Data-driven prediction of flow parameters in a ventilated cavity using high-fidelity CFD simulations

Speaker:

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Outline

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2) Test case and model description
3) Results
4) Discussion
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Introduction

- The outburst of COVID-19 has highlighted the importance of ensuring adequate indoor air quality to reduce the risk of infection contamination in confined spaces.

- Proper design and precise control of air parameters are essential for ensuring indoor air quality.

- Fast and accurate computations of indoor airflow are crucial for testing different design options or performing model predictive control (MPC).

Traditional indoor airflow models

- Multizone (airflow network) models - low computational cost but not applicable for complex flows.
- Zonal models - moderate computational cost and moderate accuracy, but high case dependence.
- Computational Fluid Dynamics (CFD) - high computational cost and high accuracy.

Data-driven models (DDMs)

- Find relations between system state variables without explicit knowledge of the physical behavior of the system using data analysis.

- A comprehensive set of the high-quality input-output dataset is needed to train these models for all possible working conditions.

- Difficulties in obtaining high-fidelity training data are compensated by the resulting model's high accuracy and low computational cost.

Objectives of the work

1) Develop machine learning based DDM, which uses the data from high-fidelity CFD simulations.

2) Investigate the capabilities and limitations of this model as a cheaper alternative to CFD, taking into account specific requirements for indoor environmental applications.

Governing equations

$$\nabla \cdot \boldsymbol{u} = 0$$

$$\frac{\partial \boldsymbol{u}}{\partial t} + (\boldsymbol{u} \cdot \nabla)\boldsymbol{u} = \nu \nabla^2 \boldsymbol{u} - \frac{1}{\rho}\nabla p + \beta \boldsymbol{g}(T - T_0)$$

$$\frac{\partial T}{\partial t} + (\boldsymbol{u} \cdot \nabla) T = \alpha \nabla^2 T,$$

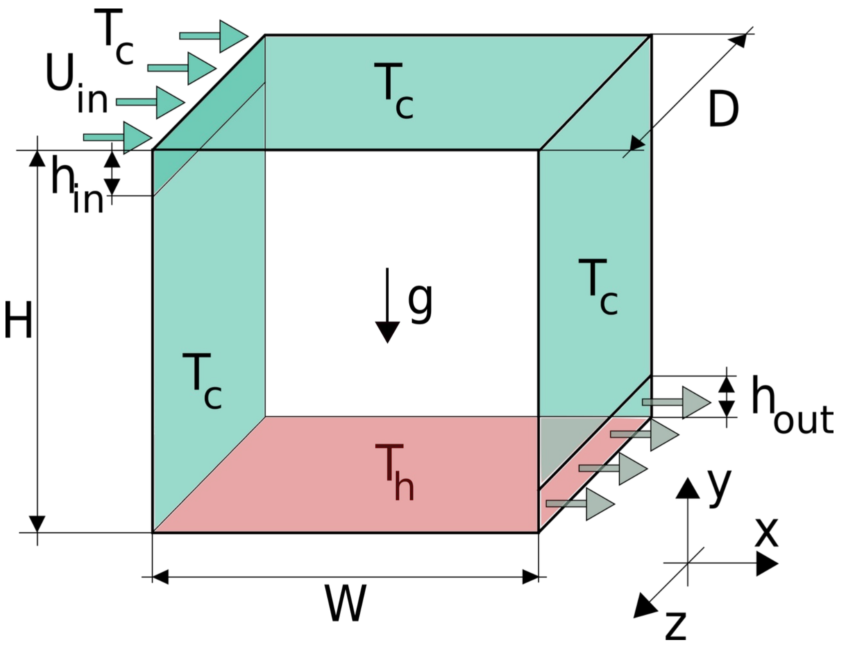
where $\boldsymbol{u}$ is the velocity vector, t the time, p the pressure, T the temperature, T_0 the reference temperature, ν the kinematic viscosity, ρ the density, $\boldsymbol{g}$ the gravitational acceleration, β the thermal expansion coefficient and α the thermal diffusivity.

