Machine learning for predicting wind loads on high-rise buildings

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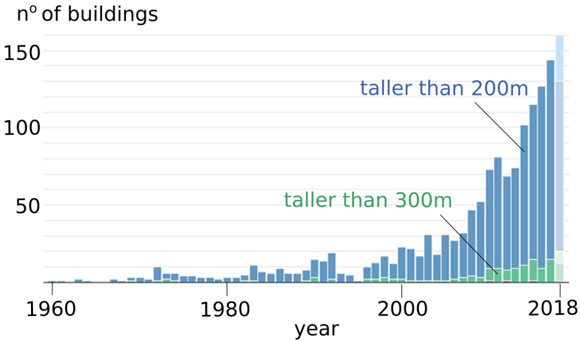
2.5 billion people expected to populate big cities by 2050 [1]



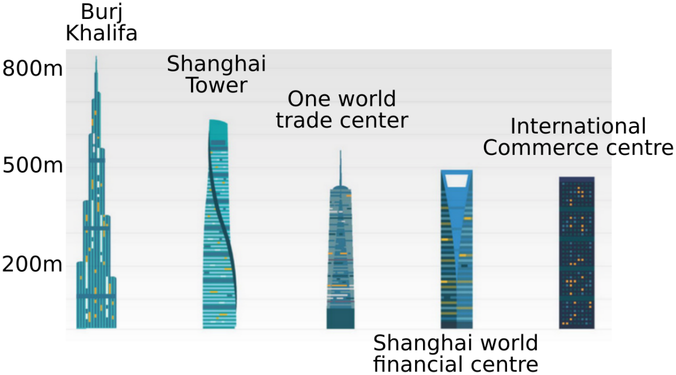
https://www.visualcapitalist.com/rush-build-new-skyscrapers/

402% increase in skyscrapers construction since 2000

39 skyscrapers taller than 300m constructed in the last two years

[1] [Population Division of the UN Department of Economic and Social Affairs (UN DESA), 2018 Revision of World Urbanization Prospects]

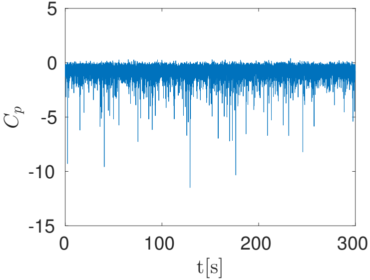
Tall buildings are becoming taller, slender and complex in shape



Glazed panels are often employed to cover the buildings' external facades

The glazed panels covering high-rise buildings' external facades can experience **extreme suction** events, which can be catastrophic for the panels

Photo courtesy of the U.S. Navy/Interior Communications Electrician 1st Class Jason Stephens



Objective:

- Enable the computation of the design pressure of the glazed panels, throughout the different phases of design

Available methods:

- Wind tunnel experiments
- Computational Fluid-Dynamics (CFD)

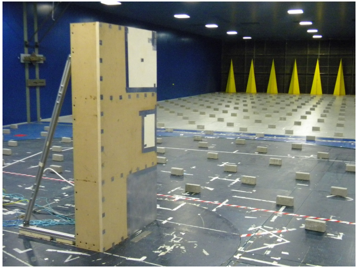
Wind tunnel experiments

Pressure time-series are recorded in several points on the building's surface by means of a synchronous multi-pressure sensing system (SMPSS)

Pros: most reliable method

Cons:

- Need of ABL facility
- Limited measurement locations and resolution



CFD

CFD simulations discretize and solve the Navier-Stokes equations, enabling the computation of the pressure acting on the building

Pros:

- Provide complete 3-dimensional flow field in complex geometries
- Unlimited number of pressure taps

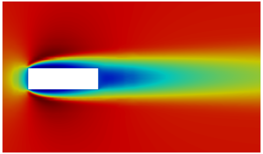
Cons:

- Trade-off between accuracy and cost

Reynolds-averaged Navier-Stokes (RANS)

