Deep neural network modeling for CFD simulation of drone bioinspired morphing wings

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Abstract: *In this paper we present a deep neural network modelling using Computational Fluid Dynamics (CFD) simulations data in order to optimize control of bioinspired morphing wings of a drone. Drones flight needs to consider variation in aerodynamic conditions that cannot all be optimized using a fixed aerodynamic profile. Nature solves this issue as birds are changing continuously the shape of their wings depending of the aerodynamic current requirements. One important issue for fixed wing drone is the landing as it is unable to control and most of the time consequences are some damages at the nose. An optimized shape of the wing at landing will avoid this situation. Another issue is that wings with a maximum surface are sensitive to stronger head winds; while wings with a small surface allowing the drone to fly faster. A wing with a morphing surface could adapt its aerial surface to optimize aerodynamic performance to specific flight situations. A morphing wing needs to be controlled in an optimized manner taking into account current aerodynamics parameters. Predicting optimized positions of the wing needs to consider (CFD) prior simulation parameters. The scenarios for flight require an important number of CFD simulation to address different conditions and geometric shapes. We compare in this paper neural network architecture suitable to predict wing shape according to current conditions. Deep neural network (DNN) is trained using data resulted out of CFD simulations to estimate flight conditions.*

Key Words: *deep neural, modelling, CFD, drones*

1. INTRODUCTION

Aerospace engineering has witnessed remarkable progress in recent years, with a focus on enhancing aircraft performance, fuel efficiency, and adaptability. One innovative area of research is the development and analysis of morphing wings, where the geometry of the wing can be dynamically reconfigured in flight.

Morphing wings involve the intentional and controlled alteration of the wing's shape during flight.

This concept draws inspiration from nature, where birds and insects adapt their wing shapes to various flight conditions.

The ability to modify the wing's geometry enables aircraft to optimize performance across different flight regimes, from takeoff and cruising to landing. There are several advantages of morphing wings.

Birds are continuously adapting to current flight conditions, modifying the shape of the wing modifying mainly the area as seen in Figure 1.

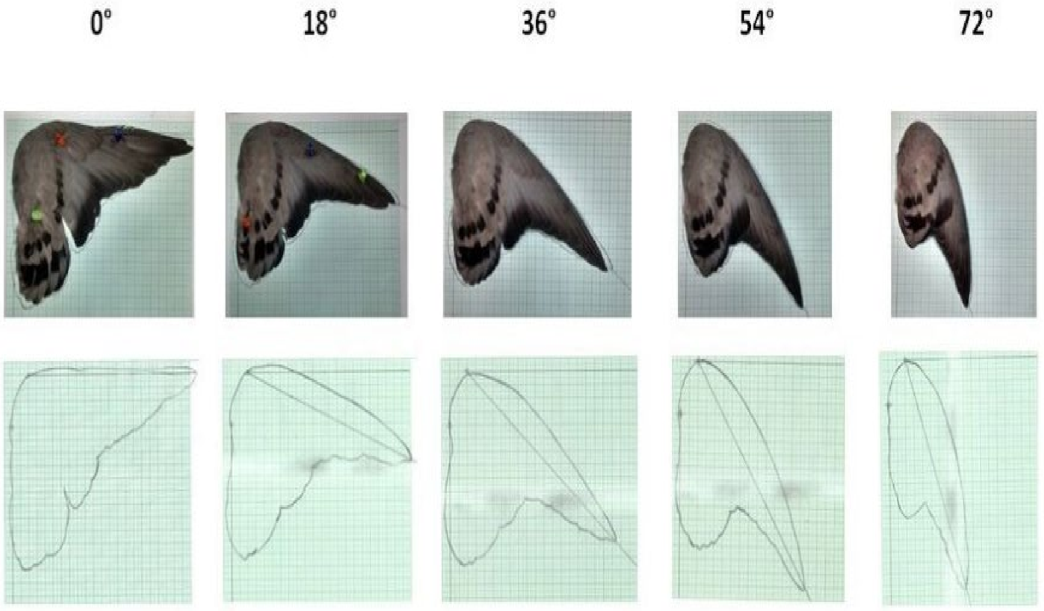

Fig. 1 - Leading edge variation and area measurement [1]

CFD simulations play a crucial role in understanding and optimizing the aerodynamic performance of these morphing wings.

