1. INTRODUCTION

Today, the focus of the aviation industry is to build efficient, sustainable planes. This is being done in many ways, such as composite material fuselages and wings, high-bypass ratio engines, and eco-friendly fuel sources. At the forefront of such development, as in many other spheres of development today, are computer systems, especially computer systems that can learn from previous experiences and reduce the computational cost of simulation-aided design.

1.1 The Development of Computer Science in Aviation

Computer science is an integral part of the research and development done in aviation. From not being used at all in designing aircrafts such as the Concorde and the early generation Boeing 747s to being used to design the entire aircrafts today, the role of computers has increased greatly in the aviation sector.

Aircraft design is an interdisciplinary task, with multiple mutually interdependent systems. The analyses of such systems that is conducted in the design process tends to be computationally expensive due to the correlated nature of the system. It is here that machine learning plays a vital role by reducing the costs (technical, human, computational, and time) incurred during design. This is done by using numerous algorithms that can approximate the design simulation solutions.

1.2 Introduction to the Paper

This seminar, and its associated report, is based on '*Knowledge Transfer Through Machine Learning in Aircraft Design*'. The paper was published in the November 2017 issue of IEEE Computational Intelligence Magazine. The research for this paper was done by researchers at the School of Computer Science and Engineering, Nanyang Technological University, Singapore, in conjunction with Rolls-Royce@NTU Corporate Lab.

As stated in Section 1.1, the paper aims to summarise the role that machine learning currently plays in the discipline of aircraft design, and explore the possibilities of incorporating contemporary advances in the field of machine learning to increase its impact in the domain.

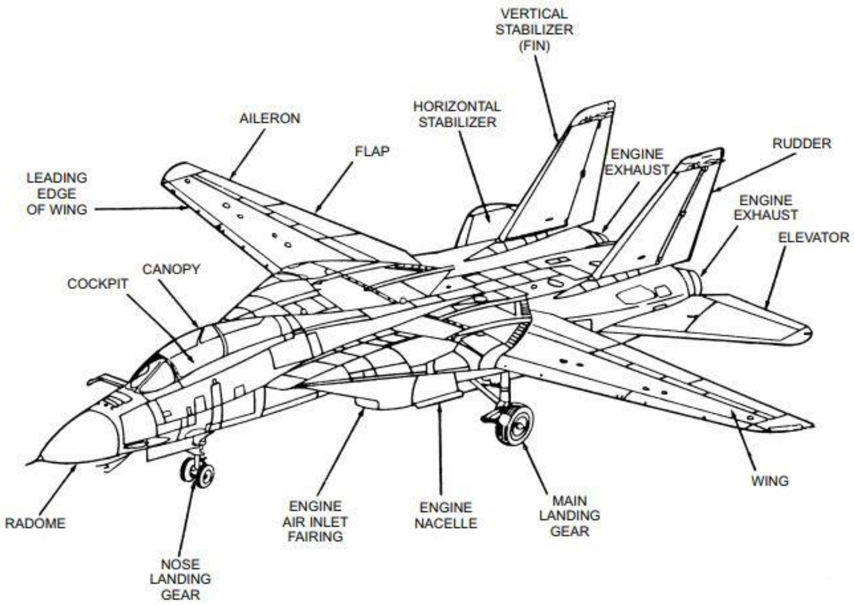

Figure 1: The various parts of a Grumman F-14 Tomcat

2. BACKGROUND WORK AND LITERATURE SURVERY

2.1 The Current Use of Machine Learning in Aircraft Design

Aircraft design is an incorporative and multidisciplinary task. It can be described as a multidisciplinary design optimisation (MDO) problem. A MDO is explained in detail in Section 3.1.

Before the advent of computer aided design technologies such as CATIA, aircraft design was a labour intensive, physical experiment. Multiple models had to be created and tested for each aircraft system and subsystem, including models for the multiple interdependent systems of an airplane. Such a design effort required time, and ample human and monetary resources.

With the use of specialised design software running on high-performance computer systems, it has become possible to develop high precision mathematical models of physical systems. Modern analyses are heavily reliant on such models. These aforementioned models are solved for a discretised domain to obtain numerical solutions.

