

**WIND LOADS ON NON-RECTANGULAR FLAT-ROOF BUILDINGS:
DESIGN PROVISIONS AND APPLICATION OF MACHINE LEARNING**

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ABSTRACT

WIND LOADS ON NON-RECTANGULAR FLAT-ROOF BUILDINGS:

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Buildings with rectangular plans were, in the past 50 years, the main focus in the wind engineering field. Consequently, the wind design provisions of rectangular buildings are well established in the wind codes and standards. On the other hand, wind design provisions for non-rectangular buildings are generally not available in wind codes and standards. This study investigates wind pressures on roofs and walls of non-curved and non-rectangular buildings with four shapes L, U, T, and X with different plan dimensions and heights. This study aims to provide design guidelines for cladding and components of the envelope of non-rectangular low-rise buildings.

The experimental results of roofs and walls were analyzed and compared with the design provisions and guidelines of NBCC 2020 and ASCE/SEI 7-22, 2022 for rectangular buildings. The comparison with NBCC 2020 indicated that roof design provisions are comparable to the experimental results in the corner zone and lower than the experimental peaks in the edge and interior zones. The comparison with ASCE/SEI 7-22, 2022 shows that the standard roof design provisions of rectangular buildings are conservative and applicable for the design of non-rectangular buildings. The experimental results also indicate that the size of the roof pressure zone is mainly dependent on the roof height.

The wall pressures were also compared to the wall design peaks of the North American codes and standards. The experimental results indicate that relatively high suctions occur on the wall areas at the corners and the reentrant corners (wall edges) and lower suctions on the wall middle areas. The rectangular building provisions of ASCE 7-22 were satisfactory and can be used for the design of walls of non-rectangular buildings, while the rectangular building provisions of NBCC 2020 require further modifications to become applicable to non-rectangular buildings.

Furthermore, the wind tunnel measurements not only provided valuable data but also served as a dataset when applying Machine Learning (ML) as a tool to predict wind loads on non-rectangular buildings. This involved the utilization of ensemble ML and Artificial Neural Networks (ANN), using two data split approaches: random and structured splits. The ML models exhibit significant predictive accuracy, achieving minimal Mean Squared Error (MSE) and coefficients of determination (R-squared) of about 0.97 for wind pressure coefficients. In addition, the study demonstrated that a structured split of the dataset reflects a more realistic assessment of the ML models.

Keywords: non-rectangular buildings; wind tunnel testing; roof pressures; wall pressures; pressure zonal system; NBCC 2020; ASCE 7-22; ensemble Machine Learning; Artificial Neural Networks; wind-induced loads.

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LIST OF SYMBOLS

A_i	Tributary area of the i th pressure tap
$C_g C_p, GC_p$	Peak pressure coefficients
$C_{pi}(t)$	Pressure coefficient of the i th pressure tap at instant t
$C_{p,averagd}$	Area-averaged pressure coefficient
h	Mean roof height
I_u	Longitudinal turbulence intensity
n	Frequency
$P_i(t)$	Wind-induced pressure on the i th pressure tap at instant t
P_o	Reference pressure
Re	Reynolds number
σ^2	Coefficient of determination
$S(n)$	Spectral density function for longitudinal component
$\bar{V}_g$	Mean wind velocity at gradient height
$\bar{V}_h$	Mean wind velocity at roof height

y_i	Wind tunnel measurement (True value)
y_p	Predicted value
Z_g	Gradient height
z_o	Roughness length
α	Mean speed exponent
ν	Kinematic viscosity
ρ	Air density
σ^2	Variance

Chapter 1

Introduction

Low-rise buildings form the majority of buildings all over the world, and the wind design of such buildings governs when it comes to lateral strength (Krishna, 1995). Therefore, the necessity for wind load estimation on such buildings is crucial to provide economic and safe designs.

1.1 Background

Low-rise buildings can be classified into two main categories: buildings with rectangular plans and buildings with irregular (non-rectangular) plans. The rectangular low-rise buildings category can be further classified into several subcategories, based on the roof types and slopes. This includes flat-, gabled-, hipped, mono-sloped-, and stepped roof buildings. Rectangular low buildings can also be found in other types, such as multi-span gabled roof buildings and sawtooth and domed-roof buildings. On the other hand, categorization of nonrectangular low buildings is more complex. Beyond their varied roof types, nonrectangular buildings can be further categorized based on the plan shape (e.g., L, T, U, X, M, and other configurations).

Buildings with rectangular plans form the majority of structures worldwide. This predominance is probably attributed to the efficiency of room arrangement within rectangular spaces (Steadman, 2006). However, buildings with non-rectangular plans are seen frequently nowadays; this is probably due to the advancement in architectural design and the improvement in the building construction field. A survey was conducted by the author on four cities in Canada, Montreal, Longueuil, Ottawa, and Vancouver, to know the number of buildings with non-rectangular plans and the percentage of such buildings in the urban areas. These cities were selected for their diverse

architectural styles and urban characteristics. Montreal presents a mix of historical and modern, high- and low-rise structures; Longueuil is mostly characterized by modern low-rise buildings; Ottawa features a varied architectural landscape; and Vancouver primarily consists of high-rise developments.

The survey was performed using Google Earth. Specific areas were considered in each of the four cities, as shown in Figure 1.1 for Montreal. The buildings were then counted manually block by block in the chosen areas of each city. Figure 1.2 shows a U-shaped building within the chosen area in Montreal.

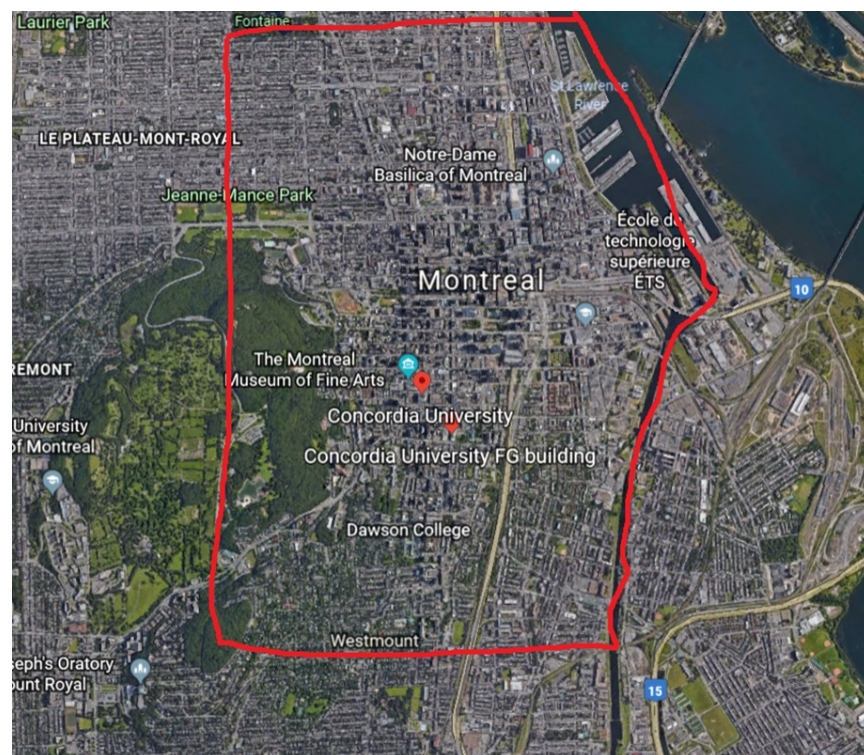


Figure 1.1: Selected area in Montreal.



Figure 1.2: A U-shaped building in Montreal.

The survey indicated that there exists a significant number of irregular buildings in urban cities, 1400 buildings in four cities, and non-rectangular buildings form 8% of the existing buildings, as shown in Figure 1.3. Figure 1.4 categorizes the irregular buildings based on shape, e.g., L-shaped and T-shaped buildings; it was found that L-shaped buildings are the most common. The complex shape category refers to buildings with non-common shapes in Figure 1.4.

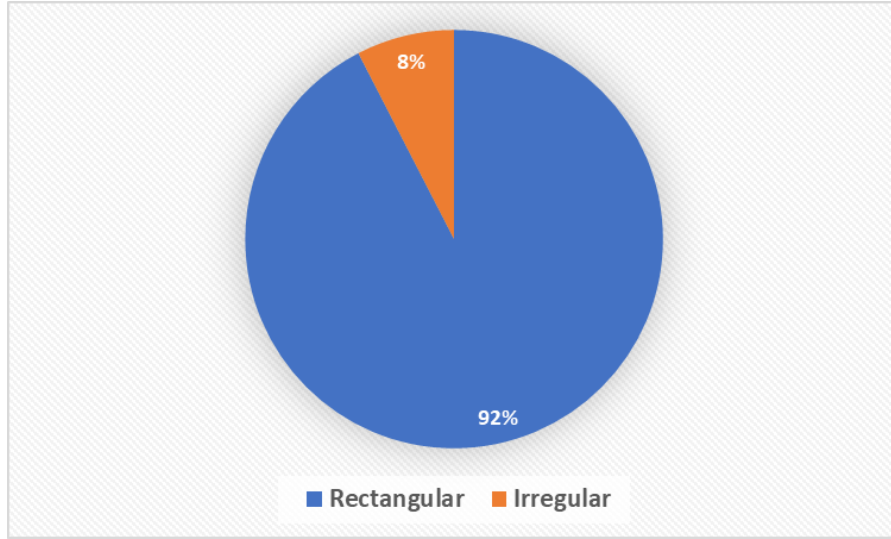


Figure 1.3: Percentage of existing irregular rectangular buildings in the four cities based on the survey.

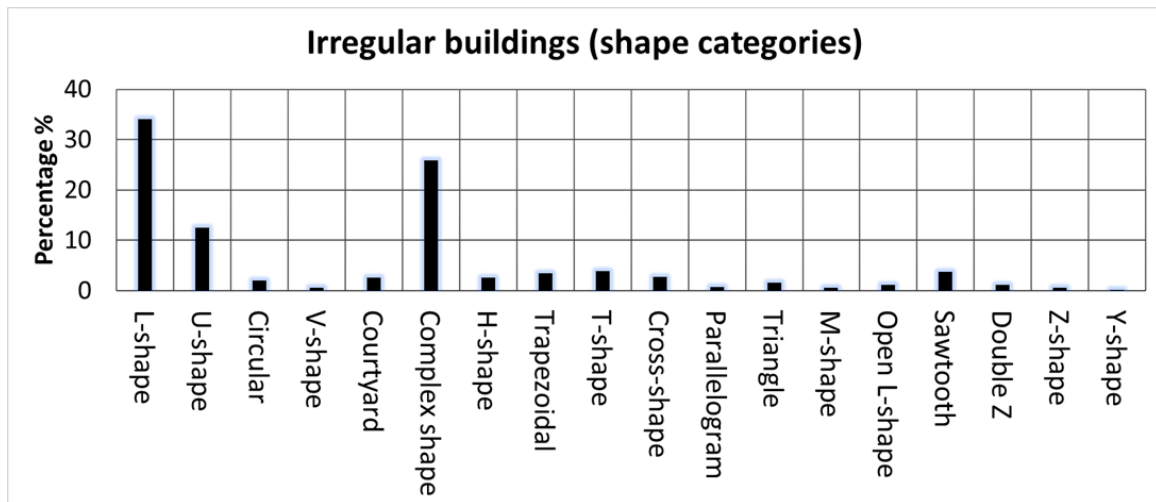


Figure 1.4: Categories of irregular buildings based on shape.

The large number of low-rise buildings available globally highlights the need for verifying and estimating wind loads on their structural and non-structural components through wind tunnel testing. Additionally, the complex geometries of non-rectangular buildings pose significant variability in their wind pressures, making generalization and modeling of these pressures

challenging. In this context, Machine Learning (ML) offers a powerful solution. ML is well known for its capability of performing multiple multivariate regression analyses on large datasets effectively. Leveraging the WT datasets, ML can effectively build a generalized model for estimating wind loads on non-rectangular buildings.

1.2 Motivation

Wind load provisions for buildings with non-rectangular plans are not generally available in the North American wind codes and standards, the American standards and the National Building Code of Canada. ASCE/SEI 7-22, 2022 provides short guidance in the commentary of Chapter 30 for the determination of cladding and components design peaks on non-rectangular buildings. However, the guidance is based on wind committee judgment and the design peak pressures of rectangular buildings and needs to be verified through wind tunnel testing of non-rectangular models. A few wind studies have targeted non-rectangular buildings in the past three decades. However, these past studies are of limited interest. This includes unvalidated numerical studies or studies based on wind loads of rectangular buildings. Therefore, comprehensive WT testing is required to estimate wind pressures on such buildings.

Utilizing Machine Learning (ML) offers a potent means to conduct multiple and multivariate regression analyses on huge datasets. ML models are powerful at uncovering hidden, complex relationships within data, often offering superior predictive capabilities compared to traditional models. In wind engineering, ML has found application in predicting wind loads, wind speeds, and various other topics within the field.

In the past years, the ML was implemented to predict wind load pressure coefficients for rectangular and non-rectangular buildings. The focus of ML implementation for non-rectangular

and non-curved buildings was on the mean pressures; the peak pressures were not considered. In addition, the past research on employing ML for non-rectangular buildings targeted single shapes without attempting to include multiple non-rectangular shapes in a single ML model. Therefore, a large wind tunnel dataset that includes pressure measurements on multiple irregular models is required to achieve such generalized ML models with the capability to provide excellent predictive performance for pressure coefficients on non-rectangular models.

1.3 Research domain and objectives

This study focuses on wind loads on roofs and walls of low-rise buildings with flat roof non-rectangular plans by conducting extensive wind tunnel testing. It also implements ML to provide a further generalization of wind loads on non-rectangular buildings and obtain a cost-effective model to estimate wind loads on these buildings.

The following are the objectives of the study:

- Quantify the wind loads on non-rectangular buildings and highlight the trends of wind pressure change across wind directions, building heights, plan dimensions, and the various non-rectangular shapes.
- Compare wall and roof pressure coefficients of non-rectangular buildings with their counterparts on a typical rectangular building and specify similarities and differences between the two types.

- Compare the experimental wind pressure coefficients of the envelope of the non-rectangular building models with the rectangular provisions of the American Standard (ASCE/SEI 7-22, 2022) and the National Building Code of Canada (NBCC 2020).
- Propose a methodology for the design of cladding and components of non-rectangular buildings based on the wind provisions of rectangular buildings.
- Build an ML model to provide a feasible and cost-effective tool for quantifying wind loads on the roofs and walls of non-rectangular buildings.

Multiple wind tunnel models were considered for testing in the atmospheric boundary layer wind tunnel of Concordia University to quantify wind loads on non-rectangular buildings. This includes testing three L-, three U-, and two T-shaped models with different plan dimensions and heights. In addition, two extra models with plans of an X and a trapezoid were tested in the wind tunnel. The resulting wind tunnel dataset, comprising the results from all these tests, was then used to achieve the study objectives.

1.4 Thesis outline

Including the current introduction chapter, Chapter 1, this thesis consists of seven chapters. The organization of the thesis is as follows:

Chapter 2 presents a review of the literature, including the past studies conducted to estimate wind loads on walls and roofs of non-rectangular buildings and the application of Machine Learning in

wind engineering. It also reviews the rectangular provisions of ASCE 7-22 and NBCC 2020, as well as the guidance of ASCE 7-22 for the design of non-rectangular buildings.

Chapter 3 includes the details of the simulation of the atmospheric boundary layer, selection of wind tunnel testing models, and the approach adopted to form the non-rectangular models, pressure measurements, and validation of the experimental data.

Chapter 4 presents the effect of plan dimensions and building height of non-rectangular buildings. It also presents a comparison between wind loads on walls and roofs of non-rectangular building models and a rectangular building model.

Comparison of the experimental results with the rectangular provisions in the North American wind codes and standards is included in Chapter 5. The chapter includes recommendations for the design of cladding and components of non-rectangular buildings.

Chapter 6 provides further generalization of wind loads on non-rectangular buildings through Machine learning models,

Finally, Chapter 7 provides concluding remarks and recommendations for future work.

Chapter 2

Literature review

This chapter includes a review of the past studies on non-rectangular buildings and ML implementation in wind engineering. It also presents the provisions and guidelines of codes and standards for flat roof buildings with rectangular and non-rectangular buildings.

2.1 Past studies

2.1.1 Irregular buildings

Cook (1990) provides a procedure to determine wind loads on walls of nonrectangular buildings, including polygonal-plan buildings, buildings with re-entrant angles (shapes of L, T, X, and Y), recessed bays, and central wall buildings. In the beginning, wind loads on walls of rectangular buildings are introduced by following ten steps, then the pressure coefficients on walls of rectangular buildings are used with modifications to determine wind loads on walls on nonrectangular buildings. For walls of polygonal-plan buildings, the pressure coefficients on walls are specified using the same ten steps as in the rectangular building walls but modified by reduction factors; the reduction factors were derived through tests at a slenderness ratio of one and assumed to be applicable to other slenderness ratios. Another example is buildings with re-entrant corners; the method is described based on reference plan of X for determining pressure coefficients on walls of X-shaped buildings that can be generalized to other shapes that include re-entrant corners such as L, T, and Y. Again, the ten steps apply to the walls of rectangular buildings should be used with extra four steps to modify the coefficients due to the presence of the re-entrant corners. The complex procedures introduced by Cook (1990) depend mainly on

rectangular building data and create a general way of determining wind loads on nonrectangular buildings. However, Cook (1990) method has not been validated yet and was not incorporated in the codes and standards, probably due to its complex steps.

Jamieson et al. (1992) examined wind pressures on tall building models experimentally. The models were constructed using a 1:300 length scale with a height of 600 ft and different roof shapes: rectangular, rounded corners, beveled corners, and recessed corners, see Figure 2.1. The pressures were recorded on walls at $2/3$ of the height in simulated suburban terrain conditions for a range of wind-attack angles, 0° to 360° . It is well known that the Reynolds number controls the location of wind flow separation on curved buildings; therefore, the results of wind tunnel experiments on curved buildings are questionable due to the inability to resemble the Reynolds number. Suggestions have been made to overcome this issue by roughening the models to ensure separation points similar to those on the full-scale building. However, this paper reported that a negligible difference was obtained by increasing the model roughness.

Jamieson et al. (1992) presented the experimental measurements in terms of peak pressure coefficients normalized by the dynamic pressure at the roof height. Jamieson et al. (1992) reported wind peak pressure coefficients on walls at $2/3$ of the building height. This does not reflect the most critical suction loads, which should be considered in the building design



Figure 2.1: Plan shapes of buildings, after Jamieson et al. (1992).

Stathopoulos and Zhou (1993) numerically investigated wind loads on stepped roof and flat roof L-shaped buildings with a height of 20 m. The buildings were simulated using a length scale of 1:400, and the wind speed profile was assumed to be governed by the power-law with an exponent of 0.17 to represent an open country terrain condition. For the stepped roof building and a wind direction perpendicular to the step, negative and positive pressures were recorded on the lower windward roof (positive pressures attributed to the drastic reduction of wind speed near the front wall of the higher roof); however, negative pressures were recorded on the higher roof and the back wall.

Figure 2.2 shows the flat roof L-shaped model with a perpendicular wind direction. The study reported that negative pressures were developed on the entire roof with higher values on region G, the narrow roof. On the other hand, positive pressures were recorded on the windward wall, E. In addition, the side walls A and F experienced suctions with higher values on wall A. Negative pressures were also recorded on walls B, C, and D with similar values on walls B and C.

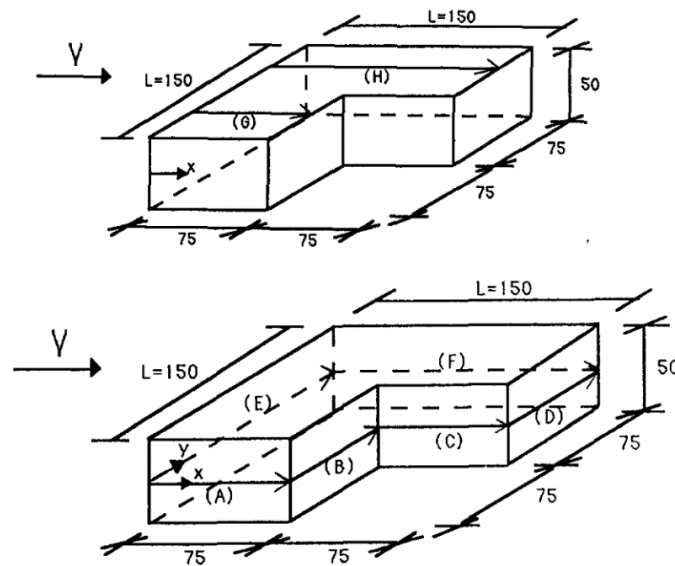


Figure 2.2: Flat roof L-shaped model, after Stathopoulos and Zhou (1993).

Morse (2003) conducted wind tunnel testing to measure wall pressures on three L-shaped models. The experimental pseudo-steady pressure coefficients were compared with the wind pressure coefficients of an encompassing rectangle model and Morse's method. While using the ASCE7-2003 pressure coefficients for zones 5 and 4, the two wall zones were applied as recommended by the standard on the rectangular parts of the L shapes, except for the recessed walls, where zone 4 was applied at the reentrant corners as shown in Figure 2.3. It was found that the encompassing rectangle method underestimates the experimental results, while Morse's method significantly overestimates wind pressures on the walls of the L-shaped models.

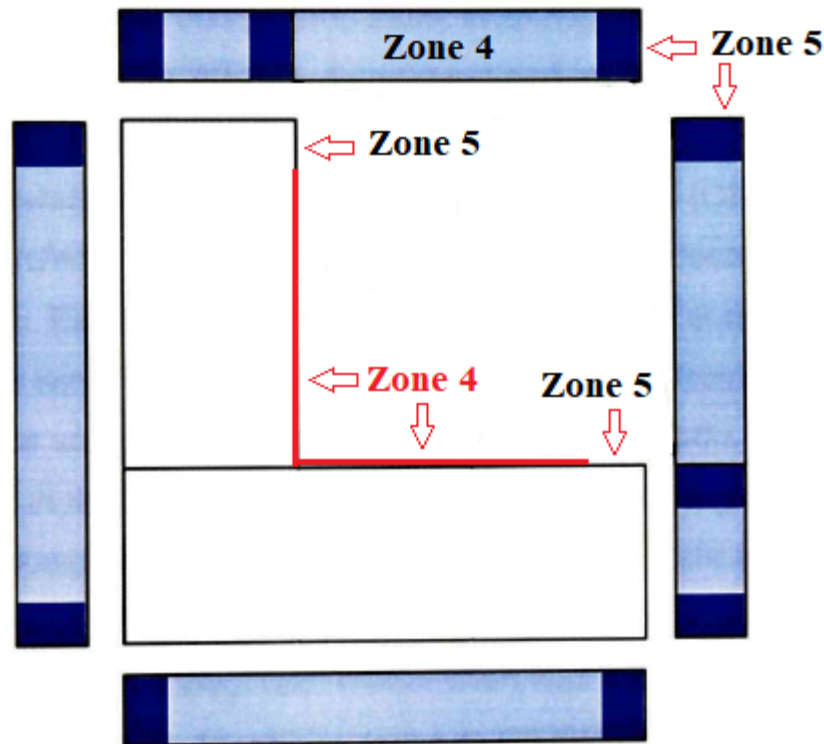


Figure 2.3: Application of the ASCE 7-2003 zones (after Morse, 2003).

Gomes et al. (2005) studied wind effects on cubical, L-shaped, and U-shaped models in a wind tunnel and using a CFD program. The experimental models were constructed at a length scale of

1:100 with a full-scale height of 30 m and tested in a uniform-flow (aeronautical) wind tunnel. The L-shaped and U-shaped buildings were equipped with pressure taps in the inner walls only assuming the wind load distribution on the exterior walls is similar to that on walls of a rectangular model. Mean pressure coefficients normalized by velocity pressure at the building height were calculated and presented in the paper; peak pressures were not included.

Parackal et al. (2016) studied wind loads on low-rise hipped-roof buildings with complex geometries (see Figure 2.4) and a roof slope of about 22° through wind tunnel testing. The experimental results of the roof and walls were compared to the wind loads of the AS/NZS 1170.2 (2011). The comparison indicated that the standard underestimates the wind pressures at the roof edges, while the standard cladding loads were found sufficient for walls.

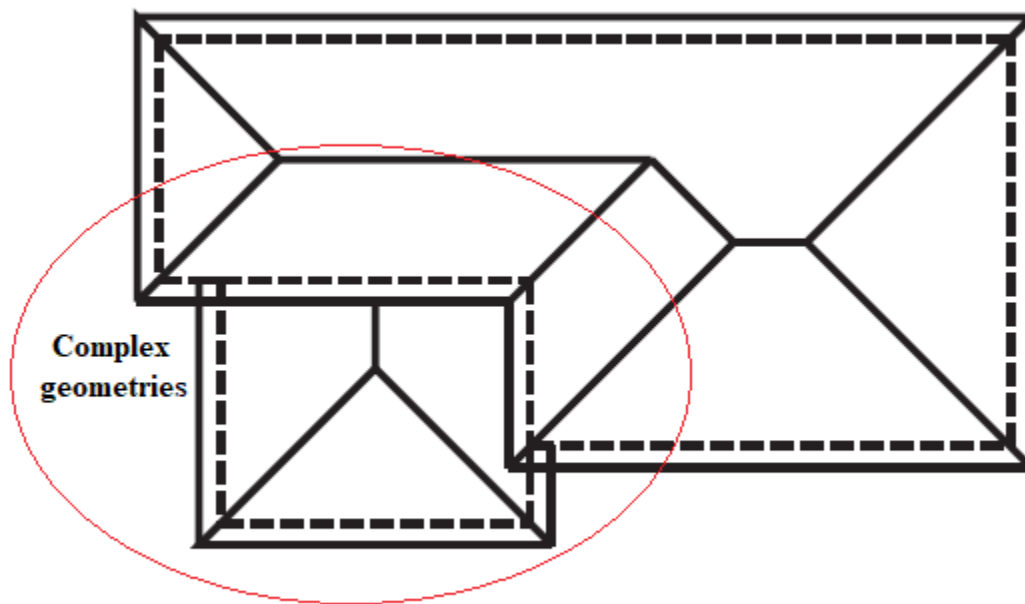


Figure 2.4: A plan of complex geometry (After Parackal et al., 2016)

Wind loads on hipped roofs of L and T-shaped low buildings were investigated by Shao et al. (2018). The experimental results were compared with the provisions of ASCE 7-10, the standard peaks were found satisfactory except for Zone 2 along the ridge and hips. Shao et al. (2019) provided insightful details on wind loads on hipped roof buildings, the study included mean, peak, and area-averaged wind loads. Wind pressures of irregular buildings with gable and hipped roofs were also investigated experimentally (Matus and Zisis, 2021; and Sarma et al., 2023).

Sarma et al. (2023) found that high peaks were observed at the inner edges of non-rectangular building roofs and provided an important finding regarding the vulnerability of roof sheathing; it was concluded that the probability of roof sheathing failure of the L and T shapes is higher near the reentrant corners than at the outer edges, while the opposite was noted for the U shapes. A recent study presented experimental findings on non-rectangular buildings (Van Den Heuvel and Kopp, 2024).

2.1.2 Machine Learning

Utilizing Machine Learning (ML) offers a potent means to conduct multiple and multivariate regression analyses on intricate datasets. In wind engineering, ML has found application in predicting wind loads, wind speeds, and various other topics within the field. Khanduri et al. (1997) provides a generalized model for the evaluation of the wind loads on non-isolated buildings using a neural network (NN), the study used a small dataset for the training of the NN to predict the ratio of base overturning moment of buildings with surroundings and isolated buildings, interference factor (IF), trained NN exhibited a good generalization for along wind mean IF values when was compared testing set. Bitsuamlak et al. (2007) employed a neural network to forecast speed-up ratios for diverse topographic features such as escarpments and hills. Elshaer et al.

(2017) and Alanani & Elshaer (2023) utilized Artificial Neural Networks (ANN) in optimizing the aerodynamics corners in tall buildings and the layout of shear walls.

ML was implemented to model wind loads on buildings with rectangular plans (Gavalda et al. 2011, Dongmei et al. 2017, Bre et al. 2018, Fernández-Cabán et al. 2018, Tian et al. 2020, Hu et al. 2020, Kim et al. 2021, Sang et al. 2021, Lamberti and Gorlé 2021, Ding et al. 2022, Weng and German Paal 2022, Meddage et al. 2022, Chen et al. 2022, Du and Chen 2023, Meddage et al. 2024, and Tong et al. 2024).

Bre et al. (2018) constructed three ANNs to predict surface average pressure coefficients (C_p) on walls and roofs of flat, gabled, and hipped roof low-rise buildings, using the TPU database. Higgins and Stathopoulos (2021) built ANNs to predict wind speeds in urban areas to find the optimal location of wind turbines. The ANN showed excellent results with high success rates. Fernández-Cabán et al. (2018) employed a feed-forward ANN with backpropagation to predict mean, root-mean-square (rms), and peak pressure coefficients on roofs of low-rise building models with different geometric scales and approaching flow conditions characterized by a range of turbulence intensities. The study used the turbulence intensity and the roof taps coordinates as inputs for the ANN.

Tian et al. (2020) used ANNs to generalize wind pressure coefficients on low-rise gabled roof buildings, leveraging NIST experimental data. The study used the x, y, and z coordinates and the wind direction as input features. Sang et al. (2021) evaluated wind drag coefficients on high-rise rectangular buildings numerically, the study used the numerical results to train and test ANNs. Lamberti and Gorlé (2021) employed Large-Eddy Simulations (LES) and Reynolds-Averaged Navier-Stokes (RANS) to assess wind pressures on a 100-meter-tall building. The data generated from these simulations was then leveraged to predict root-mean-square (rms) pressure coefficients

using an ANN. Du and Chen (2023) used a semi-supervised regression model to predict peak wind pressure coefficients on a group of buildings.

A recent study, conducted by Tong et al. (2024), used a deep learning model to extend wind pressure coefficient time-series. The study showed that the deep learning model is superior to traditional methods (Correlation Distortion Static Transform and Gaussian Kernel Density Estimation) in constructing wind pressure sequence through comparing the statistical parameters, spectra, and distribution of extreme values.

Weng and German Paal (2022) and Meddage et al. (2024) employed decision tree-based regressors, specifically, the two studies utilized the Gradient Boosting technique for wind load regression. Gradient Boosting was used by Weng and German Paal (2022) to forecast wind pressure coefficients for non-isolated low-rise buildings using the TPU database. On the other hand, Meddage et al. (2024) employed Extreme gradient boosting (XGBoost) for the prediction of wind loads on tall buildings.

