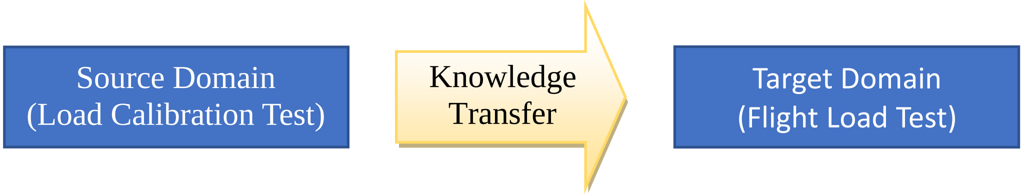

Fig. 1: Problem Setting

For this particular study, data collected by the Defence Science and Technology (DST) Group using a Pilatus PC-9/A trainer aircraft operated by the Royal Australian Air Force (RAAF) was used. During the calibration, known loads were applied to the empennage of the PC-9/A and the resulting strain responses were recorded. Using these strain responses, load equations capturing the relationships between applied load and measured strain for various load components were subsequently derived using standard multiple linear regression techniques. These equations were then used during the flight load test campaign, flown with the same aircraft, to measure the empennage loads. More detail on these datasets is given in [1].

In this study, data collected from five strain gauges installed on the port horizontal tail during the load calibration and flight load tests were used as inputs for the estimation of the vertical shear force on the port horizontal tail. While there are 1,518 examples in the load calibration dataset, there are 4.75 million examples in the flight load test.

The k-fold cross-validation method was applied to show the performance of the training process over the whole data. K-fold is a validation technique in which the data is split into k-subsets. Then, the holdout method is repeated k-times where each of the k subsets is used as a test, and a validation set, and other k-2 subsets are used for training purposes. For this aim, load calibration and flight load test data were divided by 80:10:10 for training, validation, and testing sets, respectively, for 10-fold cross-validation. The Root Mean Square Error (RMSE) metric, indicating the error between the measured and calculated shear load, was used in error calculations.

The instance transfer learning approach was used in the problem set-up. In training with calibration test data, a feed-forward network with a single hidden layer containing 16 neurons, and a single output was used. Adam optimiser [6] was applied with a scheduled learning rate decreasing by 10 per cent every 250 epochs. In the second step, the parameters of the pre-trained model were optimised with flight data. To achieve this, the model parameters of the input and hidden layer are fixed and only the output layer parameter is optimised to generalise better for the flight data. In this step, a stochastic gradient descent optimiser with a scheduler reduces the learning rate when a metric has stopped improving. A general schematic of the model is given in Fig. 2.