Physical problem

$A_D = D / W = 0.3$
$A_{in} = h_{in} / H = 0.017$
$A_{out} = h_{out} / H = 0.023$
$Pr = 0.71$
$Ra_H = 2.4 \times 10^9$

$\mathbf{A_H} = H / W = [0.25, 0.5, 1, 2, 4]$

Fr = [1.10, 1.50, 2.00, ..., 5.00, 5.24, 5.50, ..., 10.00]



Model input data

$A_D = D / W = 0.3$
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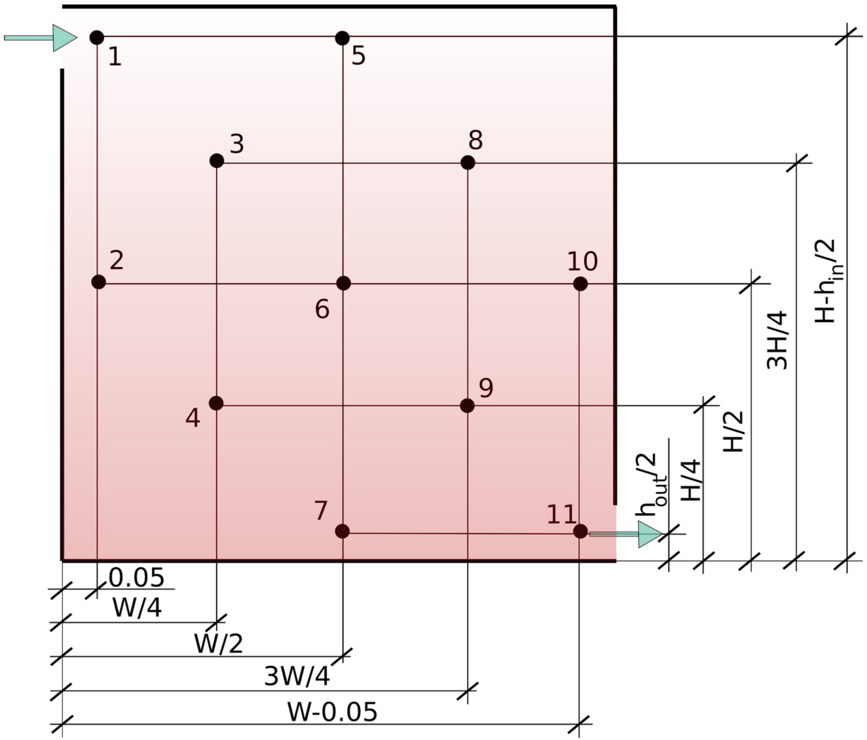


Model output data

Nusselt number on the hot wall - $$<Nu> = -\frac{1}{A}\int_A \frac{\partial T}{\partial y} dA \quad \text{at} \quad y = 0$$

Average cavity temperature - $$<T_V> = \frac{1}{V}\int_V T dV$$

Flow separation point - $$x_{sep} = x, \ \text{at} \ <\tau_W> = \int \frac{\partial u}{\partial y} dz = 0, y = H,$$

Average kinetic energy - $$<E> = \frac{1}{V}\int_V \frac{\mathbf{u}^2}{2} dV$$

Average enstrophy - $$<\Omega> = \frac{1}{V}\int_V \omega^2 dV,$$

Details of the CFD simulations

- **LES-S3PQ** turbulence model with second-order symmetry-preserving staggered discretization.
- All simulations run for 500 non-dimensional time units.

N_x	N_y	N_z	N_{tot}
100 x A_H	160	32	5.12×10^5 x A_H

- 100 CFD simulations.
- 15% - for testing and 85% - for training.