A limited number of studies have explored the application of ML to predict wind loads on non-rectangular buildings. This includes Circular cylinders (Hu and Kwok, 2020), C-shaped (or U-shaped) buildings (Mallick et al., 2020 and Meddage et al., 2021), and Y-shaped buildings (Sanyal and Dalui, 2022). These studies primarily focused on predicting wind loads for specific single-building shapes, limiting the generalizability of the ML models to other architectural geometries. This study aims to address this limitation by incorporating four nonrectangular building shapes (L, U, T, and X) into a single ML model, developing a more generalized approach for predicting wind loads on non-rectangular buildings.

The data split approach influences the training process and the predictive performance of ML models. The random split often results in significant similarities between the training and testing sets, indicating implicit data leakage. The predictive performance of ML models trained and validated using sets selected randomly was found to be overestimated by Plonton et al. (2020) and Sogaard et al. (2021). While a structured split (e.g., split based on wind direction) results in more divergent training and testing sets. This often provides a realistic evaluation of the model's effectiveness in testing.

2.2 Codes and standards

This section presents the provisions of flat-roofed rectangular buildings that will be the basis for proposing a methodology for the design of non-rectangular buildings. It also presents the ASCE 7 guidance for the design of non-rectangular buildings.

2.2.1 Rectangular buildings

Design wind loads of cladding and structural components of rectangular buildings are given as pressure coefficients in the Canadian code and American standard. These coefficients are applicable for buildings with rectangular plans only.

Figure 2.5 shows the design peaks of the nearly flat-roof building in NBCC 2020. The Canadian code divides the flat roof into three pressure zones: corner, edge, and middle or interior zones. The highest design peaks are given for the corner zones, and the lowest are recommended for the middle zone. In addition, z , in Figure 4.1.7.6.-C, is the lesser of 10% of the least horizontal dimensions and 40% of height H , but not less than 4% of the least horizontal dimensions or 1 m.

Figure 2.6 presents the ASCE 7-22 external pressure coefficients for the design of nearly flat roofs. The main differences between NBCC 2020 lie within the pressure zones: (1) the corner zone is an L-shaped area, (2) there are four pressure zones, and (3) the size of the roof zone is a function of the height only.

The ASCE 7-22 and NBCC 2020 also provide provisions for the design of wall cladding and components of buildings with a rectangular plan. Figure 2.7 presents the design peaks of the wall cladding and secondary structural members in NBCC 2020. The walls are divided into two zones: zone e and zone w. The end zone width is the same as presented above for the roofs.

Figure 2.8 presents the design peaks of cladding and components of walls in ASCE 7-22. The wall pressure zonal system in the American standards is similar to the corresponding zonal system in NBCC 2020. However, the names of the wall zones are zones 5 and 4, which correspond to zones e and w, respectively.

Figure 4.1.7.6.-C

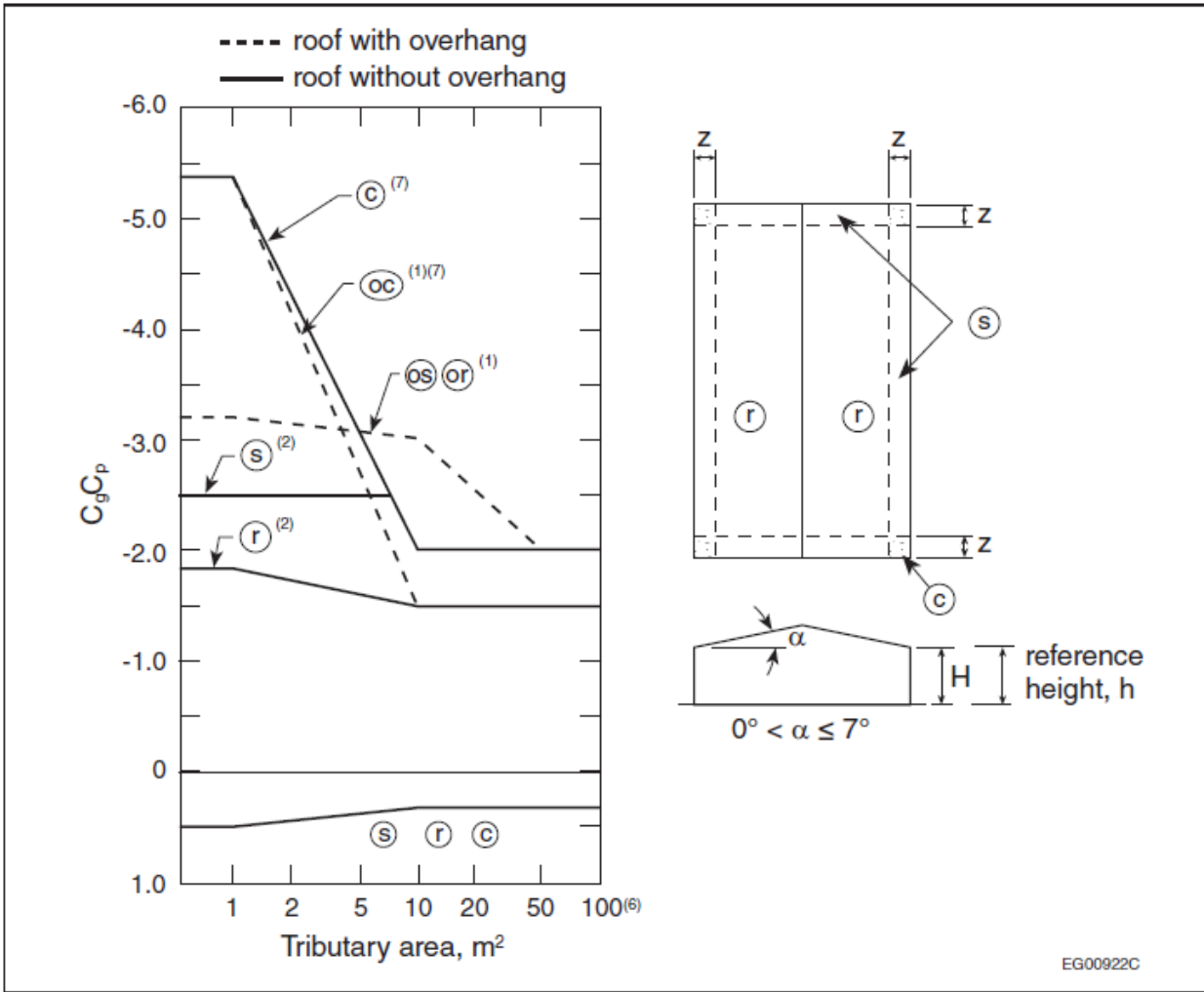
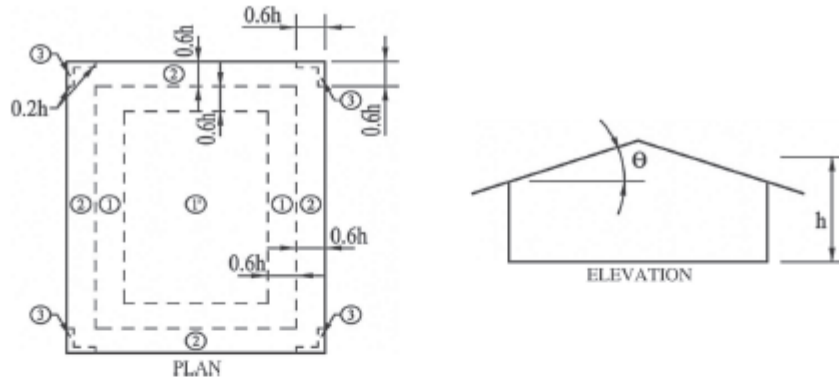


Figure 2.5: Values of $C_p C_g$ for the design of structural components and cladding of nearly flat roof buildings (Figure. 4.1.7.6.-C, NBCC 2020).

Diagrams



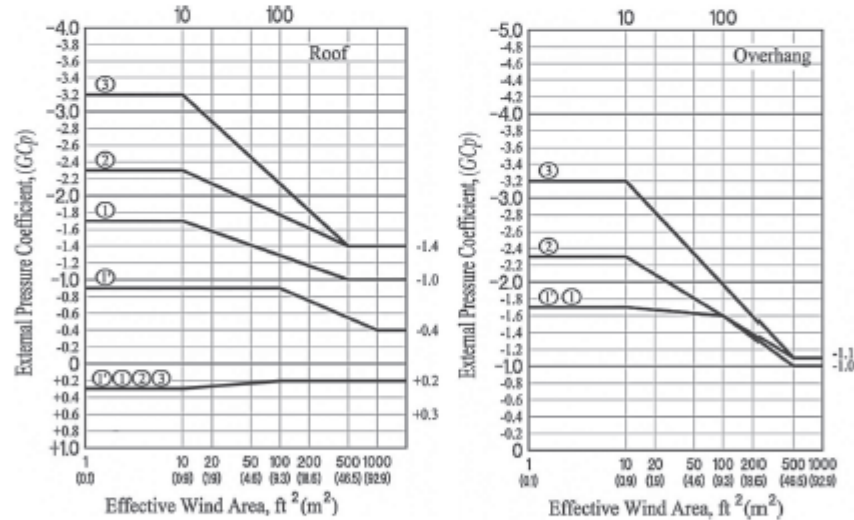
Notation

B = Horizontal dimension of building measured normal to wind direction, ft (m).

h = Eave height shall be used for $\theta = 10^\circ$.

θ = Angle of plane of roof from horizontal, degrees.

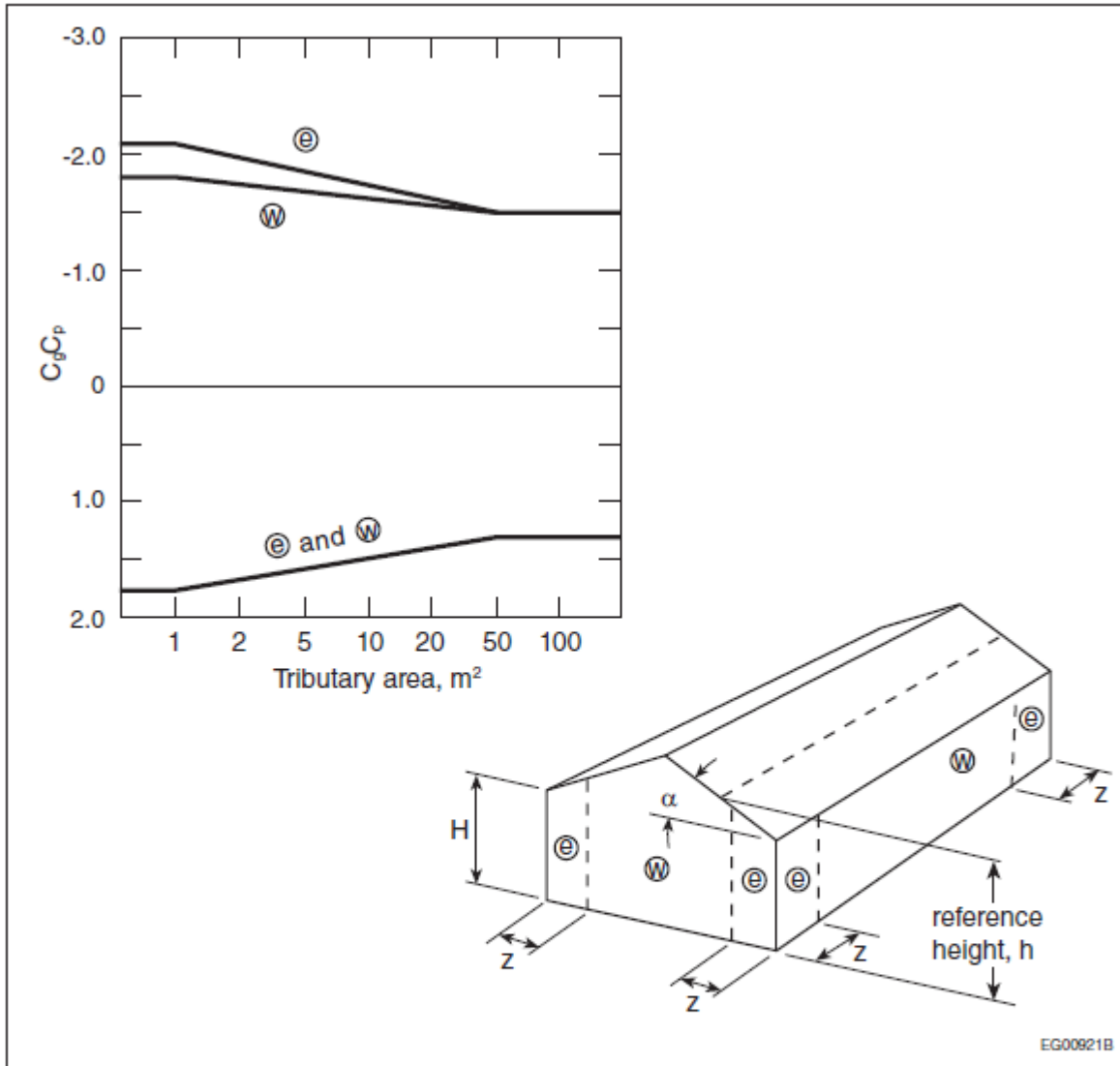
External Pressure Coefficients



Notes

1. Vertical scale denotes (G_{CP}) to be used with q_h .
2. Horizontal scale denotes effective wind area A , $ft^2 (m^2)$.
3. Plus and minus signs signify pressures acting toward and away from the surfaces, respectively.
4. Each component shall be designed for maximum positive and negative pressures.
5. If a parapet equal to or higher than 3 ft (0.9 m) is provided around the perimeter of the roof with $\theta \leq 7^\circ$, the negative values of (G_{CP}) in Zone 3 shall be equal to those for Zone 2, and positive values of (G_{CP}) in Zones 2 and 3 shall be set equal to those for wall Zones 4 and 5, respectively, in Figure 30.3-1.
6. Values of (G_{CP}) for roof overhangs include pressure contributions from both upper and lower surfaces.
7. If overhangs exist, the lesser horizontal dimension of the building shall not include any overhang dimension, but the edge distance, a , shall be measured from the outside edge of the overhang.

Figure 2.6: External pressure coefficients for nearly flat roofs (ASCE 7-22, Figure 30.3- 2A).

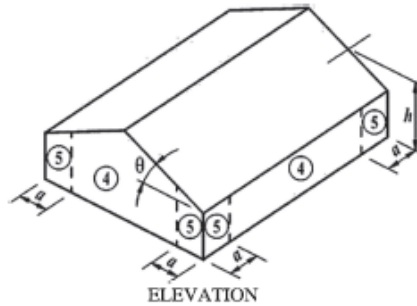


Notes to Figure 4.1.7.6-B:

- (1) These coefficients apply for any roof slope, α .
- (2) End-zone width z is the lesser of 10% of the least horizontal dimension and 40% of height, H , but not less than 4% of the least horizontal dimension or 1 m.
- (3) Combinations of external and internal pressures must be evaluated to obtain the most severe loading.
- (4) Positive coefficients denote forces toward the surface, whereas negative coefficients denote forces away from the surface. Each structural element must be designed to withstand forces of both signs.
- (5) Pressure coefficients generally apply for facades with architectural features; however, where vertical ribs deeper than 1 m are placed on a facade, a local C_gC_p of -2.8 applies to zone e .

Figure 2.7: Values of C_pC_g for the design of structural components and cladding of walls
(Figure. 4.1.7.6.-B, NBCC 2020).

Diagram



Notation

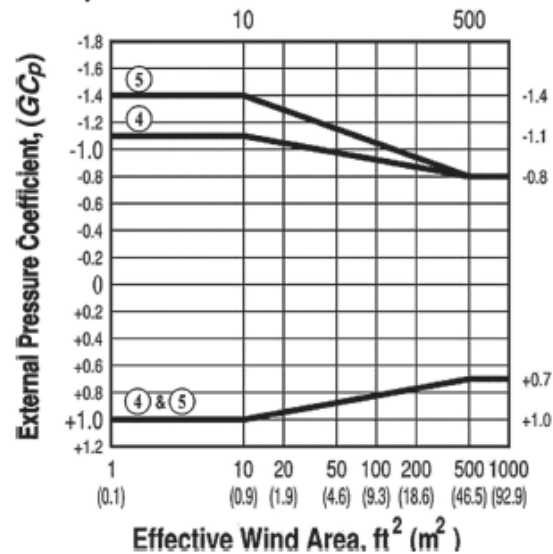
a = 10% of least horizontal dimension or $0.4h$, whichever is smaller, but not less than either 4% of least horizontal dimension or 3 ft (0.9 m).

Exception: For buildings with $\theta = 0^\circ$ to 7° and a least horizontal dimension greater than 300 ft (90 m), dimension a shall be limited to a maximum of $0.8h$.

h = Mean roof height, ft (m), except that eave height shall be used for $\theta \leq 10^\circ$.

θ = Angle of plane of roof from horizontal, degrees.

External Pressure Coefficient, (GC_p) - Walls



Notes

1. Vertical scale denotes (GC_p) to be used with qh .
2. Horizontal scale denotes effective wind area A , ft² (m²).
3. Plus and minus signs signify pressures acting toward and away from the surfaces, respectively.
4. Each component shall be designed for maximum positive and negative pressures.
5. Values of (GC_p) for walls shall be reduced by 10% when $\theta \leq 10^\circ$.

Figure 2.8: External pressure coefficients for nearly flat roofs (ASCE 7-22, Figure 30.3- 2A).

2.2.2 Irregular buildings

As mentioned previously, ASCE 7-22 provides limited guidance of a single figure in the commentary for buildings with non-curved and non-rectangular plans. This guidance is shown in Figure 2.9 and helps determine the components and cladding (C&C) wind loads on walls and roofs. The key concept in the figure is to decide whether or not to apply the high-pressure zones (i.e., zone 3 for roofs and zone 5 for walls) within the edges and corners of the non-rectangular sides. The two zones, as suggested in the figure, need not be applied when the interior angle is more than 135° or the protrusion X is less than the width of the pressure zone, a , and the peaks recommended for zones 2 and 4 are allowed at the reentrant corner. It should be noted that no references were provided to support this guidance. It was generated and included in the commentary “based on the collective judgment of the wind load committee” of ASCE 7-22.

Once the zone is decided, the C&C peaks recommended for buildings with rectangular plans are applied. It should be mentioned that the suggestions provided in Figure 2.9 apply to all walls and roof slopes and types. This includes the walls in Figure 30.3-1, gable and hip roofs in Figure 30.3-2 (A-G), in addition to multispans, monoslopes, and sawtooth roofs in Figures 30.3-4 to 6. The guidance also extends to apply for roofs and walls of buildings with heights greater than 60 ft (18.3 m) (Figure 30.4-1). However, the domed and stepped configurations are excluded.

A review through the ASCE 7 guidance reveals one main assumption for non-rectangular buildings. The figure assumes wind loads on inner edges and corners are comparable to those on outer edges and corners of both non-rectangular and rectangular buildings. This assumption seems reasonable for the outer sides of non-rectangular buildings due to aerodynamic similarities with rectangular buildings. However, the inner zones are expected to experience different aerodynamic

effects, leading to potentially distinct wind loads on inner edges and corners compared to outer ones and those of rectangular buildings.

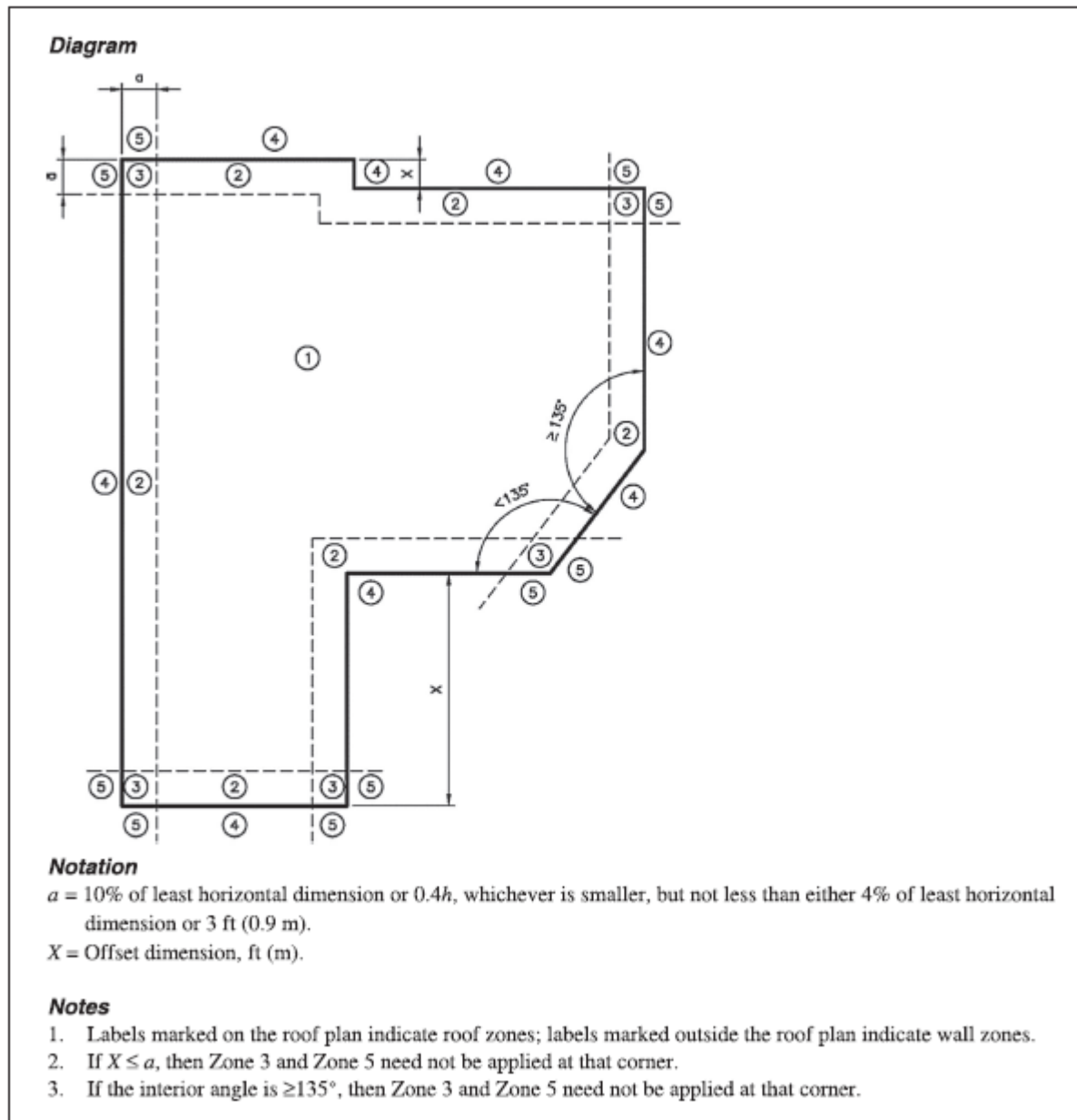


Figure 2.9: Plan view of roof and wall zones for component and cladding loads on buildings with nonrectangular plans (Figure C30.3-2 in the commentary of ASCE 7-22).

The code of practice on wind effects in Hong Kong (HK wind code, 2019a) also provides force coefficients for buildings with plan shapes of L, U, X, Y, and Z, as well as pressure coefficients for building elements (i.e., cladding and components) for buildings with non-rectangular plans.

The rectangular buildings force coefficients apply to non-rectangular buildings, using the dimensions of an equivalent rectangle as shown in Figure 2.10 for L, U, X, single Y, Double Y, and Z-shaped buildings. The force coefficients are based on data from rectangular buildings as stipulated in the Explanatory Notes to the same code (Explanatory Notes to HK wind code, 2019b).

For the pressure coefficients on building elements, the code of practice provides pressure coefficients for buildings with “rectangular corners”. This includes rectangular buildings and buildings with noncurved plans, such as L, U, and T. The code of practice (Buildings Department, 2019a) divides the walls into two zones: zone A (the edge) and zone B (the middle zone), while the roof is divided into zone C (corner), zone D (edge), and zone E (middle). Figure 2.11 presents the pressure zones in the code of practice on wind effects; these zones are clearly defined for rectangular buildings. However, for non-rectangular buildings, the edge zone is defined in a single key Figure in the explanatory notes (Explanatory Notes to HK wind code, 2019b) as shown in Figure 2.12. The Figure provides, probably, Zone A (the edge of the wall) with no details about the roof zones, zones C, D, and E.

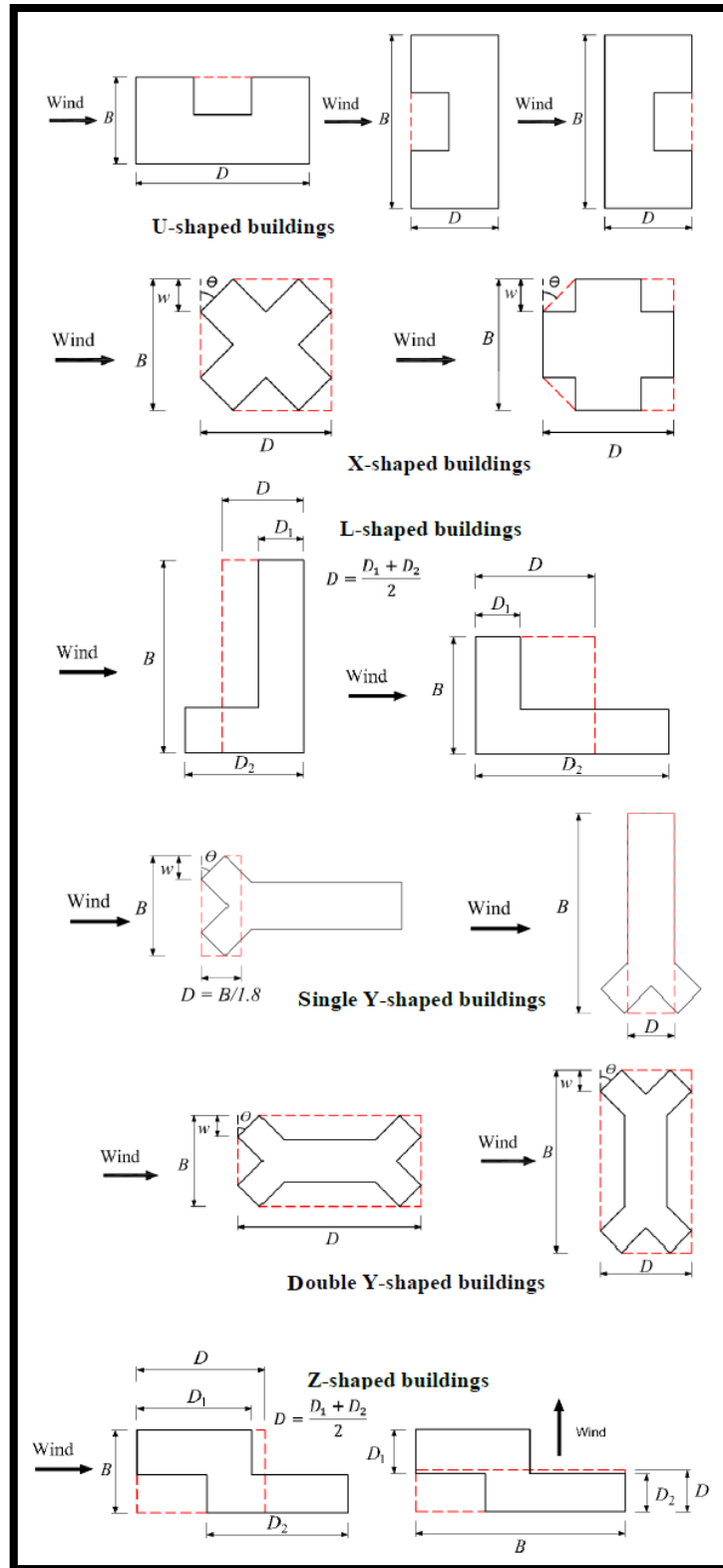


Figure 2.10: Basic dimensions of equivalent rectangles (After HK wind code, 2019a).

