A Conceptual Framework for Combining Artificial Neural Networks with Computational Aeroacoustics for Design Development

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Abstract

This paper presents a preliminary method for improving the design and development process in a way that combines engineering design approaches based on learning algorithms and computational aeroacoustics. It is proposed that machine learning can effectively predict the noise generated by a coaxial jet exhaust by utilizing a database of computational experiments that cover a variety of flow and geometric configurations. A conceptual framework has been outlined for the development of a practical design tool to predict the changes in jet acoustics imparted by varying the fan nozzle geometry and engine cycle of a coaxial jet. It is proposed that computational aeroacoustic analysis is used to generate a training and validation database for an artificial neural network. The trained network can then predict noise data for any operational configuration. This method allows for the exploration of noise emissions from a variety of fan nozzle areas, engine cycles and flight conditions. It is intended that this be used as a design tool in order to reduce the design cycle time of new engine configurations and provide engineers with insight into the relationship between jet noise and the input variables.

Keywords
Computational aeroacoustics, artificial neural networks, jet noise

1. Introduction
Although the sound energy emitted by modern aircraft is just one per cent of those designed forty years ago (Rolls-Royce plc, 2015), thirty-one percent of people questioned have reported being bothered, annoyed or disturbed to some extent by noise from aircraft, airports and airfields (Notley *et al.*, 2014). This can be attributed to a rise in air traffic volume and the number of flight paths, leading to an increase in noise exposure. This noise problem has led to the introduction of FlightPath 2050: Europe's Vision for Aviation and a strategic research agenda which requires that an aircraft's effective perceived noise level (EPNL) be reduced by sixty-five percent by 2050 (ACARE, 2012).
The U_j^8 law for subsonic jets (Lighthill, 1952) demonstrates that a jet's radiated acoustic power is proportional to the eighth power of the jet exhaust velocity U_j. This characteristic has been exploited through the introduction of high bypass ratio (HBR) turbofan engines. These engines consist of a primary stream of hot combustion gases and a lower velocity bypass stream of cooler air. As the bypass stream exits the fan nozzle it surrounds the primary stream, lowering the overall velocity of the combined exhaust and dramatically decreasing jet noise. Although large jet noise reductions have been achieved through the introduction of HBR engines, jet noise is still a dominant noise source.
Turbofan engines have a fixed-area fan nozzle designed for optimum performance during the most common flight mode. Varying the fan nozzle area and subsequently the bypass ratio would allow the performance to be optimized for various flight conditions. For example, increasing fan nozzle area would increase the bypass ratio. This, in turn, reduces the jet velocity leading to an increase in propulsive efficiency and a reduction in jet mixing noise, ideal for noise reduction during take-off. A variable area fan nozzle (VAFN) could also be complemented by the cycle changes of variable cycle engines (VCE) allowing the jet noise emissions and propulsive efficiency to be optimized across the entire flight envelope.
In order to optimize the performance and noise emissions of new VAFN-VCE configurations, multiple tests would be performed during the design development stage. Experimental analysis could be performed on prototype nozzles but

this method can be expensive. Instead, computational methods could be used, as advances have made them viable tools for the numerical analysis of aeroacoustic noise. Methods based on computational fluid dynamics (CFD) and computational aeroacoustic (CAA) can be used to solve flow problems numerically and predict acoustic fluctuations and far-field acoustic propagation.

Computational methods can predict noise using direct or hybrid approaches. Direct methods calculate the flow field and a portion of the acoustic field in the same computation. This can be performed using direct numerical simulation (DNS) but the requirements are so large that this method may never be a practical approach for real nozzle design. For instance, a 3D DNS performed by (Sandberg and Tester, 2016) took 3936 cores to compute the noise from a single isothermal jet. Other direct methods use large eddy simulation (LES). This is cheaper than DNS and allows for more complex flow configurations at higher Reynolds numbers to be resolved but it is still computationally demanding. For example, LES conducted by (Paliath *et al.*, 2011) took 8000 cores to predict the noise from a heated coaxial jet with realistic nozzle geometry.

