

Investigating the capabilities of CFD-based data-driven models for indoor environmental design and control

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Outline

- 1 Introduction
- 2 High-fidelity CFD simulations
- 3 Data-driven models
- 4 Conclusions
- 5 Future work

Introduction

Simulations of indoor environment. State of the art

- HVAC systems account for approximately 40% of the energy consumption in buildings.
- The air distribution in buildings is usually evaluated either by simplified reduced-order models or by CFD.
- Simplified models provide very rapid predictions but offer limited information due to assumptions required.
- CFD simulations are computationally too expensive.

Introduction

Requirements for indoor environmental simulations

Main challenges

- The indoor airflow is usually multi-scale and turbulent.
- Several long-lasting simulations are required for each project.
- Computational resources are very limited.

Computational requirements

- Be faster than real-time ($R = t_{sim}/t_{phy} < 1$).
- Provide sufficient accuracy (relative error - RE).
- Be computationally affordable (fit into an office computer).

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Introduction

Objectives of the study

- 1 Study the feasibility of affordable high-fidelity CFD for indoor environmental applications.¹
- 2 Estimate the computational cost of CFD on office computers for these applications in the future.
- 3 Explore the cheaper alternatives to CFD for indoor environmental applications.

¹N. Morozova, F. X. Trias, R. Capdevila, C. D. Pérez-Segarra and A. Oliva. On the feasibility of affordable high-fidelity CFD simulations for indoor environment design and control. *Building and Environment* (2020) **184**:107144.

Governing equations

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

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

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

where \mathbf{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, \mathbf{g} the gravitational acceleration, β the thermal expansion coefficient and α the thermal diffusivity.

Physical problem

Three-dimensional mixed convection in a ventilated cavity²

$$A_H = H/W = 1$$

$$A_D = D/W = 0.3$$

$$A_{in} = h_{in}/H = 0.017$$

$$A_{out} = h_{out}/H = 0.023$$

$$Pr = 0.71$$

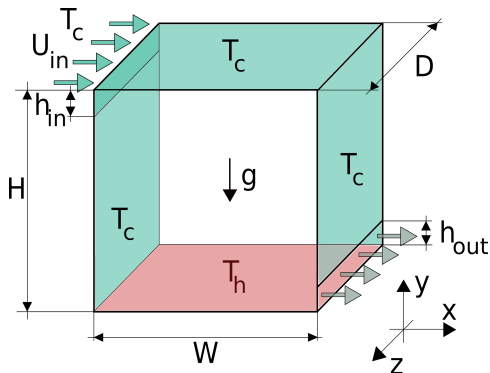
$$Ra_H = 2.4 \times 10^9$$

$$Fr_h = 5.24$$

$$t_{ref} = u_{ref}/H$$

$$u_{ref} = u_{in}$$

$$T_{ref} = \Delta T = T_h - T_c$$



²D. Blay, S. Mergui, J.L. Tuhaut and F.Penot. Experimental turbulent mixed convection created by confined buoyant wall jets. *First Eur Heat Transf Conf*, UK, Sept 1992, 821-828.

Numerical simulation details

Case	N_x	$N_{outlet} + N_{bulk} + N_{inlet} = N_y$	N_z	N_{total}
M0 (DNS)	512	$57 + 398 + 57 = 512$	128	3.36×10^7
M1	10	$2 + 10 + 3 = 15$	4	6.00×10^2
M2	15	$2 + 20 + 3 = 25$	4	1.50×10^3
...
M11	120	$20 + 120 + 20 = 160$	30	5.76×10^5
M12	160	$20 + 140 + 20 = 180$	40	1.15×10^6

All simulations run for 500 and 10 non-dimensional time units, respectively for steady and transient cases.