However, just as the manual design effort had a set of problems associated with it, so do simulation models, namely computational complexity. The improvement in the accuracy of any model, particularly complex models of interconnected systems, comes with the price of increased computational complexity. For example, depending on the size and accuracy requirements for a computational fluid dynamics (CFD) simulation, the simulation can take between a few minutes and a few weeks to complete. As any large-scale design effort requires potentially hundreds or thousands of simulations, it is evident that such long simulations are undesirable. One could reduce the accuracy of each simulation, but this can potentially result in a less fault-proof and more error-prone system, which is again, an objectionable and unwanted situation.

It is in such design simulations that machine learning is used. In aircraft design, machine learning is principally used to approximate these complex and expensive physics-based simulations. Supervised regression and surrogate models tend to be used for such tasks. The range of models used include Gaussian process regression (GPR, kriging), co-kriging, neural networks, and radial basis functions. Currently, a large proportion of machine learning based research and application for aircraft design has been in the following fields:

1. Data-driven surrogate modelling of physical phenomenon
2. Machine learning complemented physics solutions

The next two subsections will be describe each of the fields mentioned above.

2.1.1 Data-driven Surrogate Modelling of Physical Phenomenon

Regression models have been a popular choice in the domain of aircraft design. They are chiefly used to approximate computationally expensive physics-based numerical simulations.

For example, in [1], a polynomial regression model and radial basis neural network combination was used to obtain the optimised shape of a supersonic turbine with multiple design variables. In [2], the authors constructed a GPR model to approximate the computational structural mechanics analysis of a turbine disc under mechanical and thermal load conditions.

Variable-fidelity physics simulations is another popular application of regression models. In the field of scientific simulation and modelling, fidelity refers to the degree to which a simulation or a model reproduces the behaviour and state of a real world object. A model with a high accuracy level is termed a 'high-fidelity' model. As stated earlier in 2.1.2, greater levels of exactness in a simulation come with the added cost of increased computational complexity. Therefore, a low-fidelity model is less accurate but is computationally cheaper, while a high-fidelity model is more accurate and computationally taxing.

For example, the divergence between low and high-fidelity computational fluid dynamic simulations was predicted using a kriging model by the authors in [3].

2.1.2 Machine Learning Complemented Physics Simulations

A set of highly complex partial differential equations (PDEs) called the Navier-Stokes equations are the governing equations for CFD. These equations must be solved numerically as they do not have an analytical solution. However, a direct numerical simulation of these equations can be expensive, especially in the case of turbulent flows ubiquitous in aerodynamic applications.

The Reynolds-Averaged Navier-Stokes (RANS) equations form a suitable simplification of the equations, and it is common to solve these equations instead. In order to enhance the accuracy and consistency of RANS, [44] proposed the following idea: generalisable machine learning algorithms that can be used to build a representation of turbulence modelling closure terms. These terms are a pivotal part of the any RANS-based approach. The authors of [44] proved the feasibility of this approach by training a neural network using data from a set of RANS-based CFD simulations with the Spalart-Allamaras turbulence model, after which they then ran a new set of RANS-based CFD runs using the aforementioned neural network as the turbulence model, and successfully reproduced the original results.

The RANS equations based model is one of the simple physics based models. Too account for the shortcomings of these simpler models in contrast to higher-fidelity, more precise models, a correction factor was identified [5] [6] [7]. The methodology for this identification procedure was as follows: the correction factor for multiple variations of a problem was identified using inverse modelling, after which a Gaussian process regression model was built to learn the correction factor as a function of problem-specific features. This model was then added to the simplified physics simulations to produce more accurate results, while remaining computationally viable.

3. METHODOLOGY

As stated in Section 1.2, the design of aircrafts involves the complex analyses of numerous interdependent systems. This is a multidisciplinary effort with the objective of optimising and improving a certain target task that has a set of constraints associated with it, for instance maximising the amount of lift generated by a wing of a particular set of dimensions that is made of a certain material. This is called a multidisciplinary design optimisation problem.

3.1 Multidisciplinary Design Optimisation

This multidisciplinary design optimisation (MDO) problem can be formally described as a non-linear programming task with the goal of optimising the objective, subject to a set of constraints.

