A CFD-based multi-fidelity surrogate model for prediction of flow parameters in a ventilated room

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Outline

Introduction

Simulations of indoor environment. State of the art

- Modern heating ventilation and air conditioning (HVAC) systems are required to maintain a trade-off between maximizing human thermal comfort and minimizing 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.

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Introduction

Objectives of the study

1. Explore the capabilities of the surrogate modeling as a cheaper alternative to CFD for indoor environmental applications.
2. Reduce the computational cost of the dataset generation by implementing multi-fidelity approach.

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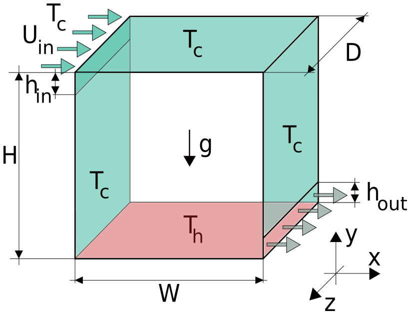
Physical problem

Three-dimensional mixed convection in a ventilated cavity

- 3D ventilated room filled with air, where the floor is heated, side walls are cold, front and rear walls are periodic. The inlet flow is cold.
- Experimental parameters:
  1. Cavity width aspect ratio A_W;
  2. Froude number $Fr = U_{in}/U_{buo}$;
  3. Rayleigh number $Ra_H = g\beta\Delta TH^3/(\nu\alpha)$.



Problem description

Configuration of the experiments

Experimental parameters

A_w	$0.25, 0.50, 1.00, 2.00, 4.00$
Ra_H	$1.5 \times 10^8, 6.0 \times 10^8, 2.4 \times 10^9, 9.6 \times 10^9$
Fr	$0.15, 0.20, 0.25, ..., 0.55, 0.60, 0.70, ..., 1.50, 1.60$

CFD simulations

Total number of low-fidelity (LF) simulations - 360
Total number of high-fidelity (HF) simulations - 240
Total number of simulations - 600

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Problem description

Input-output parameters

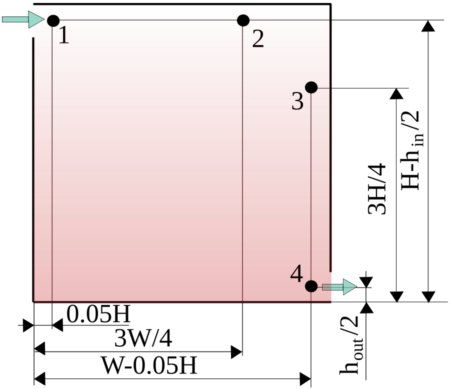
Input parameters

1. A_w
2. $T_1, ..., T_4$
3. $V_1, ..., V_4$

Output parameters

1. Nusselt number on the hot wall - $< Nu >$
2. Average enstrophy - $< \Omega >$

1



[1]N. Morozova, F. X. Trias, R. Capdevila, E. Schillaci and A. Oliva. *A CFD-based surrogate model for predicting flow parameters in a ventilated room using sensor readings*. Energy Build, **266**:112146, 2022.

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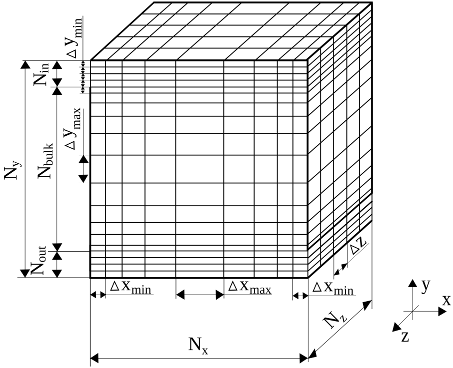
Numerical methods

CFD simulations

Automatic mesh generation

1. $\Delta x_{max} = \Delta y_{max} \approx C_r \eta_{Grö}$
2. $\Delta y_{min} \approx C_r \frac{h_{in}}{2} Re_\tau^{-1}$
3. $\Delta x_{min} = 4\Delta y_{min}$
4. $\gamma_x, N_x, \gamma_y, N_b ulk$ - are found iteratively using the hyperbolic tangent function
5. $N_z = 1.1D/\Delta y_{max}$



Grid resolutions

- $C_r = 3$ - high-fidelity simulations
- $C_r = 6$ - low-fidelity simulations

Numerical methods

Surrogate models - 1

- The work is based on the Gaussian process regression (GPR).
- All of the models use an open-source library scikit-learn.