As direct methods are expensive, acoustic predictions are usually confined to the near-field. In order to calculate far-field sound, cheaper hybrid methods have been employed. Numerical simulations can be combined with surface integral techniques where near-field data is recorded on a surface and is extrapolated to the far-field by solving linear acoustic equations. These include the application of Kirchhoff (Kirchhoff, 1883) or FW-H (Ffowcs Williams and Hawkings, 1969) surfaces, as used by (Andersson, Eriksson and Davidson, 2005) and (Naqavi *et al.*, 2016), respectively. Other far-field noise prediction methods determine flow statistics and noise source terms from the flow-field calculations and apply them to acoustic analogies such as (Lighthill, 1952; Lilley, 1974). LES has been used to obtain source terms for acoustic analogy, for example (Bogey, Bailly and Juvé, 2001), and various studies have used Reynolds averaged Navier Stokes (RANS) based methods, see (Engel, Silva and Deschamps, 2014; Venkatesh and Self, 2015; Rosa *et al.*, 2016; Papamoschou, 2017). RANS has been shown to be much less computationally demanding with researchers finding that an acoustic analogy informed by a 3D RANS simulation can take just 8 hours to complete on a desktop computer (Afsar, Leib and Bozak, 2017) with RANS resolution requirements being 500 times smaller than LES (Rosa *et al.*, 2016). This allows for calculation of complex flow-fields such as 3D coaxial jets with the inclusion of nozzle geometry. In an industrial context, RANS is the most feasible option for this type of simulation (Engel, Silva and Deschamps, 2014) making it a practical solution for industry and essential for the development of quieter jet engines (Venkatesh and Self, 2015).

2. Proposal

Although many jet noise studies have been performed using CFD/CAA, these approaches are time consuming and computationally costly and many computational noise prediction methods have been confined to academic research (Venkatesh and Self, 2015). Computational requirements render them impractical for engineering applications and unsuitable for use as a design tool. An artificial neural network (ANN) has been shown to reduce the computational time of CFD analysis by a factor of 600 (Lauret *et al.*, 2015). Therefore a framework is proposed whereby a cheaper learning algorithm can be used to predict jet noise. It is proposed that ANNs could be used as a computationally efficient surrogate for numerical jet noise prediction, providing results within a fraction of the time.

The prediction capabilities of ANNs have already lent themselves to many applications in CFD/CAA. Researchers have trained ANNs using a combination of experimental, flight or simulation data. ANN have been used to predict 2D CFD flow patterns for a Karman vortex street (Zhang *et al.*, 1996) and the flow-field of cylinders (Lauret *et al.*, 2015). ANN have also found various uses with regards to aviation such as the prediction of airfoil aerodynamic coefficients (Wallach and Curvo, 2006) and aircraft wing loads (Allen and Dibley, 2003). Other research has used ANN for noise prediction. This includes the use of ANNs to predict of the noise spectra of small-body commercial aircraft (Pietrzko, 1997), the EPNL values of a helicopter for a specific flight condition (Cenedese, 2007), the classification of aircraft with respect to acoustic descriptors (Osses and Glisser, 2012), for optimizing an airfoil with respect to noise reduction (Jun and Gang, 2016) and for the prediction of radiated acoustic power from a wings slat (Aflalo and Ferrari, 2012).

The development of new VAFN-VCE configurations can rely on experiment or numerical analysis but data collection carried out in this way can be both costly and time consuming. It is proposed that CAA analysis can be used to generate a training, testing and validation database for an ANN. The trained ANN will then predict noise data for any operational configuration. As results can be achieved in much shorter times, the use of a CAA-ANN model would allow for exploration of various fan nozzle areas during different flight conditions and reduce the design cycle time of new engine configurations.

The aim of this paper is to present a framework for combining data obtained from CAA analysis with an ANN with the goal of improving jet noise prediction and shortening design lead time. It is intended that merging CAA with ANNs will provide design and test engineers with data that may prove useful to the design development process of a

VAFN-VCE concept. It can offer insight into the relationship between jet noise and the input variables and provide information upon which design development decisions can be made. The main objective is to outline a methodology by which a CAA-ANN model can be used as an industrial design tool for optimizing the performance and noise emissions of a VAFN-VCE turbofan engine.

3. Design Model

The preliminary engineering design phase is shown in Figure 1. This process is loosely based on the transitional model of (Asimov, 1962). It can be seen that a feasibility study must first be performed and the design problem explored in order to formulate a design specification. Next, preliminary design solutions are generated and evaluated. Reference (Asimov, 1962) states that evaluation is performed using experimental analysis but contemporary methods may employ computational analysis (highlighted in Figure 1), experimental analysis or a combination of both. The results from the preliminary design phase are then used to inform the detailed design phase (not shown here).