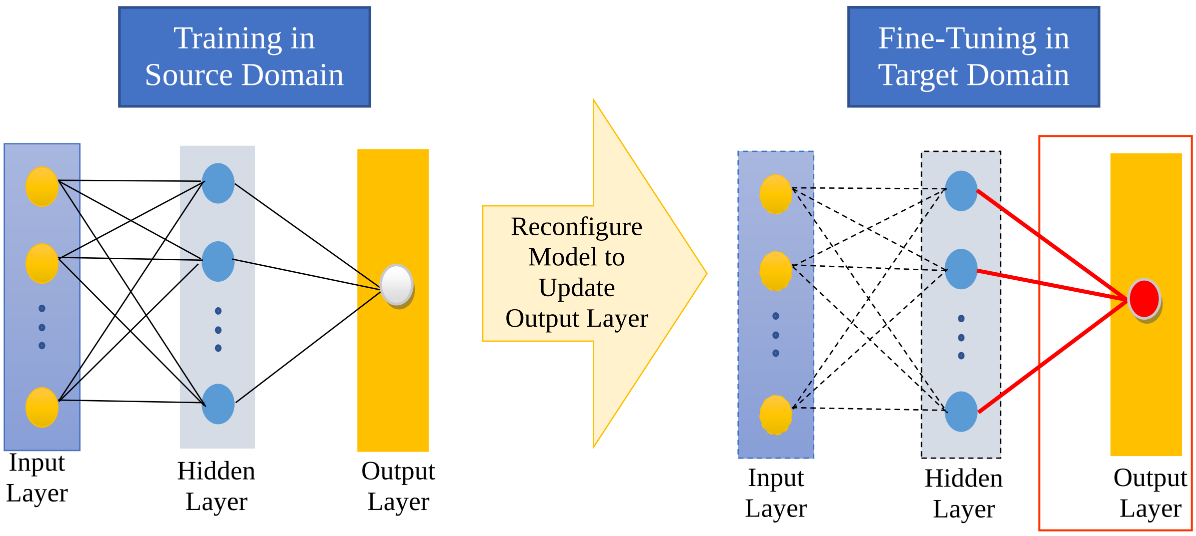

Fig. 2: Model fine-tuning on output layer. (Dotted lines represent fixed parameters)

Results and Discussion

The results of investigated transfer learning system have been compared to two different systems to show the performance of each system. Results were generated for the vertical shear (Fz) at Port Horizontal Stabiliser Rib 2 (PHR2).

The first comparison was made with a learning system that uses only flight test data in training the model (traditional). A very similar model architecture to that defined in training in the source domain in the previous section was used. Flight data was split with 80:10:10 training, validation, and test sets respectively for 10-folds validation. The same flight data with the same split used in transfer learning model was used. The model consisted of a feed-forward network with a single hidden layer containing 16 neurons, and a single output layer. Adam optimiser [6] was applied with a learning rate which is reduced when a metric has stopped improving during training. This schedule for learning rate decay provided better performance with this dataset.

Table 1 shows that the given transfer learning system can provide similar or even better RMSE results than the traditional machine learning system. In Table 1, while the first row shows errors on flight data with a traditional learning system trained with flight data, the second row shows errors on flight data with a transfer learning system trained with calibration and then flight data. Besides having less errors, learning time was reduced to 75% of the time spent on the traditional learning system; because the first step of the transfer training uses a small calibration dataset in the training and provides a base for quicker learning in the second step.

Table 1: Comparison of traditional learning system and transfer learning system PHR2 Fz

	Fold 1	**Fold 2**	**Fold 3**	**Fold 4**	**Fold 5**	**Fold 6**	**Fold 7**	**Fold 8**	**Fold 9**	**Fold 10**	**Mean± Std. Dev.**
Traditional Learning System RMSE (N)	38	45	44	44	44	44	45	44	45	44	44±2
Transfer Learning System RMSE (N)	36	40	37	38	54	42	38	36	38	37	40±5

It was known that the model trained only in the source domain generalised poorly when used in flight domain (original system) [1]. By applying the transfer learning technique, the ability to improve the performance of the neural network increased about 90% (Table 2). This was accompanied by a 50% increase in analysis time, however as the original system training time was very short, this increase has a relatively minor impact on overall processing time.

Table 2: Change in RMSE (N) with transfer learning for PHR2 Fz

	Fold 1	**Fold 2**	**Fold 3**	**Fold 4**	**Fold 5**	**Fold 6**	**Fold 7**	**Fold 8**	**Fold 9**	**Fold 10**	**Mean± Std. Dev.**
Original System	295	361	278	722	307	291	362	615	439	364	403±150
Transfer Learning System	36	40	37	38	54	42	38	36	38	37	40±5
% Change in RMSE											-90%

Conclusion

This paper describes a transfer learning system that can use the knowledge in a load calibration test and improve the results when transitioned to flight test. The proposed transfer learning system significantly reduces the error in the predicted flight load data at the cost of a relatively small increase in the run time of the training process. This shows that transfer learning applications may provide a good baseline for any other load estimation problems related to flight tests.

The system introduced in this paper is based on a supervised transfer learning method which fully uses the labelled data. Because of this, the system can provide a significant improvement in performance. As a next step, the potential advantages of transfer learning with a semi-supervised learning ability will be investigated. This further research may overcome the poor generalisation problem of neural networks in flight load prediction.

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