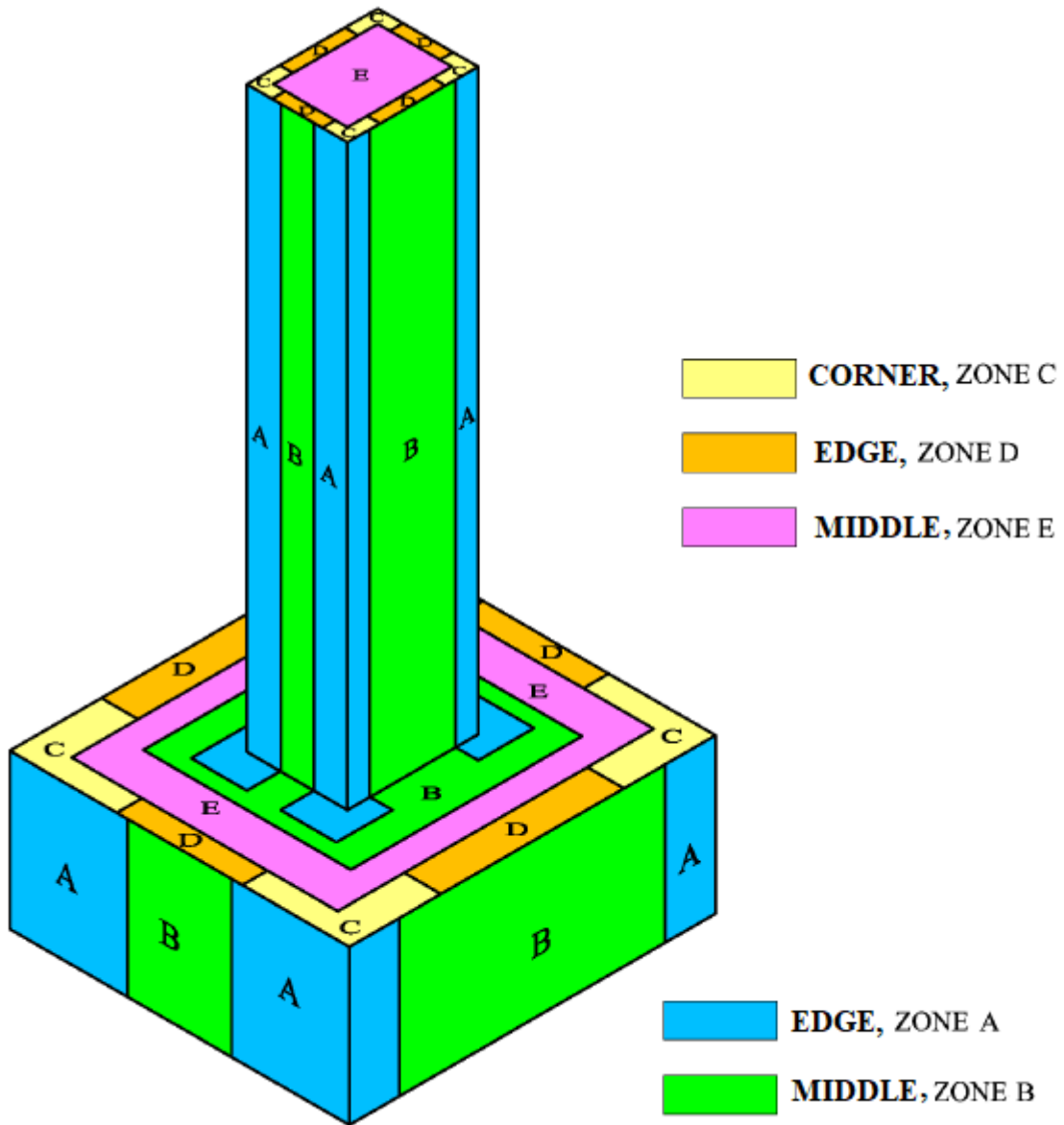


Figure 2.11: Pressure zones in the Code of Practice on Wind Effects in Hong Kong (After HK wind code, 2019a, Figure 4-6(a))

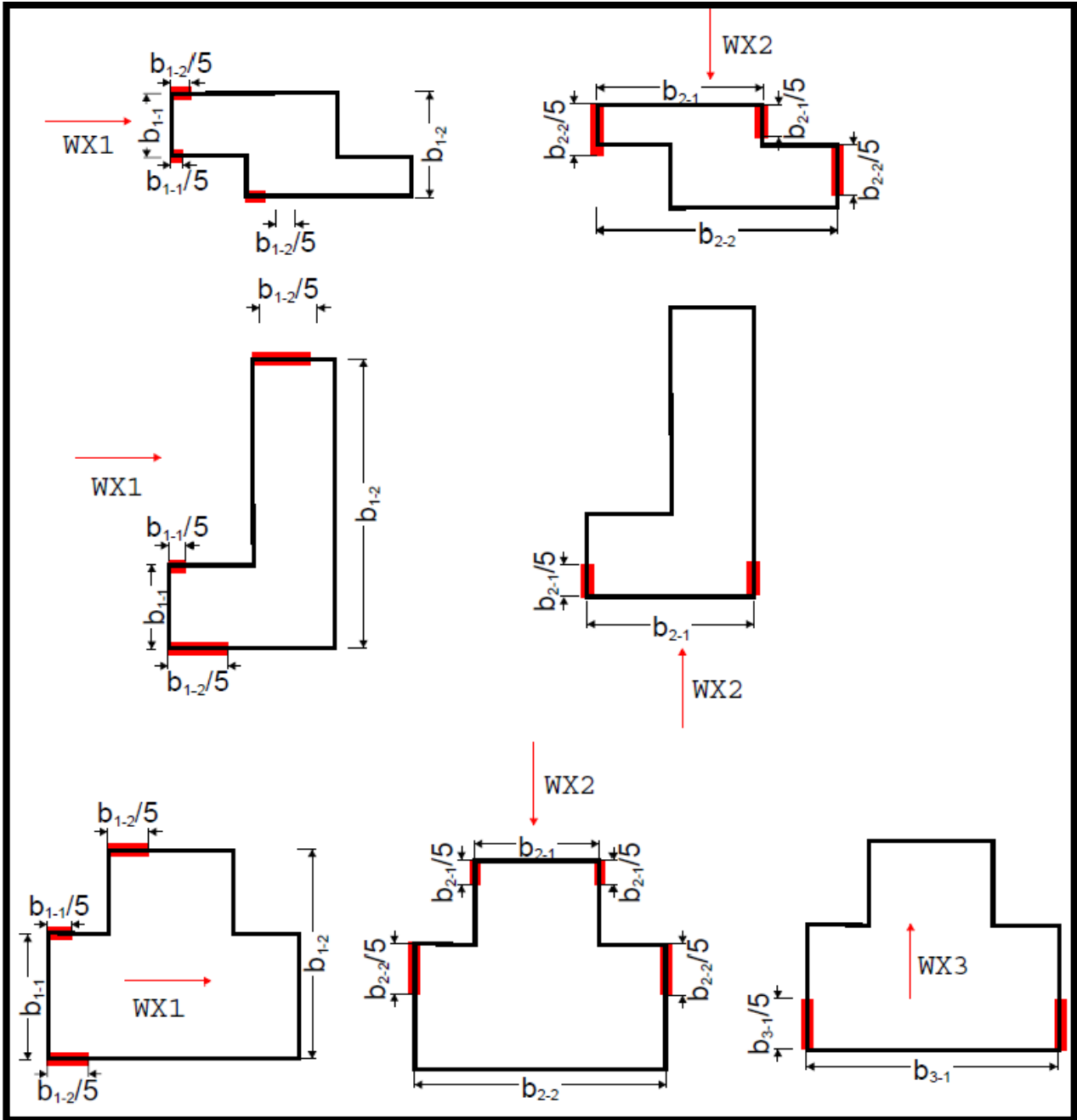


Figure 2.12: edge zones for non-rectangular buildings (After Explanatory Notes to HK wind code, 2019b).

Chapter 3

Experimental methodology

This chapter presents the details of the study models and wind simulation conditions. The chapter includes the experimental models, simulation of the atmospheric boundary layer, details of pressure measurement and data processing, and validation of the experimental results.

Part of the materials presented in this chapter have been published in the Journal of Structural Engineering (Aldoum and Stathopoulos, 2025a).

3.1 Model selection and tested configurations

Atmospheric boundary layer wind tunnels (ABLWT) are considered reliable for reproducing wind-induced pressures on buildings. Wind tunnels play an important role in understanding and quantifying the wind loads developed on buildings. Fabrication of testing models is deemed one of the challenges for wind tunnel testing. Building these models is expensive and time-consuming. Pressure tap installation, in particular, is a protracted task requiring significant effort. Irregular (non-rectangular) buildings could take several shapes, including L, T, U, X, M, and even a trapezoid. Given the variety of shapes of non-rectangular buildings, it would be intractable to construct an individual model for each unique shape. A feasible solution is to utilize a single base rectangular model equipped with pressure taps. This base model can be combined with simple and affordable dummy rectangular models (i.e., without pressure taps) to form models of the various non-rectangular shapes. These dummy models serve as fillers, adapting the base model to the desired shapes.

The base and dummy models were constructed with flat roofs using a geometric scale of 1:200, the full-scale plan dimensions of the base model are 15m x 30m. The 1:200 geometric scale was adopted for the construction of the testing models because it best satisfies the wind tunnel testing criteria, as will be discussed in the next subsection. The base model is composed of four sub-models. Three triangular models and one trapezoid, and the four sub-models form a rectangle when combined as indicated in Figure 3.1 (a). The base model was constructed in four parts to provide flexibility in forming the non-rectangular models, including those with trapezoidal plans. However, the base model was mostly used as one unit to form the non-rectangular buildings.

Figure 3.1 (b) presents the roof pressure tap layout; the roof is equipped with 193 pressure taps distributed almost uniformly on the roof. Figure 3.2 presents a 3D view of the base rectangular model and the distribution of the pressure taps on the walls. The base model is 30 m x 15 m in plan dimensions and equipped with a total of 48 pressure taps distributed evenly all over the four walls; the number of taps on the short wall and long wall is 8 and 16, respectively, as shown in Figure 3.2.

The adopted approach is to place the base model on a certain position within the non-rectangular shape and complete the rest of the shape using the dummy models, then test the non-rectangular configuration in the wind tunnel for a full-circle wind azimuth range ($0^\circ - 360^\circ$). Then the base model would be moved to another position until the entire non-rectangular shape is covered. The detailed approach for combining the base and dummy models is illustrated in Figure 3.3 for three models with L shapes, L1, L2, and L3. The hatched and blank areas represent the base and dummy models, respectively. For L1, it was required to conduct one test and use the base model one time to obtain the wind-induced pressures on the entire configuration because the dummy area can be

inferred by symmetry. On the other hand, two tests were required to scan roof pressures on L2 and L3. In other words, the base model was placed in two places within the configurations to cover the entire plan area. It should be noted that L2 was completely covered by the base model through two tests, while the L3 configuration had an untested square area that can be concluded by symmetry.

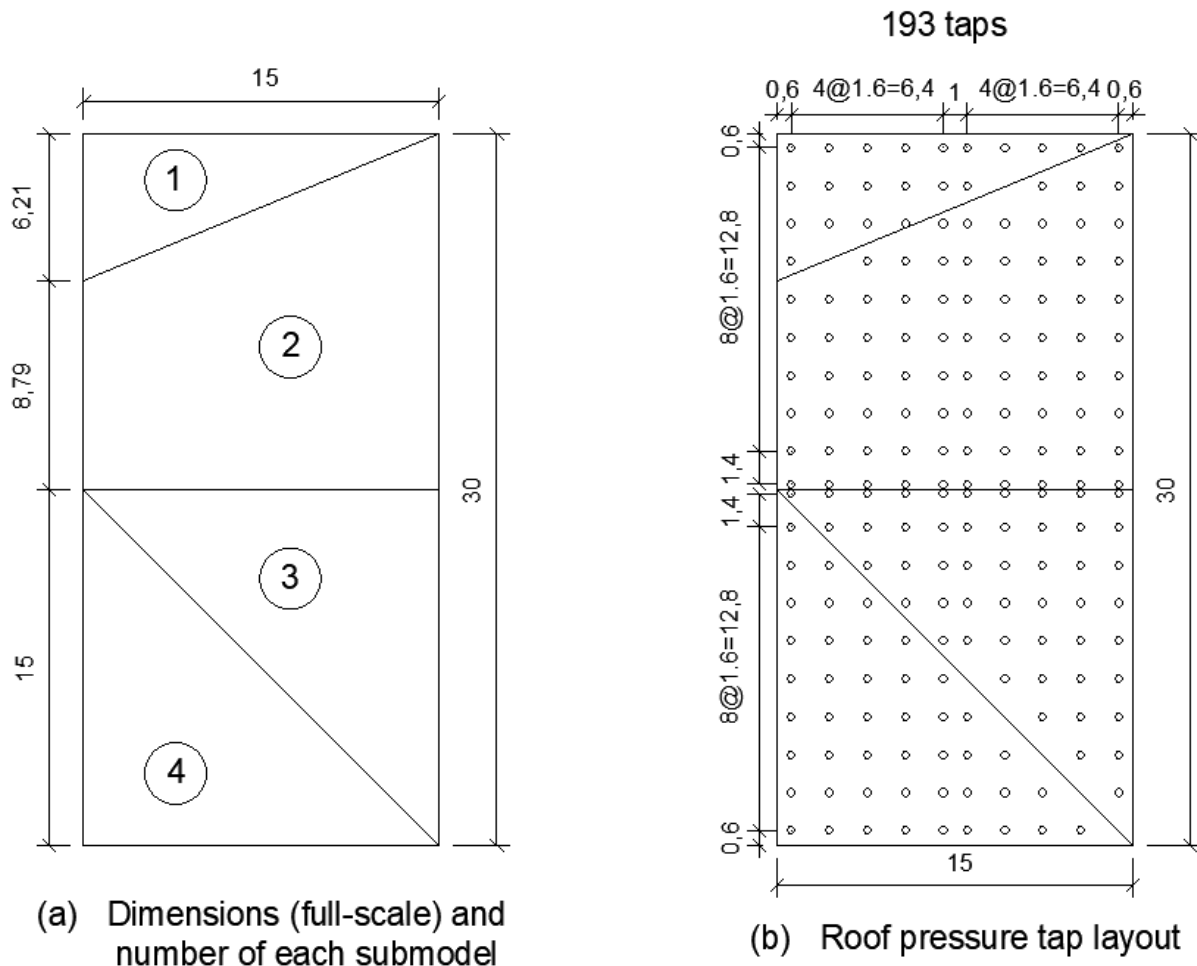


Figure 3.1: (a) Plan of the base model, and (b) Roof pressure tap layout.

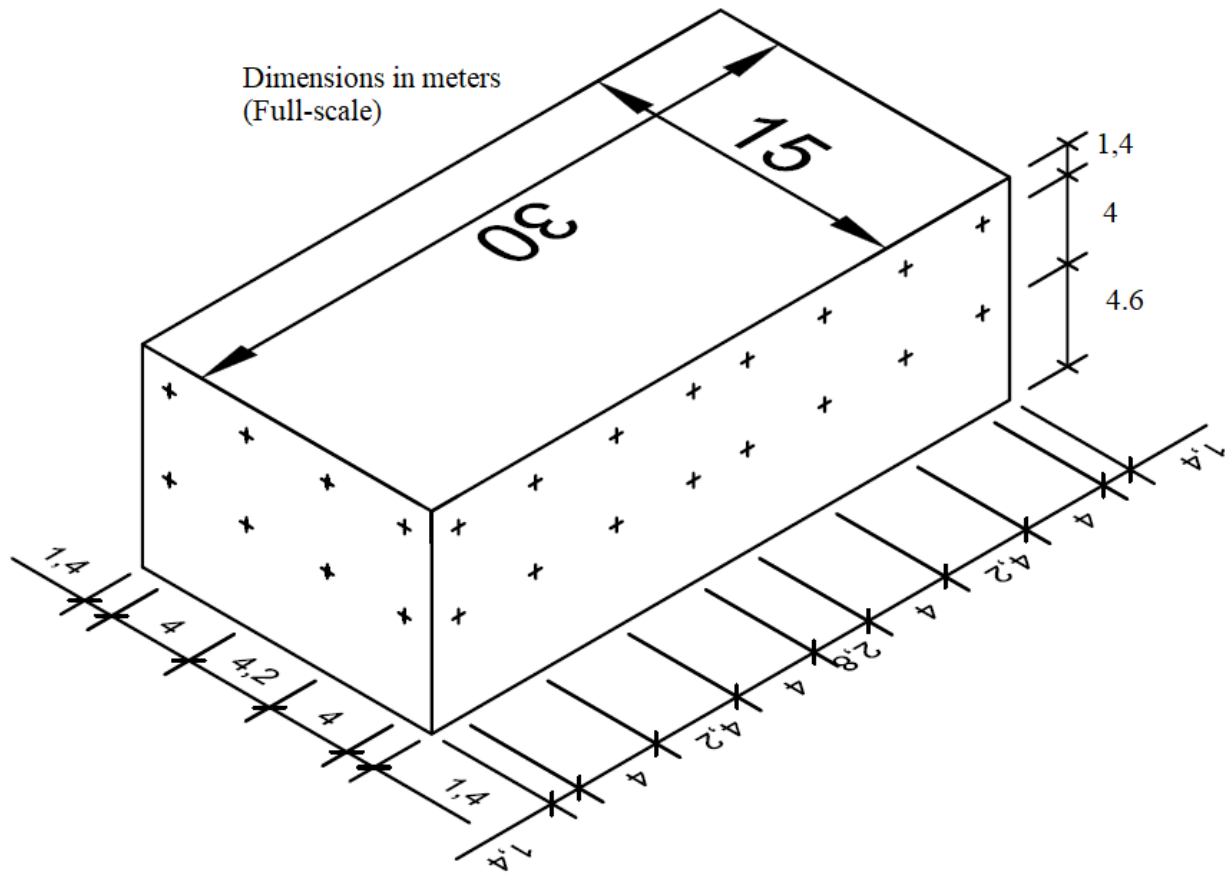


Figure 3.2: The base rectangular model along with the short and long wall pressure tap layouts.

Figure 3.4 presents the tested non-rectangular configurations; the configurations represent three L models, as indicated in the previous figure, three U models, two T models, and one X model. The tested models are included with different plan dimensions to investigate the effect of the building geometry on the wind loads on such buildings. The hatched areas in the plans shown in Figure 3.4 represent the parts of the plans in which the pressures were scanned by placing the base model in that part. The blank areas represent the parts of the non-rectangular configurations in which the wind pressures were not scanned and can be concluded by mirroring the wind pressures from the tested (hatched) areas. Furthermore, wind loads on the inner edges are expected to be different from those on the outer edges. Therefore, the inner edges of the configurations are

marked in blue for reference. L1 and L3 were tested for three full-scale heights of 5 m, 10 m, and 20 m, and the rest of the models were tested for a full-scale height of 10 m only. Regarding wind directions, the wind loads were measured for a full 360-degree wind azimuth range. Additionally, the base model and a trapezoidal model were tested for a height of 10 m, the plan for the trapezoidal model is shown in Figure 3.5.

Figure 3.6 shows the T-shaped model fixed at the wind tunnel. It was required to use the base model along with two square dummy models to form the T shape. Figure 3.7 is an example of combining the base model and dummy models for T1, the blank areas represent the locations of dummy models, and the grey areas represent the base model. In order to test the entire roof of T1, it was required to perform two tests: test 1 was conducted to scan wall pressures on the bottom left part of the plan, and test 2 was performed to cover the upper part of the T1 plan. The area represented by a blank square on the right side of the plan of test 1 can be inferred by symmetry. The same approach was applied to test the rest of the models in the wind tunnel.

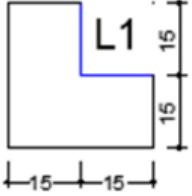
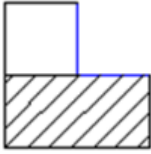
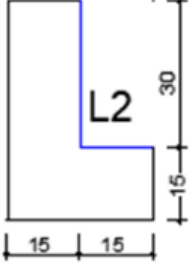
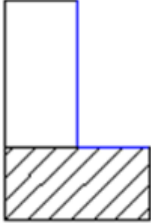
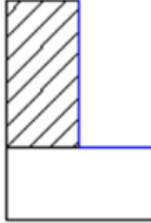
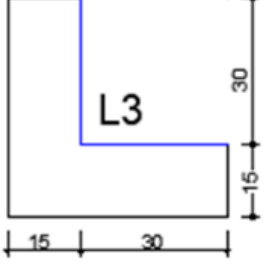
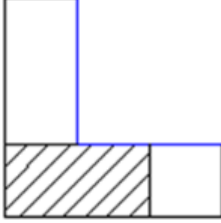
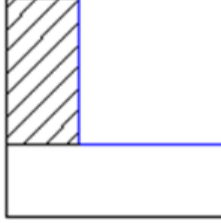
	Test 1	Test 2
 L1		Not required (Symmetry)
 L2		
 L3		

Figure 3.3: Illustration of the combination of base and dummy models to cover the entire non-rectangular shape.

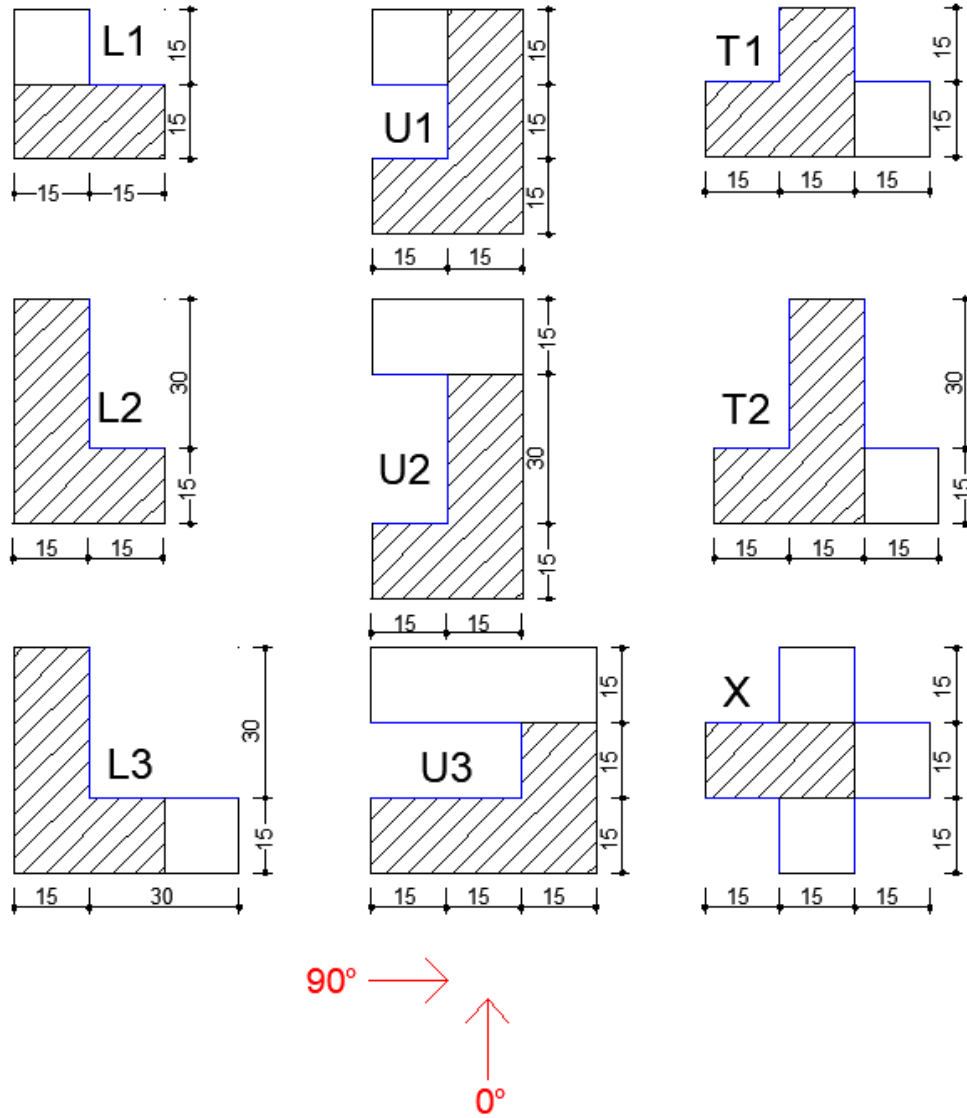


Figure 3.4: Plans of the tested models with the reference wind directions, dimensions in meters (full-scale).

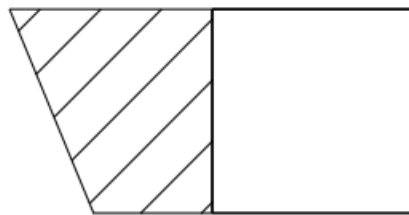


Figure 3.5: Plan of the trapezoidal model.

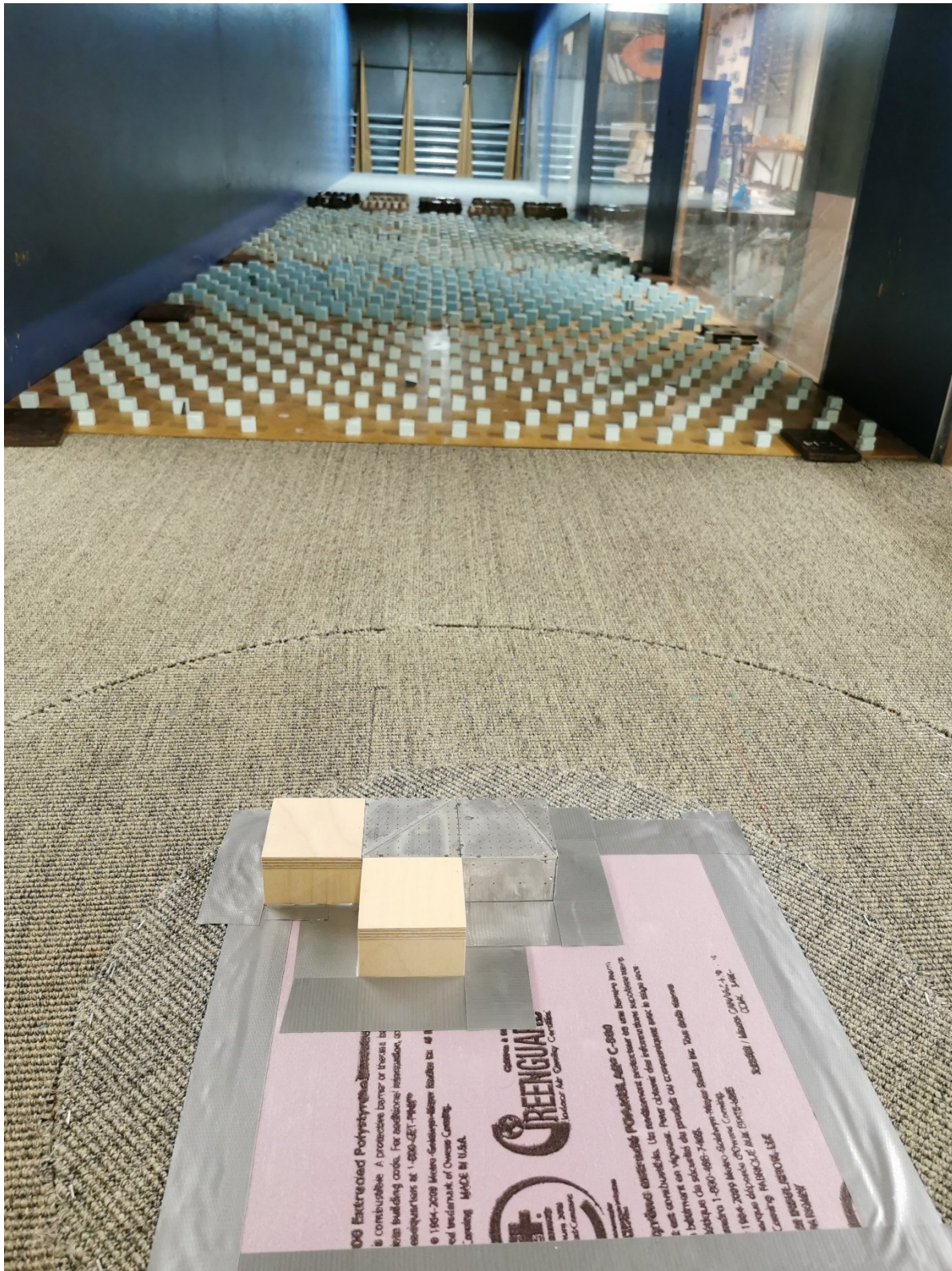


Figure 3.6: Photo of a T-shaped model.

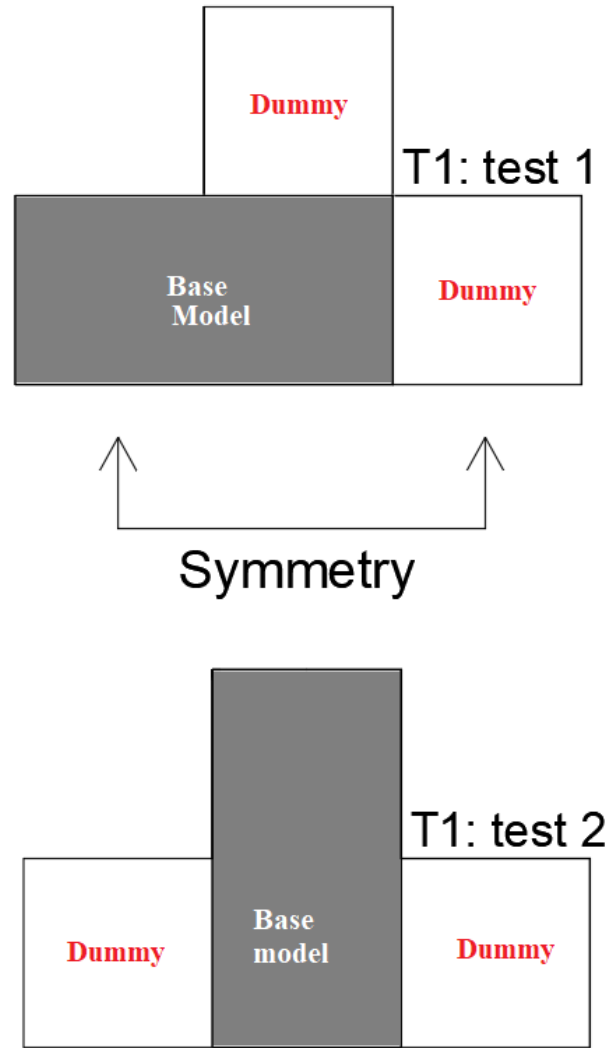


Figure 3.7: Combination of the dummy and base models to form and test the T1 configuration, plan views.

3.2 Atmospheric boundary layer simulation

The non-rectangular models were tested in simulated open country terrain in the wind tunnel. This exposure was chosen because the primary goal of the current study is to propose design provisions for non-rectangular buildings. Therefore, the wind tunnel was prepared to obtain a wind profile

that reflects the full-scale conditions. Figure 3.8 shows the longitudinal wind speed and turbulence intensity profiles in the wind tunnel; the wind speed profile has a power-law exponent, α , of 0.14, representing an open country exposure. Figure 3.9 shows good agreement of the longitudinal wind speed spectrum of the wind tunnel when compared with Von Karman and Davenport spectra (Von Karman, 1948; and Davenport, 1961). For wind flow simulation in wind tunnels, the wind flow characteristics in the vertical and transverse directions are not considered significant in this study. Figure 3.10 presents the open exposure setup at the wind tunnel.

ASCE 49-21, the ASCE standard for wind tunnel testing, requires the Reynolds number to be greater than 11,000 for correct wind tunnel simulation. The lowest full-scale testing height is 5 m (25 mm in the wind tunnel), and it was decided to be considered as the characteristic length for Reynolds number calculation. Based on the lowest testing height, 5 m, the Reynolds number is 15,000, which satisfies the ASCE 49-21. Consequently, the Reynolds number criterion is satisfied when any other characteristic length is considered.

Another criterion in ASCE 49-21 is to satisfy the similarity between Jensen numbers of the full-scale building and the wind tunnel model. The full-scale roughness length is suggested to be 0.03 m by the ASCE 49-21. Based on the lowest testing height (5 m in full-scale), and knowing that the estimated wind tunnel roughness length is 0.07 mm (evaluated using the logarithmic law), the ratios can be calculated as follows:

$$\left(\frac{L_b}{z_o}\right)_{full-scale} = \frac{5\text{ m}}{0.03\text{ m}} = 167,$$

$$\left(\frac{L_b}{z_o}\right)_{model(1:200)} = \frac{25\text{ mm}}{0.07\text{ mm}} = 357$$

The Jensen number of the model is about double the full-scale Jensen number. However, ASCE 49-21 allows the Jensen number similarity to be satisfied within a factor of 2 to 3 to reflect the uncertainties associated with estimating the roughness length. Further, the wind tunnel testing standard limits the blockage ratio to 5%. The maximum blockage ratio of the testing models was estimated to be 1%.

Satisfying both the Reynolds number and the Jensen number standard criteria was the primary reason for adopting the 1:200 length scale. Considering a full-scale height of 5m, smaller models (e.g., 1:400) would result in a Reynolds number less than 11,000, and larger models would violate the Jensen number criterion.