Firstly, it allows an improved aerodynamic efficiency, as the wings allow for real-time adjustments to the wing's shape, optimizing aerodynamic efficiency under current varying flight conditions.

This adaptability reduces drag and enhances stability, a critical factor in developing autonomous drones.

Secondly, allows enhanced maneuverability as enable drones to achieve better maneuverability, making them more responsive to changing operational requirements. This is particularly valuable in harsh weather and emergency situations where quick and precise maneuvers are paramount.

Thirdly, it provides optimized performance across flight phases, Traditional fixed design wings are designed with the same geometry for specific all flight phases (takeoff, cruising, landing). Morphing wings, however, can adapt to each phase, maximizing performance at all stages of flight.

This flexibility contributes to more versatile and adaptable drone designs. CFD simulations enable engineers to study the aerodynamic effects of morphing wing geometries in a dynamic environment [2], [3].

This includes simulations of the wing morphing process and its impact on airflow patterns with th goal of optimizing efficiency [3], [4]. Optimization of morphing mechanisms through CFD can fine-tune the design of morphing mechanisms, ensuring smooth and efficient wing shape transitions [5]. This involves analyzing stresses, strains, and aerodynamic forces on the wing structure during morphing.

CFD simulations help predict and quantify the performance benefits of morphing wings in terms of drag reduction, lift enhancement, and overall efficiency. This information guides engineers in making informed decisions during the design phase.

Also, CFD simulations are integral to understanding and optimizing fluid flow behaviors in various engineering applications.

However, the computational demands of these simulations often pose challenges in terms of time and resources. A groundbreaking solution to this issue is the integration of deep neural network algorithms into CFD simulations, offering a faster and more efficient means of estimating results.

Traditional CFD simulations require significant computational resources and time, particularly when dealing with complex geometries or large-scale fluid flow problems. The intricate calculations involved in solving the Navier-Stokes equations demand high-performance computing resources, limiting the amount of simulations.

DNNs are a part of artificial intelligence domain, have emerged as a transformative tool in expediting CFD simulations [6-8].

By leveraging the power of machine learning, DNNs can be trained to approximate complex fluid dynamics solutions, significantly reducing the computational burden associated with traditional methods.

DNNs excel at learning patterns and relationships within large datasets. Once trained, a DNN can rapidly estimate fluid flow outcomes for specific scenarios, providing results in a fraction of the time required by conventional CFD simulations.

The implementation of DNNs in CFD diminishes the need for extensive computational resources [9], [10]. This not only accelerates simulations but also makes CFD studies more accessible to a broader range of researchers and engineers, including those without access to high-performance computing facilities.

For the drones flying in autonomous mode, reliable navigation is crucial. To operate drones in challenging environments such as changing winds and strong gusts affect the flight the velocity of the air must be known accurately, in order to estimate shape of the wings.

DNNs have become the cornerstone of modern artificial intelligence, powering a wide array of applications from image recognition to natural language processing. The design and configuration of DNN architectures, coupled with careful parameter selection, play pivotal roles in determining the performance and efficiency of these networks [11].

DNNs parameters dictates the model prediction rate. Beyond choosing an architecture, fine-tuning the parameters of a DNN is paramount for achieving optimal performance. The following parameters are central to the training and functioning of DNNs: activation functions which determinate learning rate. Learning rate is defined as the step size at which the model adjusts its weights during training.

An optimal learning rate ensures efficient convergence during training. Too high a rate may cause wrong learning data, while too low a rate may result in slow or stalled learning [12]. Activation functions introduce non-linearity, enabling the model to learn complex relationships.

Popular choices include functions as ReLU, sigmoid and tanh. Regularization techniques are the methods to prevent overfitting by penalizing complex models.

Its importance is that help generalize the model to untested data and prevent it from memorizing the training set.

2. METHODOLOGY

In this paper we consider a morphing wing drone allowing of shape reconfiguration inspired by bird wing geometry. However, the materials and the methods to control and manufacture the wings is not the subject of this research. Each wing has three segments allowing different shape.

Traditional CFD simulations may struggle with highly complex geometries, leading to increased computational costs. DNNs, through their ability to generalize from diverse data, offer a more flexible approach in handling intricate geometries, thus improving simulation accuracy and efficiency. DNNs exhibit adaptability, enabling them to handle changes in the flow conditions or geometry without the need for extensive recalibration.

