Accelerating Low Noise Axial Fan Design Space Exploration: A Surrogate Modelling Framework for Multi-Objective Optimisation

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Abstract

Axial fan noise remains a persistent engineering challenge, requiring optimisation methods that balance computational efficiency and accuracy. To address this, we introduce a novel multi-objective framework for rotor-only fan optimisation, leveraging a non-parametric surrogate model (NPSM) for rapid, robust performance evaluation and visualization during the low-fidelity design stage. This framework processes simulation data from diverse parameterization and meshing strategies. A comprehensive training database, validated against experimental data, forms the foundation of this study. Steady-state computational fluid dynamics (CFD) simulations are conducted using ANSYS CFX with fan geometries generated via a MATLAB®-based design tool incorporating blade element theory, vortex-based design principles, and XFOIL for airfoil performance prediction. This is developed to ensure an automated and streamlined workflow for large database construction. A Non-Parametric Surrogate Model evaluates objective functions across a range of flow rates, capturing on- and off-design fan behaviour and applying aeroacoustic metrics and constraints through network architecture and loss functions. A design classifier identifies surrogate predictions with high error, triggering additional simulations, while genetic algorithms efficiently explore large design spaces for global optima. In the era of big data, this framework has potential to significantly reduce computational costs and enhance versatility in early design phases of new product development. Its ability to accommodate varying parameterisation and meshing techniques underscores its utility for industrial applications in multi-objective design.

Keywords: Axial fan noise, non-parametric surrogate model, Computational fluid dynamics

1. Introduction

1.1 Motivation

Axial fan noise is a persistent problem exacerbated by a low-carbon electrification drive across domestic, commercial and industrial sectors. Acoustic noise is, at best, an annoyance but also have psychological and physiological health implications [1] with axial fans tending to be noisier and often placed in sensitive areas. For example, residential heating, cooling, and ventilation systems all house axial fans as they best meet operating requirements. Drivers towards societal change are often interconnected - whereas aerodynamic efficiency brings economic acceptance, low noise will bring social acceptance to a lower carbon society, therefore reducing acoustic emissions must be a high priority in the design and selection of low-pressure axial fans.

1.2 Aeroacoustics of axial fans

Aeroacoustics is the study of aerodynamic noise and arises from two basic phenomena [2]:

(i) *Impulse* noise, due to the interaction of pressure waves with solid surfaces. This is tonal and emits narrow noise frequencies.

(ii) *Turbulence* noise, which mainly occurs near sharp edges and has broadband noise characteristics due to varied scales.

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The major proportion of noise emissions is generally from the aeroacoustic self-noise of the blading itself *[2], [3], [4]*, these can be defined as:

- Turbulent boundary layer (TBL) noise: generated by the wall pressure fluctuations due to boundary layer turbulence.
- Separated flow (SF) noise: the significant increase of the emitted noise in case of boundary layer separation
- Vortex-shedding (VS) noise: generated by the coherent vortices shedding over the blade profile and the trailing edge.
- Turbulent boundary layer-trailing edge (TBL-TE) noise: the noise generated by the interaction of the turbulent boundary and the trailing edge.
- Tip leakage flow (TLF) noise: generated by the turbulent leakage flow over the blade tip.

1.3 Numerical noise prediction

The disparity in length scales between acoustic and aerodynamic pressure waves arises from significant differences in amplitude and frequency, making numerical prediction of radiated sound challenging. Accurate computational aeroacoustics (CAA) requires spatially and temporally resolved, high-fidelity simulations with low modelling errors in the turbulent flow field. However, the high cost of such simulations limits their use to research rather than early design exploration. High-fidelity methods like Lattice Boltzmann Method (LBM) [4] and Large Eddy Simulations (LES) [5] have shown that flow-induced noise can be mitigated by reducing the impact of vortical structures and their interactions with neighbouring blades. Zuh and Carlos [4] found that unsteady interactions between the TLF and neighbouring blades initiated rotating instabilities. They concluded that fans with low tip noise would have reduced vortical structures at the tip gap, leading to fewer blade interactions. Sorguven et al. [5] presented a correlation between large averaged vorticity magnitudes and powerful dipole sources using LES.

