



ENGINEERING APPLICATIONS OF METAMODEL-BASED OPTIMIZATION: GENETIC ALGORITHMS COUPLED WITH ARTIFICIAL NEURAL NETWORKS

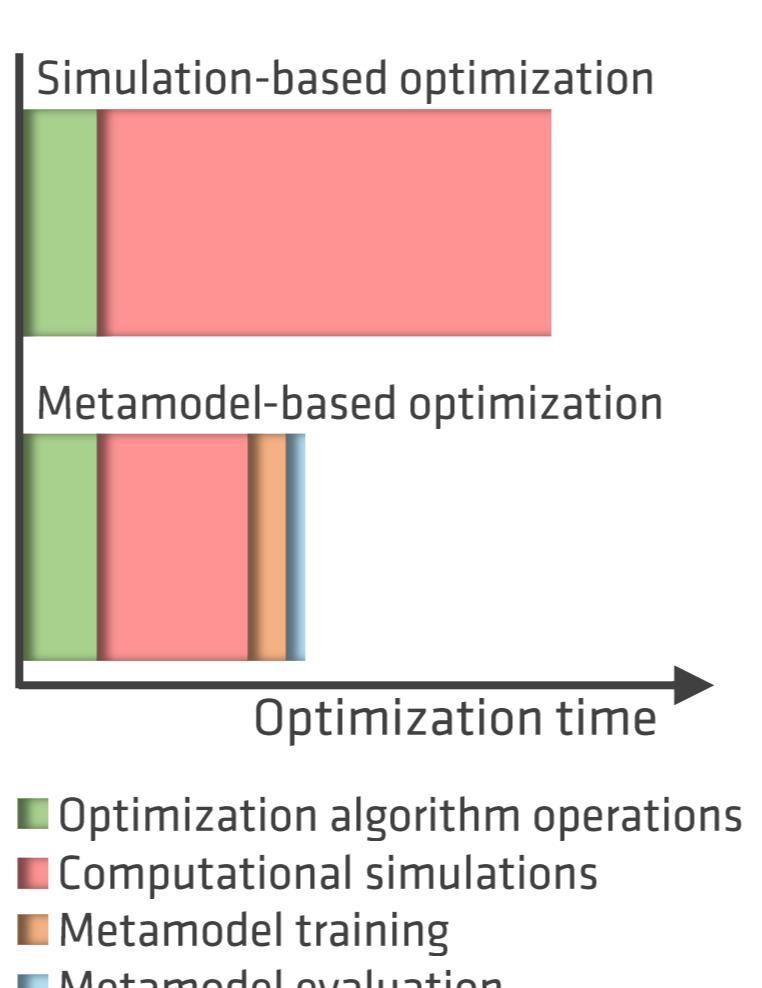
Nadia D. Roman

CIMEC (UNL-CONICET), Predio "Dr. Alberto Cassano", Colectora Ruta Nacional 168 s/n, 3000, Santa Fe, Argentina