Turbulence models and discretization approaches

Software	Model	Discretization
OpenFOAM	URANS $k - \epsilon$	collocated
	URANS SST $k - \omega$	collocated
Termofluids	LES WALE	collocated
	no-model	collocated
STG	LES S3PQ	staggered
	no-model	staggered

Results

Requirements for indoor environmental simulations

Computational requirements

- 1 Be faster than real-time:
 - $R \leq 0.5$ (twice faster than real-time) - for design;
 - $R \lesssim 0.15$ (six times faster than real-time) - for control.
- 2 Provide sufficient accuracy:
 - $RE \leq 5\%$ - for detailed design;
 - $RE \leq 15\%$ - for conceptual design and control.
- 3 Be computationally affordable - fit into an office computer (Intel Core i9-9900K processor with 41.6Gb/s memory bandwidth).

Results

Flow parameters analyzed

Nusselt number at the hot wall

$$Nu = -\frac{1}{A} \int_A \frac{\partial T}{\partial y} dA \quad \text{at } y = 0$$

Mean kinetic energy

$$E = \frac{1}{V} \int_V \frac{u^2}{2} dV$$

Mean enstrophy

$$\Omega = \frac{1}{V} \int_V \omega^2 dV$$

Mean temperature

$$T_V = \frac{1}{V} \int_V T dV,$$

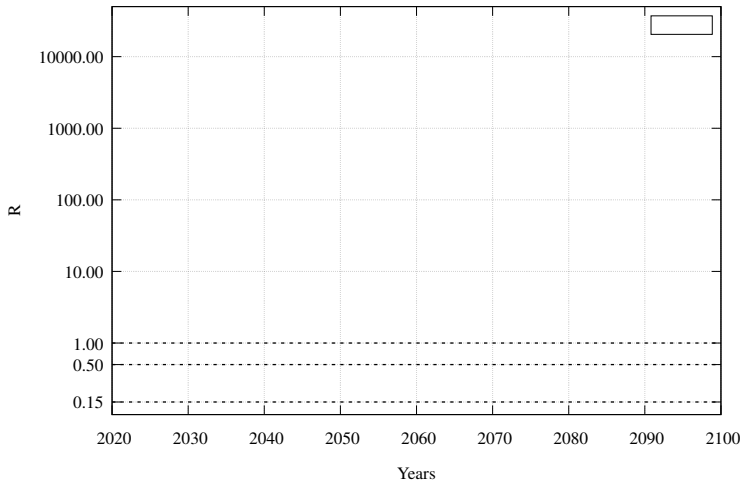
Results

Summary of the results

Case	Model					
	LES WALE C	LES S3PQ S	URANS $k-\epsilon$ C	URANS SST $k-\omega$ C	No-model C	No-model S
< 15% error steady (Conceptual design)	Dark Blue	Light Blue	Dark Blue	Dark Blue	Medium Blue	Light Blue
< 5% error steady (Detailed design)	Dark Blue	Dark Blue	Dark Blue	Dark Blue	Dark Blue	Dark Blue
< 15% error transient (control)	Dark Blue	Dark Blue	White with Red X	White with Red X	Dark Blue	Dark Blue
Notation	Light Blue	Light Blue	Medium Blue	Dark Blue	Dark Blue	White with Red X
	$R \leq 1$	$1 < R \leq 10$	$10 < R \leq 100$	$100 < R \leq 1000$	$R > 1000$	Low accuracy