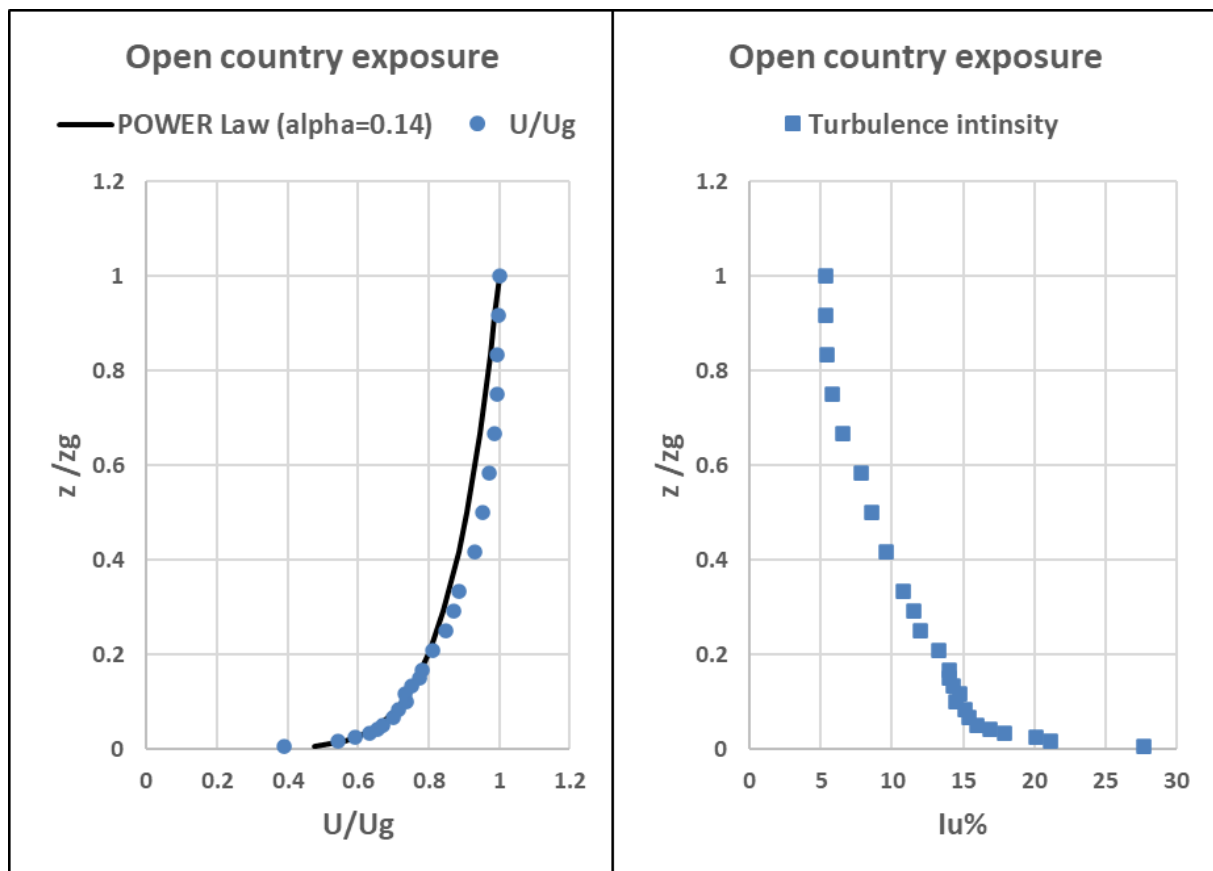


Figure 3.8: Wind speed and turbulence intensity profiles in the wind tunnel.

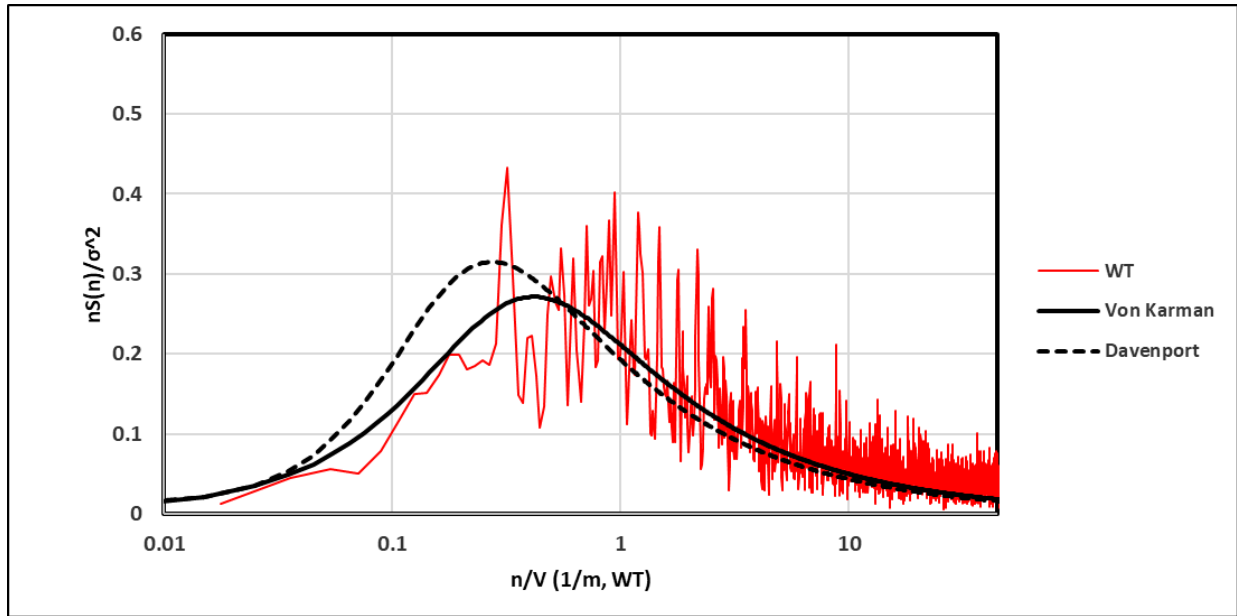


Figure 3.9: Longitudinal wind speed spectrum compared with Von Karman and Davenport spectra.



Figure 3.10: Photo of the wind tunnel (an open exposure setup).

3.3 Pressure measurements

The instantaneous pressure at instant t , $P(t)$, in the wind tunnel was scanned at a frequency of 300 Hz for about 30 seconds through Scanivalve Inc. pressure transducers (ZOC33, $\pm 1\%$ accuracy). The time scale, considering a velocity scale of 1:3, is estimated to be 1:67. This means that 30-second sampling duration in the wind tunnel represents 2000 seconds in the full-scale. The instantaneous pressure coefficient, for a certain tap j , $C_{pi}(t)$, was obtained by normalizing the instantaneous wind pressure by the wind velocity pressure at the roof height as follows:

$$C_{pi}(t) = \frac{P_i(t) - P_o}{0.5 \rho V_h^2}$$

where V_h is the average wind speed at the roof height, P_o is the static pressure and ρ is the air density. The roof wind pressures were quantified through two statistical coefficients, mean pressure coefficients (C_p) and negative peak pressure coefficients ($C_g C_p$). Mean coefficients are simply the statistical mean value, while the negative peak is evaluated by the standard Gumbel distribution approach. Peak pressure coefficients ($C_g C_p$) are selected by fitting 10 ordered peaks using extreme value distribution (EVD) type 1 (Gumbel distribution), $C_g C_p$ is then selected based on 80% fractile level as recommended by ISO 4354 (2009). The 10 ordered peaks are collected by dividing the record into 10 equal segments, the peak in each segment is considered and placed in order to eventually obtain 10 ordered peaks.

The area-averaged pressure coefficients were calculated for n pressure taps based on the following equation:

$$C_{p,averaged}(t) = \frac{\sum_{i=1}^n C_{pi}(t) A_i}{\sum_{i=1}^n A_i}$$

here, $C_{pi}(t)$ and A_i represent the pressure coefficient (at instant t) and the tributary area associated with tap i within the n group taps considered for evaluating the area-averaged pressure coefficient. This study used a number of adjacent pressure taps to calculate the area-averaged pressure coefficient. This varies from two to nine pressure taps at the roof corners and up to sixteen taps in the middle of the roof. This approach ensures that all possible combinations of taps are included, resulting in the highest possible area-averaged coefficients. Figure 3.11 shows an example of the tap tributary areas at roof corners of nine taps. The area-averaged pressure coefficients were calculated for 30 panel areas at the corner of the roof to include all possible combinations of adjacent taps: twelve combinations of two taps, nine combinations of three taps, four combinations of four taps, four combinations of six taps, and one combination of nine taps.

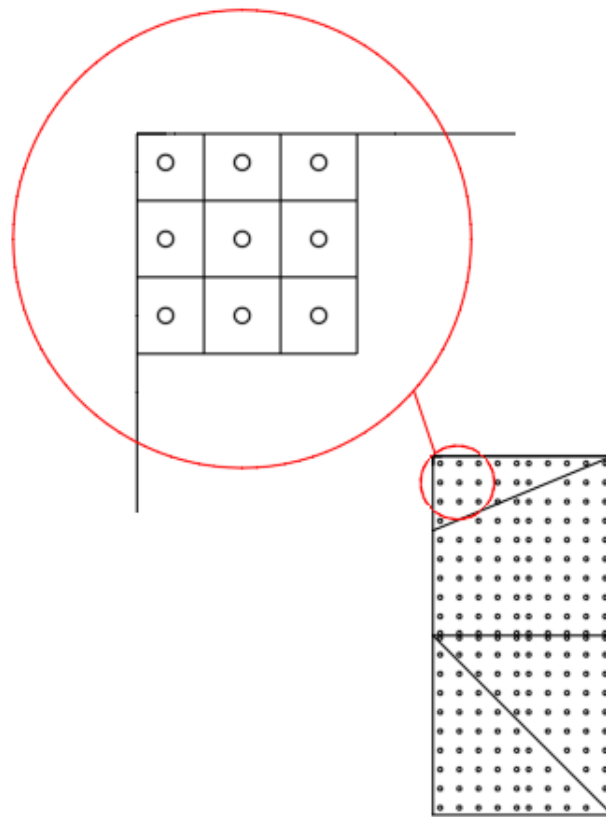


Figure 3.11: Tributary areas at the roof corner.

3.4 Validation

This section presents a validation of the experimental results through testing reproducibility and comparison of the results with past studies.

Figure 3.12 presents a comparison between the present study and Ho et al. (2005) for the mean pressure coefficients along a line in the middle of the roof, parallel to the wind. The plan dimensions and heights are indicated in the figure (full-scale, meters) for both studies. The plan dimensions are different, but the heights are comparable. Further, both models were tested in a simulated open country exposure. For x/h larger than 0.4, the means are comparable; however, small discrepancies with a value of 0.25 occurred near the leading edge. This discrepancy can be attributed to three reasons: (1) the turbulence intensity in Ho et al. (2005) is around 18% compared to around 14% in the present study, (2) the difference in the models' geometric scales used in the two studies (1:200 in the present study and 1:100 in Ho et al. (2005)); and (3) the difference in the height of the building in the two studies.

Figure 3.13 presents the contours of enveloped peaks of two tests conducted for the base model. Half of the base model was first tested with a dummy model in the other half, then the entire base model was tested again. The full-scale plan dimensions of both models are 15 x 30 m, and the full-scale height is 10 m for both models. The wind direction range for each test is indicated at the top of each contour. This was done to check the ability of the base model to reproduce the same wind pressures and to confirm that adding dummy models to the base model would not affect the wind pressure measurements. The minimum negative peak at the corner is around -5 for both models, although measured at different corners on the base model. The distribution of peaks is also similar along the edges and in the middle of the roof.

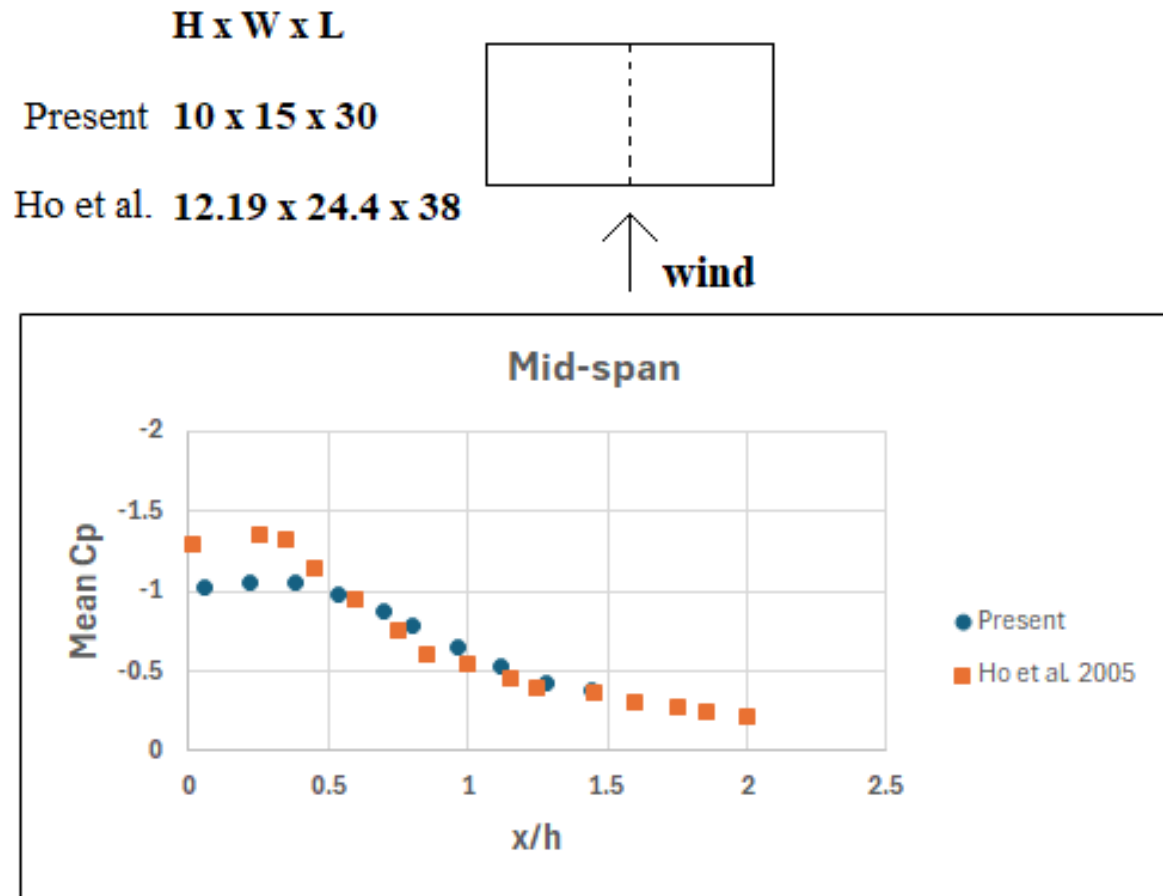
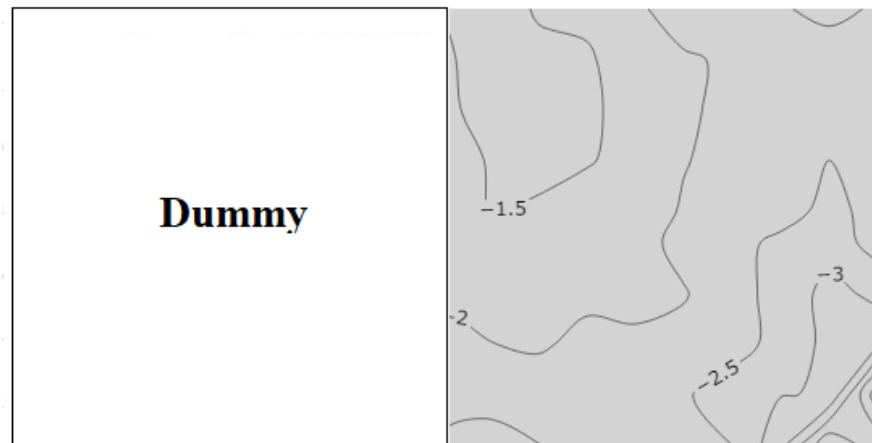


Figure 3.12: Variation of mean C_p along a line at the middle of the roof for perpendicular wind direction, comparison between the present study and Ho et al. (2005).

Wind direction: 270° to 360°



90° →

Wind direction: 0° to 90°



↑
0°

Figure 3.13: Contours of enveloped peak pressure coefficients for two tests of the base model.

For wall pressures, Figure 3.14 presents a comparison of the experimental highest mean pressure coefficients, averaged across each wall, with those reported by Morse (2003) for a perpendicular and cornering wind directions. The height of the building in Morse (2003) is 5 m, and the length scale is 1:100. the results are comparable for both wind directions, with small discrepancies in the high suction coefficients for the perpendicular case and the positive pressures when the wind blows into the reentrant corner (i.e., cornering wind direction). This is probably attributed to the difference in the length scale.

Figure 3.15 compares the pressure coefficients of two inner walls, designated as W4 and W5, of the U2 models for different wind directions. The two walls should receive similar wind pressures for a certain pair of wind directions (e.g., 0° and 180°). For example, the top two graphs show contours of the mean pressure coefficients of the W4 and W5 for 340° and 200° , respectively, with an excellent agreement between the two sets of contours. This indicates that the experimental methodology reproduces consistent wind pressures for different parts of the base model and various wind directions. the negative peak contours also show comparable results on the two walls for another pair of wind directions, 320° and 220° .

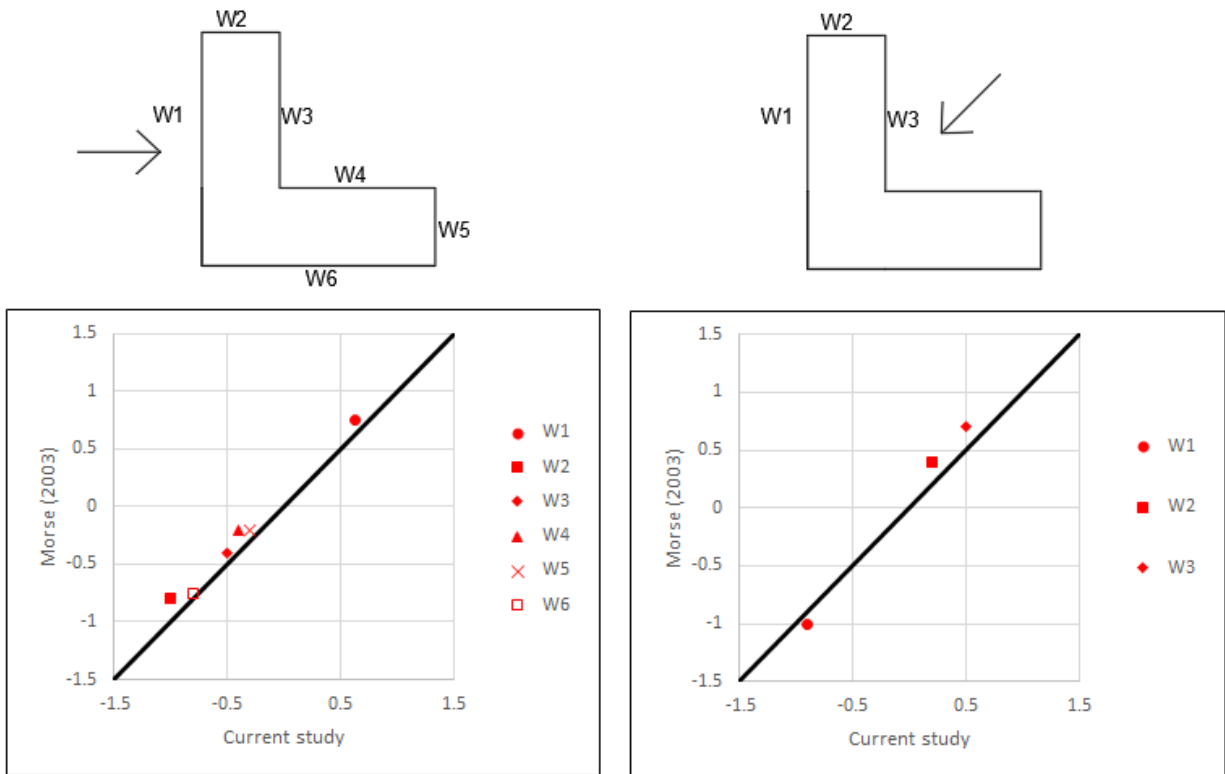


Figure 3.14: Comparison of wall mean pressures between Morse (2003) and the current study.

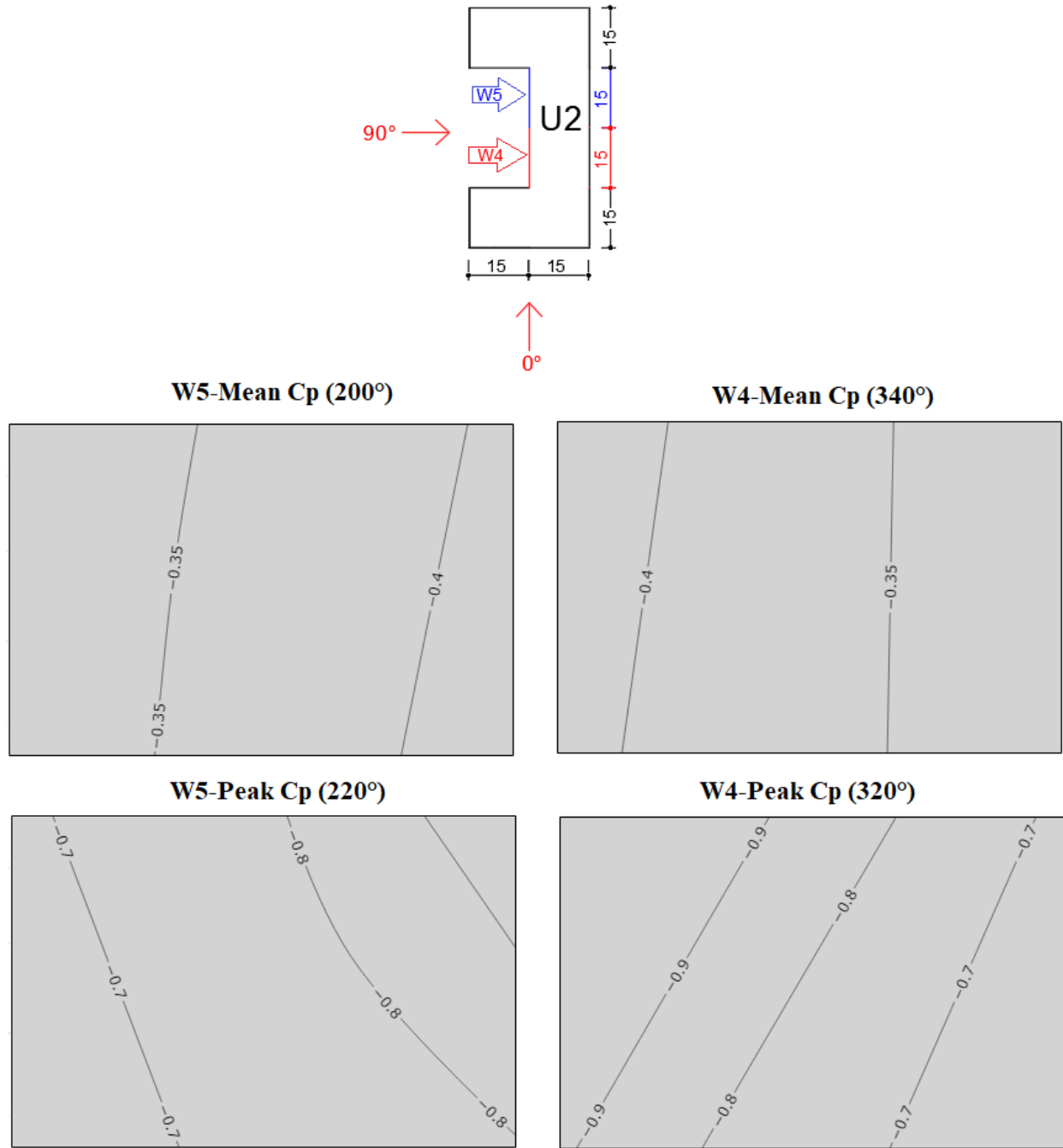


Figure 3.15: Comparison of wall pressure coefficients of the U2 model between those recorded on W4 and W5.

Chapter 4

Experimental results and discussion

In this chapter, the effects of plan dimensions and height on the roof pressures are discussed. In addition, a comparison between the roof and wall pressures of non-rectangular buildings and a typical rectangular building is included to highlight the differences between the wind loads on the two irregular and rectangular buildings.

Part of the materials presented in this chapter has been published in the Journal of Structural Engineering and Wind and Structures (Aldoum and Stathopoulos, 2025a and 2025b), and presented at two conferences (Aldoum and Stathopoulos, 2024a and 2024b).

4.1 Effect of plan dimensions

Plan dimensions are important parameters that may alter the magnitude and the distribution of wind-induced pressures on buildings (Alrawashdeh and Stathopoulos, 2015; Aldoum, 2018, Aldoum and Stathopoulos, 2020). Plan dimensions are also considered as factors in determining the end-zone-width (pressure-zone-width for components and cladding wind loads) of roof and wall in both the American standard (ASCE/SEI 7-22, 2022) and the Canadian building code (NBCC, 2020).

Figure 4.1 presents a comparison of azimuthal change of mean and negative peak pressure coefficients on an outer corner tap (indicated in the four representative shapes) for the nine models tested for a height of 10 m. It should be noted that the X shape does not include an outer corner, and therefore, the azimuthal change of mean and peak coefficients of the X shape was included for an inner corner tap. The comparison was performed in three graphs, based on shape; the X

shape was compared to the T shapes because they share aerodynamic similarities when the wind blows from 90° to 270° . For the L shapes, the wind pressure coefficients change with the same trend, particularly, for L1 and L2. This was expected as both have the same bottom leg width. The wind loads are almost identical for L1 and L2, while L3 exhibits negligible differences in means and peaks. The critical wind direction was found to be near 335° for the L models. The U shapes also exhibited similar trends in the change of mean and peak pressure coefficients with respect to the wind direction, notably, for shapes that share the same least horizontal dimension, U1 and U2. T1 and T2 show similarities in wind loads for the entire wind range with slight differences in the negative peaks. The X shape, on the other hand, experiences lower wind loads on the corner when the wind is obstructed by the bottom part of the X (i.e., from 0° to 30°), this was also observed for the fourth quarter (i.e., from 270° to 355°) of the wind azimuth range. However, the X shape experienced similar pressure coefficients, compared to the T models, when the wind direction was in the range of 120° to 270° , particularly for mean pressure coefficients. This was expected as the three shapes have a similar aerodynamic shape within that range. The minimum peaks recorded for all shapes are similar, with a value of around -4 to -4.5.

The comparison presented in Figure 4.1 shows a relatively small effect of plan dimensions on the local loads at the outer corner. Figure 4.2 presents a similar comparison but for an inner pressure tap located at the inner corner of the nine shapes for a building height of 10 m. It should be noted that there is a slight difference in the location of the pressure tap in the two cases: the corner taps are located at 0.6 m and 2.2 m (full-scale) from the short edge in Figure 4.1 and Figure 4.2, respectively, this is because of the absence of an inner tap with close proximity to the corner at the inner edges of L configurations as shown at the bottom right corner of the pressure tap layout in Figure 3.1 (b).

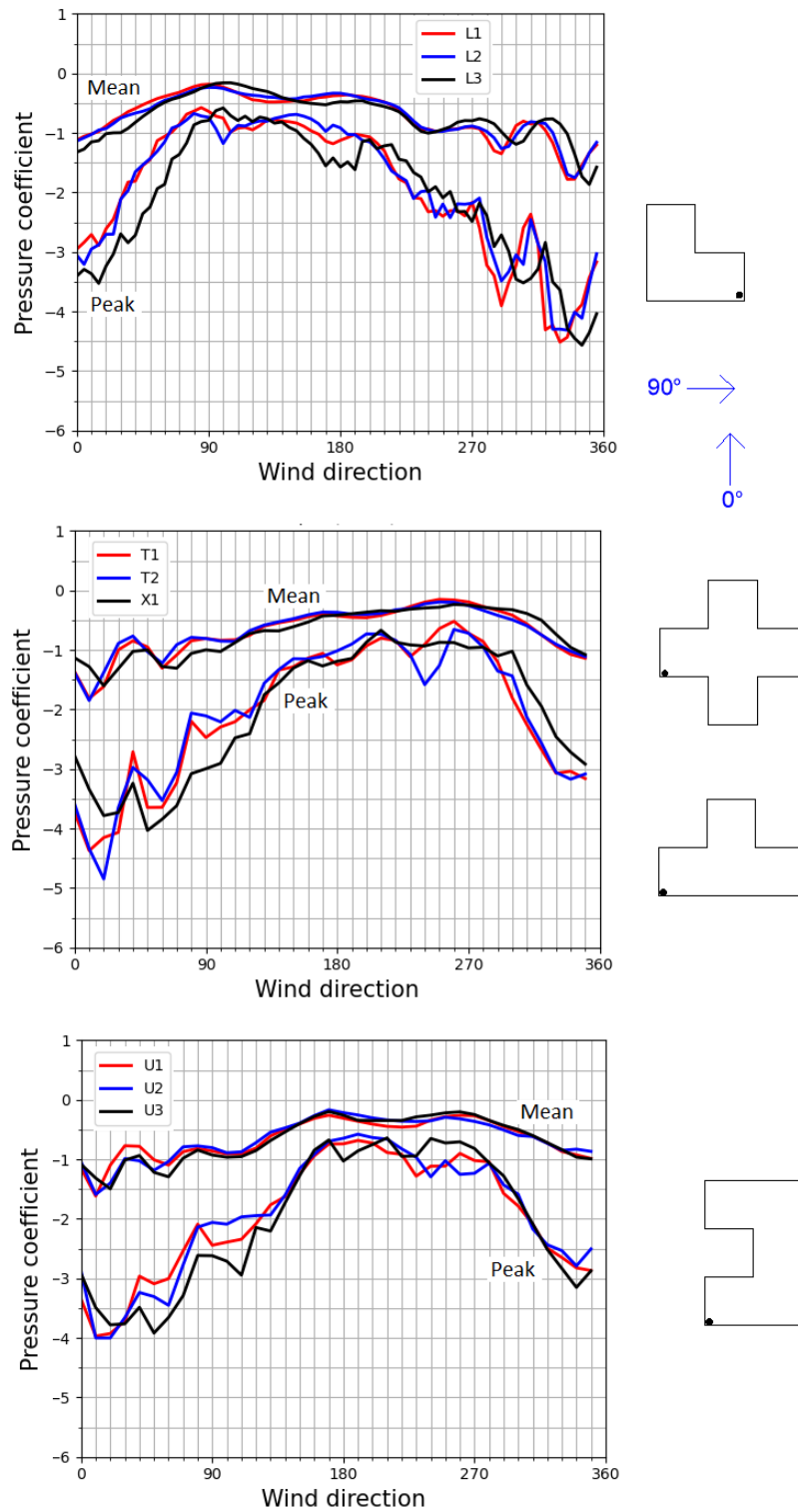


Figure 4.1: Azimuthal change of mean and peak pressure coefficient of an outside corner tap for the four shapes ($H = 10$ m).