GIMNI (UTN FRSF), Lavalle 610, 3000, Santa Fe, Argentina, nroman@frsf.utn.edu.ar

OPTIMIZATION IN ENGINEERING

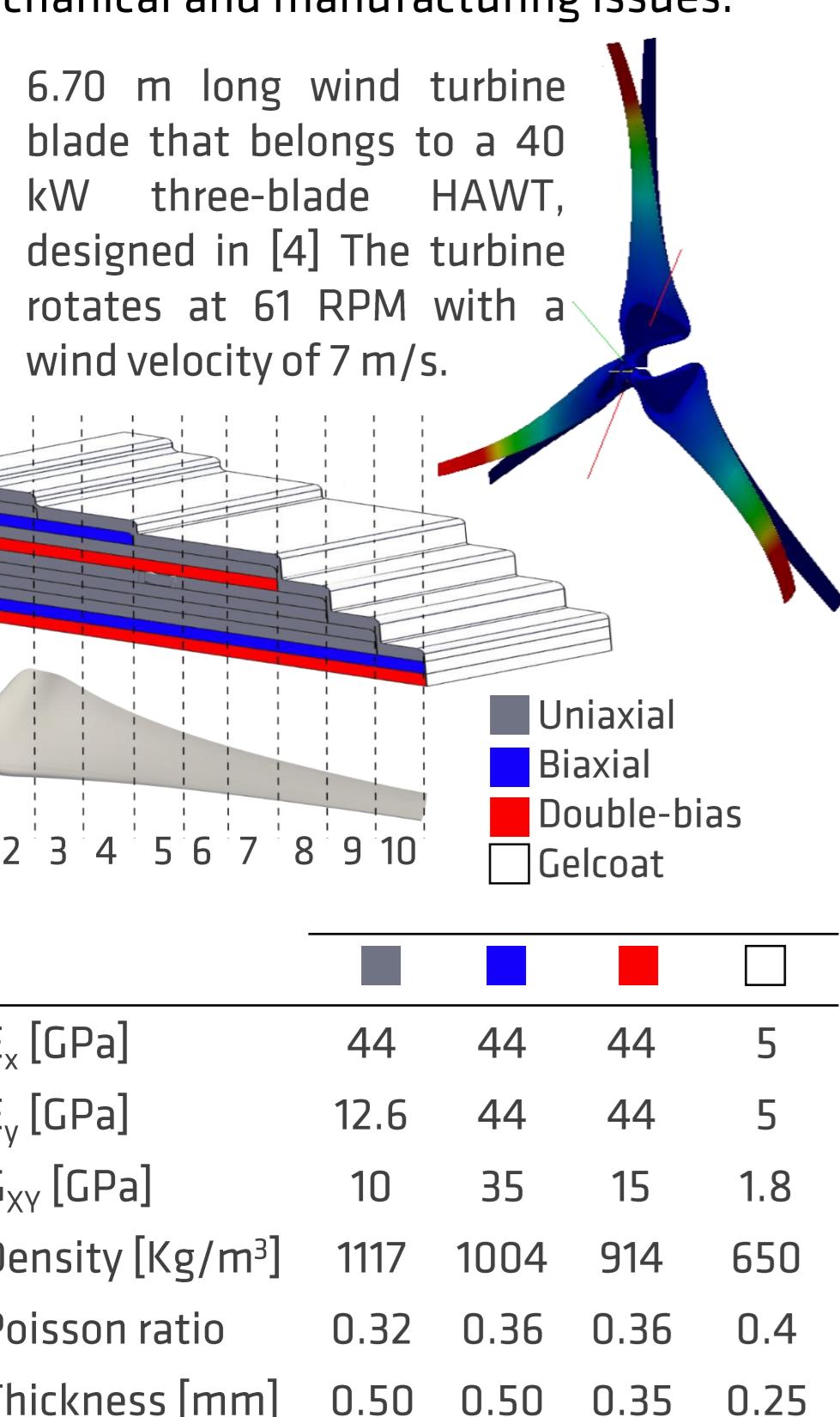
The complexity of optimization problems in engineering leads to the necessity of developing methodologies to replace the usually time-costly computational models that simulation-based optimization requires. An alternative is to implement a metamodel (model of the model), for example artificial neural networks, to evaluate the objective function of the problem. This technique, called metamodel-based optimization, has become frequently used in recent years due to the fact that it can be implemented to solve large nonlinear problems, independently of the nature of the variables involved (continuous, discrete, binary, to name a few). Artificial neural networks (ANNs) are, regardless of being an approximate method, reliable and accurate models that can be implemented on several engineering problems.



