# Summary

The purpose of this work is to study and apply data-driven models within the field of Computational Fluid Dynamics (CFD), focusing on enhancing current turbulence models with these advanced techniques. Modern CFD faces significant challenges in accurately predicting complex phenomena such as fluid separation and the transition from laminar to turbulent flow. Failures in these predictions can lead to incorrect evaluations of critical parameters like force coefficients, which are vital in the design of aerospace components. Traditional approaches, like the Reynolds-Averaged Navier-Stokes (RANS) equations, offer a simplified model of the Navier-Stokes equations but often result in low accuracy, particularly in predicting separation and transition phenomena. This research explores the use of data-driven models, with a particular focus on field inversion and machine learning (ML) methods, to improve the predictive capabilities of existing RANS models. A significant aspect of the work has been the implementation of these models almost from scratch, including the Spalart-Allmaras model and the adjoint method to compute the gradient of the target function required to perform the field inversion. A pseudo-time version of the adjoint solver was also implemented. This study involved a range of test cases, including transient flow over a flat plate, a backward-facing step, and low Reynolds number simulations around airfoils such as the SD7003 and the NACA0021. A multi-objective analysis was specifically carried out for the NACA0021 test case, offering useful insights into the optimization strategy. Both traditional neural networks and more advanced architectures, like the U-Net model, were applied to improve predictive capability. Furthermore, the impact of different objective functions within the field inversion process was closely examined to understand their influence on the enhancement of the RANS model. This work demonstrates that by integrating data-driven approaches, particularly through the use of ML and field inversion techniques, it is possible to enhance the accuracy of turbulence models in CFD, potentially reducing the need for costly high-fidelity simulations during the design of new components.