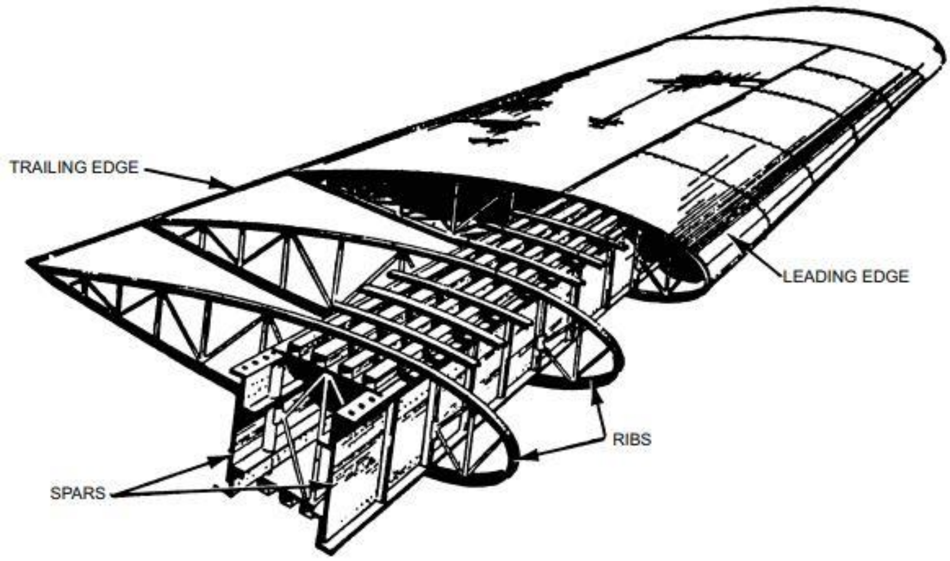

Figure 2: A simple aircraft wing

A key part of the MDO process is problem formulation. Consider the aforementioned example at the beginning of this section: maximising the amount of lift generated by a wing of a particular set of dimensions that is made of a certain material.

Problem formulation for a MDO consists of the following:

1. Selection of design variables: A design variable is an attribute of the design process that can be controlled by the team of designers, for example: the dimensions and material of the wing.
2. Constraints: A constraint is a limitation that exists in the design process for a certain reason, for example: the maximum length of the wing.
3. Objective: The objective is the attribute that the MDO is set up to optimise, for example: maximising the lift generated by the wing with the aforementioned design variables and constraints.

As a MDO process is multidisciplinary, the objectives and constraints must also be assessed from the analyses outputs of multiple disciplines. This poses an important challenge in the design process: the coupling of systems being analysed and designed needs to be managed efficiently and effectively. If all the interdependencies are considered properly, a more precise estimation and approximation of the actual system behaviour is obtained, which is naturally a more desirable solution.

Due to the depth and complexity in modern aircraft design, specialist teams are required to work together and build sound physics and mathematical analytical models that will be used to simulate both, the standalone and interdependent systems, of the airplane.

3.2 The Shortcomings in the Current Application of Machine Learning

The current applications of machine learning in aircraft design discussed in Section 2.1.2 are plagued by certain weaknesses and shortcomings. The most significant observation regarding the shortcomings is as follows: a large amount of training data, in the range of hundreds or thousands of instances, is required in order to build sufficiently good models that are at effective at making predictions. Obtaining data points from physical experiments or CFD simulations is very expensive, especially in aerodynamic and aerospace applications. This leads to an additional problem: the paucity of data.

As a result of these drawbacks, the existing usage of machine learning in aircraft design suffers from a problem called ‘cold start’. It is the problem in which considerable amount of resources are used to generate the initial database for a new problem. This process can take anywhere from hours to days, depending on the accuracy level the simulation is going to be run at. Therefore, this cold start problem can act as a severe bottleneck in aircraft design.

3.3 Overcoming the Cold Start Problem using Knowledge Transfer

With the amount of research and development that has been done, and is being carried out in aircraft design, there likely already exists a myriad of germane and admissible data related to the design of various systems in an aircraft. In the field of data science and analytics, the ability to exploit data distinguishes a domain expert from a dilettante. Due to the increasing demands of modern engineering design and the costs associated with computationally expensive simulations, there is an impetus and scope for the development of algorithms that can automatically extract and transfer knowledge from related design efforts to improve the efficiency of future design exercises.

