Gazing at clouds to understand turbulence on wind turbine airfoils

de Oliveira Andrade, Gael; Balbino Dos Santos Pereira, Ricardo; Timmer, Nando; Ragni, Daniele; Lau, F.; van Bussel, Gerard

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THE ISSUE WITH TURBULENCE MODELLING ON WIND TURBINE AIRFOILS

« Big whirls have little whirls that feed on their velocity, and little whirls have lesser whirls and so on to viscosity. »

Weather Prediction by Numerical Process Richardson LF, CUP

Airfoils
play essential role in performance of large wind turbines

Mach < 0.3 Reynolds >10e6
Wind turbine airfoil flows are incompressible and have very high Reynolds number. Mach stays constant while Reynolds grows as turbines increase in size to reduce costs

Large Wind Tunnels
needed to replicate airfoil field conditions mean experimental costs escalate as Reynolds number grows

CFD simulation
codes used with scarce validation and large uncertainties

Errors in Load Prediction
come from semi-empirical turbulence models with incomplete physics callibrated with insufficient data [2, 3]

Turbulence is a complex flow process dominated by seemingly chaotic eddy motions of multiple scales. Large eddies decompose into smaller eddies of nearly random appearance, but small eddies reorganize into larger coherent structures [1].

For high Reynolds numbers, turbulent processes are too complex to be fully resolved (DNS) in Computational Fluid Dynamics (CFD) simulations. Engineers use approximate equations (VI/RANS/LES) to handle turbulent phenomena with closure models [2, 3].

« Turbulence remains the last unsolved problem of classical mechanics. »

Deterministic Chaos, Kumar N, U. Press

« Perhaps the single, most critical area in CFD simulation capability that will remain a pacing item by 2030 (…) is the ability to adequately predict viscous turbulent flows »

CFD Vision 2030 Study, NASA CR 2014-218178

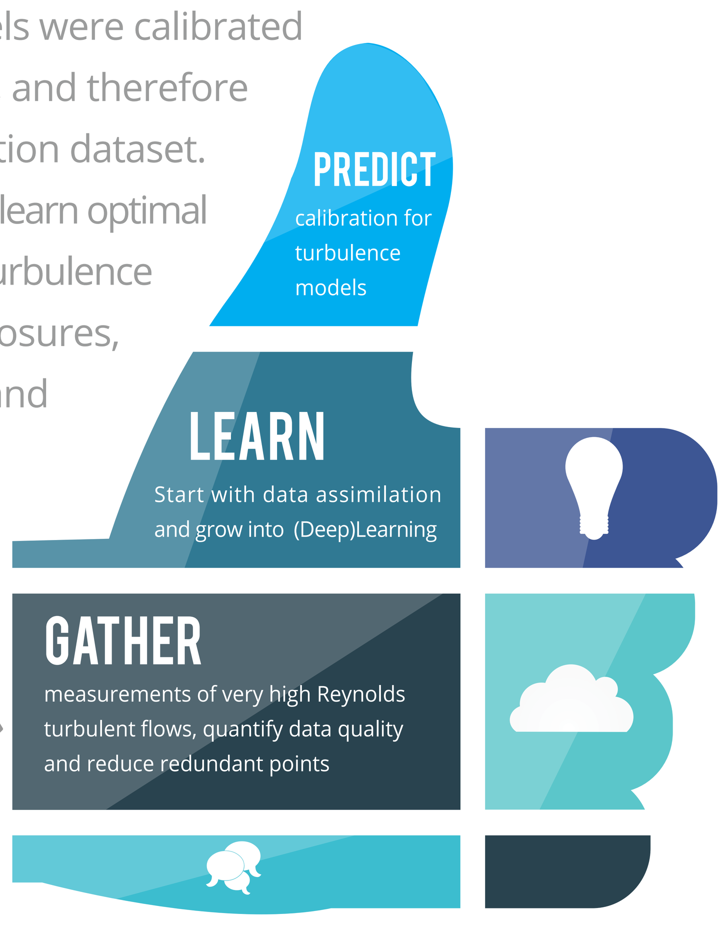
GAZING AT CLOUDS TO UNDERSTAND TURBULENCE ON WIND TURBINE AIRFOILS

SOLUTION

ADOPT DATA RICH APPROACH TO TUNE FLOW TURBULENCE MODELS

We propose to rethink the procedure for calibrating turbulence models used in popular Computational Fluid Dynamics (CFD) codes. Like Duravaisamy [4,5] , we recognize that current turbulence models were calibrated with a single handful of reference cases, and therefore attempt to create a large unified calibration dataset. The large calibration dataset will be used to learn optimal conditional calibration rules for popular turbulence models: Integral Boundary Layer (IBL) closures, RANS models like Spalart-Almaras (SA) and LES subgrid scale (SGS) closure models