Accuracy metrics

Relative error

$$RE(\phi) = \frac{|\phi_d - \phi_p|}{|\phi_d|},$$

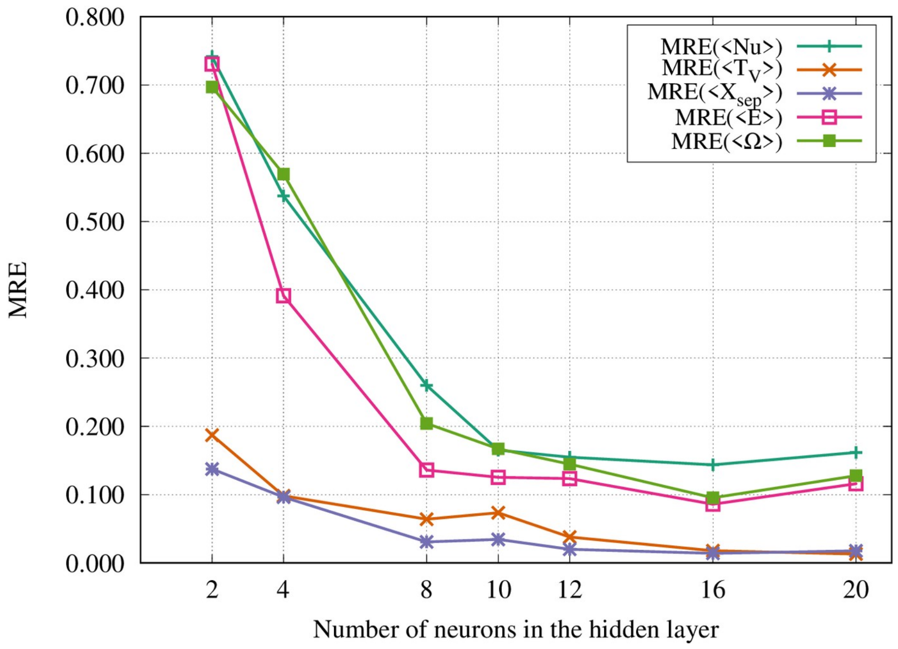
Mean relative error

$$MRE(\phi) = \frac{1}{N}\sum_{i=1}^{N} RE(\phi)$$

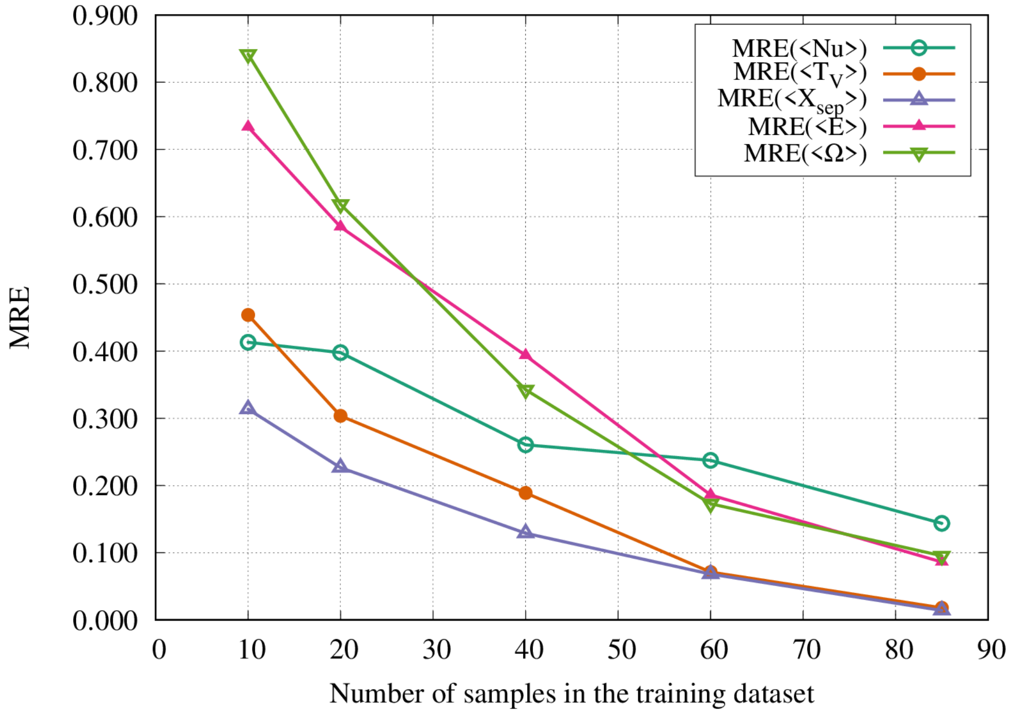
We assume that the less than 15% RE is acceptable for this model.