Pros: low computational cost

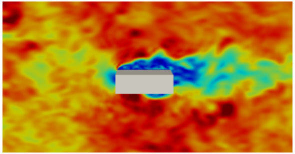
Cons:
- Low fidelity
- Need of model to retrieve time-dependency



Large-Eddy Simulations (LES)

Pros:
- High fidelity
- Provide direct estimation of pressure peaks

Cons: high computational cost



Machine learning

- Find the best functional form that relates high-fidelity wind tunnel (or LES) data of design pressure coefficient[1] of the glazed panels, to low-fidelity RANS variables

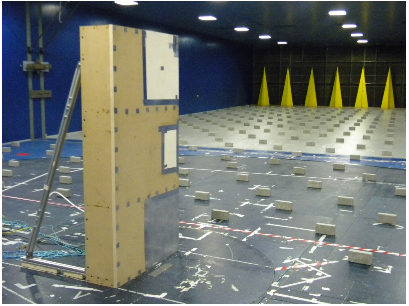
$$\underbrace{C_{p,design}}_{EXP/LES} = f(\underbrace{P, U, k, \epsilon, \nu_t, \nabla P, \nabla U, ...}_{RANS})$$

- Try to combine the accuracy of wind tunnel data to the low computational cost and high number of measurements of RANS simulations.

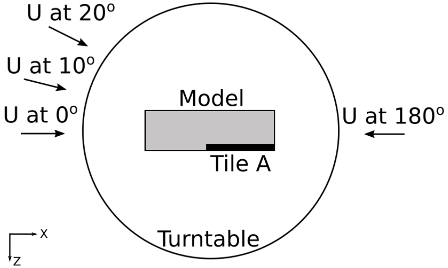
[1] Cook, N. J., and J. R. Mayne. "A refined working approach to the assessment of wind loads for equivalent static design." Journal of Wind Engineering and Industrial Aerodynamics 6.1-2 (1980): 125-137.

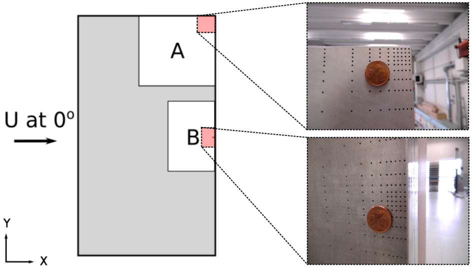
Test case

- High-rise building model $2 \times 1 \times 0.3$m (100m tall building in full scale)
- Closed-section wind tunnel of Politecnico di Milano (PoliMi)



Extensive pressure measurements at critical locations, i.e. corner and edges:





- 224 pressure taps on tiles A and B, minimum taps spacing of 3.4mm
- $0^\circ, 10^\circ, 20^\circ, 30^\circ, 45^\circ$ (and symmetric) wind directions

Dataset

Labels:

- Divide wind tunnel data on Tiles A-B into $2.5 \times 2.5\text{m}^2$ panels
- Classify each resulting panel as follows:
  - **Class 0**: $0 \geq C_{p,design} < 1$
  - **Class 1**: $1 \geq C_{p,design} < 2$
  - **Class 2**: $2 \geq C_{p,design} < 3$
  - **Class 3** $C_{p,design} \geq 3$

Features:

- Perform RANS simulations at same wind directions as the wind tunnel experiment
- Construct 8 adimensional and galilean invariant features from RANS variables
- Extract 8×2 images from RANS simulations (each panel has 8×2 cells in the CFD simulation)

Model

4-layers convolutional neural network (**CNN**)

- *Input*: $8 \times 2 \times 8$ images ($panel\_heigth \times panel\_width \times number\_of\_features$)
- *Output*: class label (0-3 depending on the design pressure coefficient of the panel)

Data split:

- Test the ability of the model in extrapolating to different regions of the building
- **Train** the model on tile A, 619 panels in total (considering all the wind directions)
- **Test** the model on tile B, 338 panels in total (considering all the wind directions)

Results

The model achieves an overall accuracy of 85% in classifying the panels in unseen regions of the building (see Table).