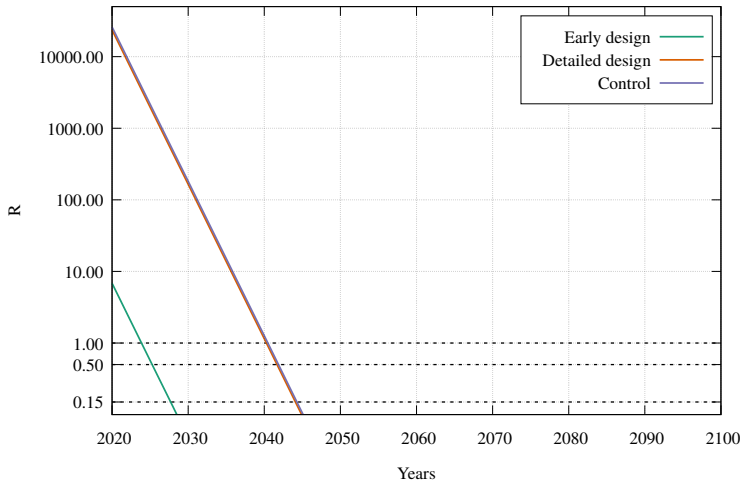
Discussion

Potential of accessing affordable high-fidelity CFD over the next years



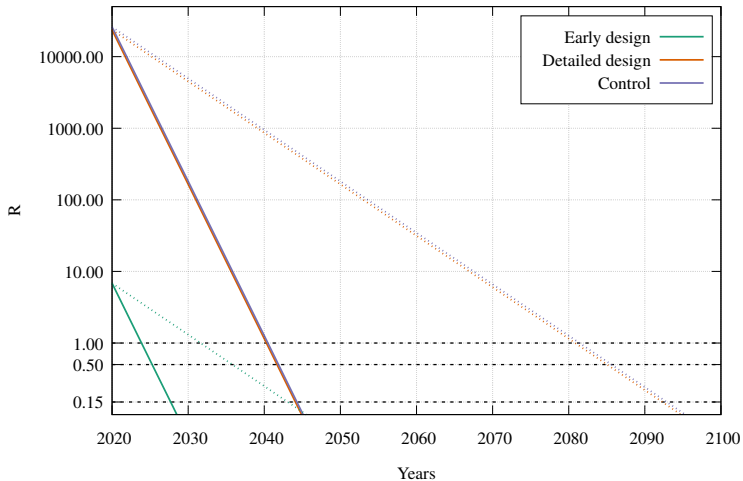
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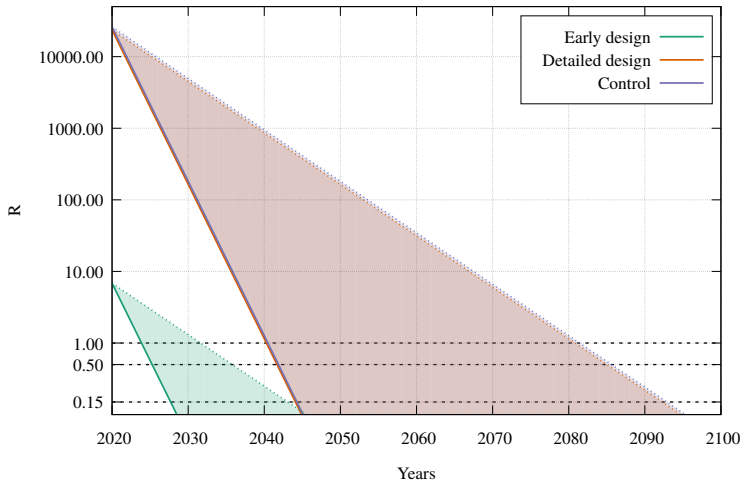
Discussion

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Discussion

Potential of accessing affordable high-fidelity CFD over the next years



Discussion

Conclusions

- Fast high-fidelity CFD simulations on office computers are not feasible neither for design nor for control of indoor environments. Obtained run-times are too long to make CFD a primary tool for HVAC applications.
- The growth of computational resources would not be enough to make CFD available for routine use in building applications in the near future.
- Cheaper alternatives to CFD are needed.

Data-driven models

Introduction

- Data-driven models (DDM) are based on using data analysis to find relations between system state variables (input, internal and output) without explicit knowledge of the physical behavior of the system.