Artificial neural network

- Densely connected ANN with layer configuration of 20-16-5.
- Rectified linear activation function (ReLU).
- 10-fold cross validation.



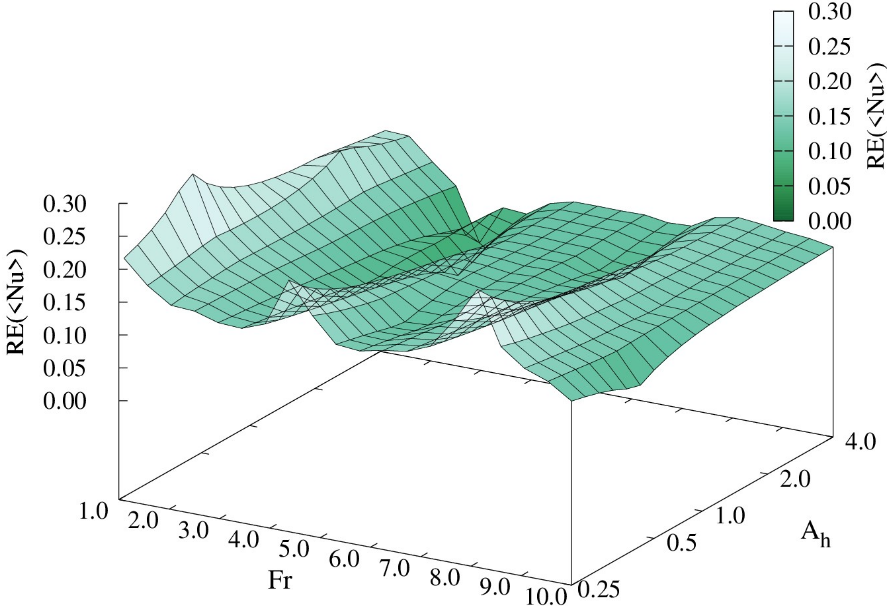
Model performance on varying number of samples in training dataset