Single-fidelity models

- **HF-GPR** - a model trained only high-fidelity (HF) data;
- **LF-GPR** - a model trained only on low-fidelity (LF) data.
- **HFLF-GPR** - a model trained on a mix of LF and HF data without distinguishing the data fidelity.

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Numerical methods

Surrogate models - 2

GPR with linear correction (LCGPR)

1. Train a single-fidelity model on LF data and test it on HF data - $M_l(\mathbf{X}_l, \mathbf{y}_l) = \tilde{\mathbf{y}}_h$.
2. Estimate an error $(\Delta \mathbf{y}_h)$ between the test results and the actual high-fidelity data and train a linear regression model $\Delta M(\mathbf{X}_h, \Delta \mathbf{y}_h)$ to predict this error.
3. Correct the predictions of low-fidelity surrogate model for the the step one - $M_l(\mathbf{X}_h)$ using the error correction model from the step two.

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Numerical methods

Surrogate models - 3

Multi-fidelity GPR (MFGPR) or co-kriging

It estimates for a poorly sampled variable $\mathbf{y}_l(\mathbf{x})$ with the help of a well-sampled variable $\mathbf{y}_h(\mathbf{x})$:

$$\mathbf{y}_l(\mathbf{x}) = f_l(\mathbf{x}) + \epsilon_l$$

$$\mathbf{y}_h(\mathbf{x}) = \rho y_l(\mathbf{x}) + y_d(\mathbf{x})$$

Numerical methods

Metrics

Mean relative prediction error (MRE)

$$MRE(\phi) = \frac{1}{N}\sum_{i=1}^{N} \frac{|\phi_{CFD} - \phi_{SM}|}{|\phi_{CFD}|}$$

We assume that less than **10% MRE** is acceptable for this model.

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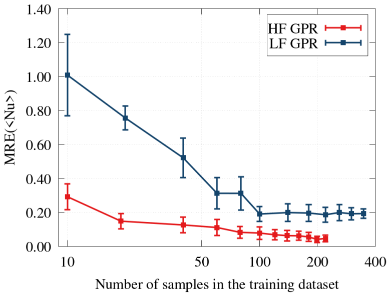
Results

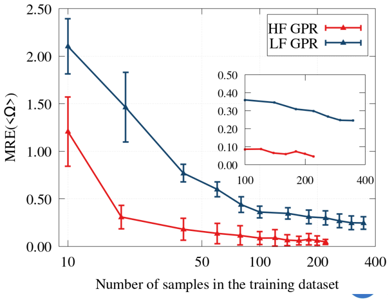
Single-fidelity models

Average computational cost

2700 core-hours - a high-fidelity simulation

285 core-hours - a low-fidelity simulation





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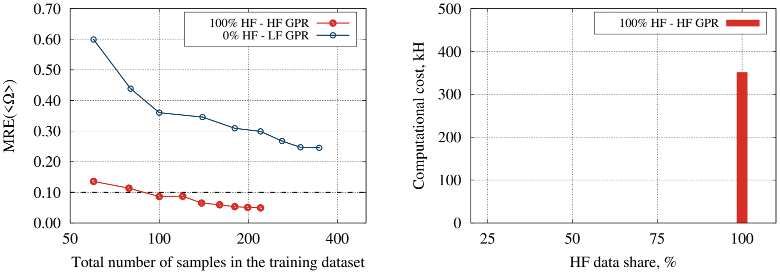
Results

HFLF GPR model



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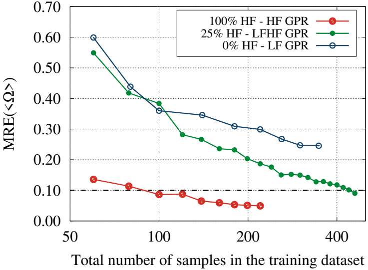

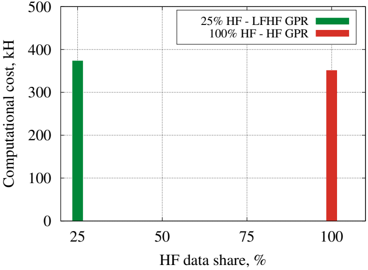

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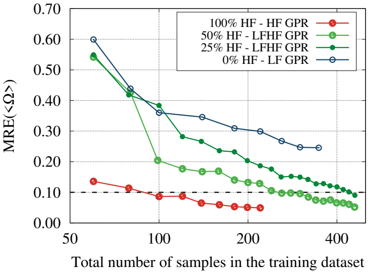