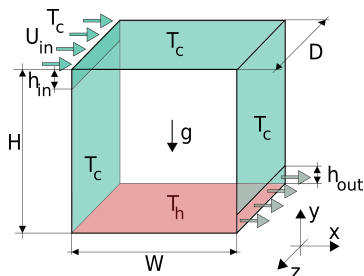
Data-driven models

Objectives of the study

- 1 Develop machine learning (ML) algorithms based on data from CFD simulations, which predict airflow parameters.
- 2 Investigate the capabilities and limitations of these algorithms as a cheaper alternative to CFD, taking into account specific requirements for indoor environmental applications.
- 3 Study how the quality of input data affects the quality of prediction.

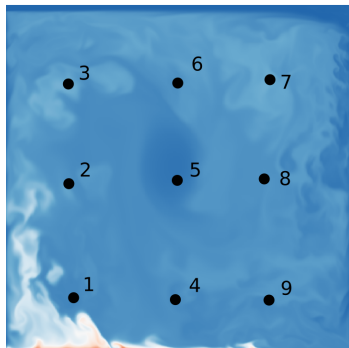
Test case description

- $A_H = H/W = \{0.25, 0.5, 1, 2\}$
- $Ra_H = 2.4 \times 10^9$
- $Fr_h = [1.38, 9.65]$ - total 20 points
- LES-S3PQ turbulence model
- Second-order symmetry-preserving staggered discretization
- Mesh M11 with $N_{tot} = 5.76 \times 10^5$
- 500 time-units
- Total 80 CFD simulation
- 80% - train, 20% - test



- ≈ 215 CPU hours per simulation
- $\approx 2\text{€}$ per simulation

Data generation setup



Input parameters

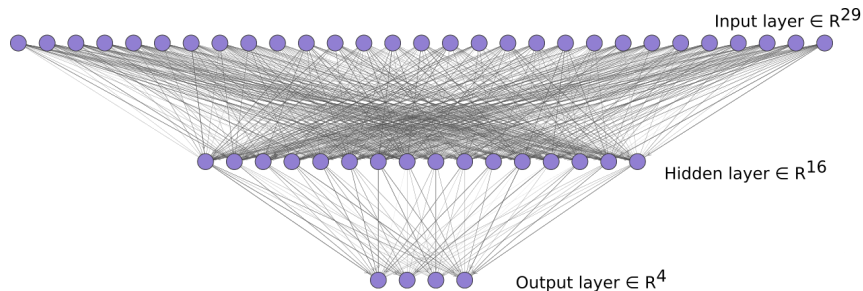
- 1 Fr_h
- 2 A_H
- 3 U_i, V_i, T_i

Output parameters

- 1 $\langle Nu \rangle$
- 2 $\langle T_V \rangle$
- 3 $\langle E \rangle$
- 4 $\langle \Omega \rangle$

Numerical methods

Artificial neural network (ANN)



- Densely connected ANN with layer configuration of 29-16-4;
- Rectified linear activation function (ReLU);
- 10-fold cross validation.

Numerical methods

Support vector regression (SVR)

- Regression is based on high dimensional hyper-plane;
- Radial basis function (RBF) kernel;
- Output parameters are trained in chain;
- 10-fold cross validation.

Gradient boosting regression (GBR)

- Based on decision trees and gradient descent algorithm;
- Output parameters are trained in chain;
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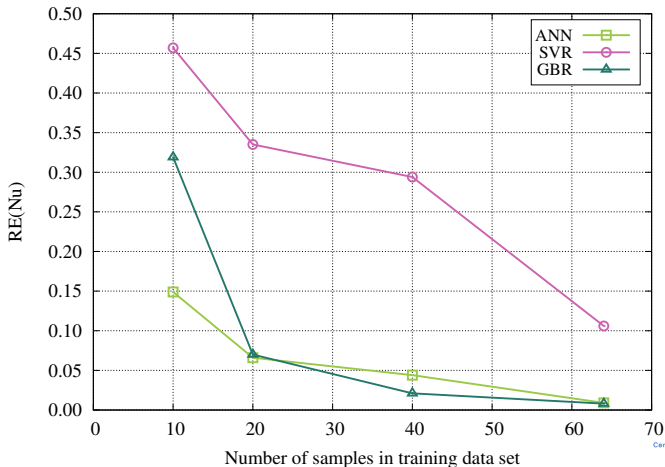
Results