For example, in research conducted for a neural network information processing system, using Gaussian process regression for cross-domain knowledge transfer, the time taken to find high-quality solutions decreased by up to 40% as compared to traditional methods that didn't use any transfer algorithms [8] [9].

The potential of saving any resources using such techniques is of value in all spheres of engineering.

Although this field is very promising, if misused, it will be detrimental for the design process. A direct transfer and reuse of past knowledge and data can be worse than no knowledge transfer at all if the data is not properly adapted for the target process. This occurs as the source process/processes may not exactly match the domain of the target function.

The following three sections, Sections 3.3.1 – 3.3.3, highlight and discuss the techniques and technologies that can be used to facilitate automatic knowledge transfer across design exercises.

3.3.1 Transfer Learning

Clean slate design i.e. design with no prior knowledge, is a very arduous process, especially for the design of complex systems, for which it is an almost impossible process. The enormity of the task of aircraft design necessitates the need for making simplifying assumptions based on past experiences and technical knowledge. This, paired with the decomposition approach of a MDO, and the intrinsic incremental nature of design, suggests that there is a copious amount of data and knowledge available from projects done in the past, and projects being done in parallel with the current target design. This data can be exploited for use in the target design to improve the accuracy of models, and the quality of decisions.

For example, a team engaged in the design of the main landing gear of an aircraft can use successful past designs as a reference. These 'source' designs can then be modified as required by the target team for their design effort. Relevant knowledge may also be obtained from different parts of an aircraft that fulfil a similar role, as that part may have similar design characteristics as the target system or part.

Until fairly recently however, transfer learning for optimisation, as described above, has barely been used, with only a few published works [10]-[14]. The algorithm used for optimisation is constructed from the beginning, as it must fit the target domain exactly.

Using knowledge transfer from a source task, transfer learning can improve the learning and accuracy of the target task's predictive function.