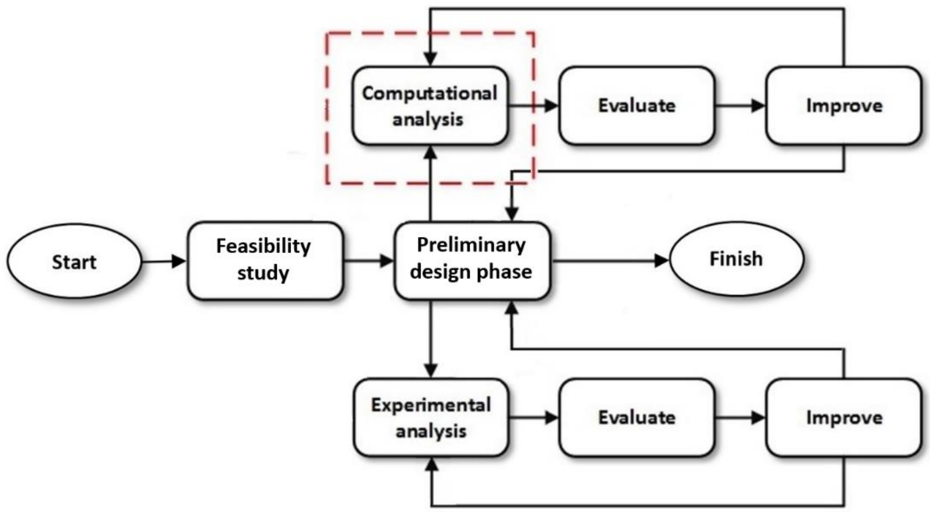

Figure 1. Preliminary design phase

In this instance, computational analysis refers to noise prediction through the use of CAA. It is proposed that at this stage in the design process CAA analysis can be combined with an ANN in order to generate more data at a lower computational cost. This will allow for the exploration of noise emissions for a larger range of fan nozzle areas, engine cycles and flight conditions. The data can then analysed and evaluated. Decisions on expensive prototype manufacture and experimental analysis can be informed by the CAA-ANN results and the design cycle time can be reduced.
A schematic of the proposed framework at its highest level is presented in Figure 2. The framework for the integration of CAA and ANN is discussed. Every stage during the proposed CAA-ANN framework requires user (engineer) interaction. This is discussed along with the inputs and outputs.

3.1 Database Design

In order to predict noise with an ANN, the engineer must design a training, testing and validation database. This must consist of the various operational conditions that reflect a variable cycle engine and variable fan nozzle geometry. For example, jet area, velocity, pressure and temperature ratios, Reynolds number and ambient conditions. The difficulty in the production of a database is that there are a large number of aerodynamic and geometric variables involved, many of which interact in a complex manner. In order to ensure efficient database generation, a test matrix must be derived that sufficiently describes the behavior of the system as this is critical to the success of the ANN. This can be accomplished using design of experiment methods similar to (Sun *et al.*, 2015). It is important to ensure that the data collected covers the complete range for which the network will be used as an ANN can interpolate results within this range but cannot be used to extrapolate results outside the range.

3.2 Computational Aeroacoustics

Once a database has been designed, CAA analysis can be performed. The engineer must carefully design a baseline study for the noise prediction from a coaxial subsonic jet. It is recommended that RANS based methods are used as they are computationally less demanding. Consideration must be given to the influence of the turbulence model, boundary conditions, domain size and resolution requirements.

As there is no prior knowledge in an ANN it can only be as accurate as the training data set. Therefore, the accuracy of the baseline study must be determined through comparison with available experimental or numerical data. Once the CAA method has been validated, database generation can commence and the engineer can perform simulations on the cases identified by the test matrix.

In order to generate noise data, the engineer must post process the results and apply the RANS data to an acoustic analogy.