« Every flow is an observation of the phenomenon of turbulence. »



GATHER 1
MEASUREMENTS OF VERY HIGH REYNOLDS FLOWS

Flow
Flat plate, Aerofoil Backward Facing Step

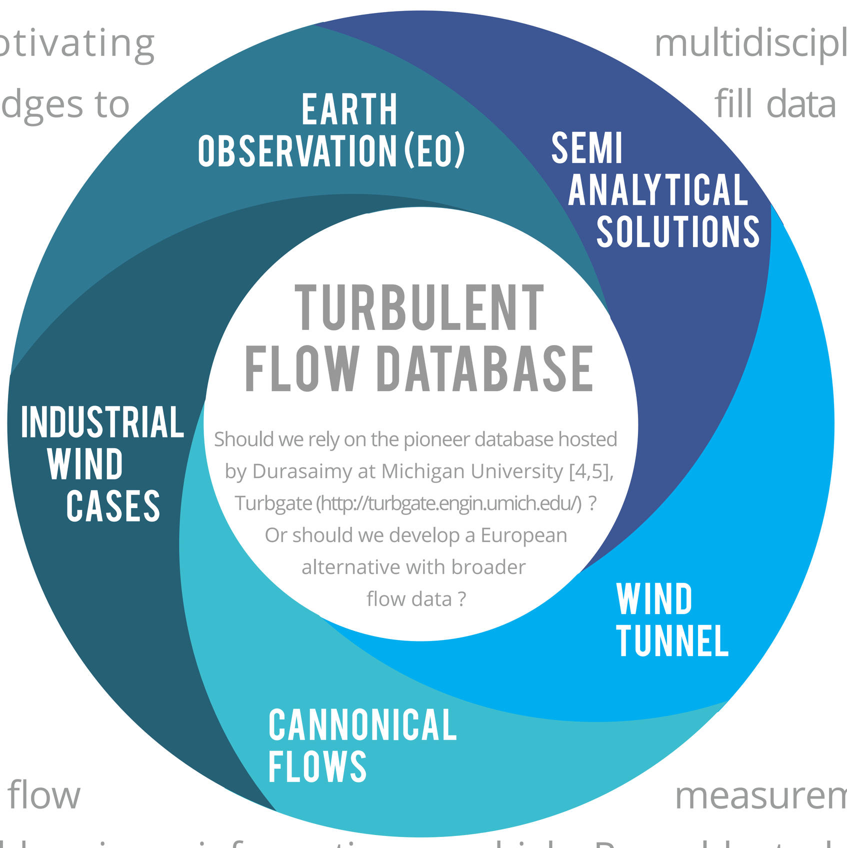
Flow
Wind Turbine Wake Power Production Loads

Flow
Law of the wall, e^N theory, Isotropic Turb.

Flow
High Altitude Winds, Clouds, Oceanic Currents

Flow
Water Pipe Experiments Taylor and Couette Flow

Early experiments show that size of calibration dataset is critical for successful data driven turbulence modelling, motivating multidisciplinary bridges to fill data gaps.



EO flow measurements hold unique information on high Reynolds turbulent phenomena, essential to identify asymptotic tendencies.

Instrument
Pressure Tap, Wake Rake, Load Balance, Particle Image Velocimetry (PIV)

Instrument
Ultrasonic Anemometry, Wind LIDAR, SCADA and Turbine Controller Data

Instrument
N.A., Direct Numerical Simulation (to provide asymptotic behaviour)

Instrument [6,7]
ADM Aeolus Instrument, Lagrangian Tracers on Optical/IR Measurements

Instrument
Hot wire, PIV, Pressure Tap and Stanton Tube

LEARN 2
TURBULENCE MODEL CALIBRATION CURVES

There are many ways to learn from data. Our first experiment consisted in reproducing the way aerodynamicists work [2] with a genetic optimizer. The data pool was too narrow and asymptotic tendencies were unreliable. Our 2nd experiment, a simple version of [4], had a virtually unlimited data pool and used neural networks. Results were better, but computationally expensive. Data assimilation approaches used in EO [7] could yield better results..