CASE STUDIES

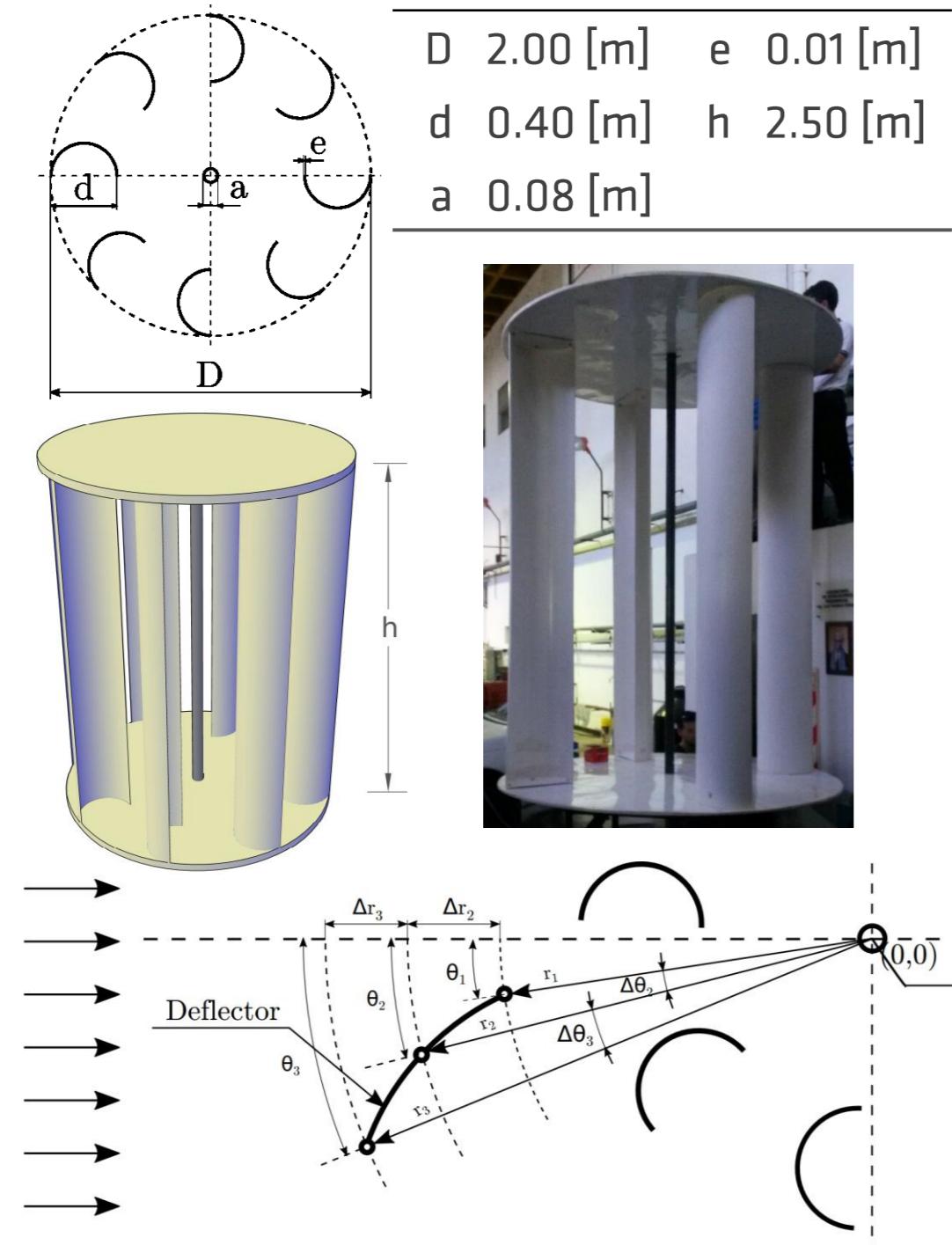
1 COMPOSITE LAMINATED WIND TURBINE BLADES: MINIMIZATION OF WEIGHT [1]

Design problem: find the proper variable stiffness laminate that minimizes the weight of the blades while satisfying a series of design constraints that include mechanical and manufacturing issues.



