Airfoil Shape Generation with Conditional Wasserstein Generative Adversarial Networks (cWGANs) for Dust Mitigation on Solar Panel Surface

NC STATE UNIVERSITY
Mechanical and Aerospace Engineering

Taha Ahmed, Veeraraghava Raju Hasti

Abstract

Dust soiling on solar panels affects the efficacy of solar panels in regions susceptible to dust storms. One possible way to combat this is by creating solar panels in the shape of airfoil cross sections. The shear stress experienced on the upper surface may aid in reducing time between maintenance of solar panels. By characterizing the shear stress on the upper surface of NACA 4-digit airfoils and training a cWGAN model to produce shapes corresponding to characteristic shear, new more effective shapes may be discovered.

Introduction

Solar energy has the potential to provide electricity to many in remote areas, especially in countries that may have reduced access to electrical infrastructure. Some of these areas suffer from dust storms and other similar weather patterns, which can hinder the efficacy of solar panel solutions due to dust soiling [1]. This effect is compounded when regular solar panel maintenance is not practical. Airfoils have the potential to prolong the time between required maintenance by automatically removing dust particles through viscous shear effects.

Figure 1

- Fig. 1 demonstrates the effects of dust soiling on solar panels.
- Continuous upkeep is required to keep these facilities operating.
- Continuous upkeep is unfeasible in widespread decentralized solutions.

- Fig. 2 represents the mechanism of dust removal through fluid flow.
- Boundary layer is formed by wind over surface
- Skin friction coefficient corresponds to boundary layer thickness

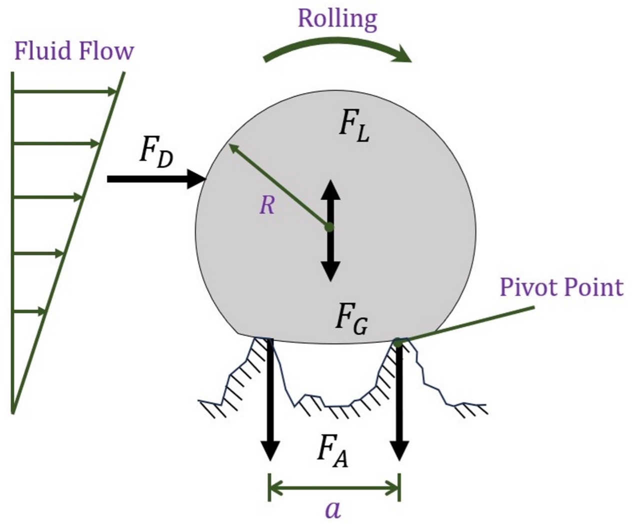


Figure 2

Objectives/ Goals of the project

- Develop novel airfoil cross sections for use in solar panel dust mitigation
- Reduce amount of upkeep required for decentralized solar solutions
- Develop new implementations of neural net powered airfoil generators with cWGANs (TensorFlow).
- Demonstrate the use of novel aerodynamic performance parameters in training of neural networks

Methodology

Overview:

- NACA 4 digit airfoils are generated (dx = c / 100).
- Xfoil analysis in dust storm conditions is performed on the data to obtain C_f, which was subsequentially used to obtain τ_{char}.

$$\tau_{char.} = 1000 * \int_{Upper} \tau_w \, ds$$

- Negative values and outlier airfoils are dropped from the dataset.
- Remaining data is up-sampled to produce a uniform distribution of labels.
- Airfoil coordinates are standardized to aid in model training.
- cWGAN model is trained until convergence (generator wins the game, discriminator is fooled)
- Model is evaluated for efficacy

Conditional Wasserstein Generative Adversarial Networks (cW-GANs) have been shown to be effective in generating airfoils with desired performance parameters by employing the Wasserstein loss function [2]. By training a cWGAN to match the shapes of NACA 4-digit airfoils with their corresponding *characteristic shear stress*, airfoils can be optimized for maximum shear stress along the upper surface, allowing for the automatic dust removal process to take place.