High-fidelity simulations are not feasible for iterative testing of new designs. Instead, during the early design phase, it is beneficial to explore a larger subset of geometrically similar designs, prioritising speed over accuracy. Acoustic predictions based on Reynolds-averaged Navier-Stokes (RANS) simulations are desirable despite inherent modelling errors. Although aeroacoustics is inherently unsteady, RANS quantities provide reasonable time-averaged approximations. Sorguven et al. [6] used steady RANS simulations to compare the Overall Sound Pressure Level (OSPL) of different fan geometries, presenting a general strategy for predicting OSPL. Generally, minimising average vorticity and pressure fluctuations reduces OSPL, which is valid for any fan with low pressure rise and low flow rate.

1.4 Optimisation frameworks

Fan development aims to optimise blade geometry through iterative stages in a multi-dimensional parameter space. Deterministic approaches, like inverse design or adjoint methods, achieve designs with fewer iterations but often find local optima. Probabilistic approaches, though computationally intensive, better identify global optima when a comprehensive design space is built with data from numerical simulations, creating a response surface that maps input parameters to output responses (Figure 1a). It is not feasible to simulate all responses - Surrogate models, or response surface models (RSM), reduce computational costs in high-dimensional aerodynamic optimisation by replacing the numerical solver with synthetic data for unsimulated outputs. They typically involve three stages: dimensional reduction (parameterisation), regression (mapping inputs to output responses), and prediction (interpolation and extrapolation) [7]. However, few current surrogate models are satisfactory in all these stages from the perspective of axial fan development: Design space limited by manual parameterisation, regression models lack interpretability, and prediction fails to generalise and extrapolate.

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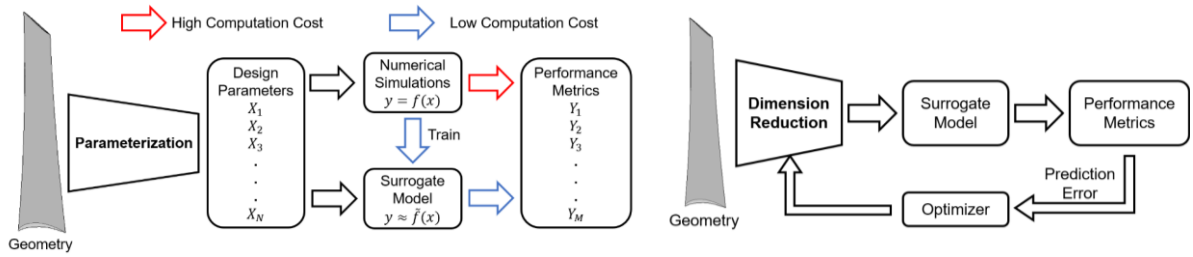

(a) (b)

Figure 1: (a) Generic surrogate model frameworks, and (b) ideal dimension reduction framework for surrogate model, from [7].

To realise a RSM that can begin to address issues identified, interpretability is crucial. Physics-informed machine learning (ML) improve extrapolation by enforcing physical laws and constraints, embedding structural similarity [8], analytic constraints [9], physical symmetries, and conservation laws [10], reducing the data needed to identify models and can promote and enforce physical solutions through selection of appropriate model architecture and optimisation search algorithms. Evolutionary methods, for example, are a desirable search algorithm candidate as they effectively handle constrained and multi-objective optimisation problems by thoroughly exploring a design space [11].

Cao et al. [12] proposed a non-parametric surrogate model (NPSM) for aerothermal optimisation, that addresses many identified concerns. Dimensional reduction is incorporated by placing sensitive geometric feature information on surface mesh nodes used for CFD, not manual parameters, allowing training data from different parameterisation methods. Regression and prediction are performed by NPSM which provides flow variable distribution as 2D contour plots by mapping relationships built by conditional variational auto-encoders (CVAE) to CFD mesh vertices and boundary information, offering more useful predictions than scalar objective functions alone and more closely emulate full simulations which build user interpretable mapping relationships through network layers.