1ST SIMPLE EXPERIMENT

Compare VI code results with trustable reference data	Optimize (NSGAII) G-Beta closure constants to match results

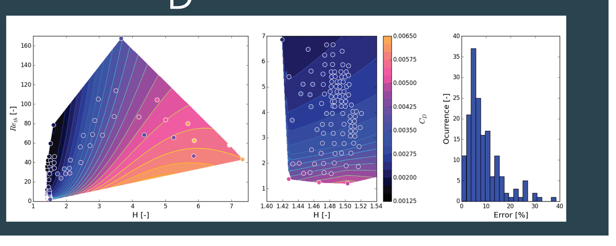
2ND SIMPLE EXPERIMENT

Learn dissipation coefficient (C_D) closure to match a VI code (RFOIL) to RANS model (Spalart Almaras)

Generate velocity fields in OpenFoam and process into C_D , H and Re_{theta}

Run Neural Network to learn the C_D in terms of H and Re_{theta}

Obtain C_D closure for VI Codes



PREDICT 3
TURBULENT FLOWS

Once established, the methodology will be applicable to any type of turbulent closure relation, thereby higlighting the common features of seemingly diverse models:

NAVIER STOKES		CLOSURE
	RANS Reynolds Averaged Navier Stokes	
	LES Large Eddy Filtered Navier Stokes	
	VI Viscous-Inviscid Asymptotic	

Even when good calibration is achieved, turbulence models will still rely on many coarse assumptions: most popular RANS and LES closures rely on the Boussinesq hypothesis and rule some (if not all) anisotropy out.

INFER 4
NEW CLOSURE TERMS

Model calibration curves can hint towards the most problematic simplifications behind current turbulence models [5], and neural networks can even learn improved closure terms [4]. But learning algorithms do not aim to replace researchers: like genetic airfoil optimizers enhance the work of airfoil designers, neural networks can empower turbulence modellers.

[1] A first course in Turbulence, Tennekes & Lumley MIT Press

[2] Modification of the boundary layer calculation in Rfoil for improved airfoil stall prediction van Rooij R, TU-Delft Report IW-**96087**R

[3] An evaluation of RANS turbulence modelling for aerodynamic applications, Catalano P & Amato M, Aerospace Science and Technology, **7** 493-509

[4] Machine Learning Methods for Data-Driven Turbulence Modeling, Zhang ZJ & Duraisamy K, AIAA 2015-**2460**

[5] A paradigm for data-driven predictive modeling using field inversion and machine learning, Parish EJ & Duraisamy K, J. Comp. Phys. **305** 758-774

[6] La turbulence par l'image, Heas P Heitz D and Memin E La Recherche: L'actualité des Sciences 2010-444

[7] Parameterization Of Turbulence Models Using 3DVAR Data Assimilation, Olbert AI, Nash S, Ragnoli E and Harnett M, 11th International Conference on Hydroinformatics

LONG TERM IDEA OPEN TO PARTNERS

2014
Tune the G-Beta constants of a viscous-inviscid (VI) solver (RFOIL) with genetic algorithms (NSGA2).

2015
Process CFD Fields to learn neural VI closure relations.

2016
Gather partners to share data and write proposals. Summer schools: JMBC Turb., LxMLS16 and 8th ESA EO.

Group D8 of the AE-2223 course developped the neural network code: Koopman, Henger, Lebesque, Mekic, Mollinga, Vijverberg, Reutelingsperger

Gael de Oliveira[1]
Ricardo Pereira[1]
Nando Timmer[1]
Danielle Ragni[1]
Fernando Lau[2]
Gerard van Bussel[1]

[2]CCTAE , IDMEC
Inst. Superior Técnico
Universidade de Lisboa
Av. Rovisco Pais 1
1049-001 Lisbon
Portugal

[1]AWEP Department
Aerospace Faculty, Delft
University of Technology
Kluyverweg 1
2629HS Delft
The Netherlands

TU Delft

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