The Wasserstein (EM) Distance is defined as follows:

$$W(p_r, p_g) = \max_{w \in \mathcal{W}} \left[\mathbb{E}_{x \sim p_r}[f_w(x)] - \mathbb{E}_{z \sim p_z}[f_w(g_\theta(z))] \right]$$

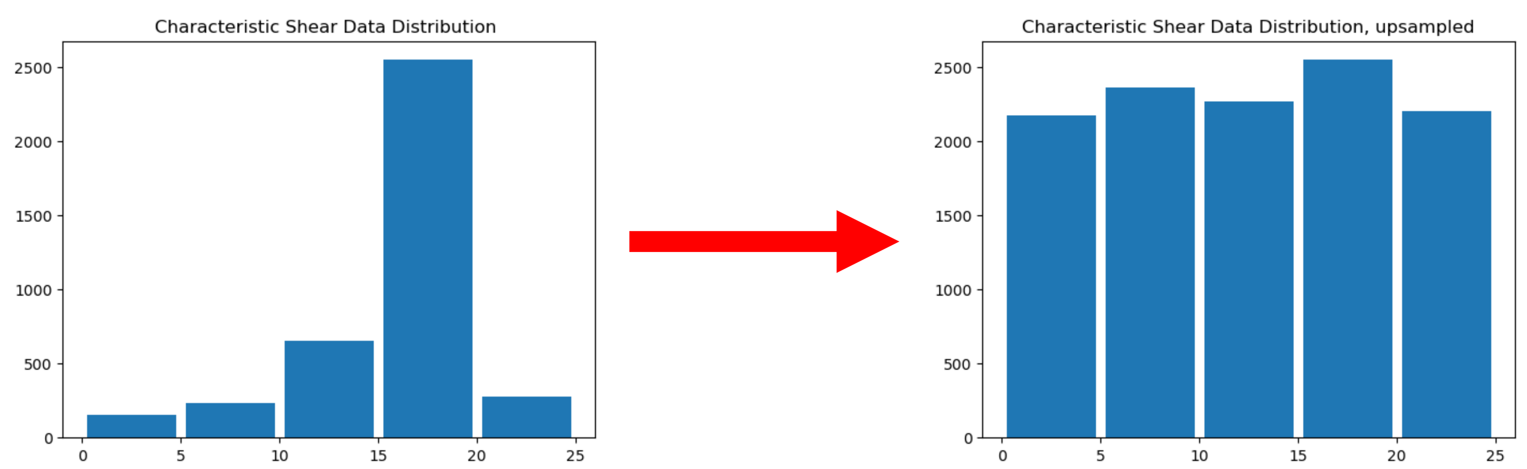
And the loss function of the cWGAN with a gradient penalty is defined as follows:

$$V_{\text{WGAN-GP}}(f_w, g_\theta) = V_{\text{WGAN}}(f_w, g_\theta) + \lambda \mathbb{E}_{x \sim p_r}[(\|\nabla_x f_w(x)\|_2 - 1)^2]$$

Where $V_{WGAN}(f_w, g_\theta)$ is equivalent to $W(p_r, p_g)$ and λ is the gradient penalty applied.

Results

- Xfoil analysis has been performed on every foil.
- All have been standardized.
- Data has been up sampled.
- Model is currently being trained.



Conclusion and Discussion

The use of Generative Adversarial Networks in engineering design promises to continue to speed up design workflows while providing engineers with insights that may be missed through normal iterative design processes. Current airfoil design workflows involve an iterative process that relies on a (sophisticated) guess and check method. Employing machine learning models in this design process could allow for automatic shape generation based on desired design parameters for several applications of airfoils.

The model trained in this project can be used to generate shapes that can later be evaluated for use in dust mitigation on solar panels. The implications for this work could aid in the design of decentralized solar systems in different regions, where requirements for the dust mitigation process may differ.

Future Work

Training this model on a dataset with different types of airfoils such as the NACA 6-series, and more accurate labels produced from more sophisticated CFD software will undoubtedly improve results. Flow over airfoils is complex, and as such, large datasets are required to train a more accurate model. Similar methods can be employed for airfoil design workflows.

Implementation of the airfoil shapes produced by the model may allow for dust soiling mitigation. Wind tunnel testing of the shapes generated, as well as higher fidelity simulations will be needed to verify the efficacy.

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References

[1] Isaacs, S., Kalashnikova, O., Garay, M.J., van Donkelaar, A., Hammer, M.S., Lee, H., Wood, D., 2023. Dust soiling effects on decentralized solar in West Africa. Applied Energy 340, 120993. https://doi.org/10.1016/j.apenergy.2023.120993

[2] Yonekura, K., Miyamoto, N., Suzuki, K., 2022. Inverse airfoil design method for generating varieties of smooth airfoils using conditional WGAN-gp. Struct Multidisc Optim 65, 173. https://doi.org/10.1007/s00158-022-03253-6

[3] Wang, Y., Shimada, K., Barati Farimani, A., 2023. Airfoil GAN: encoding and synthesizing airfoils for aerodynamic shape optimization. Journal of Computational Design and Engineering 10, 1350–1362. https://doi.org/10.1093/jcde/qwad046