Figure 1b shows an idealised RSM framework incorporating dimensional reduction within the optimisation routine, potentially accelerating aeroacoustic optimisation while being generalisable. Low-pressure axial fans have various blading design methodologies and parameterisation approaches, limiting initial blade shapes in typical optimisation schemes. Integrating dimensional reduction within the optimisation framework allows training surrogate models on sensitivity via backpropagation, avoiding overfitting and retaining important geometrical features from different data sources. The initial design space can be expanded by surrogate extrapolation driven by sensitivity analysis from NPSM and a design classifier that identifies designs predictable by NPSM or triggers the CFD solver when not, making NPSM robust for generating new designs outside the training dataset.

1.5 Critical summary and overview

Several challenges in optimising axial fans for low noise have been identified. Although the aeroacoustics are well understood, accurately predicting noise emissions requires high-fidelity simulations, which are prohibitive during early design exploration. A two-stage approach addresses this: fast localisation and precise optimisation. Low-fidelity RANS is used for a broad search, followed by high-fidelity coupled solvers and adjoint methods to find the global optima. However current optimisation frameworks for the low-fidelity stage are not robust to changing user constraints and design targets, as surrogate models are trained on datasets with predefined geometric parameters.

Manual parameterisation of geometry, a major bottleneck in optimisation frameworks, can be bypassed by placing performance-sensitive information on CFD surface mesh vertices identified through automatic differentiation and ML backpropagation. Additionally, constraining the output to

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include only relevant and physical results is needed to accelerate design space exploration for optimal designs. To prevent ML models from becoming a "black box," they must be interpretable and incorporate physical laws at each stage of the model-building process [13]: (1) Problem definition, (2) data collection, (3) model architecture, (4) loss function, and (5) optimisation strategy.

The structure of this work is as follows: Section 2 covers methodologies for design and data collection of several test fans. Section 3 proposes an optimisation framework for low-noise axial fan design space exploration. Finally, Section 4 concludes, highlighting industrial relevance and future work.

2. Design Methodology

The goal of this work is to propose a NSPM to replace the CFD solver and generate predictions interpretable by users. Therefore, this section introduces the problem description and data collection in premise of interpretable machine learning, grounding them with fundamental design laws and experimentally validated counterparts, respectively.

The primary duty of an axial fan is to provide the required volume flow rate $\dot{V}$ by raising total pressure to match downstream system losses. Euler's equation for turbomachinery relates the change in total pressure to blading shape and efficiency (equation (1)):

$$\Delta P_{tt} = \eta_{\mathrm{h}} \cdot \omega r \cdot c_{\mathrm{u2}} \cdot \rho \tag{1}$$

Where ΔP_{tt} is the total-to-total pressure difference, η_{h} is the estimated hydraulic efficiency, ωr is the blade speed at a generic streamline, c_{u2} is the circumferential velocity at blade exit and, ρ the fluid density. Equation (1) highlights radial dependence of total pressure on the circumferential velocity at blade exit. The pressure work input, and thus the blade loading, are characterised by the distribution of $c_{u2} \cdot r$. This leads to classical blading design methodologies that use either free vortex ($c_{u2} \cdot r = constant$) or controlled vortex ($c_{u2} \cdot r = f(r)$) based design. Additionally, fan blade skew angles are important parameters to include as they have a profound effect on acoustic emissions [2]. In general, skew is applied to fan blade sections radially arranged on the stacking line which connects the centre of area of corresponding blade profiles, defining the blade shape and position from hub to tip. The upstream translation of a blade section (forward / positive sweep) or downstream (backward / negative sweep) to the flow is characterised by the sweep angle λ. Translation of a blade section normal to the flow is characterised by the dihedral angle ν, where a positive dihedral shifts towards the pressure side and negative the suction side.

2.1 Geometric design procedure for training dataset

To create an initial set of geometries, the Blade Element theory approach used by Kromer [2] is recreated and expanded upon as the basis of an automated fan design code written in MATLAB ®. Rapid 2D calculations are performed at spanwise cross sections for a single blade, represented by isolated 2D aerofoils. Empirical airfoil data provides the necessary lift and drag information to dimension the blades, according to the prescribed blade loading - Either created with isoenergetic blade loading distribution (free vortex design) or a radius-dependent blade loading distribution based on a defined polynomial function (controlled vortex design).