This adaptability is particularly beneficial in scenarios where fluid flow conditions vary dynamically. While the integration of DNNs into CFD simulations presents a promising avenue, challenges such as the need for large training datasets, potential overfitting, and the interpretability of results must be addressed.

In case of CFD simulation we aim to demonstrate that even with reduced amount of training data deep neural algorithm are able to predict close to reality and provide useful information in order to control the drone. The synergy between DNNs and CFD heralds a new era in fluid dynamics research. Creating a DNN architecture for CFD simulations involves designing a model that can accurately learn and predict fluid flow behaviors. The architecture should be capable of handling the complexity of fluid dynamics while considering the importance of the loss function parameter for effective training.

The issue is finding the best deep network architecture to suite the CFD issue. The architecture for CFD simulations are taking into account several parameters such as: nodes, activation function, output layer, the loss function, etc.

Nodes represents the input features, such as initial conditions, geometry, and boundary conditions and provides the network with information about the problem setup. We used 16 hidden layers. For the activation function, a rectified linear unit (ReLU) and Sigmoid activation function to compare prediction rate were used (Tabel 1). The aim is to describe the complex relationships and patterns within the fluid dynamics data.

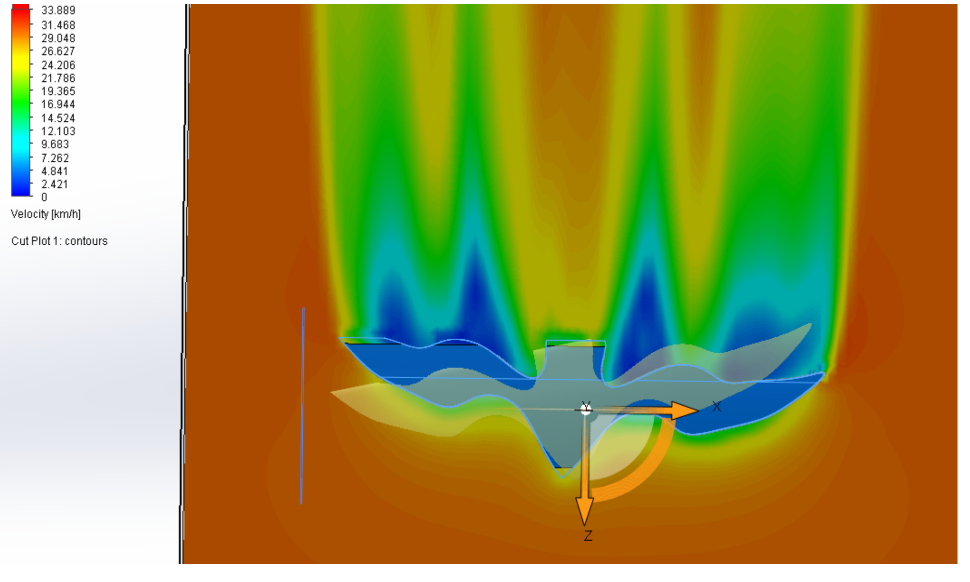

Fig. 2 - Different wind direction for the proposed model

Output layer represents the predicted fluid flow variables in our case velocity of fluid in 13 points located.

The loss function is Mean Squared Error (MSE), commonly used for regression tasks in CFD. The loss function measures the difference between the predicted values and the actual values. It guides the training process by indicating how well the model is performing. In CFD simulations, where accuracy is critical, choosing an appropriate loss function is paramount. The choice of the loss function is crucial, as it directly influences the model's ability to converge to an optimal solution.

We choose the MSE loss function as it helps minimize the squared differences between predicted and actual values, encouraging the model to learn the underlying fluid dynamics patterns. The loss function guides the training process by quantifying the model's performance. A well-chosen loss function ensures that the model converges to an optimal solution accurately.

In CFD simulations, the loss function should align with the physical quantities being predicted.

MSE is commonly used for fluid dynamics tasks, but depending on the specific problem, other loss functions such as mean absolute error (MAE) or custom loss functions may be more appropriate.

The loss function plays a role in the generalization of the model to unseen data. It helps strike a balance between fitting the training data well and making predictions that generalize to new, unseen scenarios.