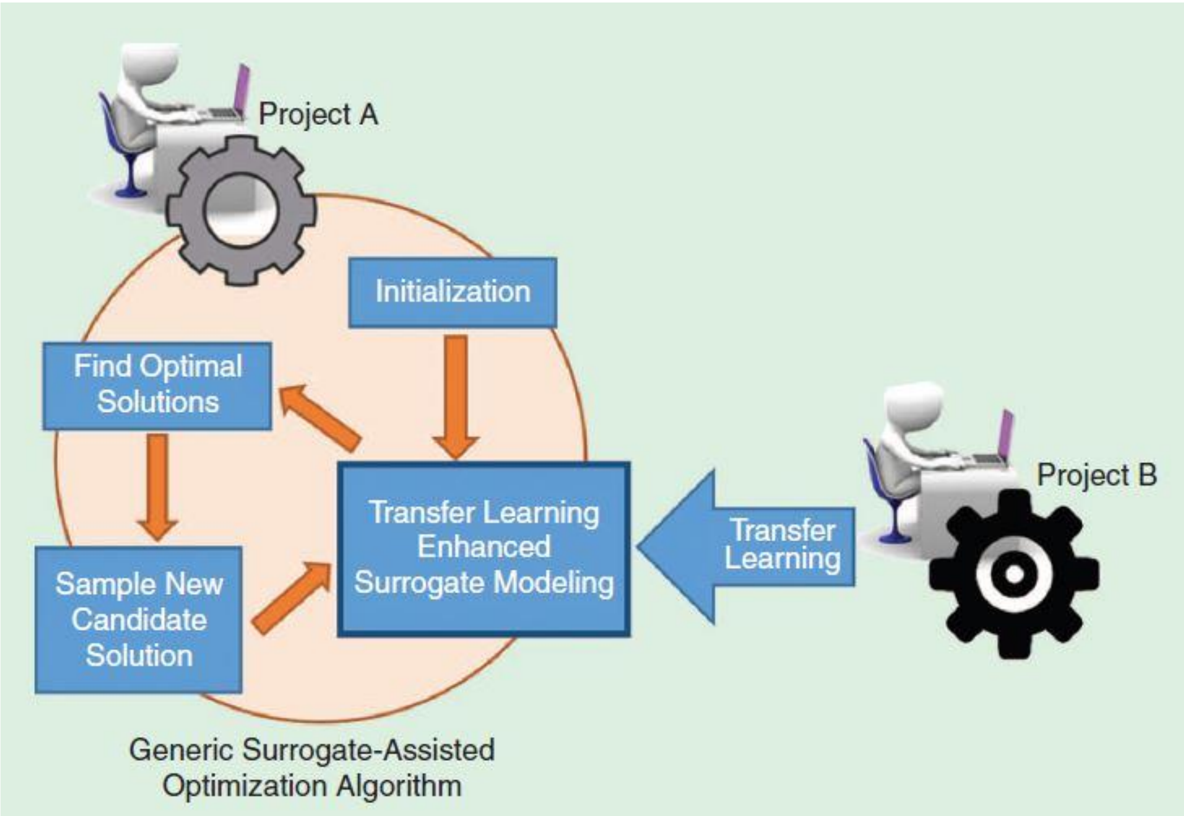

Figure 3: Transfer learning

3.3.2 Multi-Task Learning

Aircraft design involves the design of numerous interdependent and interconnected systems, leading to hundreds, if not thousands, of design parameters.

For example, consider a turbofan engine. Its functionality depends on a set of interconnected systems, such as the high-pressure compressor, booster, and combustor. The monolithic design optimisation of such a system would be very expensive due to the computational costs of running precise simulations, and the number of design variables.

Due to this, a common design optimisation technique is to form a sub-problem. This sub-problem constitutes only a small subset of all design parameters. Depending on the combination of the design variables being considered, different variations of sub-problems are obtained.

Consider, for example, the aforementioned turbofan engine design optimisation. The objective of the design team might be to maximise the thrust produced by the engine as a function of the material properties of the high-pressure compressor blades. One variation might study the engine using composite material X, while the other studies the engine using composite material Y.

Multi-task learning is suited for such design processes. Multi-task learning assumes that there are multiple related tasks that solved simultaneously in order to facilitate knowledge transfer, in contrast to transfer learning, which uses data from previous experiences. For regression models used in multi-task learning, the model aims to learn the following mapping:

$$f : X \rightarrow R^N \quad \text{...Equation 1}$$

In Equation 1, X represents a common set of input parameters, and N outputs belong to different tasks [8].

By learning related tasks together using shared representation, the generalisation performance of multi-task learning is contended to improve by exploiting shared knowledge in the training data of various tasks. A single multi-task model built from data sourced from various related design efforts can be used to improve multiple optimisation algorithms at the same time.

The overall computational cost of a design effort is reduced by using such an approach, as the design parameter space does not have to be searched repeatedly, leading to a lesser need for expensive simulations.