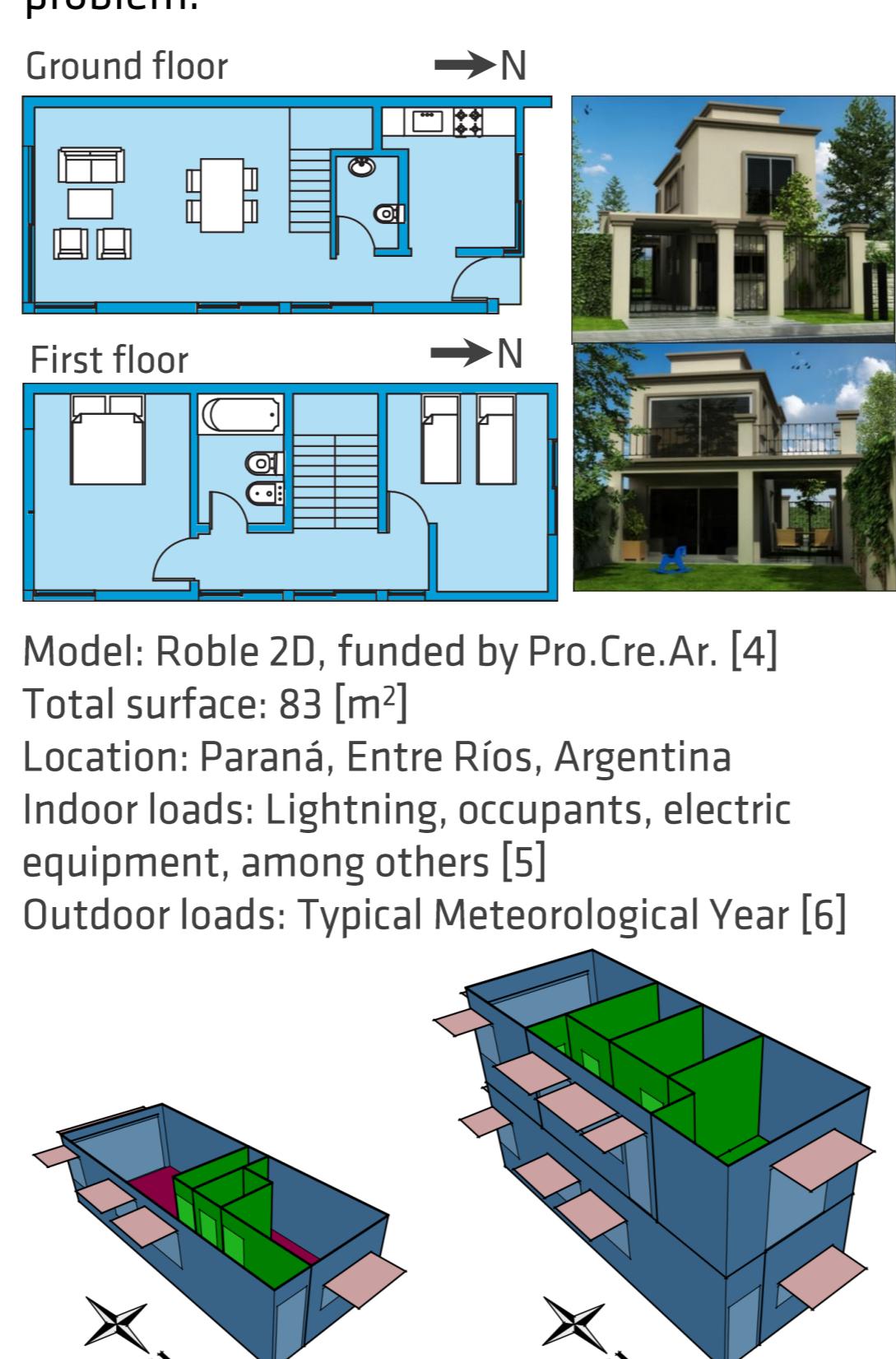
2 DEFLECTORS OF A WIND TURBINE (SAVONIUS): DESIGN AND OPTIMIZATION [2]

Design problem: find the optimal geometry and position of four fixed deflectors to improve the performance of an eight-blade Savonius vertical axis wind turbine (VAWT), which is being installed on the roof of the Santa Fe Regional Faculty of the Universidad Tecnológica Nacional.