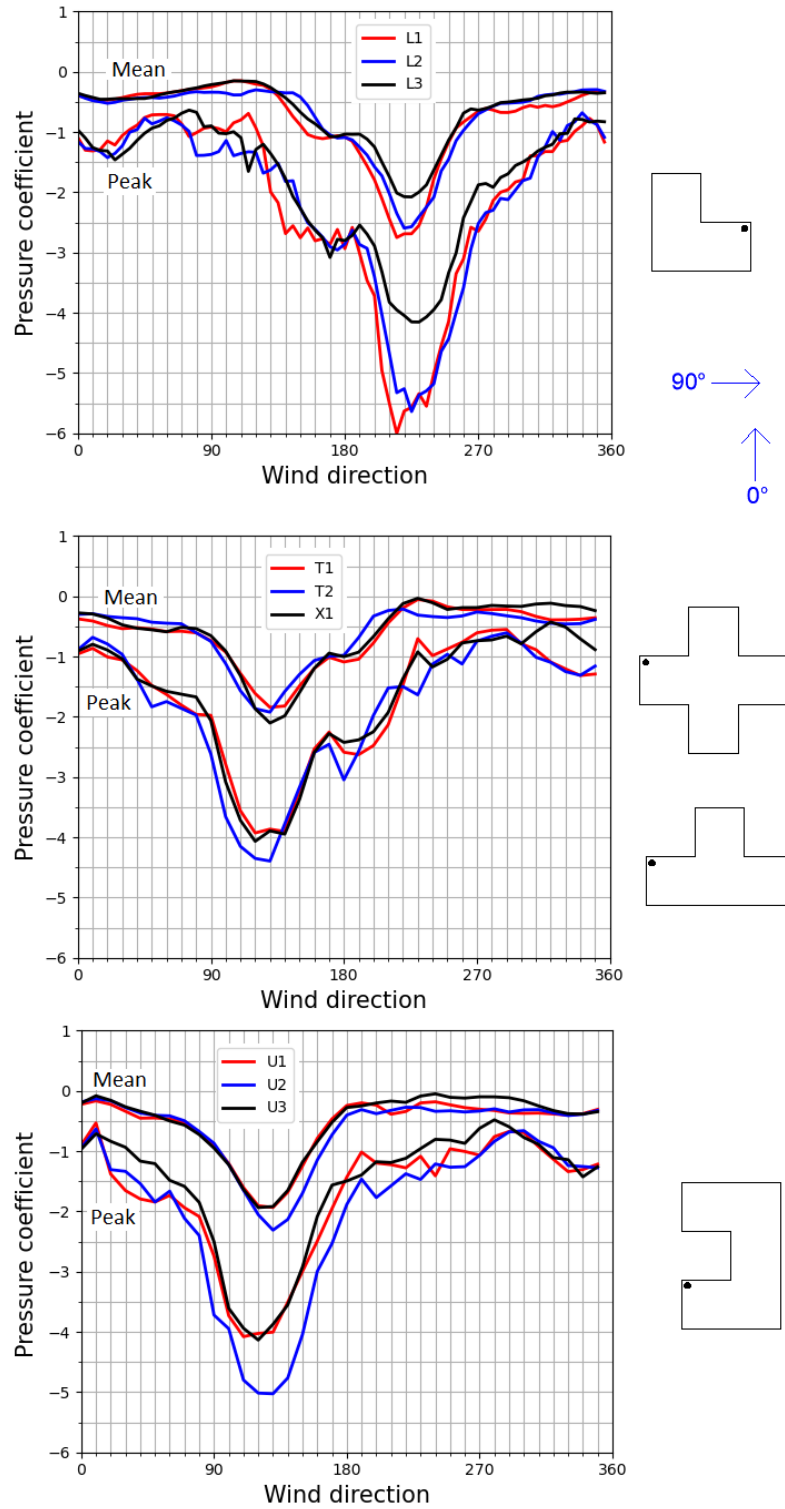


Figure 4.2: Azimuthal change of mean and peak pressure coefficient of an inner corner tap for the four shapes ($H = 10$ m).

The comparison between the three L-shaped models shows that the short-leg models, L1 and L2, experience wind loads that are significantly higher than those experienced by the long-span L3. This observation confirms that the inner corners of relatively short legs receive higher wind loads than those of the long-span legs.

This conclusion is also observed in the U-shaped configurations; for the wide recess and short edge U shape, U2, the peak reaches up to -5, and it is higher than those recorded for the narrow recess U shapes, U1 and U3, on the inner corner. For U1 and U2, and despite having the same smallest horizontal dimension, U1 experiences lower wind suctions due to its narrower recess compared to U2. This narrower recess likely positions the inner pressure tap within the wake region created by the upper leg of the model, sheltering it from experiencing a higher wind suction. Regarding the T and X shapes, the inner corners experience similar wind loads with a reduced suction on the corner of the X-shaped model in the fourth quarter of the wind azimuth range. In addition, the leg where the tap is placed has the same width for the T1, T2, and X shapes, this probably explains the similarities in mean and peak pressure coefficients observed in the comparison of the T and X shapes.

4.2 Effect of height

As mentioned previously, the L-shaped configurations, L1 and L3, were tested for three heights, 5 m, 10 m, and 20 m. The goal of targeting the three heights is to examine the impact of building height on the wind-induced loads. The effect of height is investigated in this subsection by tracing the azimuthal change of local coefficients at a critical tap in the outer corner and presenting the value and the distribution of roof envelope wind loads for the three heights. In addition, the effect of plan dimensions will be discussed again in this subsection.

The variation of mean and negative peak pressure coefficients with respect to the wind direction for L1 and L2 configurations and for three heights is presented in Figure 4.3. Generally, the mean and peak pressure coefficients are proportional to the heights, the larger the height the higher the wind load. This is evident in two troughs: the first one is when the pressure tap is windward for a cornering wind direction (i.e., wind azimuth is about 45°). The mean and negative peak C_p 's of the 20 m high building model of L1 are about -3 and -6, respectively, while those associated with the L1 model with heights of 10 m and 5 m are lower with peak values of around -5 and -4, respectively. A similar observation is also noted for L3 for wind direction of around 45° , but it can be noticed that the evaluated means and peaks are slightly higher than those of L1. The second trough occurs at a wind azimuth of around 225° ; the opposite direction of the first trough. The pressure tap location, in this case, is expected to be within a flow reattachment area for a rectangular building, experiencing minimal suction. However, for the L configurations, the tap is relatively close to the reentrant angle, making it positioned under flow separation for wind directions in the range of $225^\circ \pm 20^\circ$.

The data presented in Figure 4.3 provided insights based on wind pressure measurements on a single point. It is also essential to analyze the effect of height by tracing the change in pressure coefficients all over the roof. The next four Figures present contours of enveloped mean and peak pressure coefficients (i.e., minimum among all wind directions) for L1 and L3 and the three heights. It should be noted that the dummy areas represent the part of the model not tested in the wind tunnel and can be concluded by symmetry.

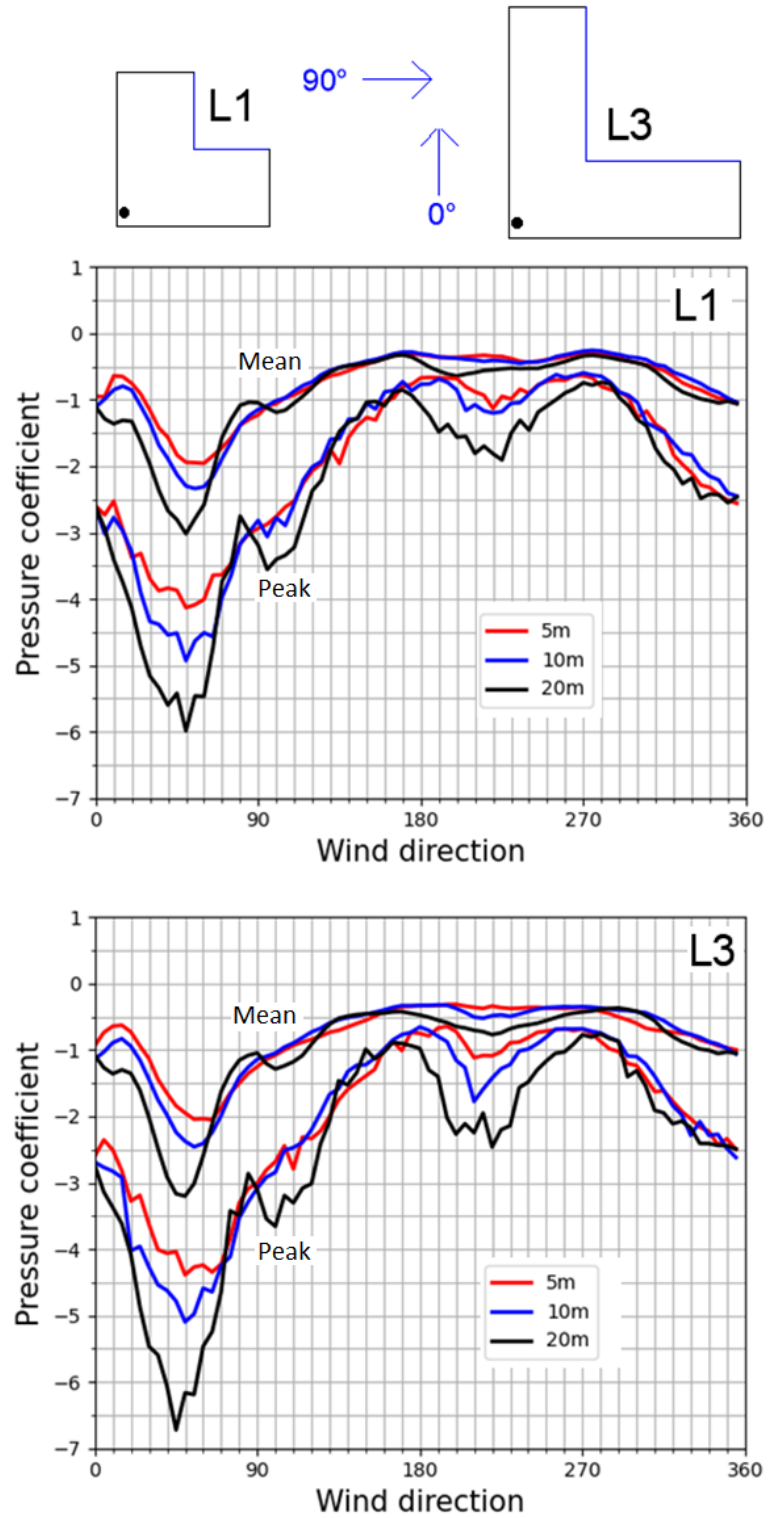


Figure 4.3: Azimuthal change of mean and peak pressure coefficient of a corner tap for three heights.

Based on Figure 4.4 and Figure 4.5, mean pressure coefficients tend to increase with building height, this applies to all roof zones, particularly the corner zone. Considering the bottom left corner, for instance, the means are about -2, -2.5, and -3 for models with full-scale heights of 5 m, 10 m, and 20 m, respectively, resulting in a percent increase of about 15%. Similar trends can also be found on the other corners and edges.

An evident observation can also be found in the middle of the roof of both L1 and L3, where a large area with mean pressure coefficients less in magnitude than -0.75 is only observed on the roof of 5 m high building models, especially for L1. Additionally, the high pressure coefficients extend over larger areas as the height increases. This is readily apparent on the inner edges, as most of the edge zone is covered with means higher than -1.25 (in magnitude) for the 20 m high building models.

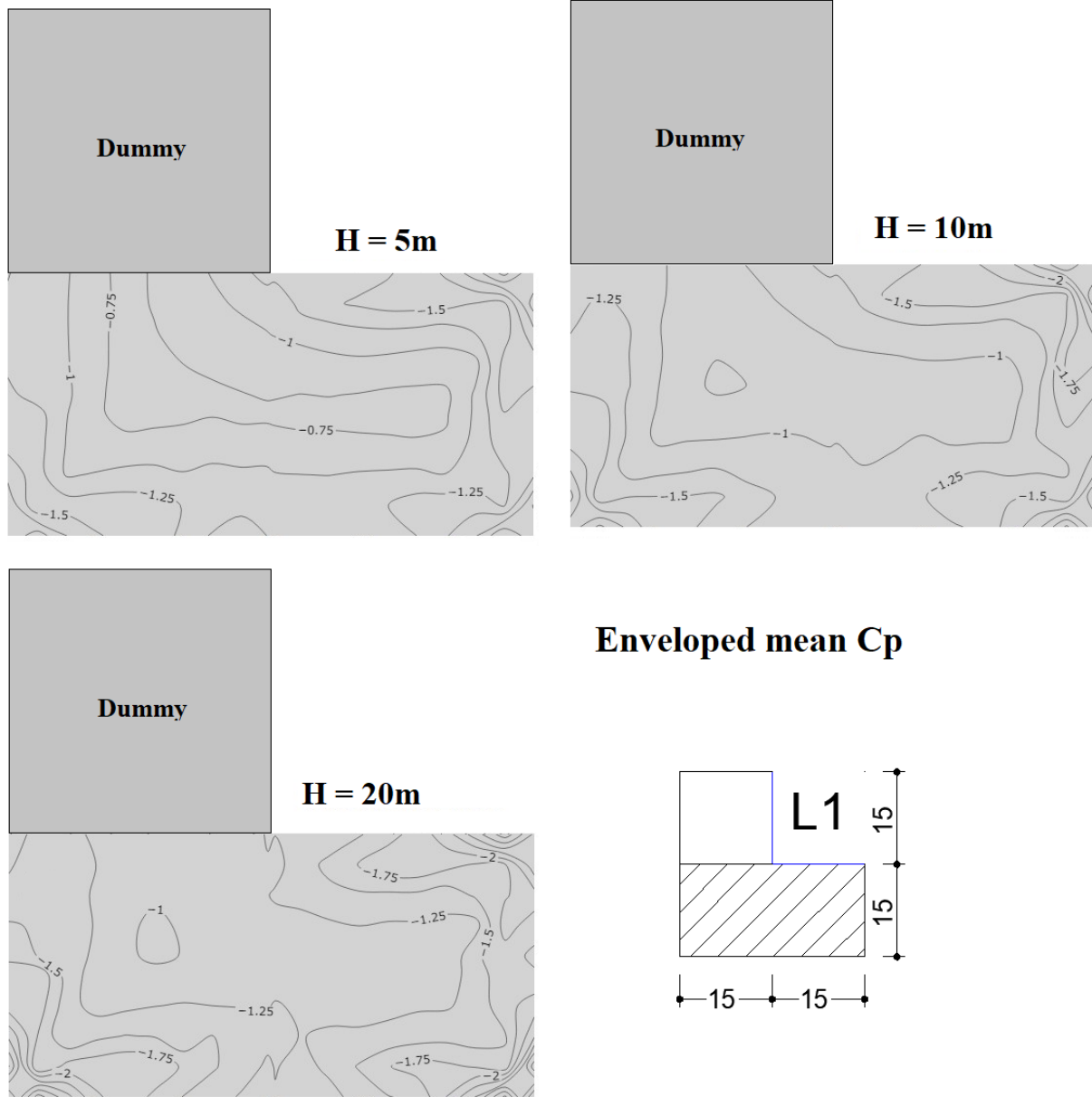


Figure 4.4: Contours of enveloped mean pressure coefficients for L1 with different heights (dimensions in meters, full-scale).

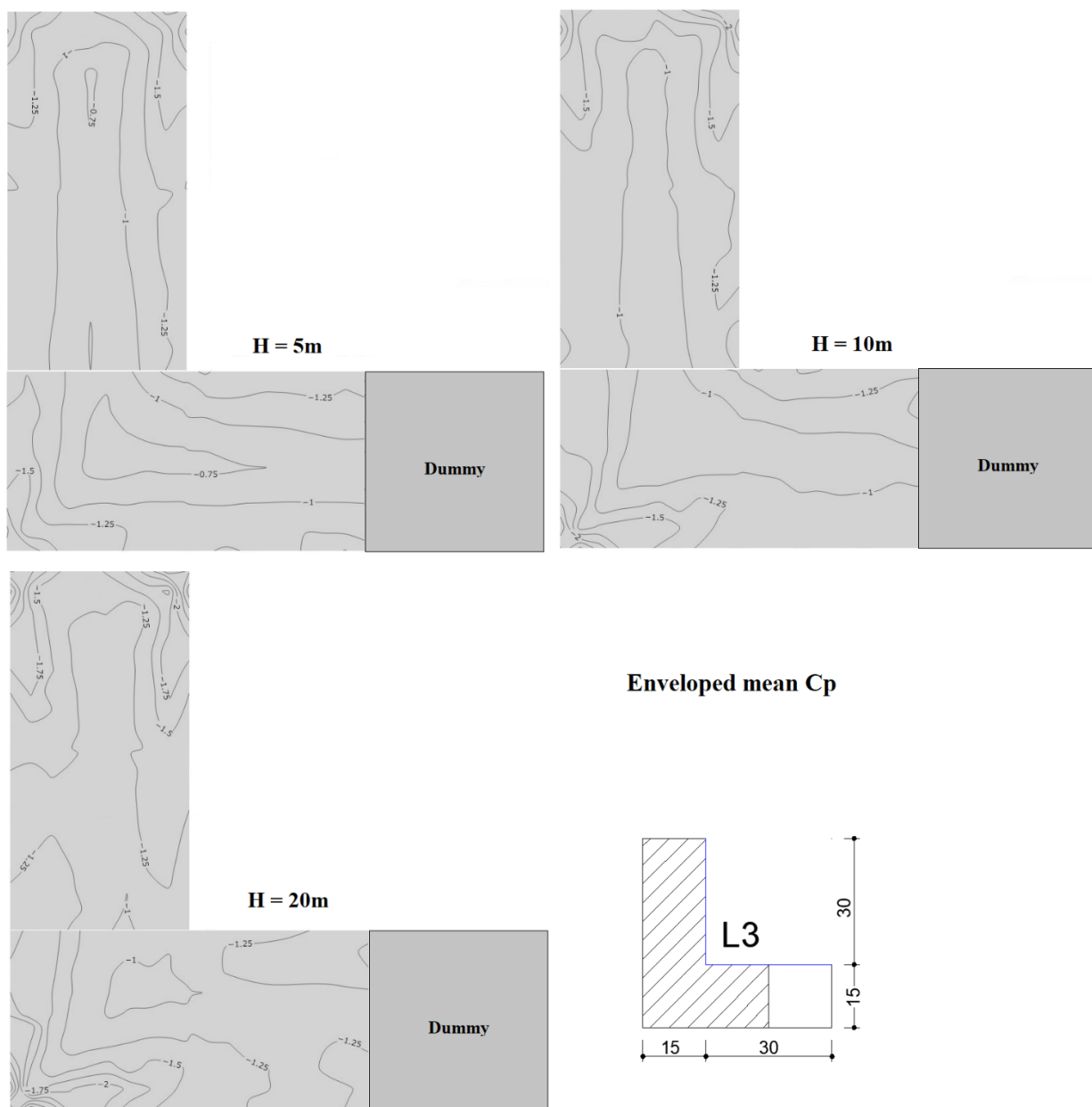


Figure 4.5: Contours of enveloped mean pressure coefficients for L3 with different heights (dimensions in meters, full-scale).

The peaks in Figure 4.6 and Figure 4.7 also indicate that the taller buildings experience higher loads. Besides the observations made for the contours of mean pressure coefficients, the peaks provide two additional insights. The first one is the high negative peaks on the edge zone of models with a height of 5 m, suctions with a value less than -3 almost cover the entire outer edge areas. This observation is not detected for the taller models, heights of 10 m and 20 m, and it is probably attributed to the increased turbulence at the lower height (5 m). The second point involves comparing wind peaks on the inner edges and corners and those on the outer edges and corners. It can be noted that the peaks are higher on the inner perimeter with a value of around 1 (about 20% increase). In addition, the contours of peaks provide extra insights into the effect of plan dimensions. In the previous section, the inner corner at the shorter leg was found to experience higher peaks, and this is evident in the contours of peaks. Additionally, the contours in the same Figure show that the peaks tend to be higher on the long legs near the reentrant corner compared to those on the short legs. For example, the 10 m high L1 and L3 buildings recorded peaks of around -3 and -4, respectively, near the reentrant corner.

Regarding the roof zonal systems of flat roofs, NBCC 2020 relates the end-zone-width (i.e., size of pressure zones) to both the least horizontal dimensions and height, while ASCE 7-22 recommends the height only for the determination of the size of the pressure zone. Although both references do not provide a roof zonal system dedicated to nonrectangular buildings, the wind tunnel findings provided in the mean and peak contours support the recommendations of ASCE 7-22, as the extent of the peaks depends mainly on the height of the building models and is almost independent of the plan dimensions. This can be observed in Figure 4.6 and Figure 4.7, considering the same height, the area in which the corner high peaks extend is almost the same for the small model, L1, and the long model, L3, which indicates the insignificance of the plan

dimensions to determine the size of the pressure zones. On the other hand, both models, L1 and L3, present a significant rise in the area in which the high peaks extend on the edges and corners as the height increases.

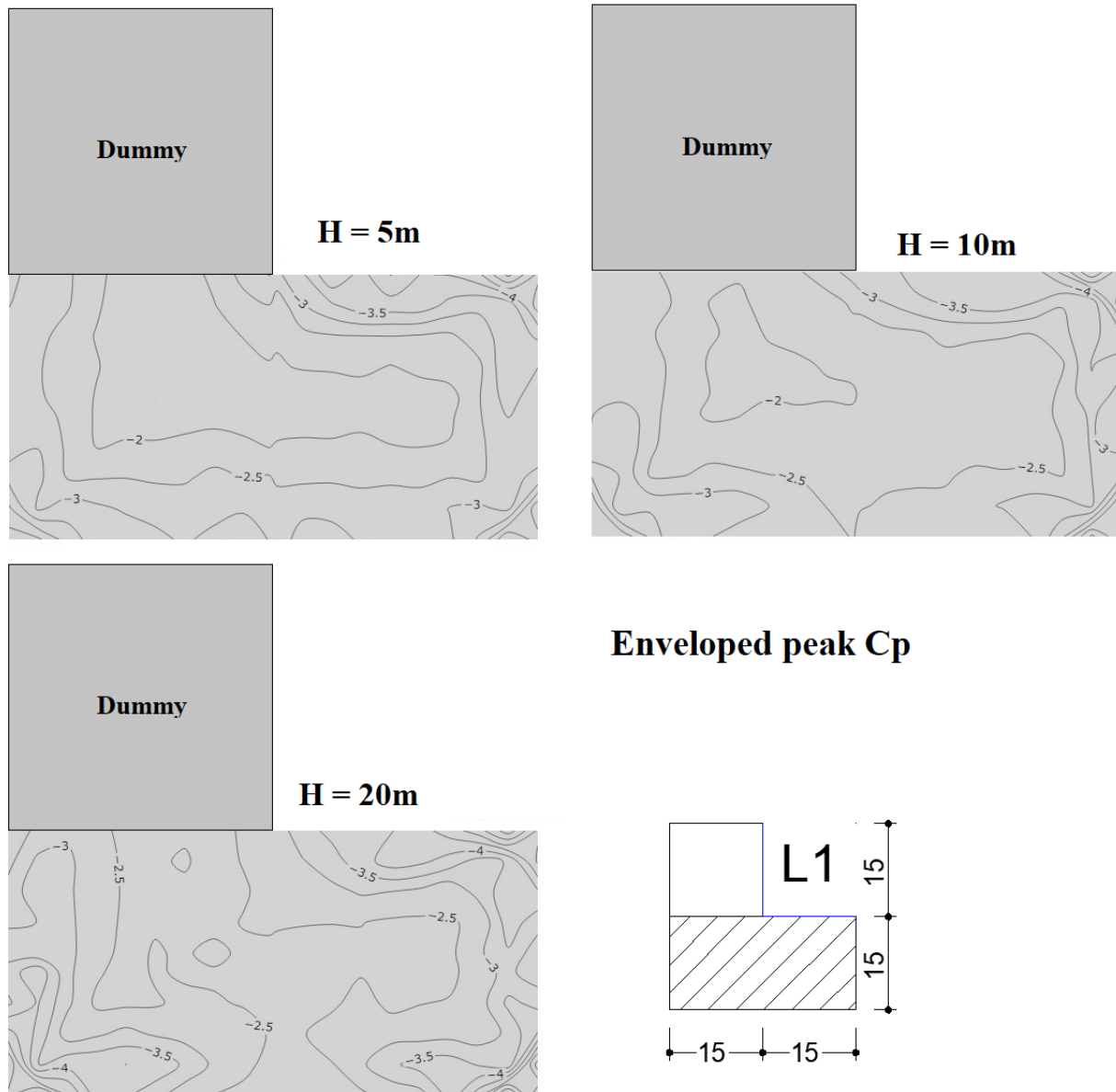


Figure 4.6: Contours of enveloped peak pressure coefficients for L1 with different heights (dimensions in meters, full-scale).

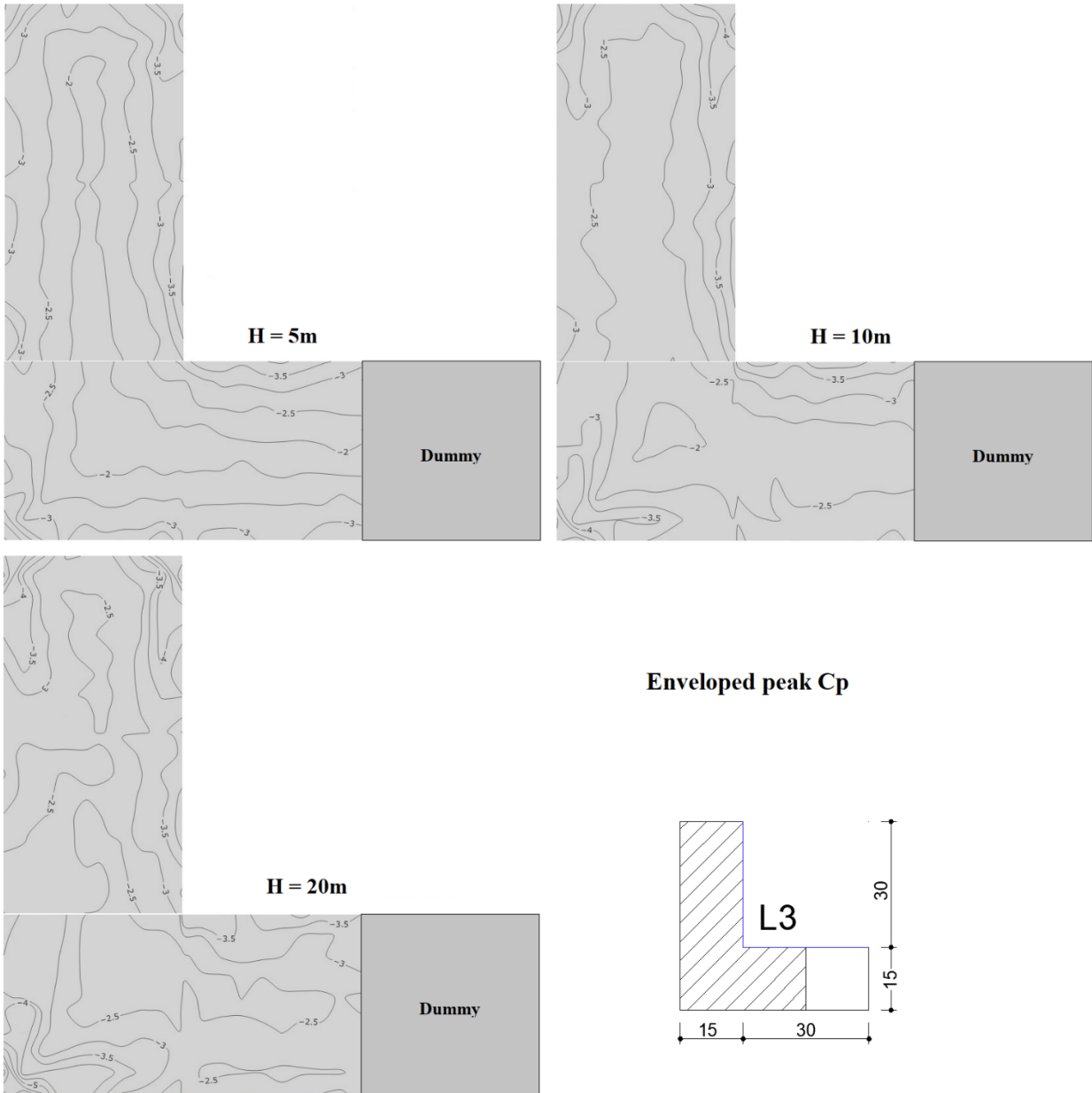


Figure 4.7: Contours of enveloped peak pressure coefficients for L3 with different heights (dimensions in meters, full-scale).

Furthermore, recent research that involved Full-scale wind load measurements and wind tunnel testing on buildings with rectangular plans and different roof slopes and shapes recommended merging the corner and edge zones into a single perimeter zone (Chavez et al., 2022; Aldoum et

al., 2023; Chavez et al., 2023; Geleta et al., 2024). The edges in Figure 4.6 and Figure 4.7 include high peaks that are close in value to those on corners, particularly the inner edges, and merging the corner and edge zone would be an applicable recommendation for the non-rectangular buildings.

4.3 Comparison with a typical rectangular building

This section starts with presenting contours of enveloped negative peak pressure coefficients for a roof of a rectangular building, as shown in Figure 4.8, and for a wind azimuth range of 0° to 90° . The rectangular building is 30 m x 15 m in plan and was tested in the wind for a height of 10 m and the same terrain conditions. Figure 4.8 indicates that the highest local peak was developed at the corner with a value of around -5, while the edge zone experienced less suction with peaks ranging from around -2.5 to -3.5.

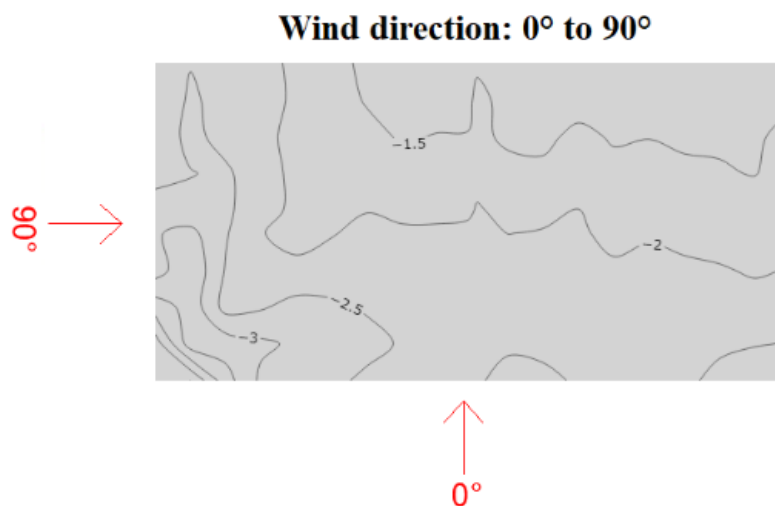


Figure 4.8: Contours of enveloped negative peak pressure coefficients for a 10 m high rectangular roof (30 m x 15 m)

Figure 4.9 presents the local enveloped wind load distributions for four nonrectangular models (L1, T1, U1, and X). Unlike Figure 4.8, these models were tested for a wider wind direction range (0° to 350°). Additionally, Figure 4.9 includes areas where pressure can be inferred by symmetry, indicated as "dummy".