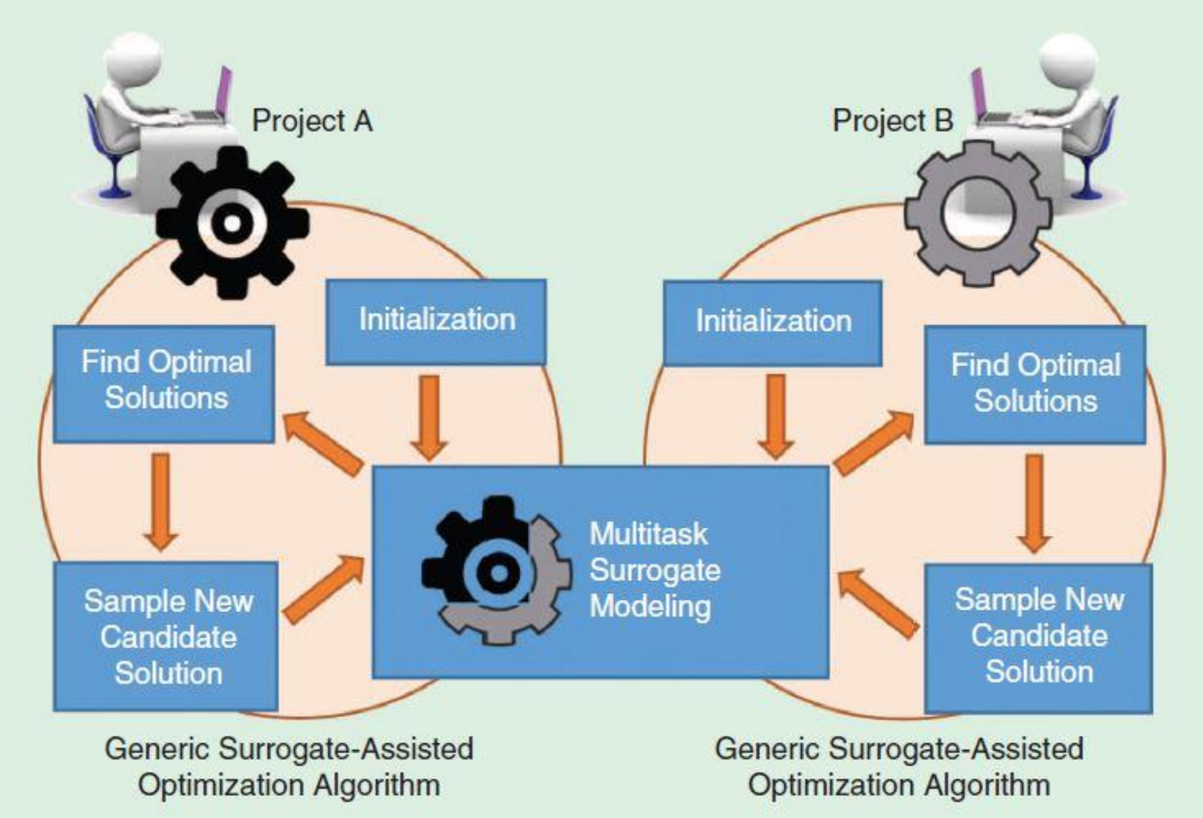

Figure 4: Multi-task learning

3.3.3 Multi-View Learning

In design simulations, models of physical structures of interest and significance can be analysed from multiple views: 3-D, 2-D, or 1-D. The view chosen for analysis depends of the type of statistics the engineering and design team is looking for, for example, while analysing the aft pressure bulkhead of an aircraft, the design team may consider either a 3-D view if the external forces acting on it are of interest, or a 2-D view if the internal forces of the bulkhead are of prime importance.

Therefore, it is possible to obtain data that provides an understanding of mechanics of the system components from different perspective, especially if the computational budget is restricted.

The field of multi-view learning is suited for analysis of multifaceted data streams of the aforementioned type. This fairly new technique jointly learns a function for each perspective in order to exploit the redundant views of the same domain, and consequently, improves prediction performance [15]. This form of learning is characterised by heterogeneous features that can be partitioned into views.

Multiple viewpoints of a certain system generally occur in the form of numerical simulations that emphasise on a specific facet of that component. This is achieved by skewing the fidelity of the simulation in favour of the phenomena of interest.