3 DWELLINGS: OPTIMIZATION OF ENERGY EFFICIENCY [3]

Design problem: improve the energy performance without affecting the thermal comfort of a single-family house, solving a multi-objective optimization problem.



PROPOSED METHODOLOGY

SAMPLE VARIABLES

Latin Hypercube Sampling [7]

The range of each input variable is divided into N equally probable intervals, and a value from each interval is selected. Then, the selected values are matched randomly, creating a sample of size N.

	Training N	Validation N	Problem size
1	2000, 2500	100	$\sim 10^4$
2	300	50	$\sim 10^7$
3	1700, 3300	100	$\sim 10^8$

METAMODEL

Multilayer Feedforward ANNs were developed for the three problems. Backpropagation with Bayesian regularization was implemented as training function, with an early stop criterion.

	Nº of HL	Total Nº of neurons	Performance Function
1	1 and 2	40 to 60	$MSE = 1 \times 10^{-5}$
2	1, 2 and 3	6 to 20 in each layer	$MSE = 1 \times 10^{-7}$
3	1, 2 and 3	$0.5 \cdot (\text{Input} + \text{Output}) + (\text{Sample Size})^{1/2}$	$MSE = 1 \times 10^{-5}$

SIMULATION

IFEM (Inverse Finite Element Method) [4,8,9] ①

It computes all of the design constraints: the maximum allowable tip deflection, the maximum stress criteria and the vibration frequency of the blades. It also determines the unloaded manufacturing shape of the blade such that, under service loads, the deformed blade attains its efficient aerodynamic shape.

CFD (Computational Fluid Dynamics) ②

A two dimensional CFD model was employed to calculate the Power Coefficient (C_p), considering a wind velocity of 5 m s^{-1} aligned with one cardinal direction and a Tip Speed Ratio (λ) of 0.4 [2].

EnergyPlus ③

EnergyPlus was used to evaluate the thermal and energy performance of the house. The house was divided into eight thermal zones (kitchen, living room, two bathrooms, two bedrooms, corridor, staircase), and was planned to be occupied by four people.

OPTIMIZATION

Optimization with GA and ANN

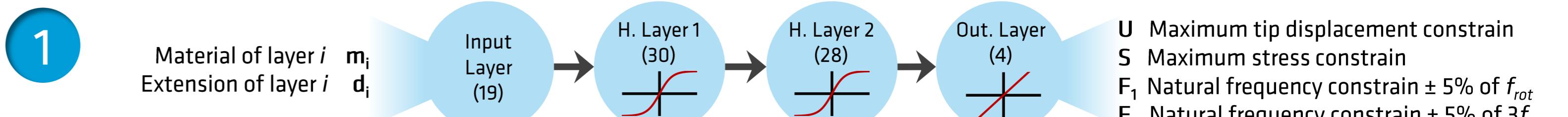
Genetic algorithm ① Selection: Tournament, Crossover method: Laplace Configuration: 48 individuals and 100 generations. Total ANN evaluations: 4800

Genetic algorithm ② Selection: Tournament Crossover method: Laplace Configuration: 48 individuals and 100 generations. Total ANN evaluations: 4848

Genetic algorithm NSGA-II ③ Non-dominated Sorting Genetic Algorithm-II [10]. Configuration: 64 individuals and 150 generations. Total ANN evaluations: 9600