The contours indicate that the highest experimental peak experienced by the outer edges of the L configuration is around -3, which is comparable to peaks developed on the rectangular roof edge. However, the inner edges experience higher suction, exceeding -4. In addition, the distribution of peaks greater than -3.5 extends over almost the entire inner edge. On the other hand, the local peaks are with value of almost -5 on the left outer corner and a bit greater than -5 on the right short-edge corner. Therefore, it can generally be said that the outer corners of the L1 configuration receive loads similar in value to those experienced by the rectangular roof corner.

The inner corner, however, experienced a higher peak of around -6, and relatively higher peaks cover the entire inner corner. This also applies to the short-leg inner corner of L2, in which the loads are higher than those of the outer corner and the corner of the rectangular building.

For the other two L configurations, L2 and L3, similar conclusive observations were made when comparing the local wind loads on the inner and outer edges, and edges of the rectangular building. However, the inner corners of L3 and the inner corners on the long leg of L2 experience local peaks similar to those of the outer corners and the rectangular buildings.

Similar observations were also made for the T- and X-shaped configurations; the pressure values and distributions on the inner edges and corners are higher than loads on the outer edges and corners and those of the rectangular building. This is, of course, expected, at least for the local pressures, as the L-, T-, and X-shaped buildings share the same aerodynamic geometry on the

inner edges side. Regarding the U-shaped configuration, building edges exhibit a pressure distribution trend that bears resemblance to the L shape; however, it experienced even higher suction of up to -5 on the inner edges as shown for the U1 contours, this is likely attributed to the increased turbulence of the flow in the recess of the U-shaped building. For the corners of the narrow recess U-shaped buildings, U1 and U3, it was found that the local peaks of the inner and outer corners, and the corner of the rectangular building are generally the same with a magnitude of around -5, while for the wide recess U configuration, U2, the peaks of the inner corner are higher than the outer corners peaks and those of the corner of the rectangular building.

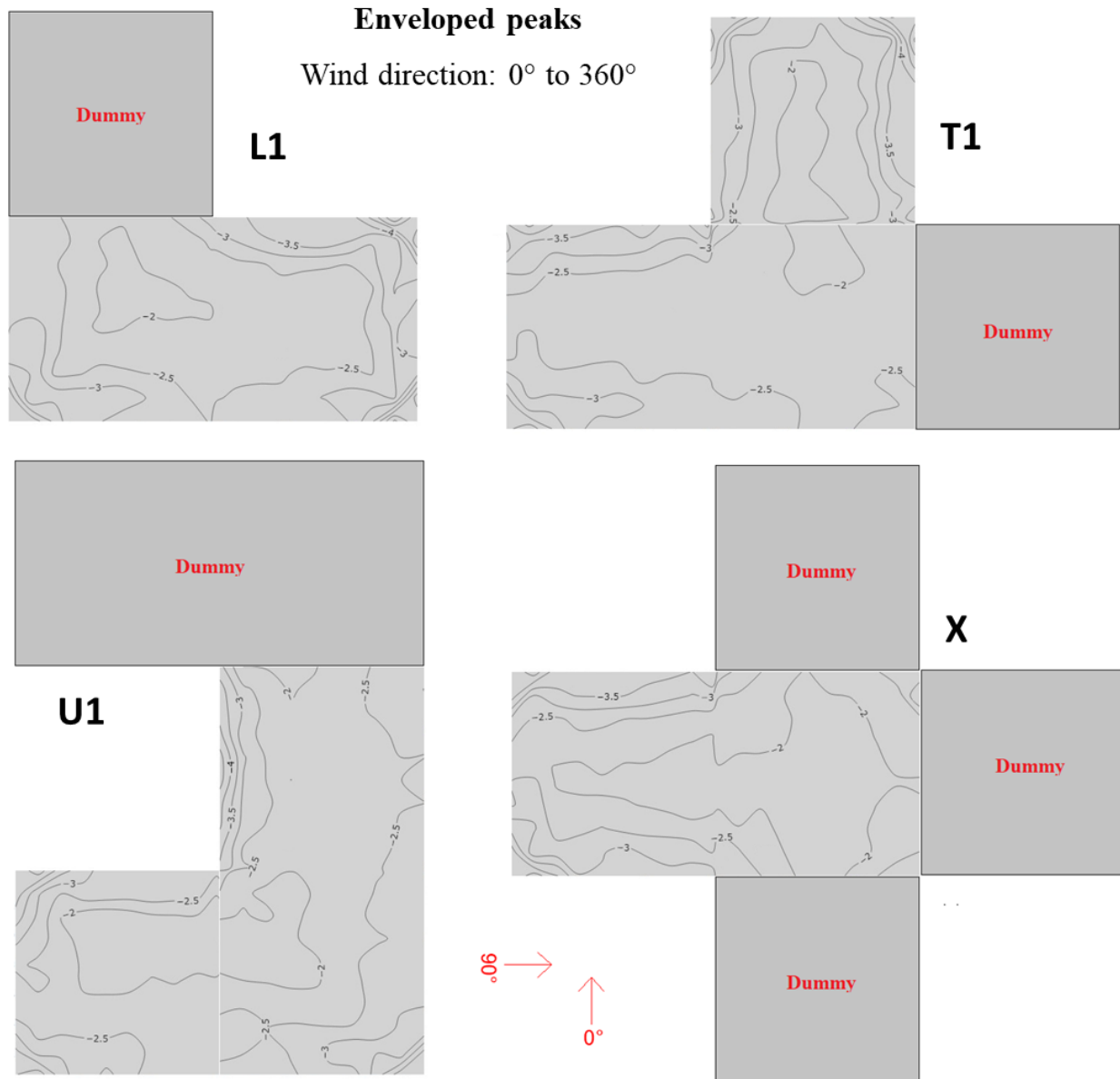


Figure 4.9: Contours of enveloped negative peak pressure coefficients.

Figure 4.10 and Figure 4.11 show the enveloped area-average peak pressure coefficients for the corner and edge zones for all configurations, respectively. All graphs consist of area-averaged peak curves for the inner and outer corners or edges and the rectangular building counterparts, except the bottom-right corner graphs which compare the T1 and the X curves; this is because the X shape does not have outer corners and edges. In addition, the plots include several tributary

areas from 0.1 m^2 to 25 m^2 , the peaks associated with 0.1 m^2 are local peaks and are included alongside area-averaged peaks to allow a side-by-side comparison of the local and area-averaged peak pressure coefficients. Furthermore, the inner and the outer zones are marked in blue and black, respectively, as indicated in the key shapes.

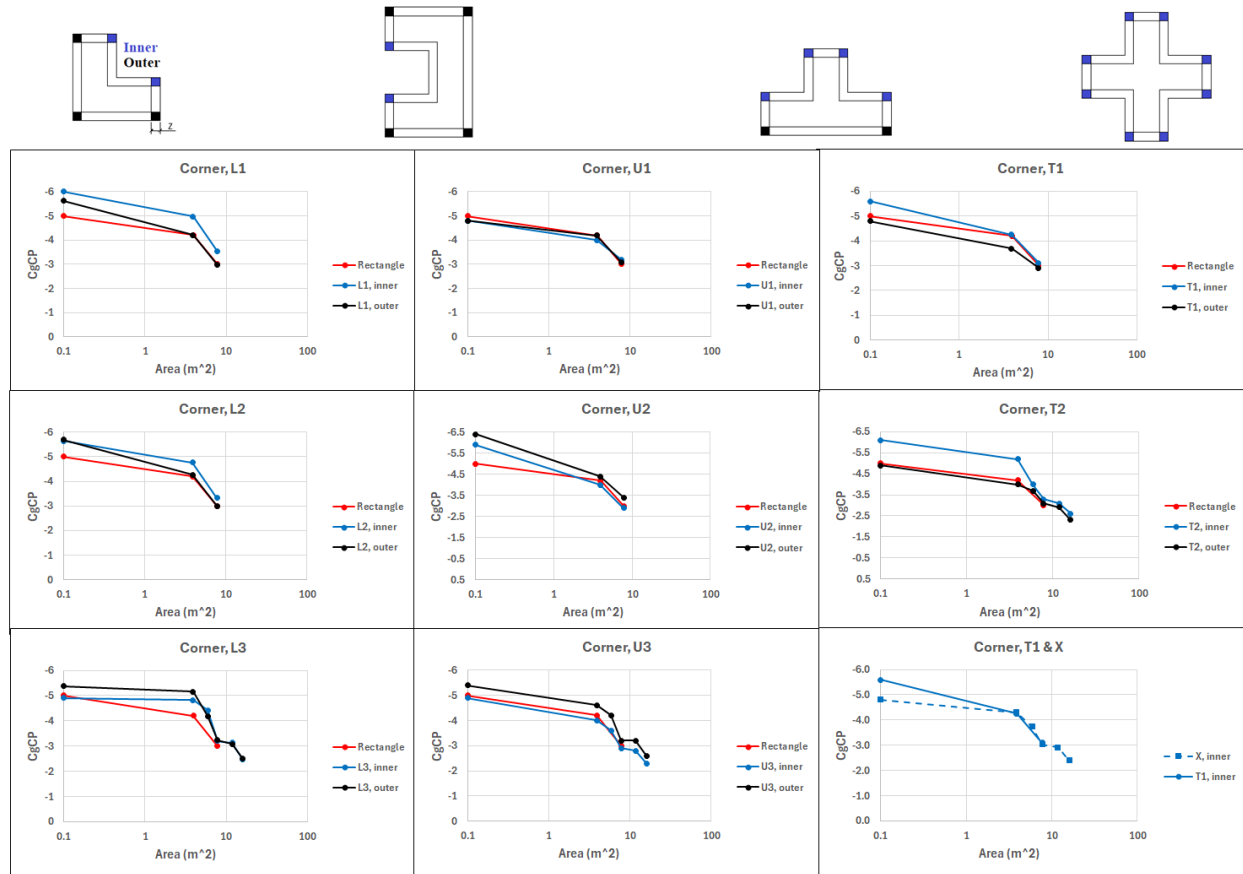


Figure 4.10: Enveloped area-averaged peak pressure coefficient, C_{gCp} , corner zone.

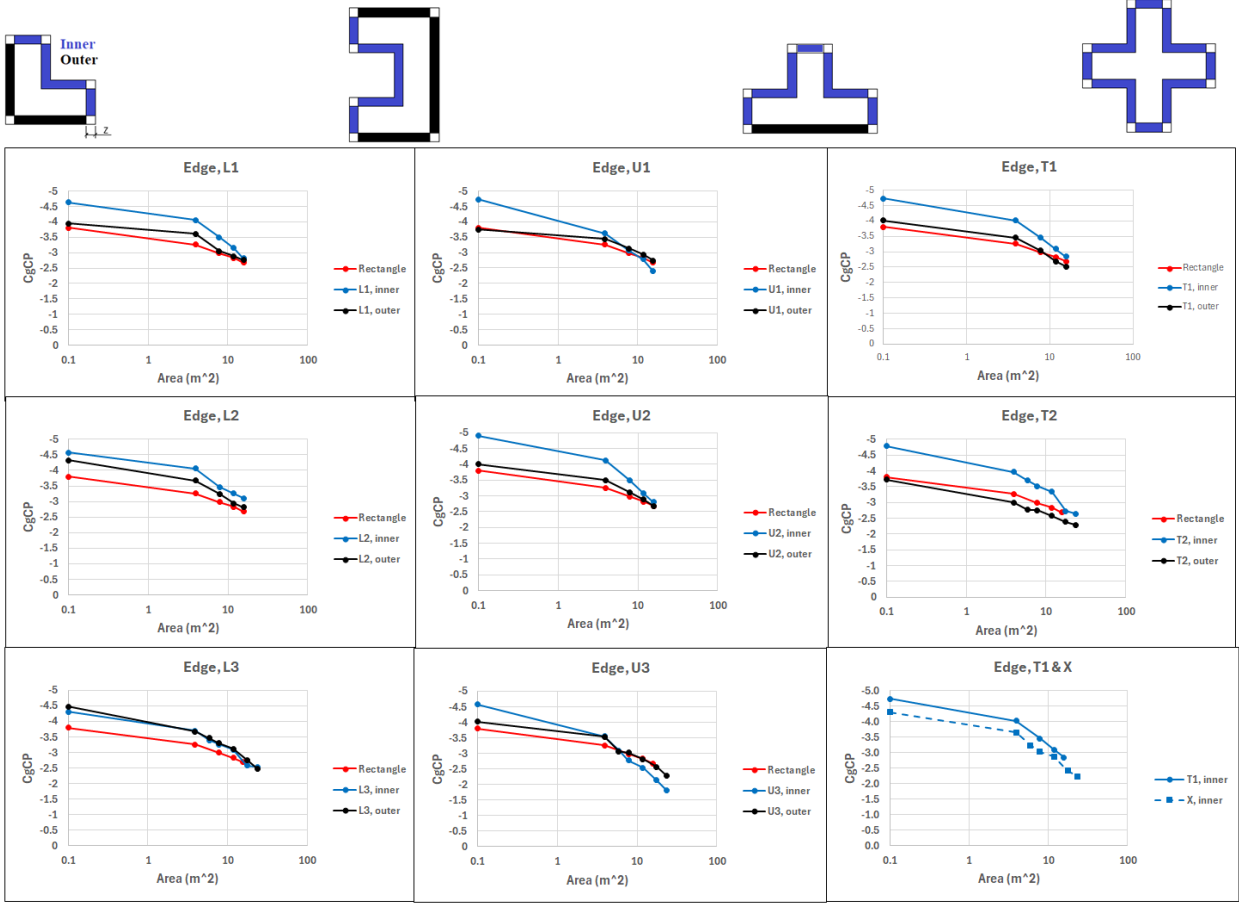


Figure 4.11: Enveloped area-averaged peak pressure coefficient, C_{gCp} , edge zone.

The presented comparison indicates that the inner corner zones of L1 and L2 configurations experienced significantly higher area-averaged wind pressure compared to the outer corners and rectangular benchmarks. On average, the inner zone peak pressures were 18% higher for L1 and 11% higher for L2. On the other hand, the inner edge pressures of L1 showed an average increase of around 10% compared to the outer edges and up to 18% compared to the edges of the rectangular building. Unlike L1 and L2, the L3 configuration showed a surprising pattern. The corner local peaks are comparable, but the area-averaged peaks are almost identical for the inner and outer corners with a significant increase compared to the rectangular building corners. Nevertheless, for an area of around 8 m^2 , the enveloped peak of the rectangular model corners

is equal in value to those of the inner and outer corners. The inner and outer edge curves of L3 displayed no difference with negligible discrepancies in the local peaks and the peak associated with an area of 18 m^2 . Compared to rectangular building edges, these edge peaks on L3 were generally 7% higher. While the L2 model's outer corner pressures were similar to those of a rectangular building, its outer edges experienced higher wind loads compared to the rectangular edges. Therefore, to ensure a conservative estimate for wind loads on the L2 model, the findings observed for the larger L-shaped model (L3) can be extended to L2.

The U configurations showed interesting wind pressure patterns; notably, the inner local peaks are higher than those of the outer perimeter and the rectangular building, particularly, the edge local peaks. The corner of U1 is an exception, where all three peaks are quite similar. In addition, the area-averaged peaks of all three configurations were similar on the inner, outer and rectangular building corners, with the outer peaks marginally exceeding the two other curves in U2 and U3. The comparison of the edge wind pressures showed comparable area wind pressures for the narrow recess shapes, U1 and U3. Conversely, the inner edge wind pressures of the wide recess U2 model displayed an average increase of around 10% compared to the outer edges and edges of the rectangular model. These findings indicate that the loads of the inner edges of the narrow recess U-shaped buildings are comparable with those of the outer edges and the edges of the rectangular buildings; however, if the recess is large (roughly double the size of the short edge), the inner edge loads tend to be higher than the outer edges and the rectangular building counterparts. In addition, these findings undoubtedly demonstrate the importance of using area-averaged pressure coefficients to quantify wind loads. Relying solely on local pressure values would have led to inaccurate conclusions, particularly for the U-shaped configurations.

The X-shaped model, featuring only inner corners and edges, was compared to the T1 configuration since the T1 aerodynamic geometry shares similarities with the X-shaped model. For T1, the local inner corner peak was the highest, exceeding both the rectangular and outer corner peaks, while the area peaks of the inner corners are identical to the rectangular peaks and around 10% higher than the outer corner peak. Regarding the inner edges of T1, the area wind pressure along the inner edge was 14% higher than the outer edges and the rectangular building edges. The T2 configuration experienced significantly higher wind pressures on both the inner edges and corners compared to the rectangular building and the outer perimeter of the T2 model itself. The increase was with an estimated 12% rise in pressure at the corners and a more pronounced 20% increase along the inner edges. The X-shaped model exhibits corner area peak pressures that are identical to those observed in the T1 configuration. However, the edge peak pressures of the X-shape are slightly lower than those of the T1. To ensure a conservative design approach for the X-shaped model, it can be assumed that the X-model wind loads are comparable to those of the T1 configuration.

Wall pressure distribution of a typical rectangular building for a perpendicular wind direction consists of positive pressures on the windward wall and negative pressures on the side walls and the leeward wall. This can vary for other wind directions, such as cornering wind directions; however, the pressure distribution is generally positive on the upwind walls and negative downwind. It is important to investigate and compare the distribution of wind pressures on the walls of typical rectangular buildings and those of non-rectangular buildings.

Figure 4.12 compares the azimuthal change of mean, minimum, and maximum pressure coefficients between a typical rectangular model and those of two L-shaped models and two U-

shaped models. The comparison was performed for three pressure taps: two taps in the outer and wall of the non-rectangular models, Taps a and b, and one pressure tap on the short wall of the L shapes (Tap c); the corresponding taps on the rectangular building are shown in the same Figure.

For the L shapes, the mean, minimum and maximum pressure coefficients of Taps a and b are comparable with those of the rectangular model. However, the tap on the short wall indicates higher minimum C_p 's on the short walls of the L-shaped model, and values of the mean and maximum C_p are more or less comparable. It should also be noted that the azimuthal change of pressure coefficients of the rectangular model walls is similar to that of the L-shaped model walls. For the U shapes, the comparison was conducted for Tap a only, and it was found that the pressure coefficients of the walls of the U shapes are comparable with those of the wall of the rectangular model.

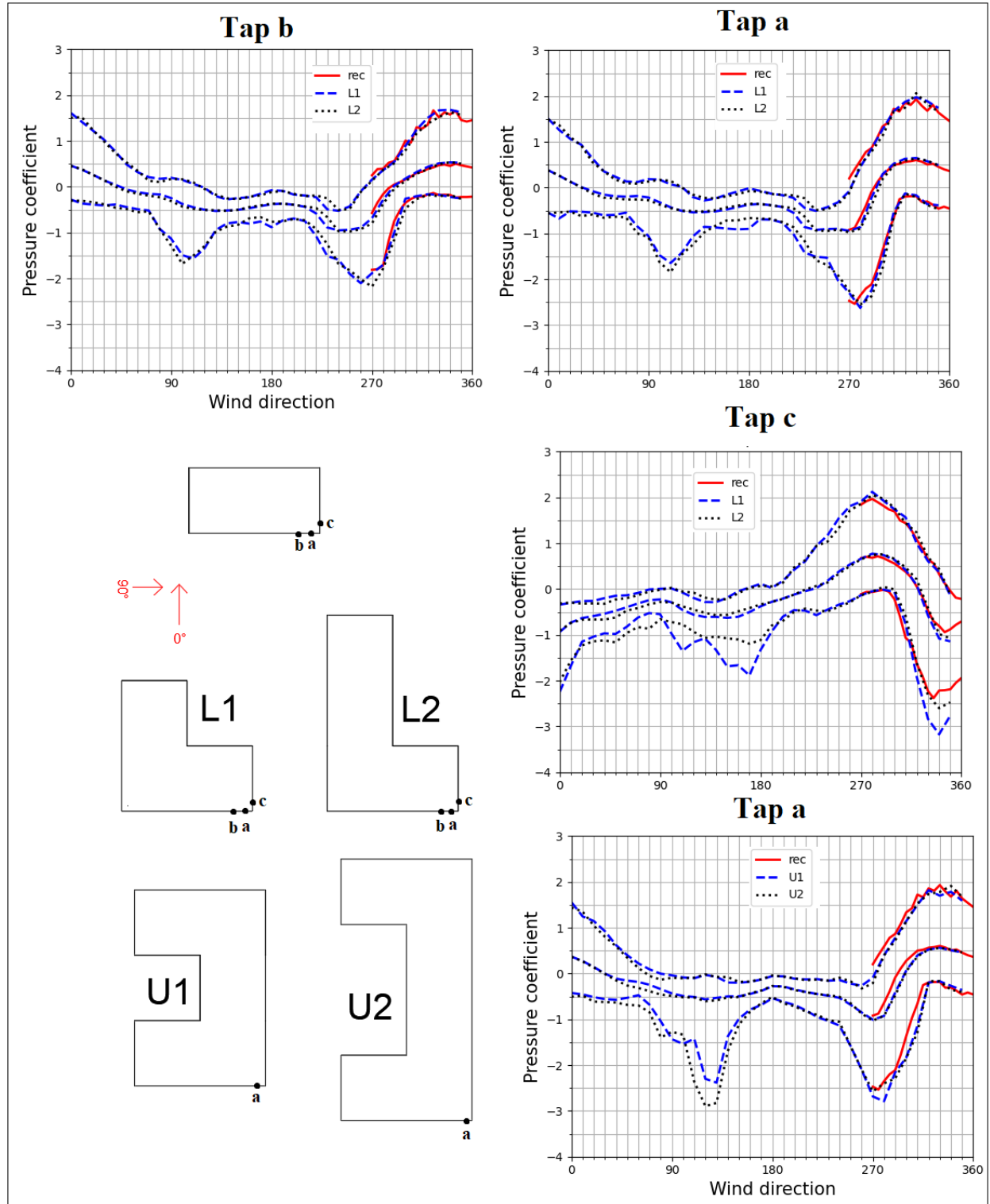


Figure 4.12: Comparison of wall pressures between a typical rectangular model and nonrectangular models for taps on the outer perimeter.

Figure 4.12 compared the wall pressures of a rectangular model and those on the outer wall pressures of non-rectangular models without including a comparison of the inner walls of the non-rectangular models. The following three Figures provide a comparison between wall pressures of a rectangular model and the inner wall pressures of non-rectangular models.

Figure 4.13 presents contours of the enveloped minimum and maximum pressure coefficients of a rectangular model tested for a wind azimuth range of 270° to 360° . The highest suction was recorded at the wall upwind edge area, with a value of approximately -2.4. The minimum C_p on the middle area is less than or equal to -1.6.

Figure 4.14 shows the enveloped minimum pressure coefficients of two L-shaped models: L2 and L3; the contours are presented for the inner walls. The free edge area of the L2 model (the right side edge, designated as “a”) is subjected to reduced suctions compared to the edge of the rectangular model wall. However, the area of the wall at the reentrant corner is subjected to relatively high suctions of up to -3.2. Similar observations can be made for the L3 model with lower minimum pressure coefficients at the reentrant corner. This was generally observed for the inner wall of the L shapes and the X-shaped model.

Figure 4.15 exhibits the contours of enveloped minimum pressure coefficients for the inner walls of T2 and U3. The observations made for the L shapes were also noted for the T shape, where the reentrant corner wall area is subjected to high suctions; in addition, the middle area is subjected to relatively high suction of -1.8. In general, this was seen for the inner walls of the T-shaped models. On the other hand, the inner wall of the U3 model experienced lower suctions compared to the other non-rectangular models and the rectangular model.

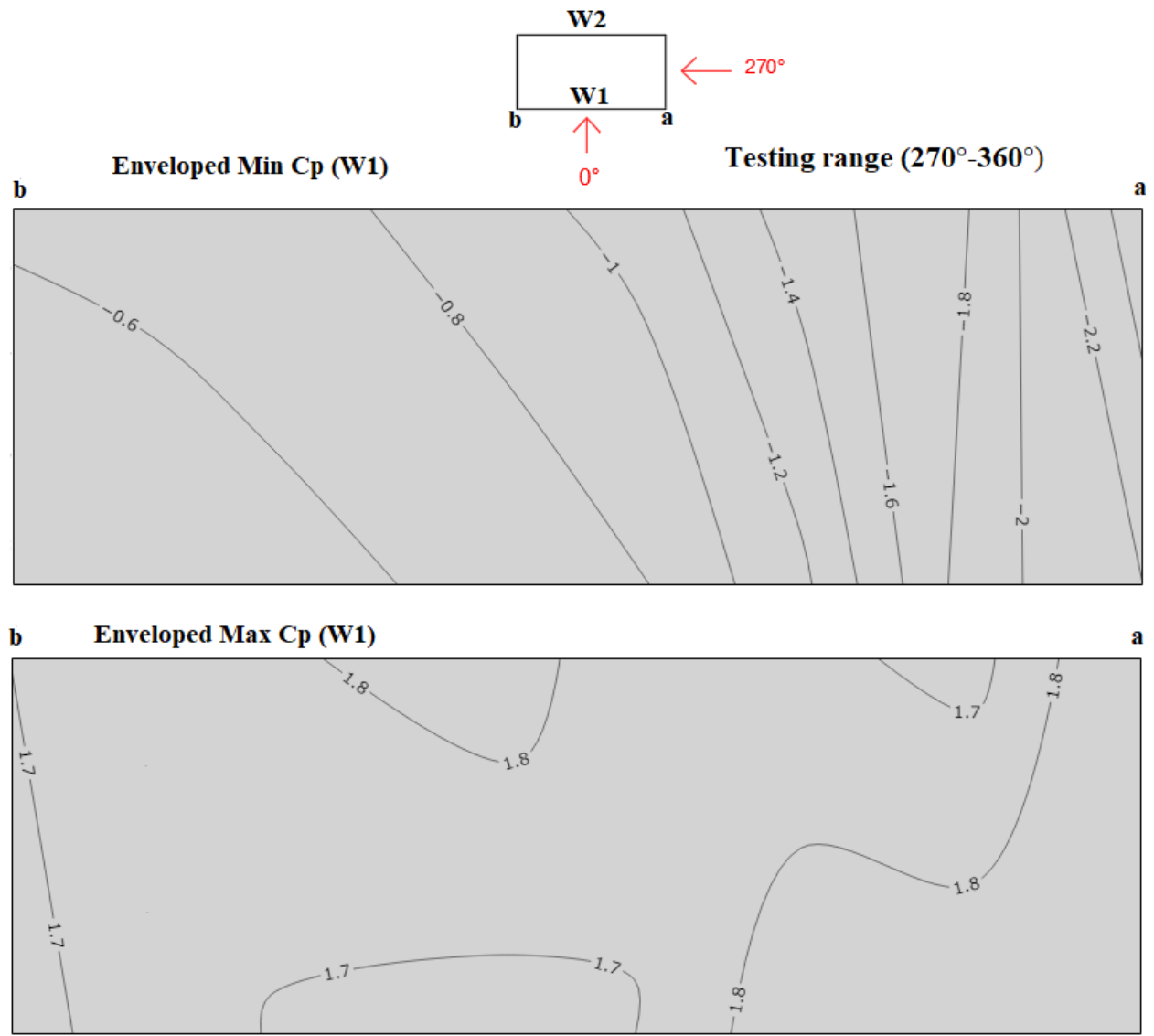


Figure 4.13: Enveloped minimum and maximum pressure coefficients on a wall of a rectangular model.

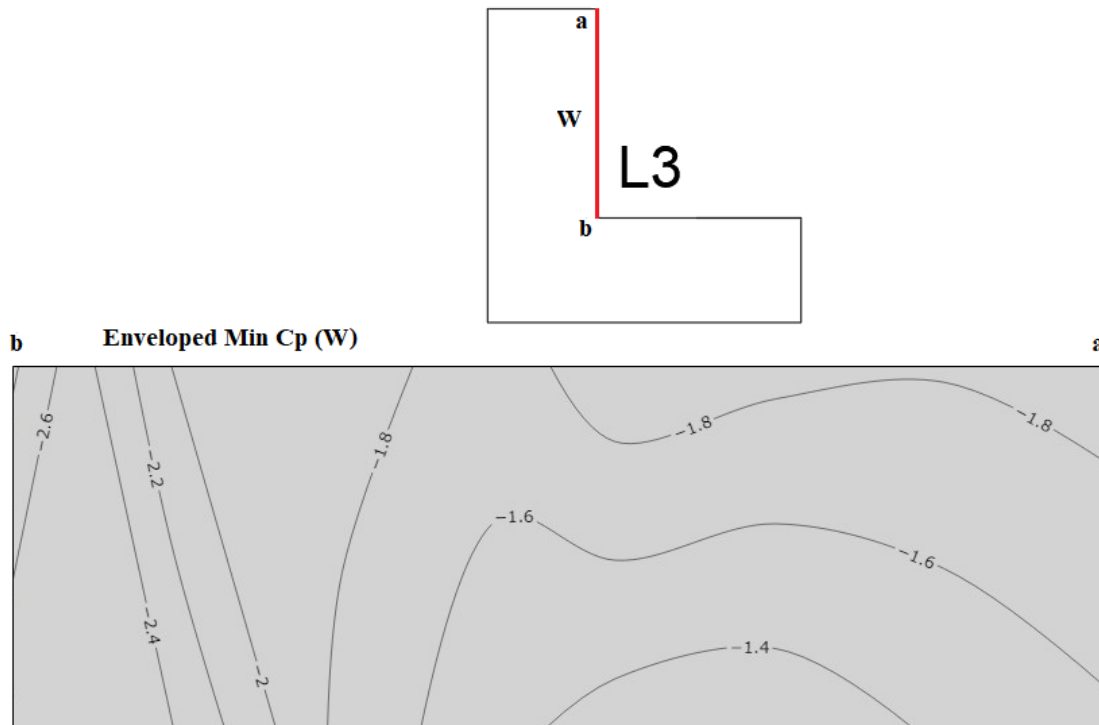
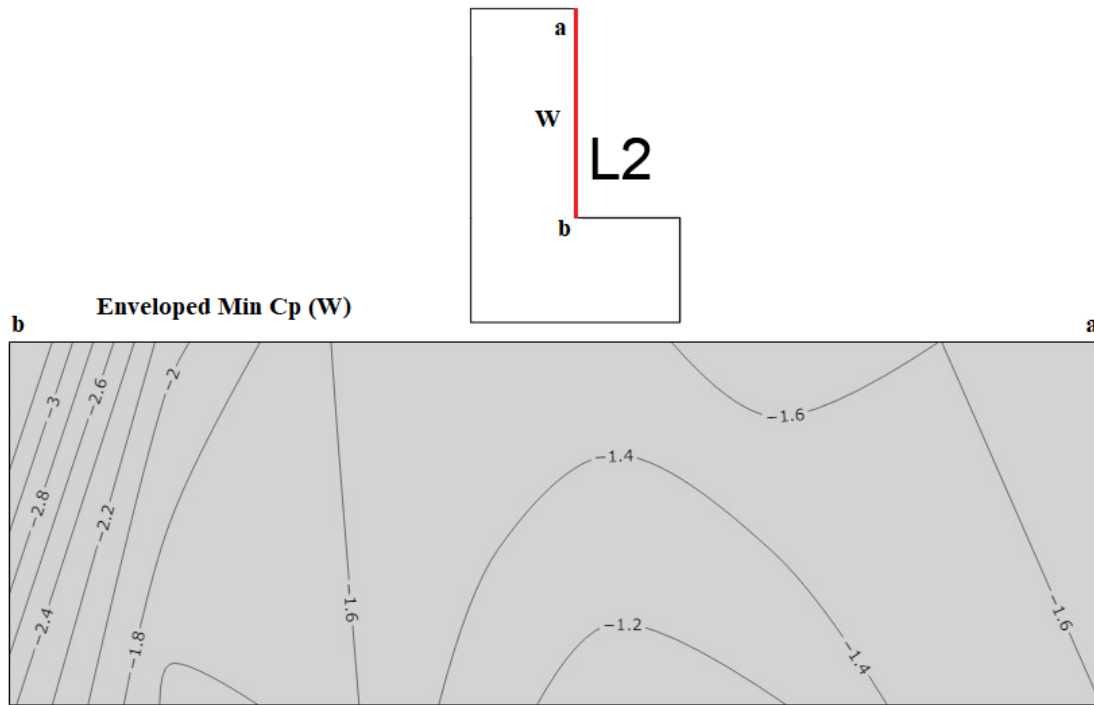


Figure 4.14: Enveloped minimum pressure coefficients on inner walls of two L shapes: L2 and L3 models.