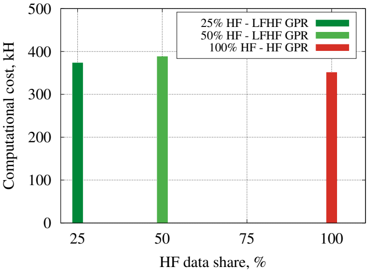

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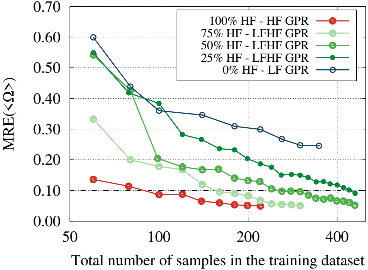
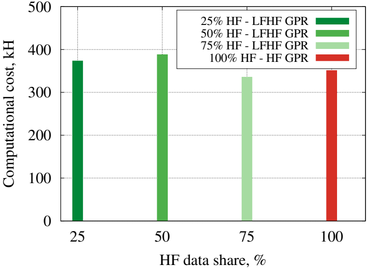
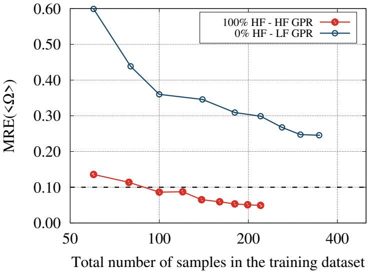
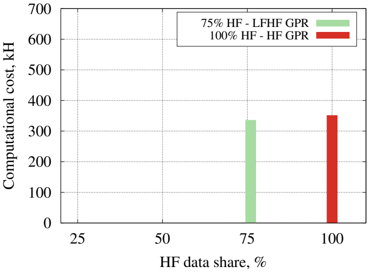




Results

LC GPR model





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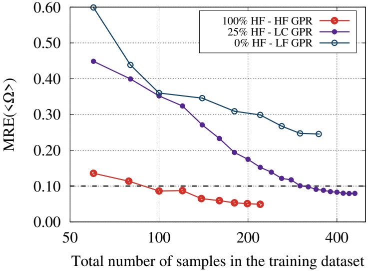

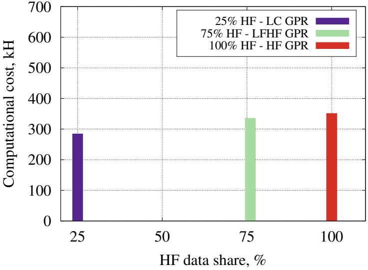

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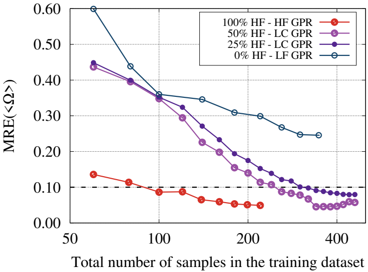

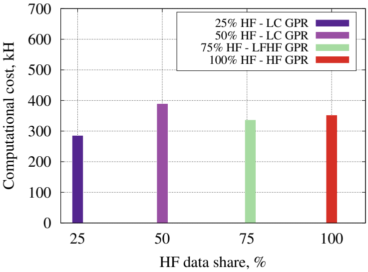

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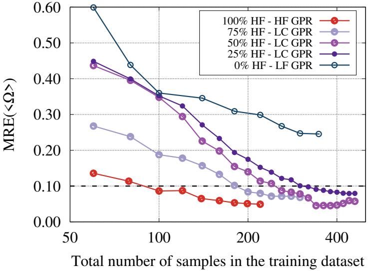

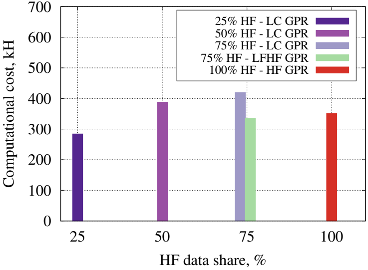

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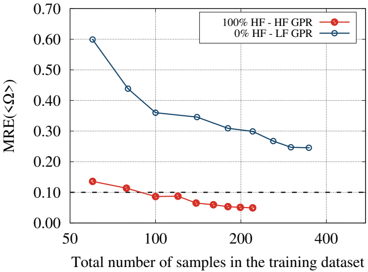
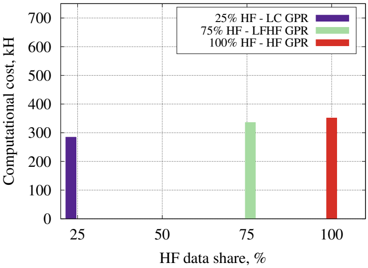
MF GPR model