Accuracy of different methods

Model	Relative error			
	$\langle Nu \rangle$	$\langle T_V \rangle$	$\langle E \rangle$	$\langle \Omega \rangle$
ANN	0.009	0.009	0.195	0.114
SVR	0.106	0.020	0.249	0.534
GBR	0.008	0.003	0.137	0.544

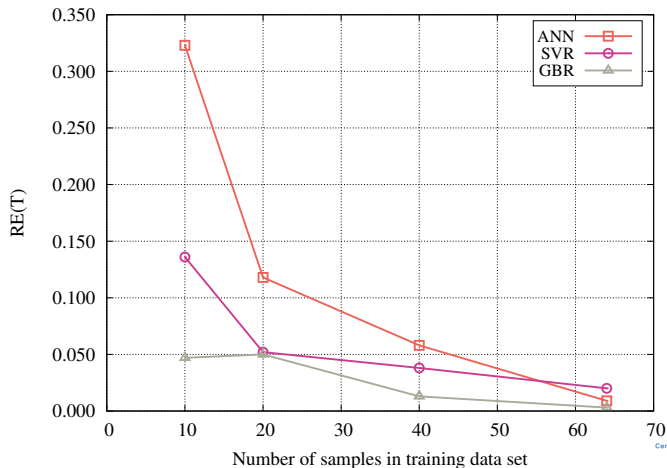
Results

Comparison of frameworks performance on varying number of samples in training dataset.
Results for $\langle Nu \rangle$



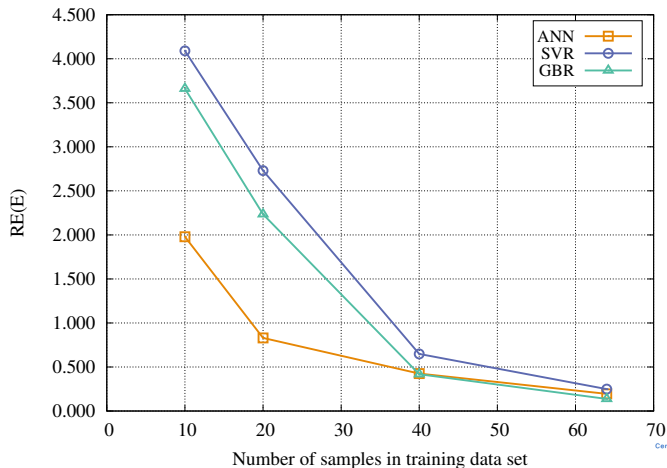
Results

Comparison of frameworks performance on varying number of samples in training dataset.
Results for $\langle T_V \rangle$



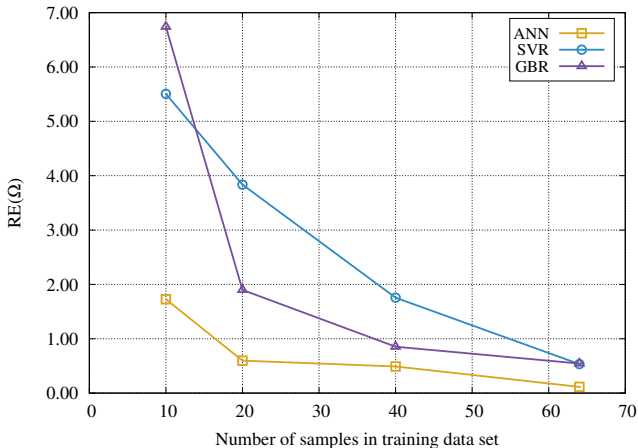
Results

Comparison of frameworks performance on varying number of samples in training dataset.
Results for $\langle E \rangle$