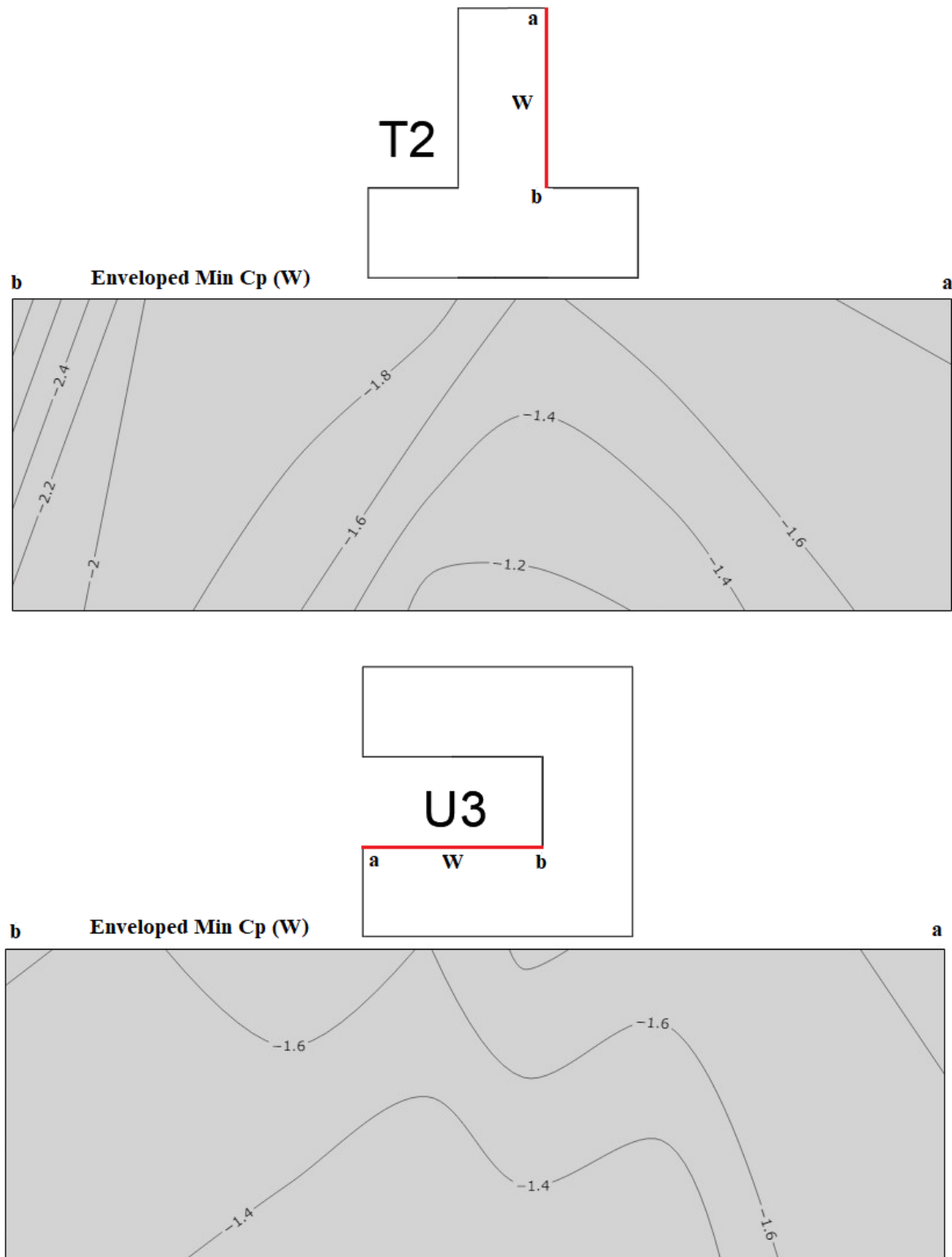


Figure 4.15: Enveloped minimum pressure coefficients on inner walls of T2 and U3 models.

In summary, the plan dimensions affect the roof pressures of the inner edges and corners. The short edge, compared to the long edges, tends to experience higher peaks at the inner corners and lower peaks at the edge zone near the reentrant corner. In addition, the roof peaks were found to be higher for taller buildings, and the high peaks of the roof corners extend over larger areas as the height increases. These areas were found to be mainly dependent on the building height. Further, the roof peaks on the inner edges and corners are higher than those on the outer edges and corners. Wind pressures on the inner roof edges and walls of non-rectangular buildings are different and generally higher than those experienced by rectangular buildings.

Chapter 5

Comparison with wind codes and standards

This chapter compares the experimental wind pressure coefficients with rectangular provisions of the American standard, ASCE 7-22, and the Canadian code, NBCC 2020. The comparison was conducted to provide a methodology for the design of cladding and components of non-rectangular buildings based on the rectangular provisions in the North American wind codes and standards.

Part of the materials presented in this chapter has been published in the Journal of Structural Engineering (Aldoum and Stathopoulos, 2025a), and presented at two conferences (Aldoum and Stathopoulos, 2024a and 2024b).

5.1 Comparison with NBCC (roof pressures)

This section presents a comparison of the experimental results associated with a height of 10 m with the provisions of NBCC 2020. Selecting the height of 10 m was based on the fact that the exposure factor in NBCC 2020 is equal to unity for a 10 m high building in open terrain exposure. Consequently, the C_gC_p 's of NBCC 2020 need not be modified using the exposure factor when compared to the experimental results. In addition, the provisions of the Canadian code include an embedded directionality factor with a value of 0.8, and therefore, the peak of NBCC 2020 or experimental results need to be modified to make the comparisons included in this section.

It is challenging to compare the experimental results of the non-rectangular buildings to the provisions of NBCC 2020. This is because NBCC 2020 provides design loads dedicated only to rectangular buildings with no guidance for non-rectangular buildings. However, comparison with

the Canadian code is still possible by carefully using the provisions for the non-rectangular roofs. The challenge lies in adapting the roof pressure zonal system of the NBCC 2020 to suit non-rectangular buildings. The roof pressure zonal system of NBCC 2020 divides the flat rectangular roof into three pressure areas, corner, edge, and interior zones, as shown in Figure 5.1(a), which shows four corners, four edges, and one interior area.

In an attempt to adapt the roof zones to non-rectangular buildings, this study adopted a way that involves dividing the non-rectangular plan into rectangular parts. The rectangular roof zones can then be applied to each part, as illustrated in Figure 5.1(b) for the four non-rectangular shapes.

The other issue is the determination of end-zone width, z , which is defined as follows:

$$z = \min(0.4H, 0.1D) \geq 1\text{m or } 0.04D$$

Where H is the height and D is the least horizontal dimensions. The height does not pose an issue when adapting the roof zonal system of rectangular buildings to non-rectangular plans; however, the least horizontal dimension is not straightforward. The rectangular buildings are characterized by two horizontal dimensions, but the non-rectangular buildings include several plan dimensions, and selecting D could be, if a plain interpretation of the NBCC zonal system was adopted, the minimum width of the many non-rectangular plan sides. However, the minimum width approach always results in a value of 15 m for D , and consequently, an end-zone width, z , of 1.5 m ($0.1D$). This width was found, based on the experimental results, to be quite small to include the highest peaks on the corners and edges of the non-rectangular buildings and would reflect non-realistic applications of the NBCC zonal system to the non-rectangular roofs.

Consequently, it was decided to find the least horizontal dimension, D , by encompassing the non-rectangular plans within a rectangle, the distance D can then be determined based on the least horizontal dimension of the encompassing rectangle. This is presented in Figure 5.1(c) for all the configurations where the distance D is marked inside each plan. The end-zone width is then calculated based on a height of 10 m and the least horizontal dimension. The plan dimensions of the encompassing rectangle and the end-zone width are summarised for all models in Table 5-1. The end-zone width, z , is 3 m when D is equal to 30 m in which the 10 percent of the least horizontal dimension governs, while it is equal to 4 m when D is greater than 40 m in which the 40% of height is the governing case.

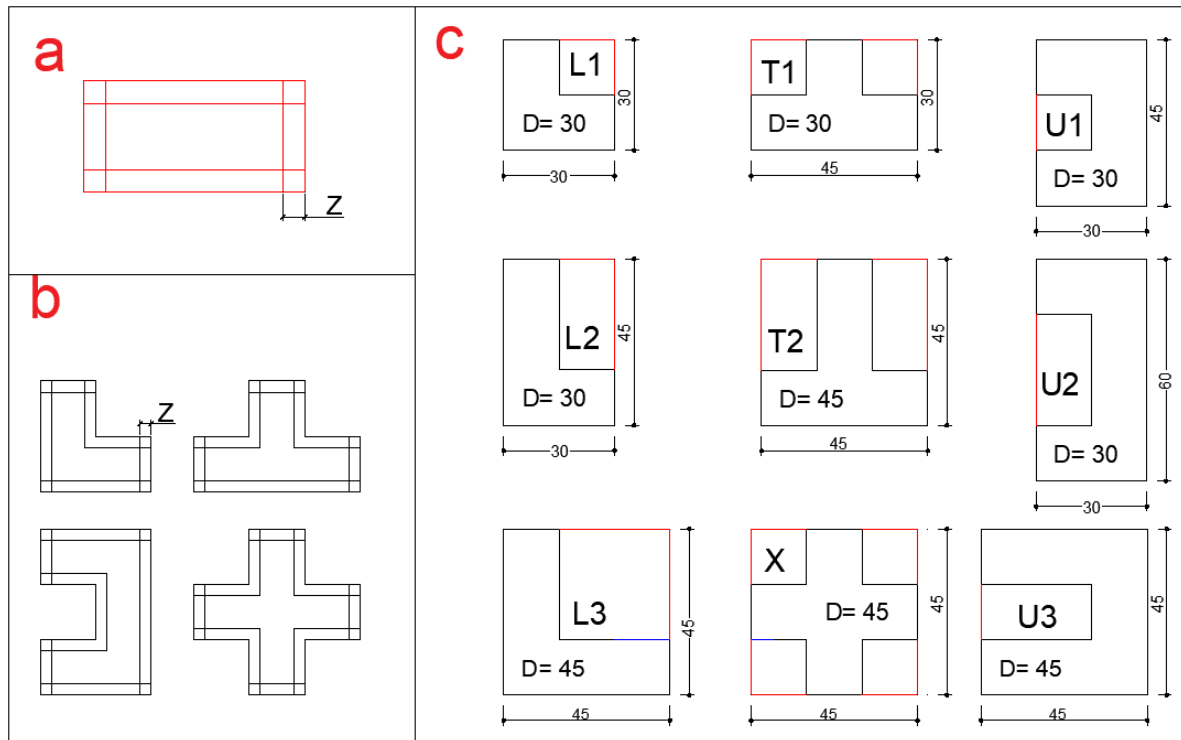


Figure 5.1: a) Roof zonal system of NBCC 2020 for rectangular buildings, b) the projection of roof pressure zones on the four non-rectangular shapes, c) determination of the least horizontal dimensions.

Table 5-1: Dimensions of the encompassing rectangle and end-zone-width of all models.

Configuration	W (m)	L (m)	z (m)
L1	30	30	3
L2	30	45	3
L3	45	45	4
U1	30	45	3
U2	30	60	3
U3	45	45	4
T1	30	45	3
T2	45	45	4
X	45	45	4

Figure 5.2 presents the enveloped peak pressure coefficients for the L shapes along with pressure zones of NBCC 2020 for a height of 10 m. The comparison was performed to determine whether the size of the pressure zone is adequate to enclose the high peaks occurring in the corner and edge zones. Typically, the threshold to assess the adequacy of the size of the corner should be based on the peak recommended for the edges in NBCC 2020, while the threshold to judge the sufficiency of the edge zone size is the $C_g C_p$ of the interior zone. However, the thresholds would be taken as a general reference in assessing the size of the zones rather than a strict threshold that needs not be exceeded.

In Figure 5.2, the highest peaks at the corners of L shapes extend beyond the limits of the corner zone, particularly at the inner corners. The peaks on the inner edges of the L shapes are higher in

value than those on the outer edges, and the high peaks extend to larger areas on the inner edges. Considering the vertical leg of L2, for example, the left outer edge experiences $C_g C_p$'s that are around -2.5 on almost the entire zone. However, the $C_p C_g$'s (suctions) of the inner edges on the right side are higher than -3, covering almost the entire inner edges with large suctions of up to -4.5, and extending beyond the red line toward the low-pressure interior zone for L1 and L2. In other words, the interior zone includes high suctions of around -3. This indicates that the pressure zone size on the outer edges of the three L shapes is sufficient, while it is inadequate to enclose the high peaks on the inner edges for L1 and L2. It should be noted that the inner edge size of L1 and L2 would be adequate if the size were 4 m, i.e., determined based on height.

For the inner edges of L3, on the other hand, the size of the end-zone width is 4 m, and the pressure zones are somehow with sufficient width to include the high peaks distributed on the edge areas. It should also be noted that the size of the inner edge of L3 was described to be adequate because it does envelope all peaks that are higher than -3. In other words, the width of the edge zone is sufficient in a way that the interior zone is subjected to low pressures (i.e., around -2.5). It should be mentioned that the inner edges of the L shapes include peaks of around -4.5, exceeding the NBCC provisions, making the entire inner zone a high-pressure zone similar to the roof corners.

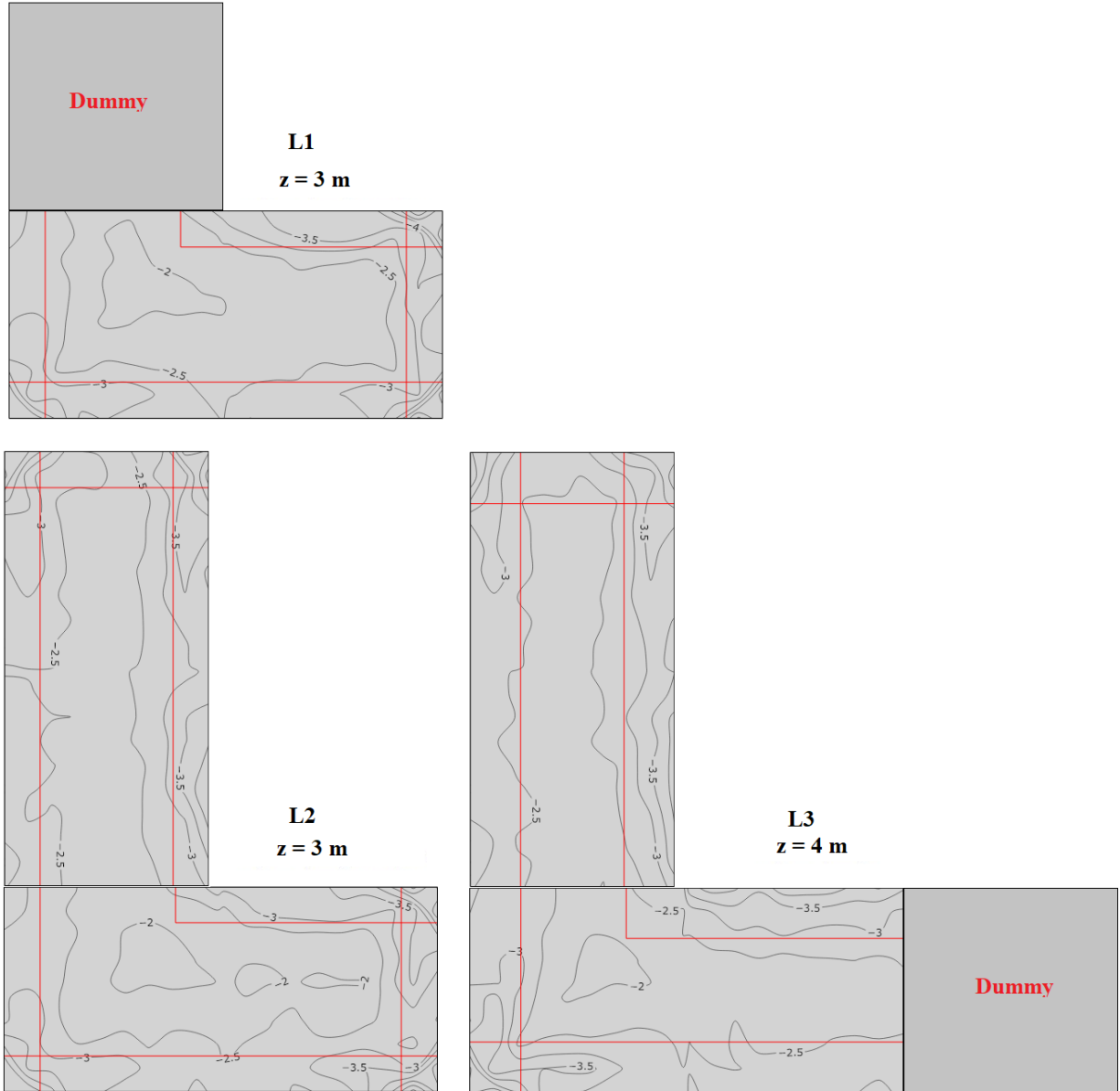


Figure 5.2: Enveloped negative peaks for the L shapes with roof pressure zones of NBCC 2020 ($H = 10$ m).

Figure 5.3 presents similar comparisons for U1, T1, and X. The end-zone width is 3 m for U1 and T1, and 4 m for X. For U1, the highest peaks of the inner and outer corners present beyond the boundaries of the NBCC corner zone, the same trend was also observed for U2 and U3. For T1, the inner corner high CgCp's also extend beyond the NBCC corners, while the edge zone width is sufficient to include suctions of more than -3. The pressure zone size of the X shape is 4 m and adequate to capture the high CgCp's on the corners and edges. However, the inner edges of U1, T1, and X include CgCp's that exceed the NBCC edge peaks, particularly, at the inner edge of the U1 configuration, where the suctions reach up to -5. It should be mentioned that the conclusion reached for T1 also applies to T2.

Based on the previous discussion, the edges of all non-rectangular configurations were found to experience high suctions, close in magnitude to those experienced by the corners, this was particularly noticeable along the inner edges. Therefore, the study suggests merging the corner and edge zones into a single perimeter zone, aligning with recent studies referenced in the previous section.

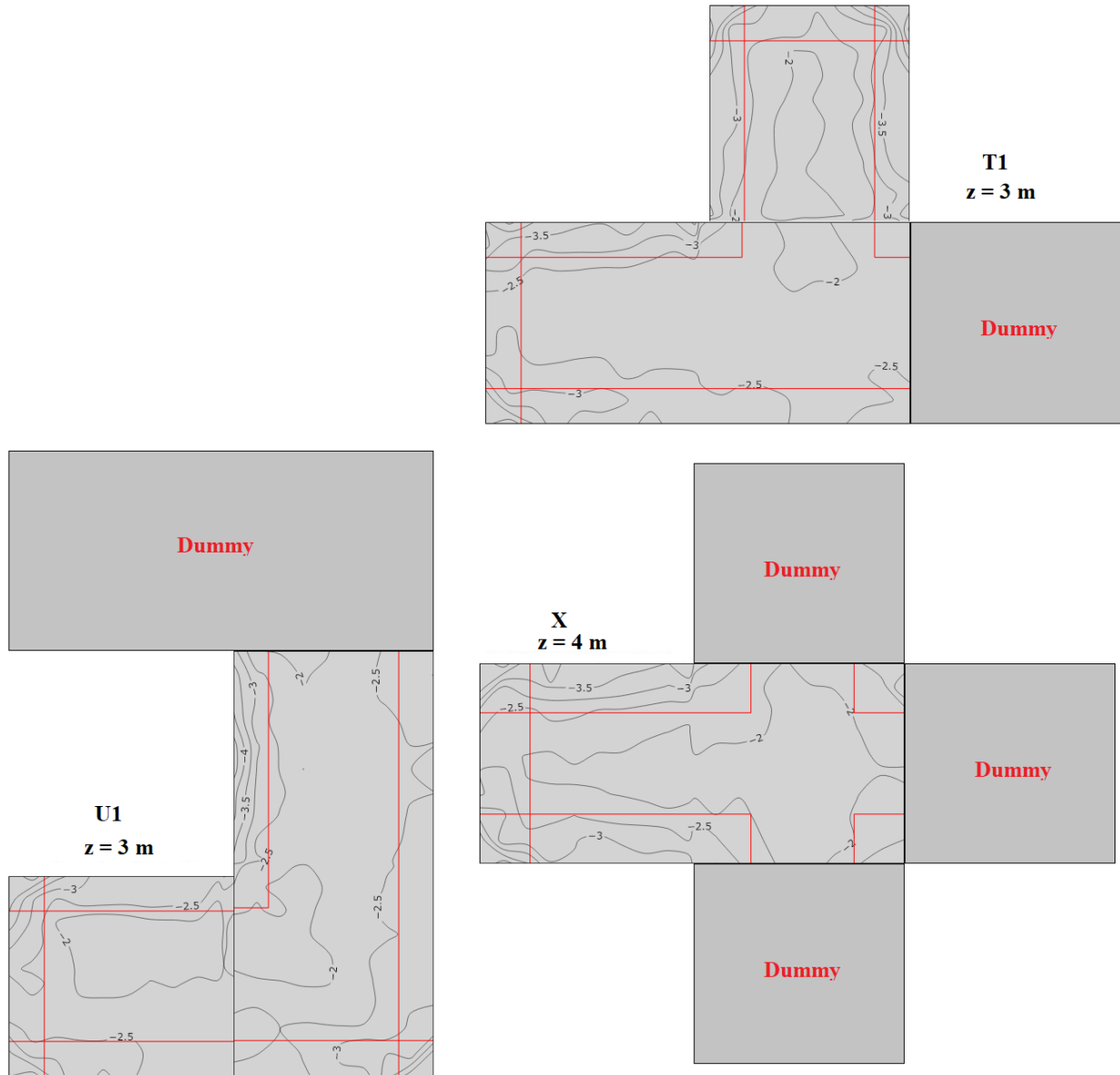


Figure 5.3: Enveloped negative peaks for the shapes of U1, T1, and X with roof pressure zones of NBCC 2020 ($H = 10 \text{ m}$).

The previously discussed figures exhibit general comparisons with the C_gC_p 's of the Canadian code, and the primary focus of these comparisons centered around the size of pressure zones and the spatial distribution of the experimental local peaks. However, area-averaged pressure coefficients are important in the design of components and cladding of the buildings, and the provisions of NBCC 2020 are included as curves of area-averaged C_gC_p . Figure 5.4 compares the experimental area-averaged peaks with the corner, edge, and interior provisions of NBCC 2020. The experimental peaks are the minimum enveloped peaks among each shape (L, U, T, X, and rectangular shapes), the wind tunnel peaks were reduced by 20% to account for the directionality factor incorporated in the NBCC peaks. Further, the 0.1 m^2 corresponds to the local experimental peaks. For the corner zone, the experimental area-averaged peaks are marginally higher than the NBCC 2020 provisions, with the lowest peaks recorded for the rectangular and X models, while the local peaks are all lower than the recommendation of NBCC. For the edge zone, the NBCC provisions are exceeded by both local and area-averaged C_gC_p 's of the non-rectangular models. The highest local peak was for the T models, and the area-averaged peaks are comparable for the T, U, and L models. The lowest peaks were recorded for the X and rectangular models. The provisions of the Canadian code for the interior zone are also exceeded by the experimental peaks except for the X configuration. This is because the interior zone of the X shape is small, which explains the reduced peaks compared to the other shapes. The study suggests increasing the NBCC interior zone provisions by 40%. This would resolve the current underestimation of pressures in the interior zone.

The local and area-averaged peaks of the rectangular model are lower than those of the L, U, and T models in the three zones. For the X shape, the peaks are marginally higher than those of the rectangular model in the corner and edge zones. However, the peaks of the X shape in the interior

zone are higher than the suctions experienced by the middle area of the rectangular model. This indicates that the wind loads on roofs of non-rectangular buildings are generally higher than those typically experienced by rectangular buildings.

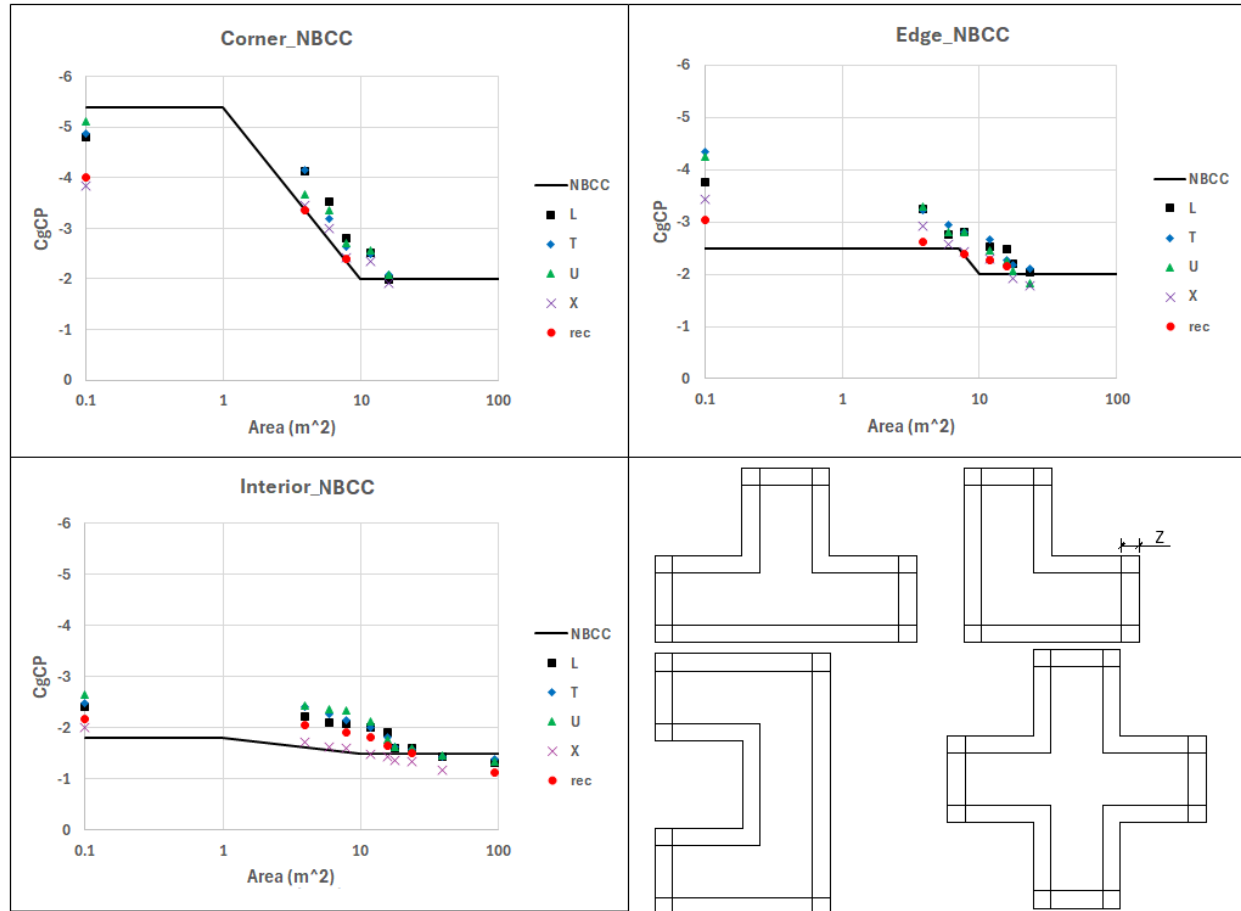


Figure 5.4: Comparison between peaks of NBCC 2020 and the minimum enveloped peaks among each shape for the three roof pressure zones ($H = 10$ m).

In summary, the size of the corner and inner edges zones of the L shapes is relatively small to include the high peaks in each, which also applies to the corners of the T and U shapes, while the

size of the pressure zones of the X shapes is sufficient to enclose the high suctions at the edges and corners of the roof. However, it was noted that the edges of all shapes experience relatively high suctions, comparable to those typically developed at the roof corners. For simplicity, the study suggests referring the size of the end-zone width to the building height for all non-rectangular shapes. Furthermore, the provisions of NBCC 2020 are comparable to the experimental peaks at the corners and exceeded by wind tunnel peaks at the edge and interior zones. The present study suggests merging the corner and edge zones into a single zone for all shapes, as it would account for the increased suctions on the inner edges and add simplicity to the code provisions, and increasing the interior zone provisions. Based on the experimental results, the NBCC provisions of rectangular buildings can be deemed applicable to non-rectangular buildings after incorporating the three mentioned changes (i.e., determination of the end-zone size based on height, merging the corner and edge zones into a single zone, and increasing the interior zone provision by 40%).