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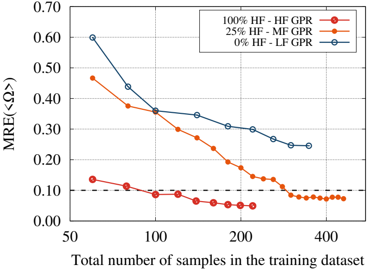

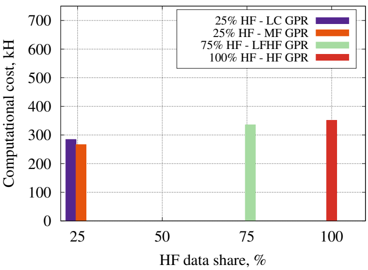

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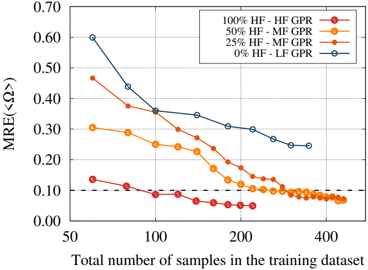

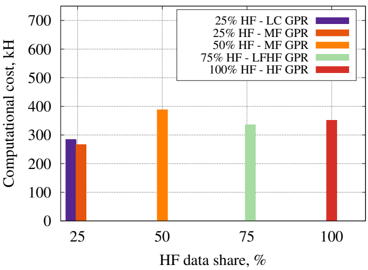

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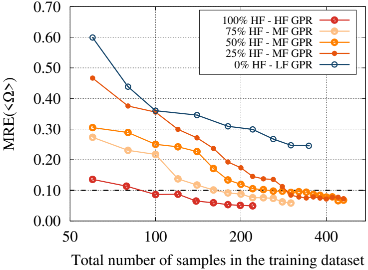

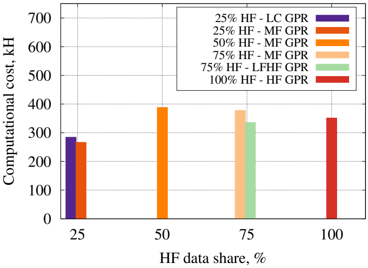

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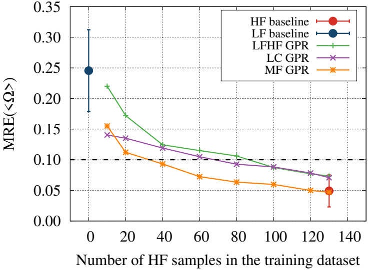
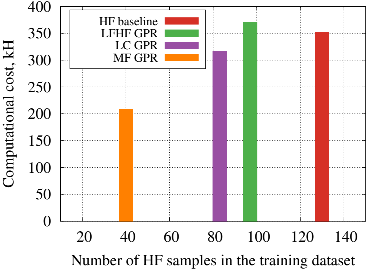
Results

MRE of the average enstrophy $<\Omega>$ for different number of HF training samples using different surrogate models





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Results

Summary of the obtained results

Model	Samples			Kh	MRE	
	HF	LF	total		$<Nu>$	$<\Omega>$
HF GPR	130	-	130	351	0.046 ± 0.02	0.046 ± 0.03
LF GPR	-	350	350	100	0.193 ± 0.03	0.246 ± 0.07
HFLF GPR	120	40	160	335	0.042 ± 0.06	0.093 ± 0.05
LC GPR	75	225	240	285	0.112 ± 0.06	0.100 ± 0.05
MF GPR	40	350	380	208	0.092 ± 0.04	0.093 ± 0.05

Conclusions

Conclusions - 1

- The developed surrogate model provides almost instant accurate predictions using an ordinary office computer.
- The input data of the developed model is structured to take the values of temperature and velocity in the locations, which could be replaced by sensor readings.
- The main computational burden of the surrogate model is the cost of its development because, at this step, a comprehensive set of HF data is required.
- We spent 650Kh on 240 HF CFD simulations and 100Kh on 350 LF simulations.

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- The use of multi-fidelity models reduced the computational cost considerably.
- Even a simple HFLF GPR model is less computationally expensive than the baseline HF GPR model.
- More sophisticated multi-fidelity models like LC GPR and MF GRP required at least 1.5 times less computational resources than the HF GPR model.
- The MF GRP has shown the best trade-off between computational cost and accuracy among studied multi-fidelity models.

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Future work

- Study the generalization properties of the developed methodology.
- Adapt the existing methodology to a direct prediction of comfort parameters, such as predicted mean vote.
- A more broad study on a proper choice of data fidelity is required.
- The model could be further analyzed in terms of extrapolation capabilities.

THANK YOU FOR YOUR ATTENTION!

Ready for your questions!

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