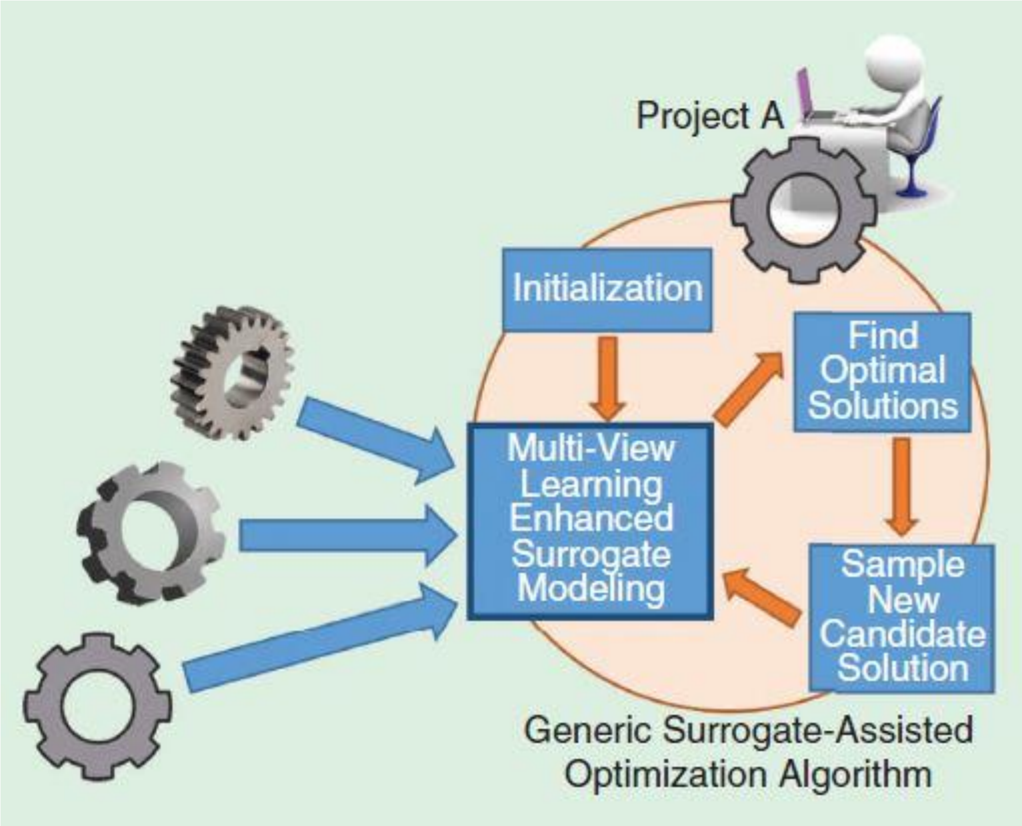

Figure 5: Multi-view learning

3.4 Case Study: An Application of Transfer Learning for Engine Development

Engine development and design has been chosen as a case study to demonstrate the use of transfer learning in aircraft design.

In the preliminary phase of engine development, a major task is the assessment of the overall engine attributes, such as thrust generated, weight of the engine, how it disrupts airflow around the wing, and its fuel consumption. These values are measured by simulations conducted by the design team, with a set of given performance parameters such as temperatures, pressures, and velocities.

Exploring this space during preliminary development allows for the discovery of a good starting point for the rest of the design process. The adoption of surrogate modelling comes as no surprise, given the sparseness of the design space due to the high dimensionality and cost of numerical simulations. Without knowledge transfer, the only data available is the data obtained from the simulations, which can be insufficient due to the costs associated with generating it. The data scarcity poses issues to the learning of the surrogate model, and will cause a poor fit of the response function.

As the design objective is to improve the accuracy of the model while keeping computational costs low, knowledge transfer represents a viable solution. The reuse of large amounts of simulation data from previous distinct, but possibly related, design efforts (in this case study, previous engine design efforts) is a part of the knowledge transfer solution. If the machine learning algorithm being used is able to exploit the latent synergy between designs, this pool of data is, computationally wise, accessible for free.

3.4.1 Case Study Parameters

In this case study, the data that has been captured is for an engine of a different specification as compared to the target i.e. the engine that is the focus of the design effort. However, some underlying relationship between both engines is recognised, and both design efforts consider the same set of input and output parameters.

The input parameters are:

1. Altitude
2. Pressure ratio – Compressor
3. Pressure ratio – Burner
4. Efficiency – Turbine
5. A8/A2 – Nozzle

The output parameters are:

1. Net thrust
2. F_{net}/W
3. Fuel flow
4. Thrust specific fuel consumption (TSFC)
5. Core airflow
6. Weight

3.4.2 Case Study Data

Real-world data for this case study was provided by Rolls-Royce. The data included 274 source, and 100 target simulations.

10-fold cross-validation was used to approximate the generalisation error.

3.4.3 Evaluation

Transfer learning (Section 3.3.1) is the technique used to improve the learning of the target task. To evaluate the performance enhancement that can be achieved by following this methodology, an empirical comparison with traditional surrogate learning is carried out. This consists of applying Gaussian process (GP) regression on the target database. To demonstrate that a direct transfer/combination of data may not improve the learning, the source and target data is combined, and Naïve-Transfer GP (NT-GP) is applied. The final two methods applied are Adaptive Transfer GP (AT-GP), and a Metaheuristic-based Instance Selection for Transfer (MIST). For each method, the error is calculated using the root mean square error (RMSE) measure.