In summary, when designing a DNN architecture for CFD simulations, the choice of the loss function parameter is crucial. It directly influences the model's ability to learn and predict fluid dynamics phenomena accurately, ensuring that the simulation results align with the underlying physical principles.

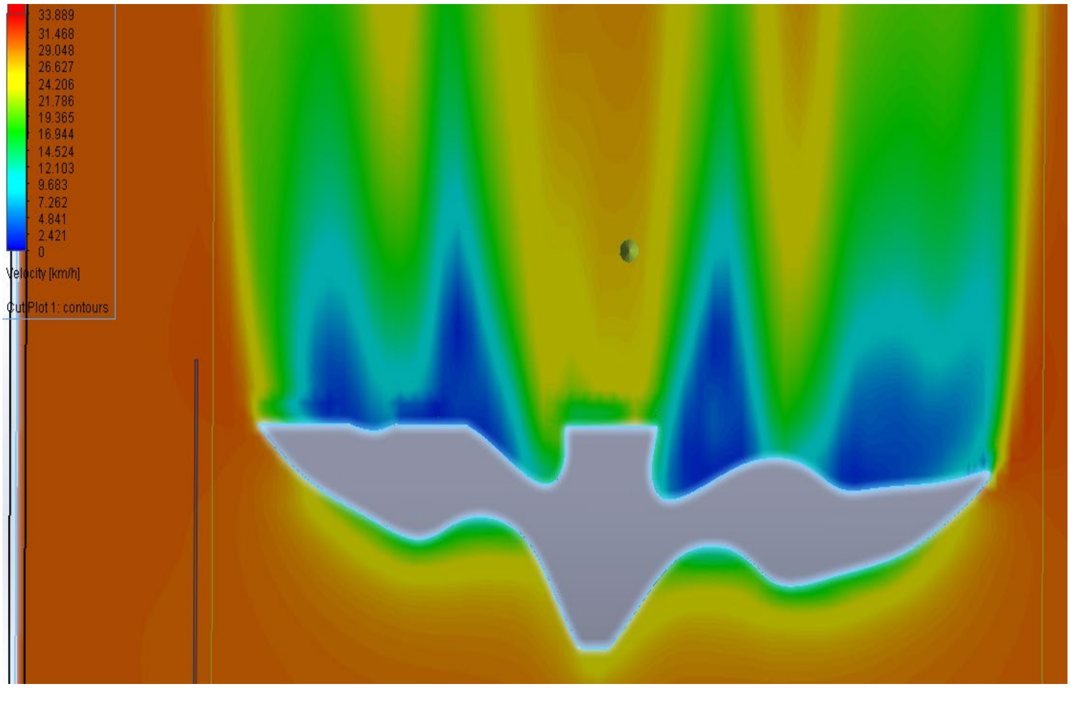

Fig. 3 - Variation of air speed for the same morphing configuration with different wind direction