The geometry is further parameterised at each blade section. For each layer, the fan blade angle of attack and skew angles (sweep angle λ and dihedral angle ν) are parameter controlled. This forms a set of training data, specifically selected for use of fundamental design laws and accompanying detailed experimental results to validate the model. For each fan design, an automated CFD workflow generates the geometry, discretises the flow domain, and runs the simulation. The adopted solver is ANSYS CFX with the k-ω shear stress transport (SST) model to predict the three-dimensional, incompressible, viscous flow field, however further details are not relevant here and are omitted.

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3. Optimisation Framework

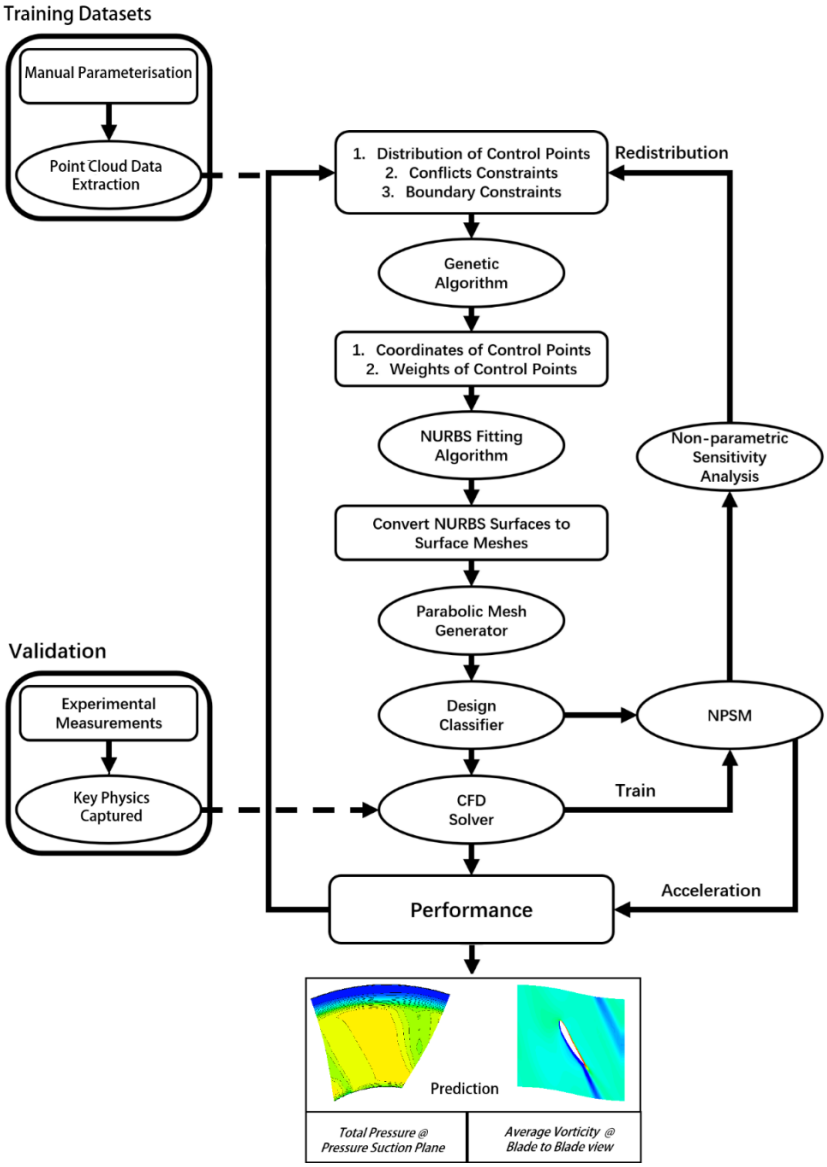

Figure 2:Non parametric surrogate model optimisation framework procedure, adapted from [12].

Figure 2 shows an optimisation framework building upon [12], incorporating methods to develop an aeroacoustic optimisation tool for low-speed axial fan design. First, CFD simulations used in optimisation are validated with experimental data. Surrogate modelling generates synthetic data after being trained solely on CFD, making the setup and meshing crucial. The surface meshes in NPSM must have the same number of mesh vertices, and the CFD solver must be consistent. To meet this requirement, the framework includes a non-uniform rational B-spline (NURBS) fitting algorithm to process blade geometries and generate surface meshes for NPSM and volume meshes for CFD, normalising the data stream.