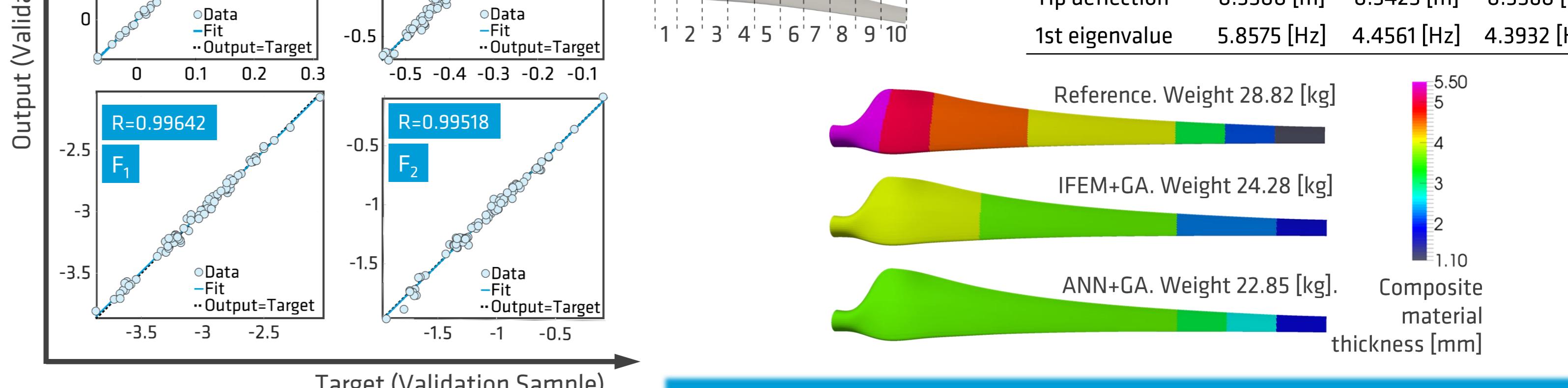
Optimization loop: Selection → Crossover → Mutation → Fitness → ANN → Stopping criteria met? → Optimal design

RESULTS

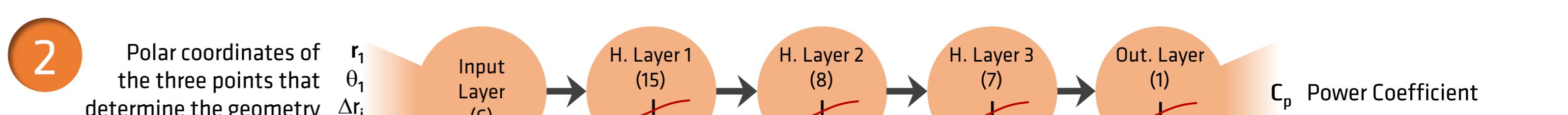


U Maximum tip displacement constrain
S Maximum stress constrain
 F_1 Natural frequency constrain $\pm 5\%$ of f_{rot}
 F_2 Natural frequency constrain $\pm 5\%$ of $3f_{rot}$

Characteristic	Reference [8]	IFEM+GA [9]	ANN+GA [1]
Number of plies	11	9	7
Blade weight	28.82 [kg]	24.28 [kg]	22.85 [kg]
Tip deflection	0.3500 [m]	0.3425 [m]	0.3560 [m]
1st eigenvalue	5.8575 [Hz]	4.4561 [Hz]	4.3932 [Hz]