The results of this study are discussed in Section 4.

4. RESULTS AND DISCUSSION

The results of the case study presented in Section 3.4 are depicted in Figure 6.

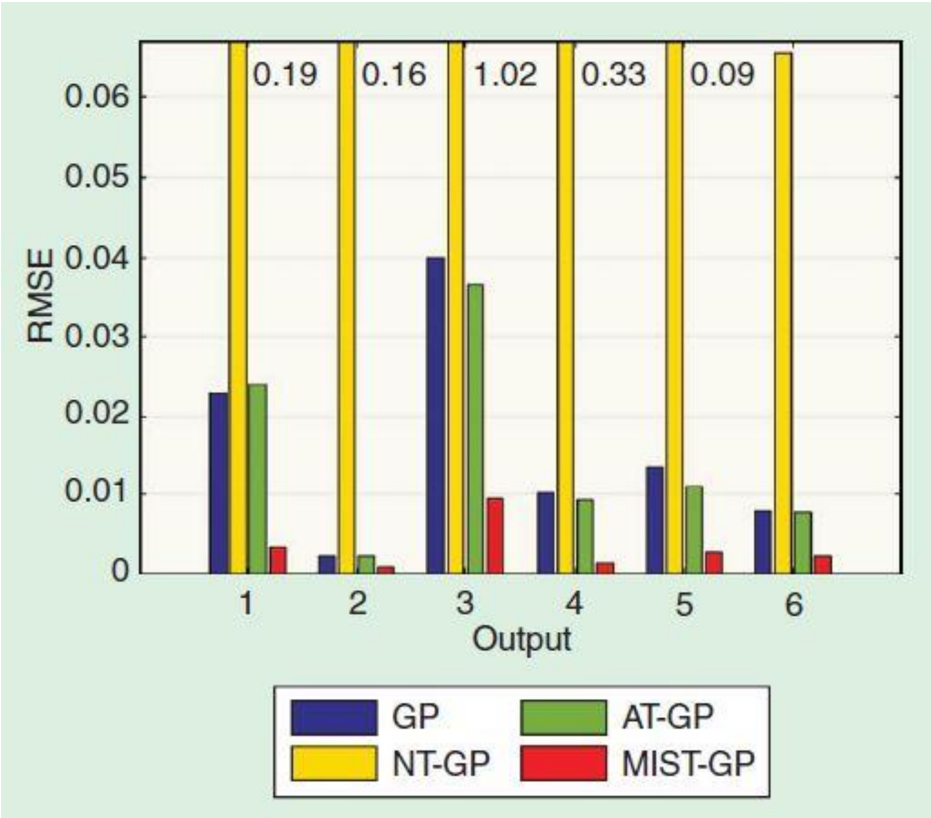

Figure 6: The results of the case study

It can be seen from the figure that there is a considerable difference between the performance of GP and NT-GP. The results of NT-GP are significantly worse for each output parameter. This proves that a direct, naïve transfer and combination of data resulted in a negative transfer that affected the accuracy of the prediction algorithm.

Meanwhile, the two adaptive methods outperform NT-GP. In this case, AT-GP offers only a slight improvement over GP, and MIST results in a dramatic increase of the accuracy of the prediction algorithm. However, MIST relies on a wrapper strategy to find the optimal subset of the source data, limiting its scalability. Hence, efficiency wise, AT-GP may be a more desirable option.

5. CONCLUSION

Aircraft are an integral part of modern society. Its design is a MDO problem, and is characterised by the complex analyses of mutually independent systems. Machine learning is used to reduce the computational costs of these analyses.

Aircraft design is an incremental task that is heavily reliant on previous data, and there exists knowledge from completed projects that can be used and exploited to improve the current design performance. The current role of machine learning in aircraft design has been summarised, and limitations have been identified. Three advanced learning techniques for knowledge transfer (transfer learning, multi-task learning, and multi-view learning) are then discussed, which can lead to better performance of the predictive algorithm while keeping the computational costs viable.

Transfer learning uses data from the source to augment the approximation of the target domain of interest. Multi-task learning aims to simultaneously learn approximations for multiple variants of a similar domain. Multi-view learning aims to utilise data from different perspectives to construct more accurate approximations.

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