Following validation, the framework can run as a NURBS-based genetic algorithm to generate geometries, accumulating training data from inputted and optimised designs to build a NPSM model. NPSM extracts geometric features from surface meshes, using information in a low-dimensional latent space to predict 2D distributions of fluid variables. To ensure robust optimisation, a design classifier is constructed using latent variables to identify and sort designs that are either predictable by NPSM or

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not, triggering additional CFD for training. The restriction on surface meshes is a major strength of NPSM as it allows users to combine geometries designed by varying generation methods as opposed to traditional parameter-based methods which are restrictive on design space growth.

The goal of the NPSM framework is to accelerate the development and optimisation of new fans by reducing reliance on the CFD solver and directly predicting key 2D flow variables based on geometry and boundary information. Components of NPSM include the mesh encoder, boundary encoder, latent space, and contour decoder (see Figure 3). The mesh encoder's input is an n×3 feature matrix (mesh vertices coordinates) and a sparse adjacency matrix (vertex connected edges), while boundary conditions are inputs for the boundary encoder. The mesh encoder uses graph neural networks (GNN), and the boundary encoder uses a convolutional neural network (CNN) to extract features from the inputs. This information is then combined into a concatenated matrix, with optional additional case specific information deemed important by users.

Next, the concatenated vector is converted to mean and variance vectors, representing a probabilistic latent space containing key geometric and boundary features. The contour decoder, using GNNs, predicts the distribution of fluid variables by utilising the mapping relationship learned between the geometry and performance through simulation training data.

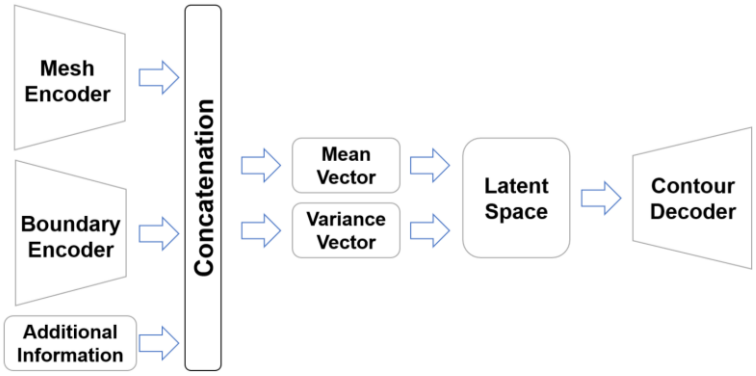

Figure 3: Non parametric surrogate model architecture, from [12].

After the NSPM module, a Non-Parametric Sensitivity Analysis (NPSA) establishes performance sensitivity between inputted surface mesh vertices and NPSM predictions. This approach uses automatic differentiation of the mapping relationship built from NPSM to calculate neural network derivatives by the chain rule. Unlike regression on geometric parameters, NPSA enables direct sensitivity distribution visualization on the geometry, helping users redistribute NURBS control points in sensitive regions.

Performance metrics indicating the goodness of a design may be competitive, focusing on either aeroacoustic or aerodynamic objectives. Aerodynamically, the total to static pressure rise across the fan (ΔP_{ts}) is the primary metric to meet requirements. It is recommended that operational ΔP_{ts} be no less than 20% of the best efficiency point, thus requiring predictions both on, and off-design point. Concerning aeroacoustics, minimising average vorticity on blade intersecting contours and minimising local deviations of pressure derivatives on the blade's pressure and suction sides, and shroud are crucial. It is left to the user to determine these competing factors in a socio-economic context.

4. Conclusions

This paper has shown progress made in developing a robust framework for axial fan optimisation with a focus on reducing noise emissions. By leveraging CFD, ML-based surrogate modelling, and genetic algorithms, we have established a methodology that balances computational efficiency with design accuracy. The Non-Parametric Surrogate Model (NPSM) framework has already shown promising

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potential in reducing design iteration time while maintaining predictive reliability, and the incorporation of sensitivity analysis enhances the adaptability of the optimisation process to highlight sensitivity distribution meaningful to the design. During aeroacoustic optimisation process, optimisation targets and geometry constraints change frequently due to new design demands or restrictions from other aspects like mechanical issues. This framework enables users to quickly respond to these changes and optimise the design at a much smaller computational cost during product development.

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