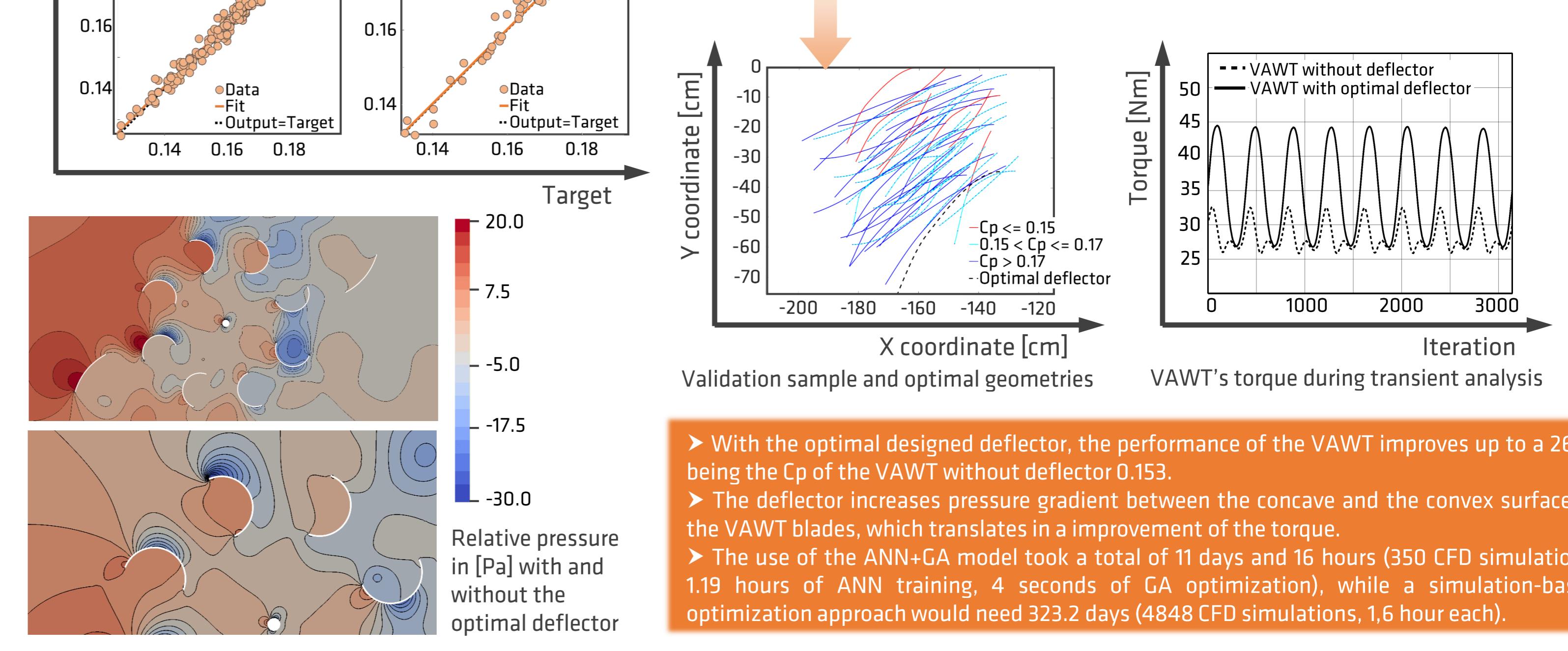


- The optimal blade weighs 22.85 [kg], being 20% lighter than the reference blade and 6% lighter than the former design with IFEM+GA. It also represents a reduction of 5 layers compared to the reference design, and of 2 layers compared to the design obtained using IFEM+GA.
- The use of the ANN+GA model allowed a 40% reduction of the computational cost in contrast with the simulation-based optimization approach (2500 versus 4800 simulations).