Split	Accuracy
Tile A (train)	0.87
Tile B (test)	0.85

Results: 0°

Classification of glazed panels at 0° wind direction:

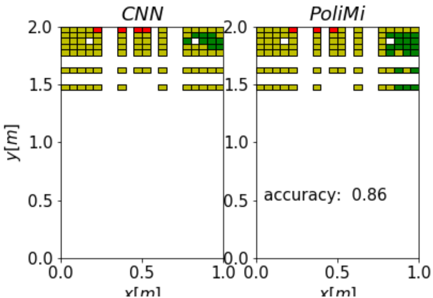


Figure: Tile A (train)

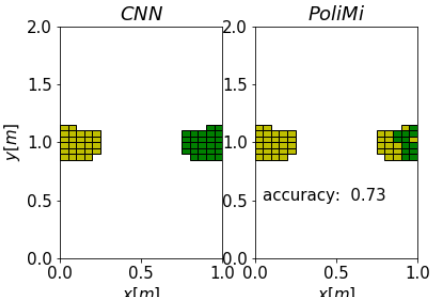


Figure: Tile B (test)

Class 0: $0 \geq C_{p,design} < 1$; **Class 1**: $1 \geq C_{p,design} < 2$; **Class 2**: $2 \geq C_{p,design} < 3$; **Class 3** $C_{p,design} \geq 3$

Results: 10°, left face

Classification of glazed panels at 10° wind direction:

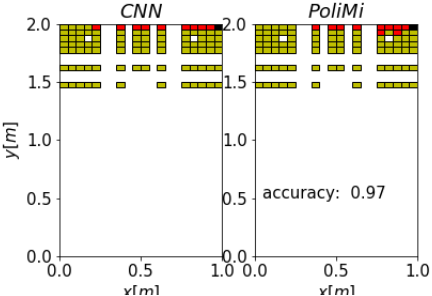


Figure: Tile A (train)

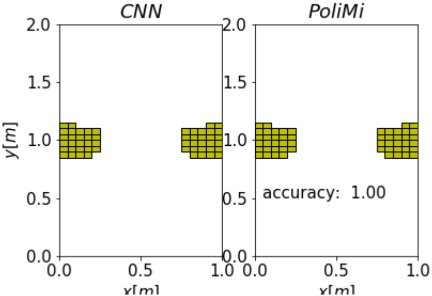


Figure: Tile B (test)

Class 0: $0 \geq C_{p,design} < 1$; **Class 1**: $1 \geq C_{p,design} < 2$; **Class 2**: $2 \geq C_{p,design} < 3$; **Class 3** $C_{p,design} \geq 3$

Results: 10°, right face

Classification of glazed panels at 10° wind direction (opposite facade):

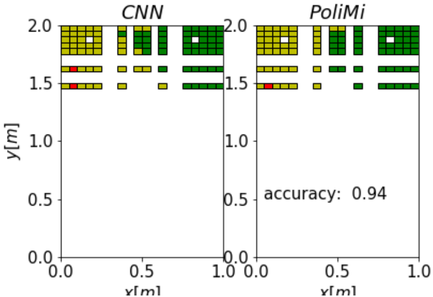


Figure: Tile A (train)

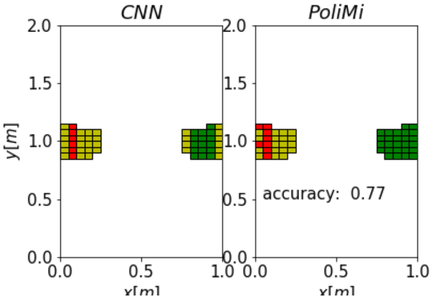


Figure: Tile B (test)

Class 0: $0 \geq C_{p,design} < 1$; **Class 1**: $1 \geq C_{p,design} < 2$; **Class 2**: $2 \geq C_{p,design} < 3$;
Class 3 $C_{p,design} \geq 3$