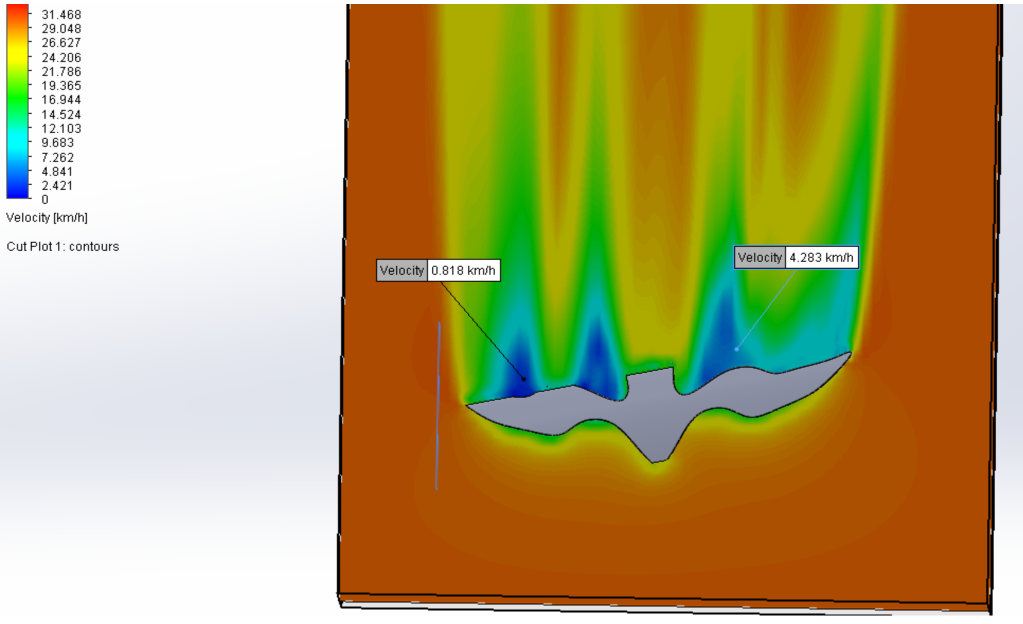

Fig. 4 - Different speed of fluid near the wing

We want to predict fluid speed in 13 points neat the morphing wing (Figure 4 and Figure 5). The input data is represented by surface of the wing, the speed of the air and the wind directions in degrees where straight ahead is 0. We consider the following annotation: the positive values are to the left in the direction of flight and we consider negative values in the right direction of flight (Figure 2).

We used 70 training data with the values extracted from CFD simulation for fluid speed in a horizontal plane at several speed (Figure 3 and Figure 2) and 10 testing different scenario different than the training. We compared ReLU activation function with Sigmoid activation function to assess prediction rate (Table 1). It seems for the reduced amount of data for training and complexity of the problem translates into a relative low prediction rate, but sufficient to control the drone. Further development of the research is to test other activation functions and also other parameters of the network architecture.

In navigating the neural landscape, the selection of DNN architectures and parameters translates in rejection of the model.

Tailoring the architecture to the task at hand and fine-tuning parameters with precision are essential for unlocking the full potential of DNNs.

Table 1 - Prediction rate between ReLU and Sigmoid activation function

No.	Wind speed [km/h]	Direction	ReLU Prediction rate [%]	Sigmoid Prediction Rate [%]
1	30	10	78	70
2	37	12	75	71
3	40	13	73	72
4	25	15	72	68
5	22	20	78	69
6	12	-10	73	68
7	27	-20	80	72
8	25	-25	83	75
9	20	-27	78	70
10	17	-27	75	68

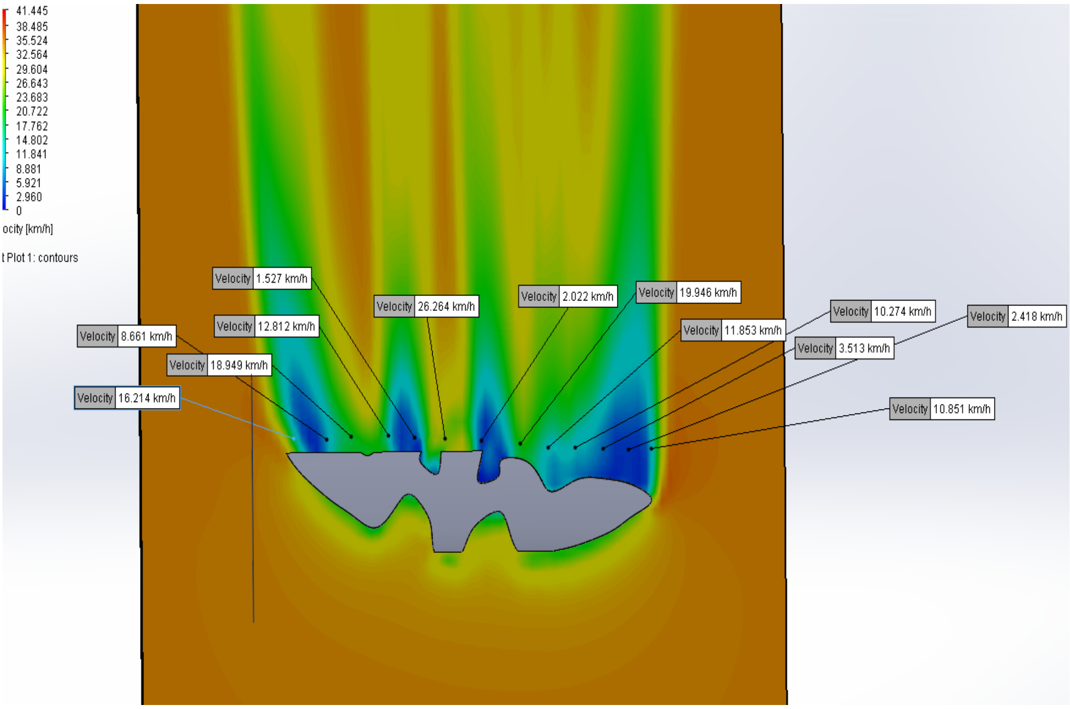

Fig. 5 - Speed of fluid in different points near the wing, direction of wind 5 degrees