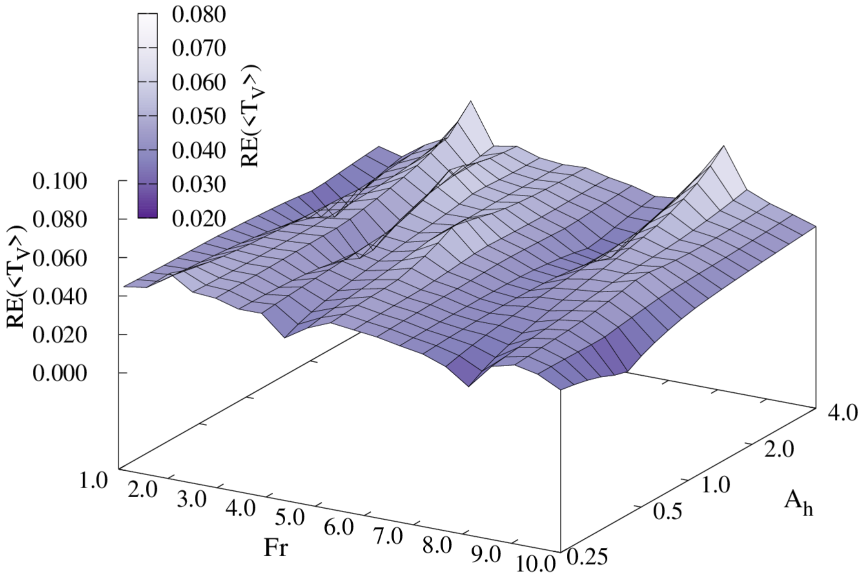


Model performance on different probe combinations

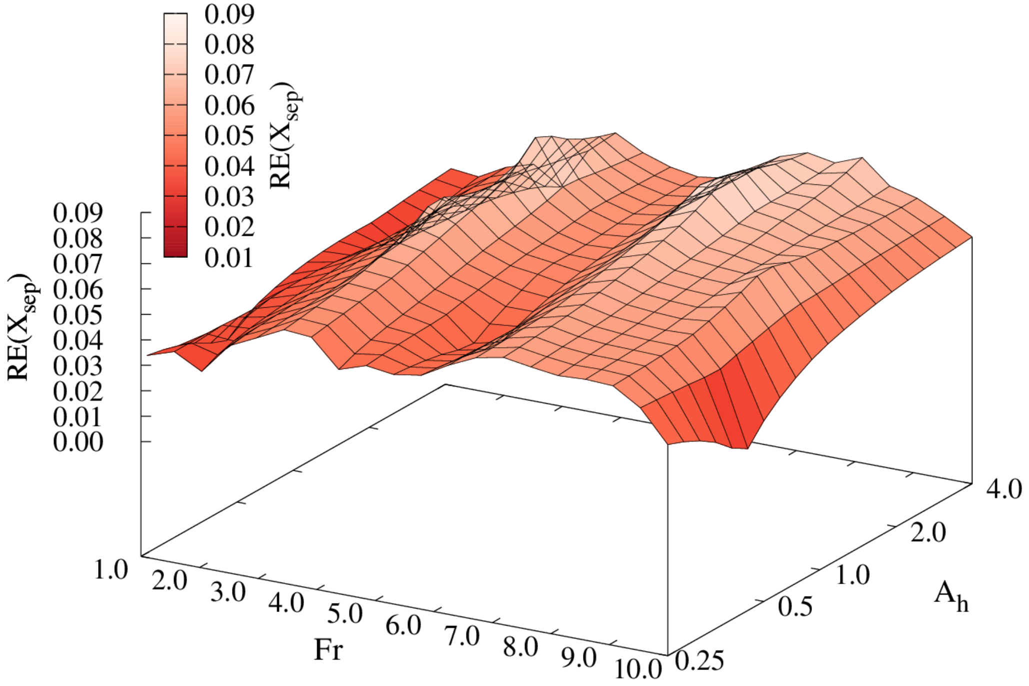
Probes removed	MRE $<Nu>$	$<T_V>$	x_{sep}	$<E>$	$<\Omega>$
none	0.144	0.018	0.014	0.086	0.095
3	0.146	0.023	0.067	0.082	0.102
3,4	0.154	0.051	0.068	0.093	0.118
3,4,6	0.197	0.076	0.084	0.145	0.144
3,4,6,7	0.343	0.165	0.115	0.195	0.228