Results: 20°, left face

Classification of glazed panels at 20° wind direction:

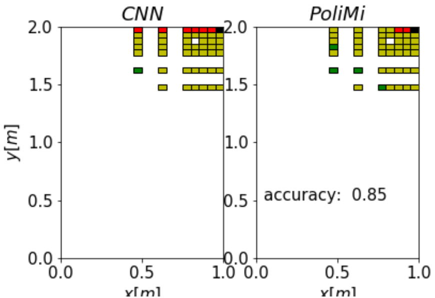


Figure: Tile A (train)

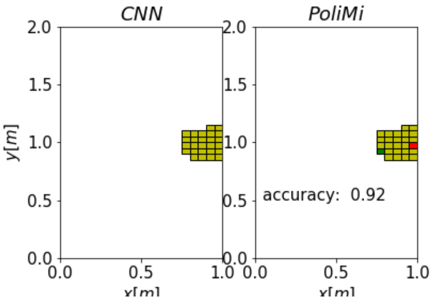


Figure: Tile B (test)

Class 0: $0 \geq C_{p,design} < 1$; **Class 1**: $1 \geq C_{p,design} < 2$; **Class 2**: $2 \geq C_{p,design} < 3$; **Class 3** $C_{p,design} \geq 3$

Results: 20°, right face

Classification of glazed panels at 20° wind direction (opposite facade):

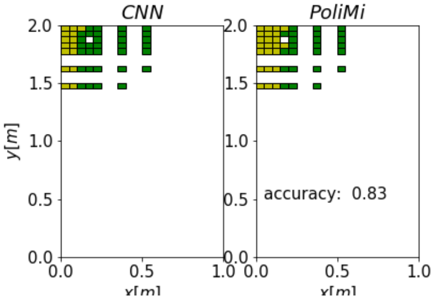


Figure: Tile A (train)

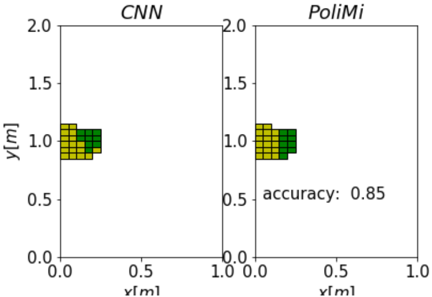


Figure: Tile B (test)

Class 0: $0 \geq C_{p,design} < 1$; **Class 1**: $1 \geq C_{p,design} < 2$; **Class 2**: $2 \geq C_{p,design} < 3$; **Class 3** $C_{p,design} \geq 3$

Results: 30°, left face

Classification of glazed panels at 30° wind direction:

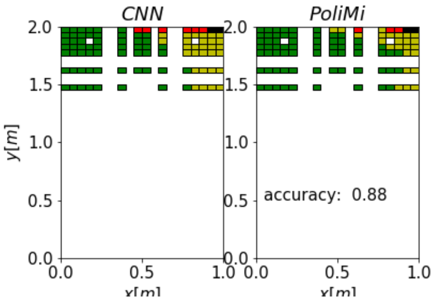


Figure: Tile A (train)

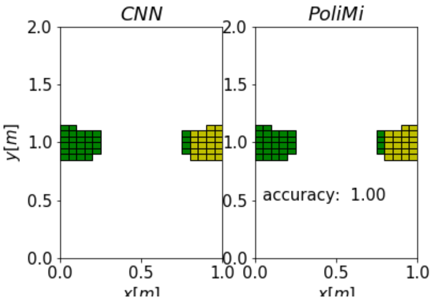


Figure: Tile B (test)

Class 0: $0 \geq C_{p,design} < 1$; **Class 1**: $1 \geq C_{p,design} < 2$; **Class 2**: $2 \geq C_{p,design} < 3$;
Class 3 $C_{p,design} \geq 3$

Results: 30°, right face

Classification of glazed panels at 30° wind direction (opposite facade):