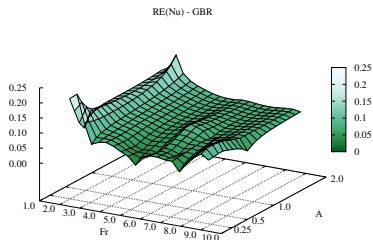
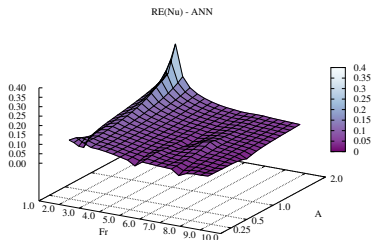
Results

Comparison of frameworks performance on varying number of samples in training dataset.
Results for $\langle \Omega \rangle$



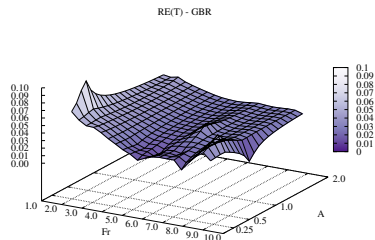
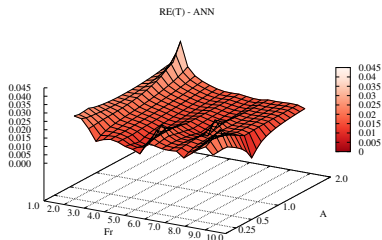
Results

Relative prediction error of $\langle Nu \rangle$ for different combinations of Fr_h and A_H



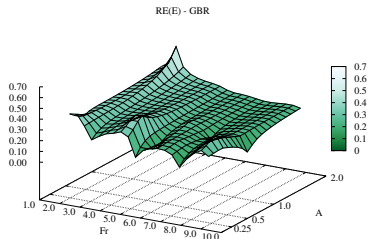
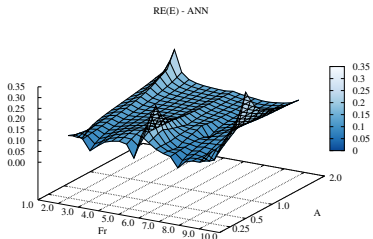
Results

Relative prediction error of $\langle T_V \rangle$ for different combinations of Fr_h and A_H



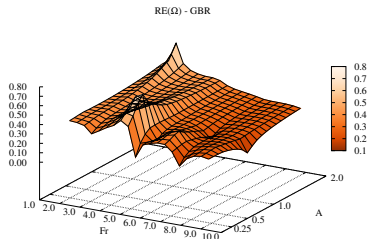
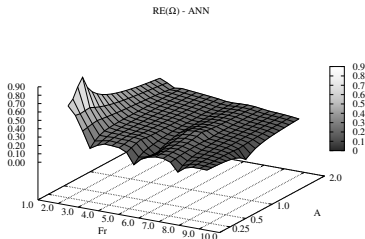
Results

Relative prediction error of $\langle E \rangle$ for different combinations of Fr_h and A_H



Results

Relative prediction error of $\langle \Omega \rangle$ for different combinations of Fr_h and A_H



Conclusions

- CFD simulations are too computationally expensive to be a primary tool for HVAC applications.
- Data driven models are capable of providing accurate results at a low computational cost.
- Data driven models is a promising tool for HVAC applications. However, more work is required on amplifying prediction range and tailoring them for HVAC specific requirements.

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Future work

- Amplify the available training data.
- Study how different input configurations affect the quality of the predictions.
- Find a trade-off between the quantity and the quality of the training data (turbulence models, discretization error, etc.).
- Explore the extrapolation capabilities of the DDMs.

THANK YOU FOR YOUR ATTENTION!

Ready for your questions!