RE of <Nu> and <T_V> for different combinations of Fr and A_H

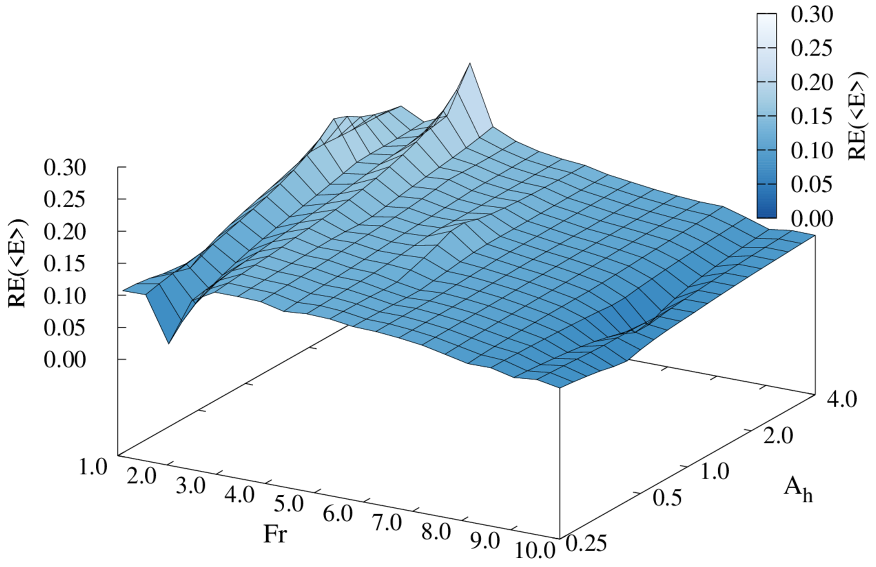


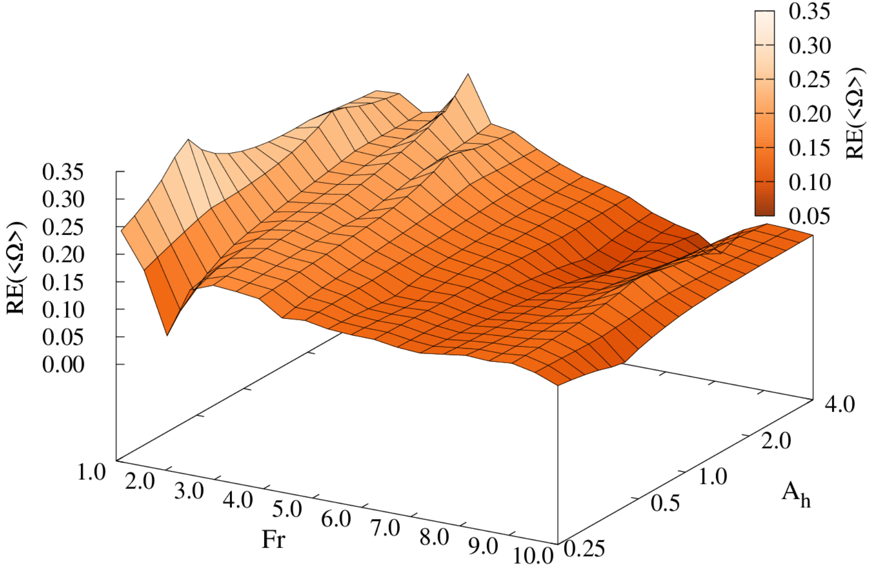


RE of <x_{sep}> for different combinations of Fr and A_H



RE of <E> and <Ω> for different combinations of Fr and A_H





Discussion. Dataset generation

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- It takes approximately 215 CPU hours per simulation.
- The total electricity cost of the dataset is 215€.
- The dataset should be increased, in order to develop a more reliable model.

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- These models work better with simple geometries.

- DDMs could be used for applications where a combination of fast and accurate predictions is required.

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Conclusions

1) We created an ML-based DDM for predicting the comfort-related flow parameters in a three-dimensional ventilated cavity with a heated floor.
2) The developed DDM provides rapid and accurate predictions using an ordinary office computer.
3) The accuracy for some of the most complex flow configurations was insufficient.
4) More high-fidelity data is required to construct a robust and reliable model.