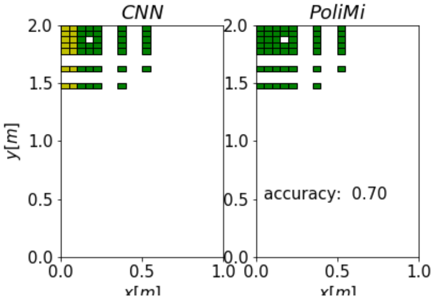


Figure: Tile A (train)

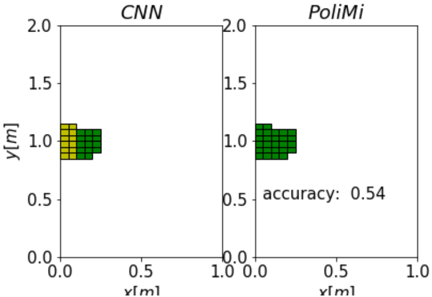


Figure: Tile B (test)

Class 0: $0 \geq C_{p,design} < 1$; **Class 1**: $1 \geq C_{p,design} < 2$; **Class 2**: $2 \geq C_{p,design} < 3$; **Class 3** $C_{p,design} \geq 3$

Results: 45°, left face

Classification of glazed panels at 45° wind direction:

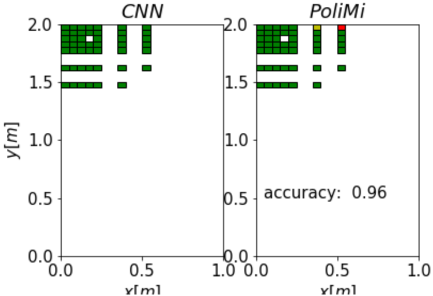


Figure: Tile A (train)

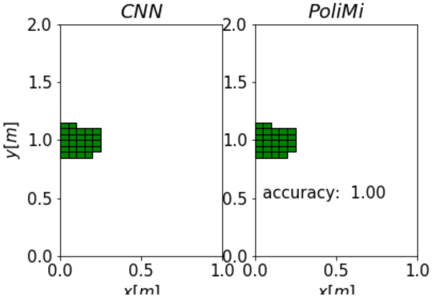


Figure: Tile B (test)

Class 0: $0 \geq C_{p,design} < 1$; **Class 1**: $1 \geq C_{p,design} < 2$; **Class 2**: $2 \geq C_{p,design} < 3$; **Class 3** $C_{p,design} \geq 3$

Results: 45°, right face

Classification of glazed panels at 45° wind direction (opposite facade):

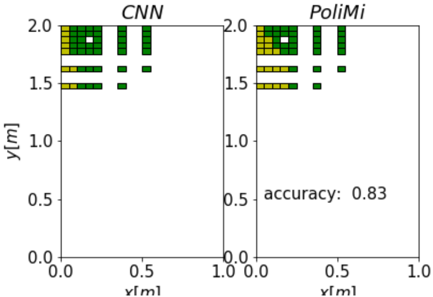


Figure: Tile A (train)

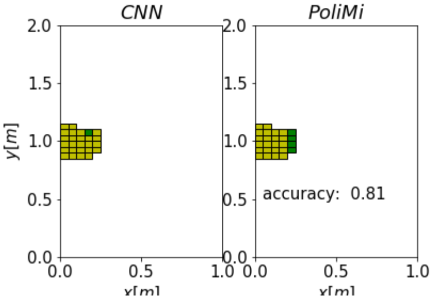


Figure: Tile B (test)

Class 0: $0 \geq C_{p,design} < 1$; **Class 1**: $1 \geq C_{p,design} < 2$; **Class 2**: $2 \geq C_{p,design} < 3$; **Class 3** $C_{p,design} \geq 3$

Conclusions

- Overall the model achieves 85% accuracy when extrapolating to unseen regions of the building
- Considering accuracy by classes, the worst performance is achieved for Class 2 (67% on the test set) due to the small number of corresponding data points in the dataset (only 9 panels of tile B have a true label of 2, and none of the panels of tile B have a true label of 3)