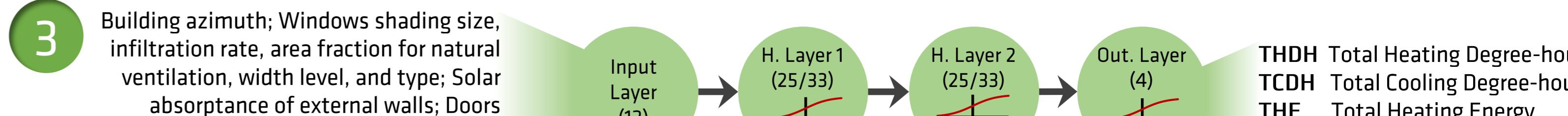


C_p Power Coefficient

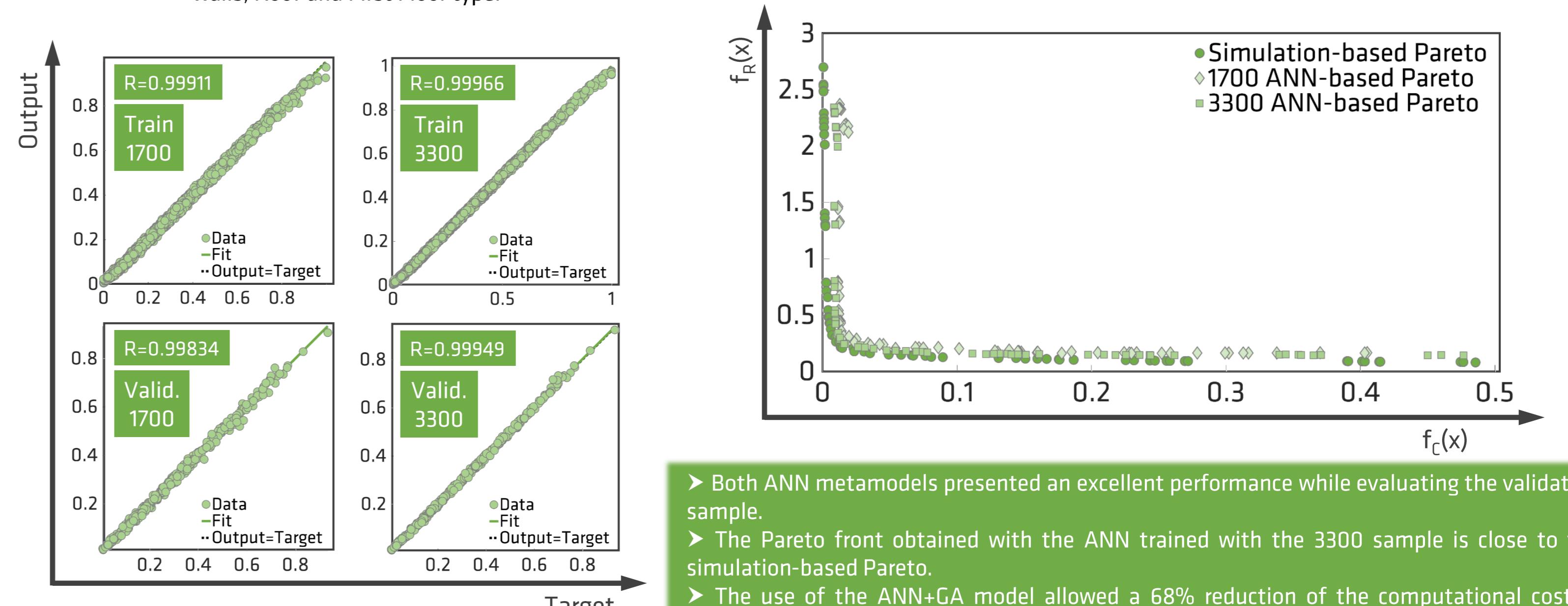
	r_1	α_1	Δr_2	$\Delta \alpha_2$	Δr_3	$\Delta \alpha_3$	C_p
1	137.3	14.6	30.0	5.0	16.9	5.0	0.193



- With the optimal designed deflector, the performance of the VAWT improves up to a 26%, being the C_p of the VAWT without defector 0.153.
- The deflector increases pressure gradient between the concave and the convex surface of the VAWT blades, which translates in an improvement of the torque.
- The use of the ANN+GA model took a total of 11 days and 16 hours (350 CFD simulations, 1.19 hours of ANN training, 4 seconds of GA optimization), while a simulation-based optimization approach would need 323.2 days (4848 CFD simulations, 1.6 hour each).



THDH Total Heating Degree-hour
TCDH Total Cooling Degree-hour
THE Total Heating Energy
TCE Total Cooling Energy



- Both ANN metamodels presented an excellent performance while evaluating the validation sample.
- The Pareto front obtained with the ANN trained with the 3300 sample is close to the simulation-based Pareto.
- The use of the ANN+GA model allowed a 68% reduction of the computational cost in contrast with the simulation-based optimization approach (9600 versus 3300 simulations).

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