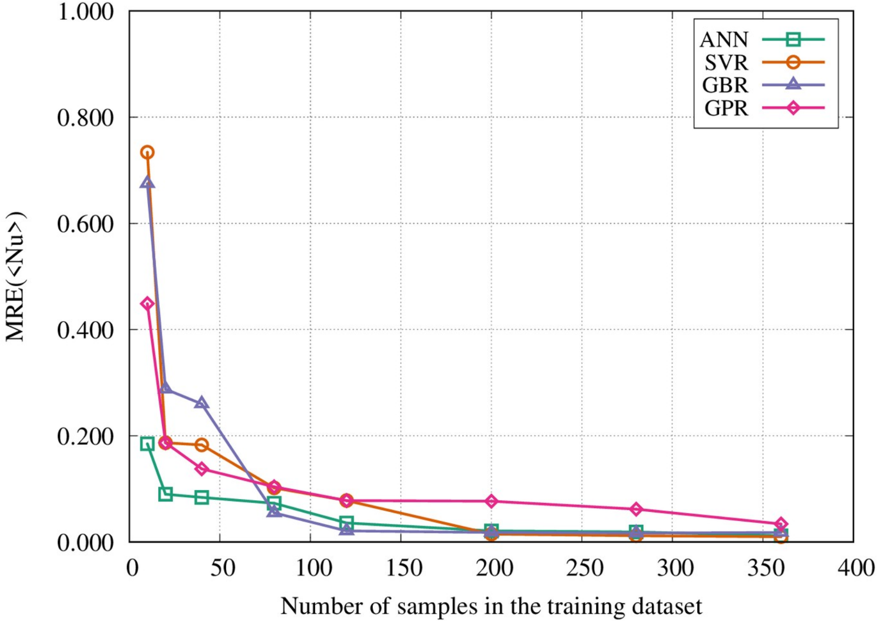
Recent advances

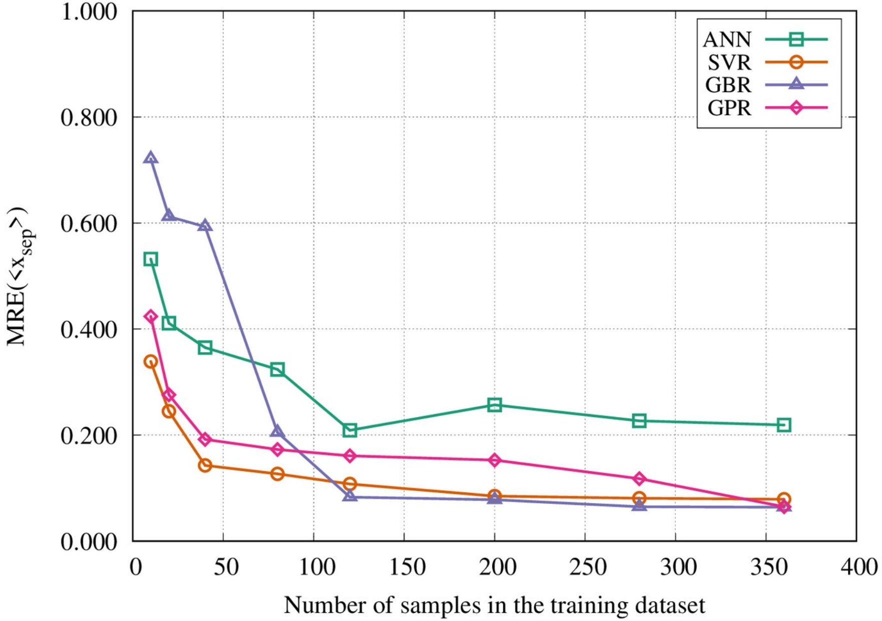
A_h	Ra			
	1.5×10^8	6×10^8	2.4×10^9	9.6×10^9
0.25	FG	FG	FG	CG
0.50	FG	FG	FG	CG
1.00	FG	FG	FG	CG
2.00	FG	FG	FG	-
4.00	CG	CG	CG	-
$Fr = [1.00, ..., 10.00]$				
Total number of coarse-grid (CG) simulations				120
Total number of fine-grid (FG) simulations				240

Recent advances

Model	MRE					
	$< Nu >$	$< E >$	$< \Omega >$	$< T_V >$	x_{sep}	Mean
ANN	0.012	0.022	0.184	0.164	0.219	0.120
SVR	0.010	0.004	0.032	0.034	0.079	0.032
GBR	0.018	0.025	0.028	0.017	0.064	0.030
GPR	0.034	0.032	0.095	0.016	0.065	0.048

Recent advances





Future work

- Adapt the model to the necessities of MPC.

- Investigate the possibilities of constructing multi-fidelity models by combing fine and coarse grid CFD.

- Study the extrapolating capabilities of DDMs.

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