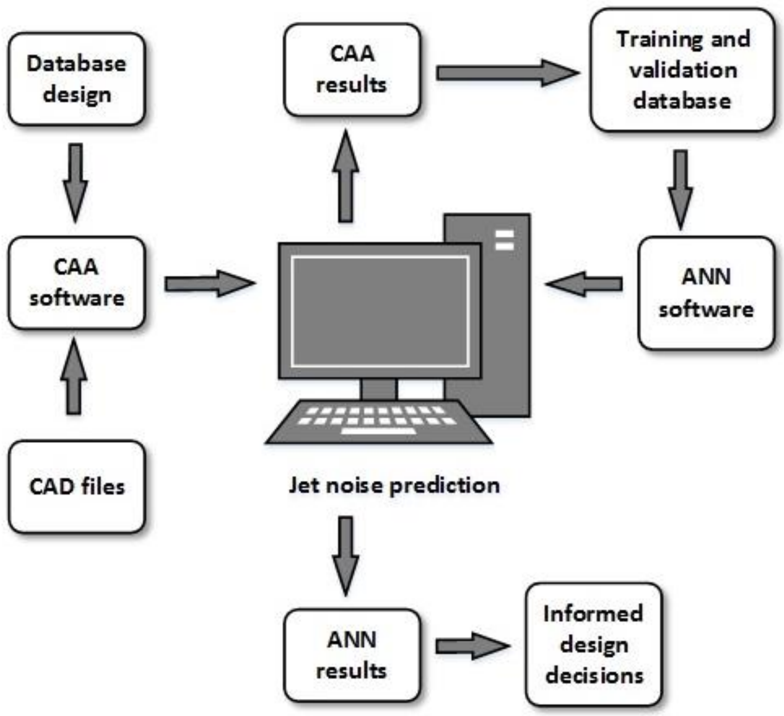

Figure 2. Schematic of framework

3.3 Artificial Neural Network

The CAA database will provide a data set for the training, testing and validation of an ANN. A learning algorithm must be designed that is capable of predicting coaxial jet noise data across a range of configurations. An example of a multi-layer feed forward ANN can be seen in Figure 3.

The number of input and output neurons is determined by the number of input and output parameters. The input layer has as many neurons as the number of design variables and the output layer has as many neurons as objective functions. The performance and complexity of the ANN, for example the number of hidden layers, neurons per layer and choice of activation functions, are design dependent and traditionally optimized on a per-application basis (Smithson *et al.*, 2016) but most ANNs consist of just two or three layers (Hagan *et al.*, 2014). Although supervised learning is suitable as the output is known and batch learning is appropriate as there will be a static data set from the CAA, the chosen architecture is very much case dependent and there are no general guidelines for the structure or parameters of an ANN for engineering applications (Sun *et al.*, 2015). As it is not possible to determine the optimal topology of an ANN in advance, the exact architecture and design of the ANN would be determined through trial and error. This would be performed after the engineer has generated the CAA database.

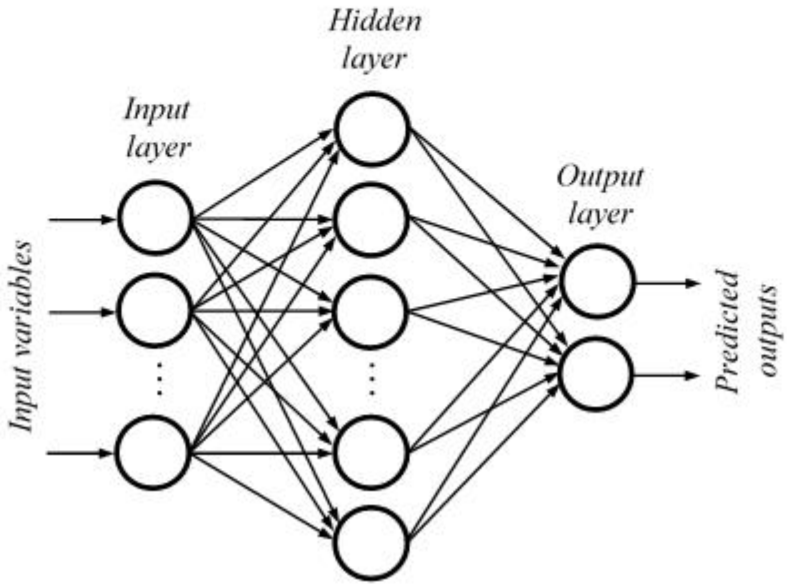

Figure 3. Example multi-layer feed forward ANN

Once the ANN is trained, the engineer can evaluate the ANN performance against the test data. The architecture can be adjusted if needed and the process repeated until the desired accuracy is achieved. Once testing is complete the engineer can then evaluate the ANN performance against the validation data and if necessary retrain the ANN to reach the desired accuracy. Once fully trained and validated the ANN can then be used to generate a complete jet noise data set that would allow the engineer to make informed decisions during the design and development process.

The system benefits include:

- The time and cost of the design development process is reduced.
- Noise or other parameters of interest can be predicted across a range of configurations without the need for extensive CAA or experimental analysis.
- CAA-ANN model allows a cheaper global exploration of the problem to be performed.
- An informed local exploration can then be carried out with a view to determining the optimum design configuration.

4. Conclusion

This paper has described the conceptual framework for a CAA-ANN based design tool for the development of a VAFN-VCE with respect to noise and operation. CAA and ANN methods have been integrated to provide a model suitable for predicting noise from a variety of flow configurations of industrial interest.

It is proposed that this model provide insight to industry through an enhanced understanding of the noise producing mechanisms of VAFN-VCE for subsonic jets and show how performance improvements can be maximized through the use of an ANN trained with a database generated using CAA methods. The usefulness of this as a design tool can be determined through the accuracy of the ANN results and the time taken to provide a result.

Now that the framework has been proposed, future work will continue to expand the concept of combining artificial neural networks and computational aeroacoustics in order to validate this methodology.

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Biographies

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