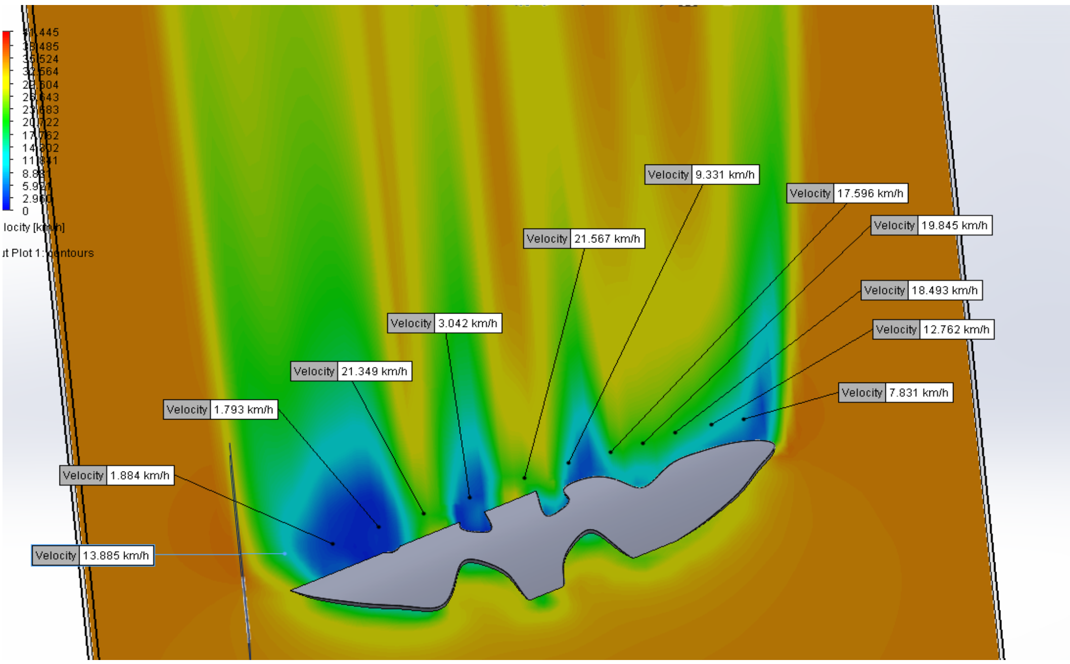

Fig. 6 - Speed of fluid in different points near the wing, direction of wind -12 degrees

3. CONCLUSIONS

The integration of morphing wings in aircraft design, coupled with advancements in CFD simulations, marks a significant stride in aerospace engineering. The ability to dynamically adjust wing geometry offers a myriad of advantages, from improved fuel efficiency to enhanced maneuverability.

CFD simulations play a pivotal role in understanding and harnessing these benefits, paving the way for the next generation of adaptable and efficient aircraft. As research in this field continues, we can anticipate even more sophisticated designs that push the boundaries of what is possible in aviation. This convergence of artificial intelligence and engineering not only accelerates the pace of scientific discovery but also opens doors to innovative applications across various industries, paving the way for a more efficient and accessible approach to fluid dynamics simulations.

A morphing wing needs to be controlled in an optimized manner taking into account current aerodynamics parameters.

Predicting optimized positions of the wing needs to consider (CFD) prior simulation parameters. The scenarios for flight requires an important number of CFD simulation to address different conditions and geometric shapes.

We compare in this paper neural network architecture suitable to predict wing shape according to current conditions. DNN is trained using data resulted out of CFD simulations to estimate flight conditions.

The comparison between CFD and DNN predictions in this research shows ReLU activation provides better results than Sigmoid activation for this specific case.

However, further development of the research should include more training data. The reduced amount of simulations used for training resulted in a acceptable rate of prediction but will increase if more data would be used for training. The approach proves that the approach is suitable for controlling morphing wing of drones.

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