5.2 Comparison with ASCE 7-22 (roof pressures)

This section compares the experimental results with the design peak pressure coefficients for components and cladding of flat roofs in ASCE 7-22. The comparison of the non-rectangular peaks with ASCE 7-22 guidelines is less complicated than the comparison conducted in Section 4. This is because the size of the roof pressure zones of ASCE 7-22 solely depends on the height of the building. In addition, ASCE 7-22, based on Figure 30.3-2A, divides the roof into four zones: Zone 3 (corners), Zone 2 (first edge zone), Zone 1 (second edge zone), Zone 1' (interior zone). However, the four zones apply only when the least horizontal dimension is greater than $2.4h$ (h is

the building height, 10 m), which is one of four scenarios included in the commentary of ASCE 7-22 as shown in Figure 5.5. For the non-rectangular shapes in this study, the least horizontal dimension is 15 m, which makes the second scenario to apply to all configurations ($2.4 > D/h > 1.2$), where zone 1' does not apply.

The peaks of the ASCE 7-22 are denoted by GC_p ; however, the use of C_gC_p will be extended in this section for consistency. It is well known that the peaks in chapter 30 of ASCE 7-22 correspond to 3-second gust duration, therefore, it was decided to convert the standard peaks to correspond to hourly averaged wind speeds. This can be done using the Durst curve (Durst, 1960), consequently, the peaks of ASCE 7-22 were multiplied by a factor of 2.33 (1.525^2) to correspond to hourly mean wind speeds. Unlike the NBCC 2020, the directionality factor is not embedded in the peaks of the American standard, and is provided as a separate factor, therefore, the experimental enveloped peak pressure coefficients can be compared directly with ASCE 7-22 without further modifications.

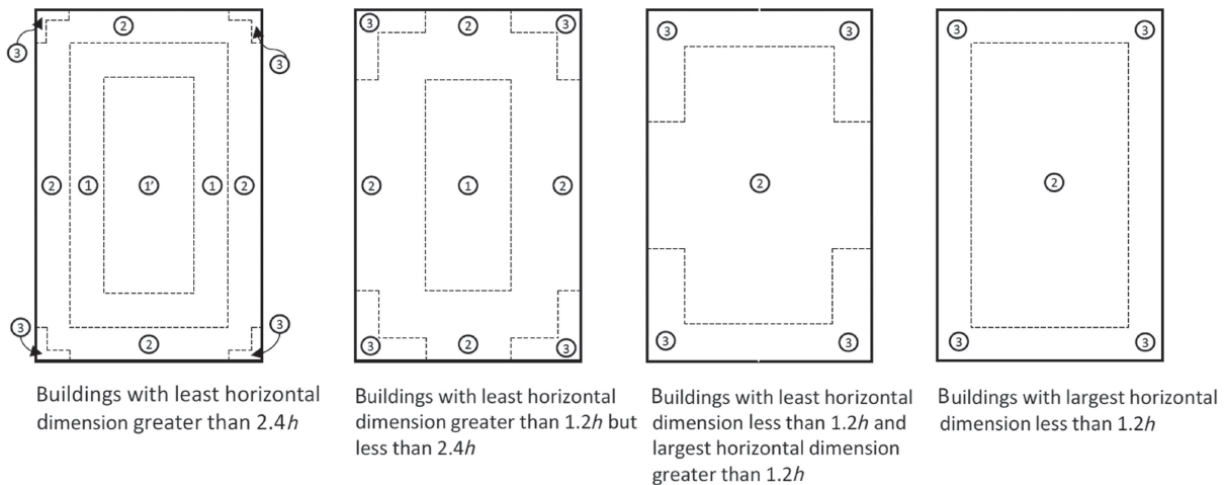


Figure 5.5: Pressure zone scenarios for low-slope roofs in ASCE 7-22 (Figure C30-1, commentary of ASCE 7-22).

Figure 5.6 compares the roof zonal system of the ASCE 7-22 to the enveloped peak pressure coefficients of the L-shaped models for a full-scale height of 10 m. The peak pressure coefficients of the ASCE 7-22 that are associated with small tributary areas for the corner, edge, and interior zones are -7.5, -5.4, and -4, respectively. This makes the three ASCE 7-22 zones sufficient to enclose the high peak at the corner and edge areas of the roof, leaving the lowest peaks enclosed with small areas in the middle of the roof. The standard zonal system was also found adequate to encompass the high suctions at the perimeter area of the U, T, and X configurations.

Area-averaged experimental peak pressure coefficients were compared with the peaks recommended by ASCE 7-22 for the three roof zones in Figure 5.7. The wind tunnel scattered points represent the minimum enveloped area-averaged peaks among shapes. In addition, the local wind tunnel peaks were included in plots for a tributary area of 0.1 m^2 . The recommendations of ASCE 7-22 are conservative -perhaps overly conservative- for all zones. The difference between the standard peaks and the experimental area-averaged peaks is relatively small in Zone 3, but more significant in Zone 2 and Zone 1. Additionally, it can be observed that the local wind tunnel peaks of the U-shape are marginally lower than the standard peak, where the inner edge of the U-shape recess recorded the highest peaks.

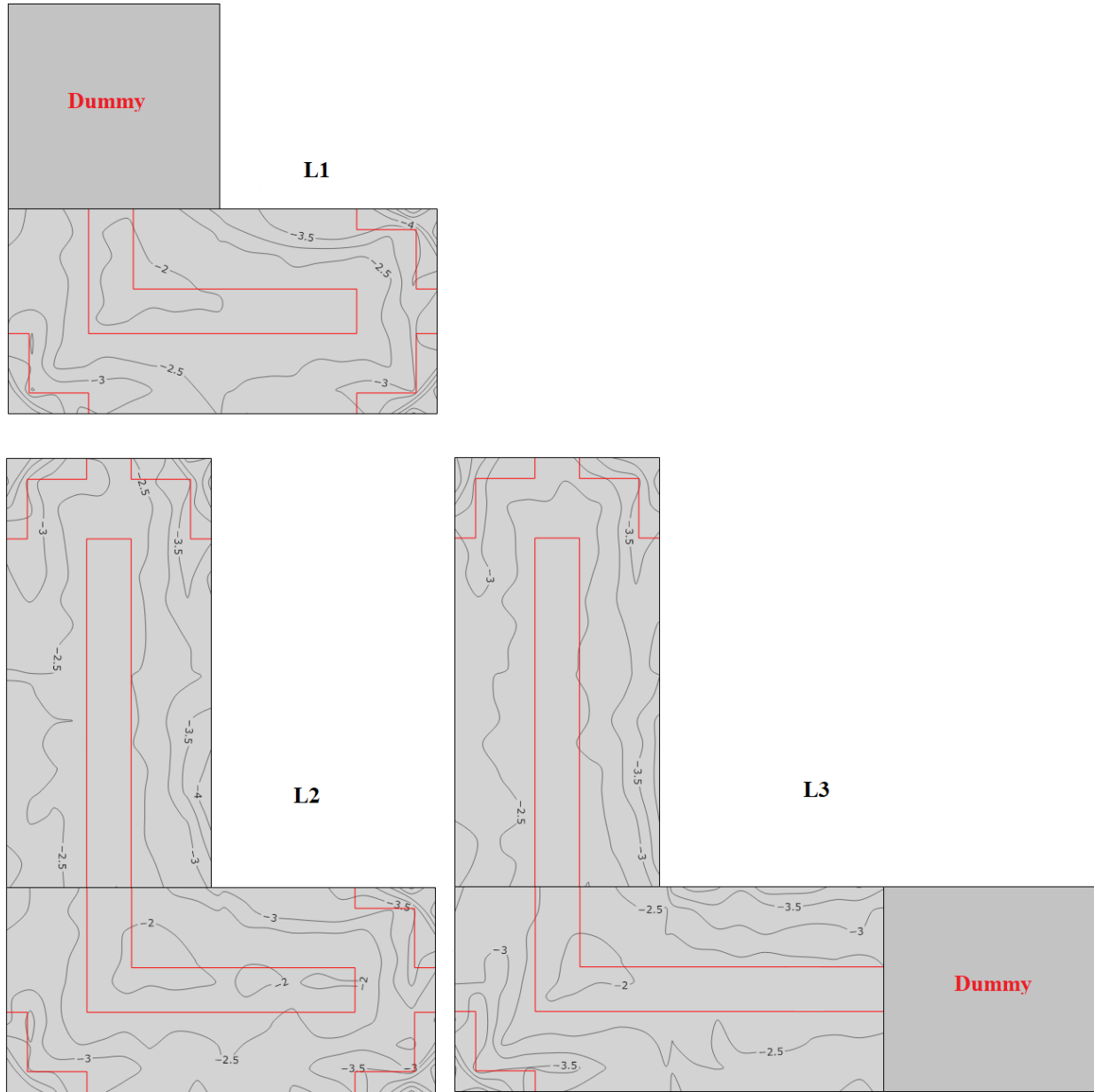


Figure 5.6: Enveloped negative peaks for the L shapes with roof pressure zones of ASCE 7-22 ($H = 10\text{m}$).

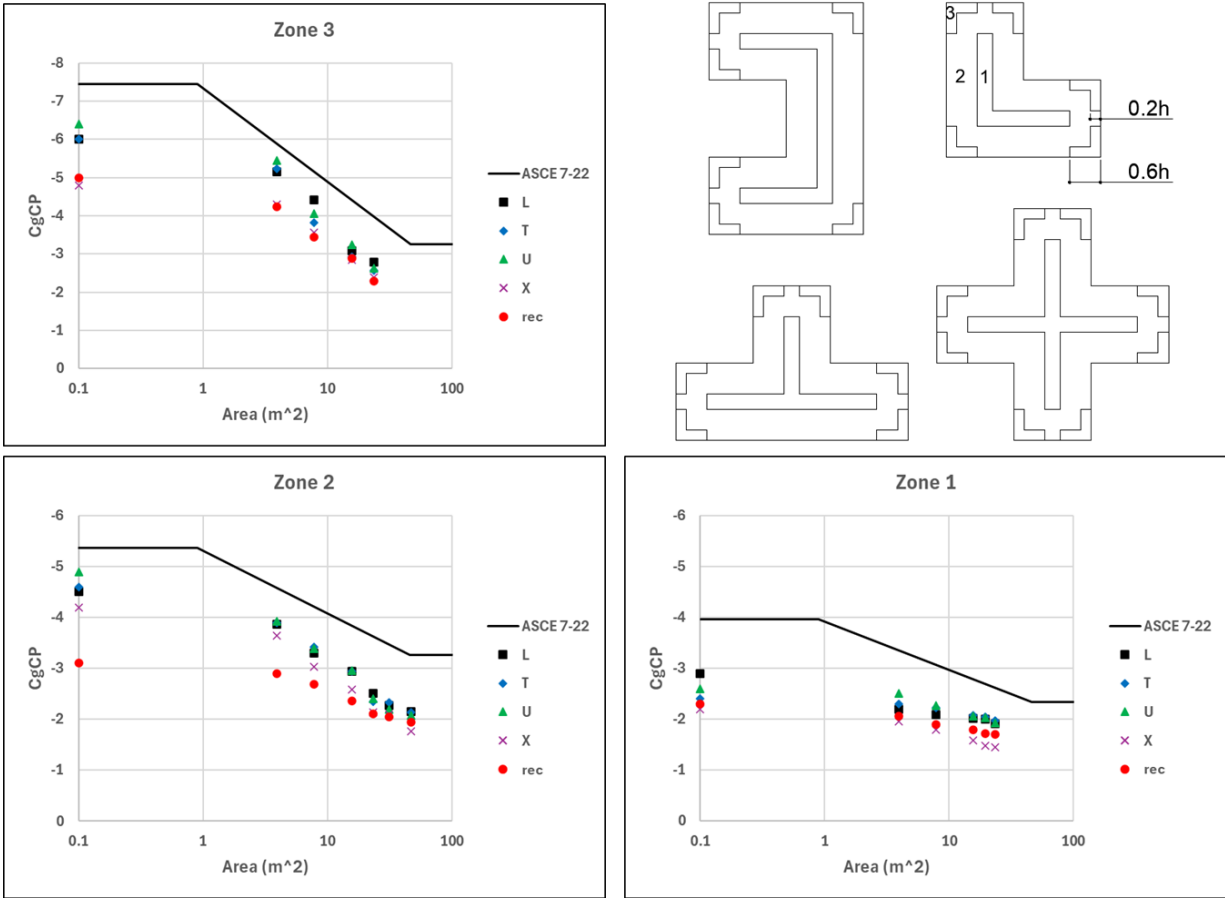


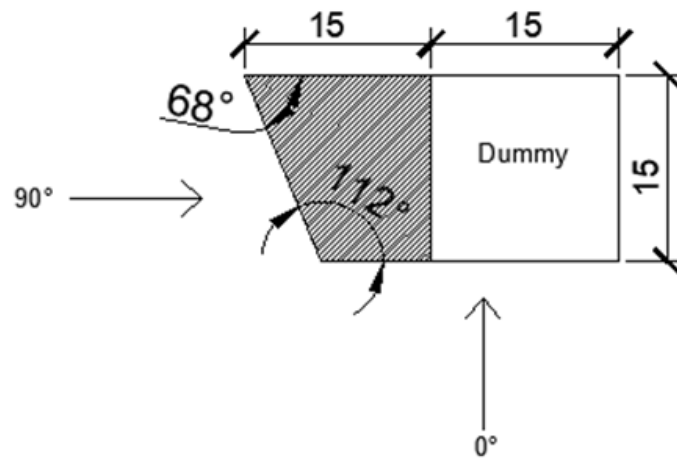
Figure 5.7: Comparison between peaks of ASCE 7-22 and the minimum enveloped peaks among each shape for the three roof pressure zones ($H = 10$ m).

As mentioned previously, the ASCE 7-22 provides guidance for the design of non-rectangular buildings. A discussion is included herein to explore the guidance suitability for roofs when the reentrant angle is greater or less than 135° . Referring to the enveloped CgCp contours in Figure 5.2 and Figure 5.3, it is evident that the highest peaks occurred on the corners with a value of around -5.5, and peaks at the reentrant corner are around -3 to -3.5. Since the reentrant angle is greater than 135° , the ASCE 7-22 guidance directs the designer to apply peaks Zone 2 (edge zone)

at the reentrant corner of the L-shape configuration. Therefore, it can be concluded that Figure C30.3-2 is satisfactory when the reentrant angle is 270° . Additionally, negative peaks at the inner edges reach up to -5. This means that the rectangular provisions of the ASCE 7-22 are satisfactory for the inner edge zones.

The trapezoidal model was tested for a wind direction range of 0° to 180° at a step of 15° and for a height of 10 m. Figure 5.8 presents the enveloped peak pressure coefficients on the roof and a plan of the trapezoidal building. Two non-right reentrant angles were considered: 112° and 68° . The roof peaks developed at the corner near the 112° angle (around -5.5) are distinctly higher than the edge peaks. On the other hand, the acute angle corner experienced slightly higher negative peaks than those recorded on the corner of the 112° reentrant angle and the corners of the L-shaped configuration. Again, Figure C30.3-2 in the ASCE 7-22 is satisfactory since the experimental results showed that when the reentrant angle is 112° , less than 135° , the corner experiences high negative pressures and the peaks of Zone 3 should apply.

In summary, the ASCE 7-22 provisions for rectangular buildings with flat roofs provided larger roof pressure zones and higher design peaks compared to NBCC 2020. More importantly, the ASCE 7-22 design guidelines are conservative based on the experimental results of the non-rectangular buildings.



Negative peaks_Enveloped

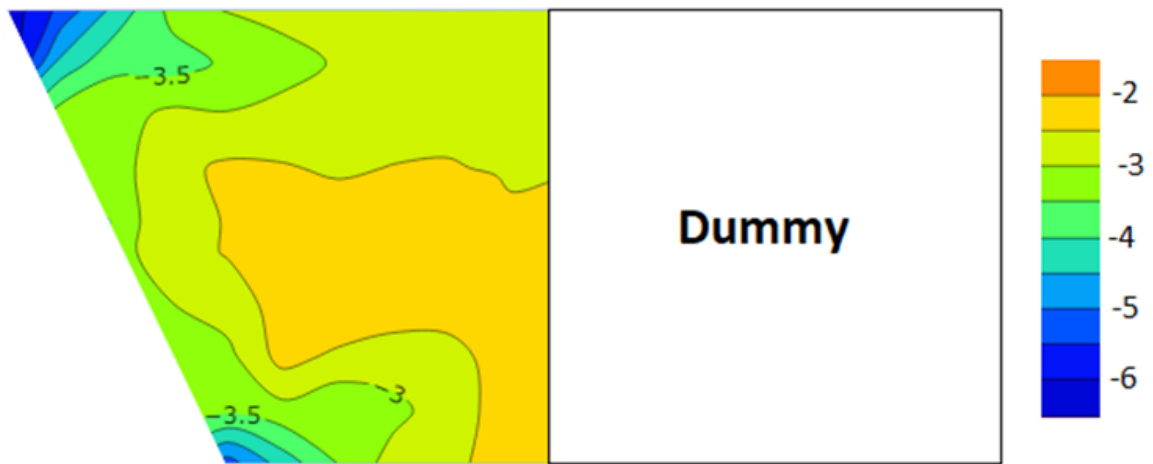


Figure 5.8: Contours of enveloped negative peak pressure coefficients for a building with a plan of a trapezoid.

5.3 Comparison with NBCC 2020 and ASCE 7-22 (wall pressures)

This section compares the experimental results with the corresponding peaks in NBCC 2020 and ASCE 7-22. The experimental peaks and the peaks were modified based on the approach presented in Sections 5.1 and 5.2 due to the embedded 0.8 factor in the peaks of NBCC 2020 and the different averaging time of wind speed in ASCE 7-22. The end zone width was determined by the same approach adopted in section 5.1.

Figure 5.9 compares the experimental local and area-averaged peaks of the four shapes (L, T, U and X) evaluated for the high wall suction zone, zone e, with the corresponding peaks in the American standard and the Canadian code. The comparison was divided into three graphs: (1) outer walls, (2) inner walls, and (3) short walls, the three types are denoted on the presented plans in Figure 5.9 by O, I, and S, respectively. It should be noted that the zones e and w are designated by zones 5 and 4 in the American standard. Further, the locations of zone e and zone w are presented on the four plans shown in the Figure. The high suction zone, zone e, is marked for all the corners of the rectangular parts except the reentrant corner. Moreover, the experimental peaks are in two clusters, the local peaks were plotted for tributary areas less than 1 m^2 , and the area-averaged peaks were plotted for their corresponding actual tributary areas with slight modifications on the tributary areas to make a distinction for the different shapes included in the comparison.

Figure 5.9 shows that the positive experimental peaks are in good agreement with the positive provisions of NBCC 2020 and ASCE 7-22, where the experimental peaks are either lower than the provisions or slightly higher than the design value. For the outer walls, the negative local peaks are lower than the ASCE 7 curve and comparable with the NBCC provisions. The area-averaged

negative peaks are also comparable with both provisions, except those of the U shapes. For the inner walls, the experimental peaks are covered by the provisions of both ASCE 7-22 and NBCC 2020. The negative peaks of the short walls are higher than those of the inner and outer walls. For local negative peaks of the short walls, the values are comparable to or less than the ASCE 7 provisions, with the exception of the peaks of the T shapes, which exceed the ASCE curve by approximately 15%. However, the local peaks of the L and X shapes exceed the NBCC curve by around 30%, and the exceedance is more pronounced for the T shape. Similar observations were also made for the area-averaged peaks.

Figure 5.10 presents a similar comparison but for the middle zone, zone w for the outer and short walls. The positive peaks of all shapes are comparable with the provisions of ASCE 7-22 and NBCC 2020. The experimental negative peak coefficients of the outer walls of all shapes agree with the curves of the ASCE 7-22 and NBCC 2020. The short wall of the open wing shapes (i.e., L, T, and X) exhibited negative peaks that are higher than the design peaks. The difference can be estimated as 30% from the NBCC peaks and a small difference with respect to the ASCE 7-22 curve. It can also be observed that the short wall negative peaks of the U shapes agree with both provisions.

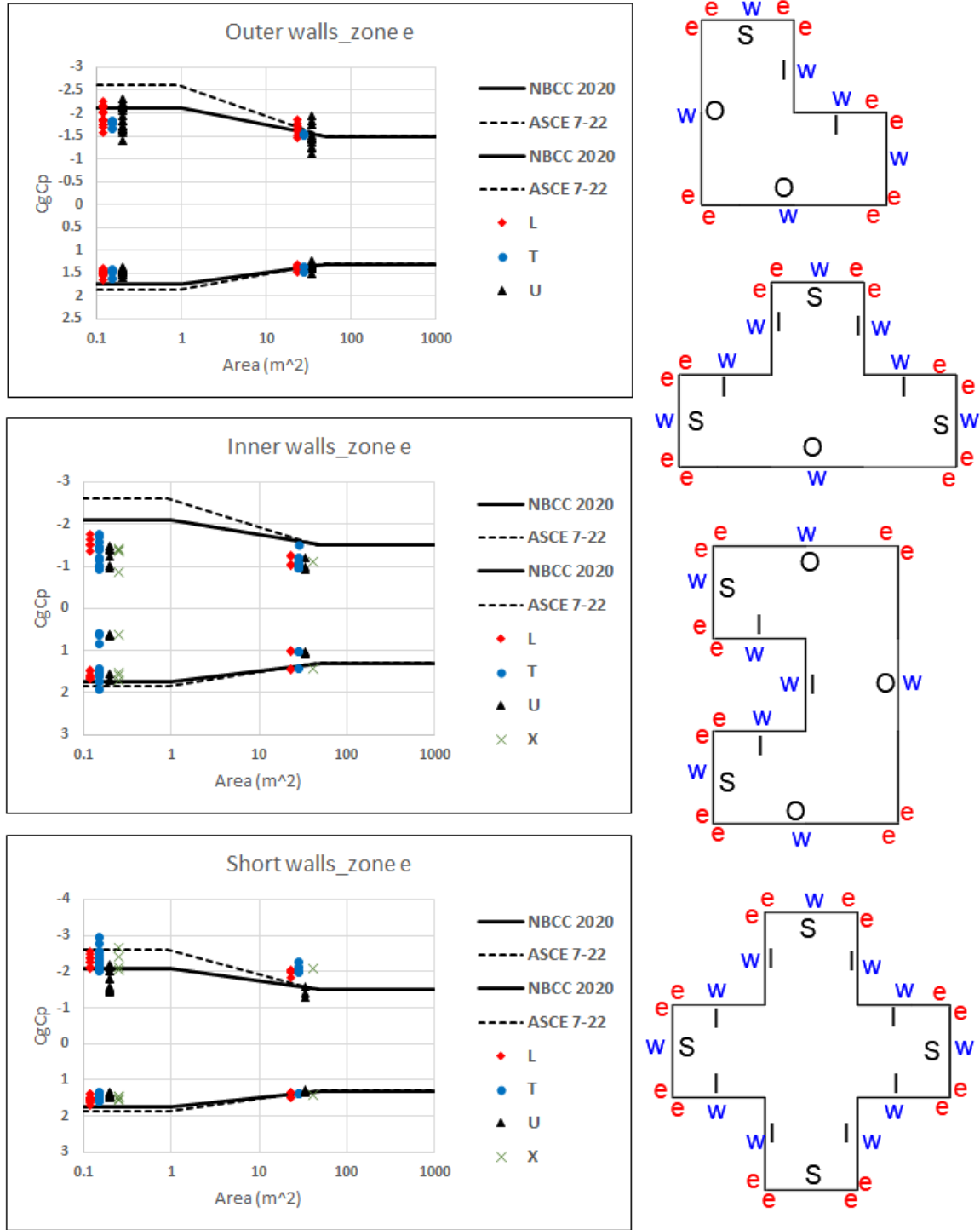


Figure 5.9: Comparison between peaks of NBCC 2020 and ASCE 7-22 and the corresponding enveloped peaks among each shape for zone e ($H = 10$ m, S: short walls, I: inner walls, and O: outer walls).

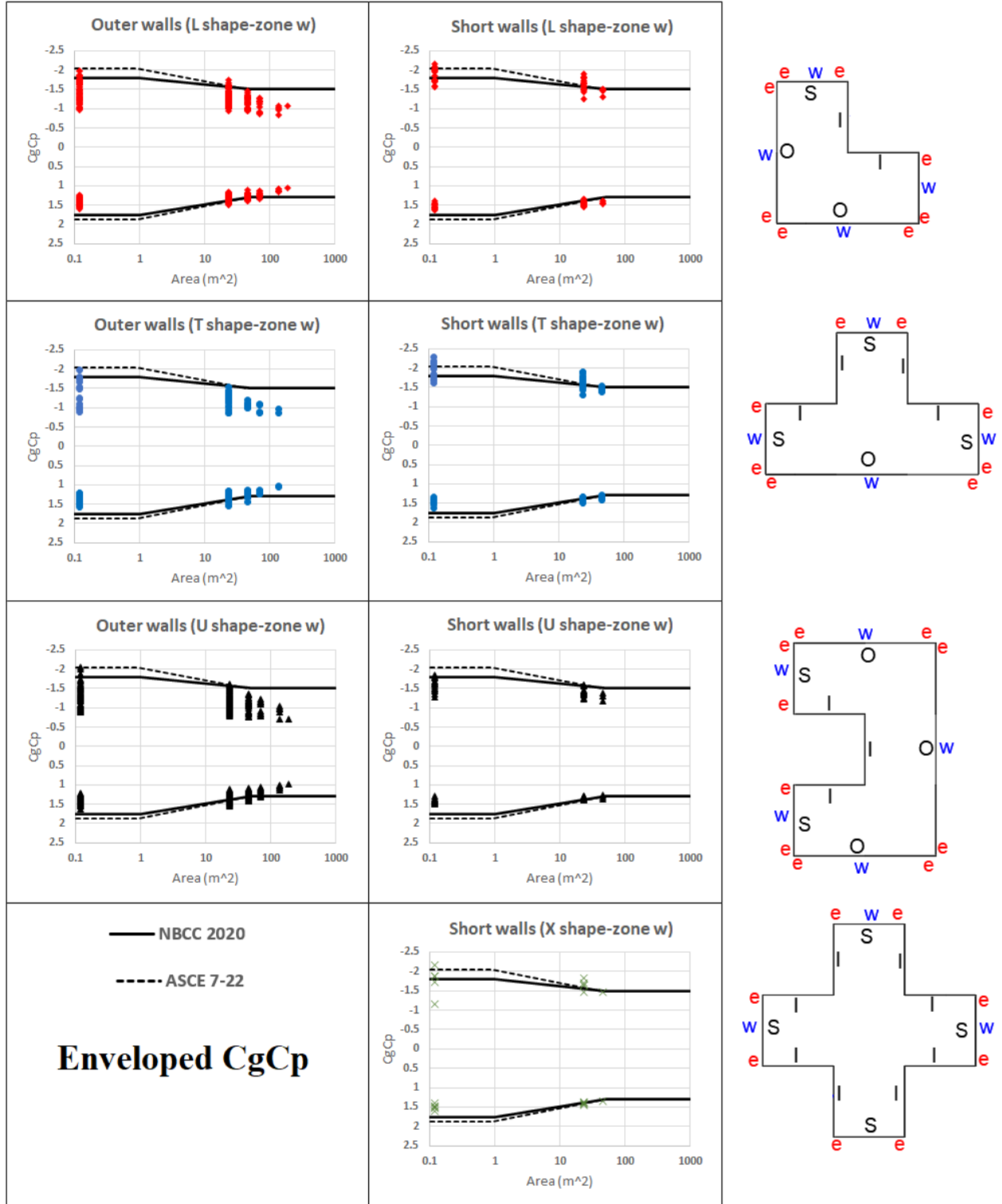


Figure 5.10: Comparison between peaks of NBCC 2020 and ASCE 7-22 and the corresponding enveloped peaks among each shape for zone w ($H = 10$ m)

Except for those presented in Figure 5.9, the peaks of the inner walls have not been investigated and compared with provisions until this point, in particular, wall pressures at the reentrant corner. This was noted previously in Figure 4.15, where the inner wall of T2 was shown to experience high pressures at the reentrant corner. The inner walls need to be further divided into zones to separate the parts of the walls at the reentrant corners from those in the middle of the inner walls. Figure 5.11 shows an example of the inner wall zones for L2. It was found, as will be presented in the following Figures, that the high pressures at the reentrant corners extend for a distance of twice the end-zone width, $2z$.

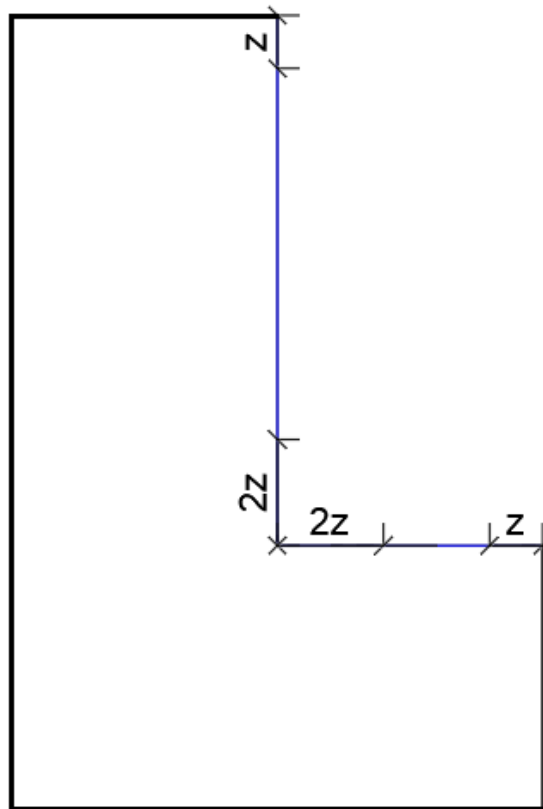


Figure 5.11: Zoning at and near the reentrant corner for L2.

Figure 5.12 compares the wall pressures at the reentrant corners and the provisions of the NBCC 2020 and ASCE 7-22 for zone e/5 and zone w/4. The Figure shows that the positive pressure coefficients are comparable to the code provisions, with the exception that the T shapes area-averaged coefficients exhibit increased values. For the negative pressure coefficients, the comparison with the provisions of zone w/4 shows that the NBCC and the ASCE 7 peaks are significantly lower than the experimental results for the L, T shapes, as well as the reentrant corner suction of the U2 model. At the same time, the other U shapes and the X shape reentrant corner suction are comparable to the peaks of zone w/4. On the other hand, the experimental results of the L, T, and U2 shapes are comparable to the ASCE 7 peaks (zone 5) with an estimated difference of less than 15%. The difference is relatively larger between the NBCC peaks of zone e and those of the L, T, and U2 shapes, and the estimated difference is around 30%. This indicates that provisions of zone w/4 are not appropriate for these shapes, and zone w/5 should apply at the reentrant corner.

The last wall areas need to be compared with the ASCE 7-22 and NBCC 2020 are the middle of the inner walls. Figure 5.13 compares the wall pressure coefficients within the middle of the inner walls. The middle area of the inner wall is defined through two examples, L2 and U2, in Figure 5.13. The comparison shows that the provisions of zone w/4 are higher or at least comparable to the experimental results. This means that the peaks of zone w/4 are satisfactory for the design of these inner wall areas.

Reentrant corners

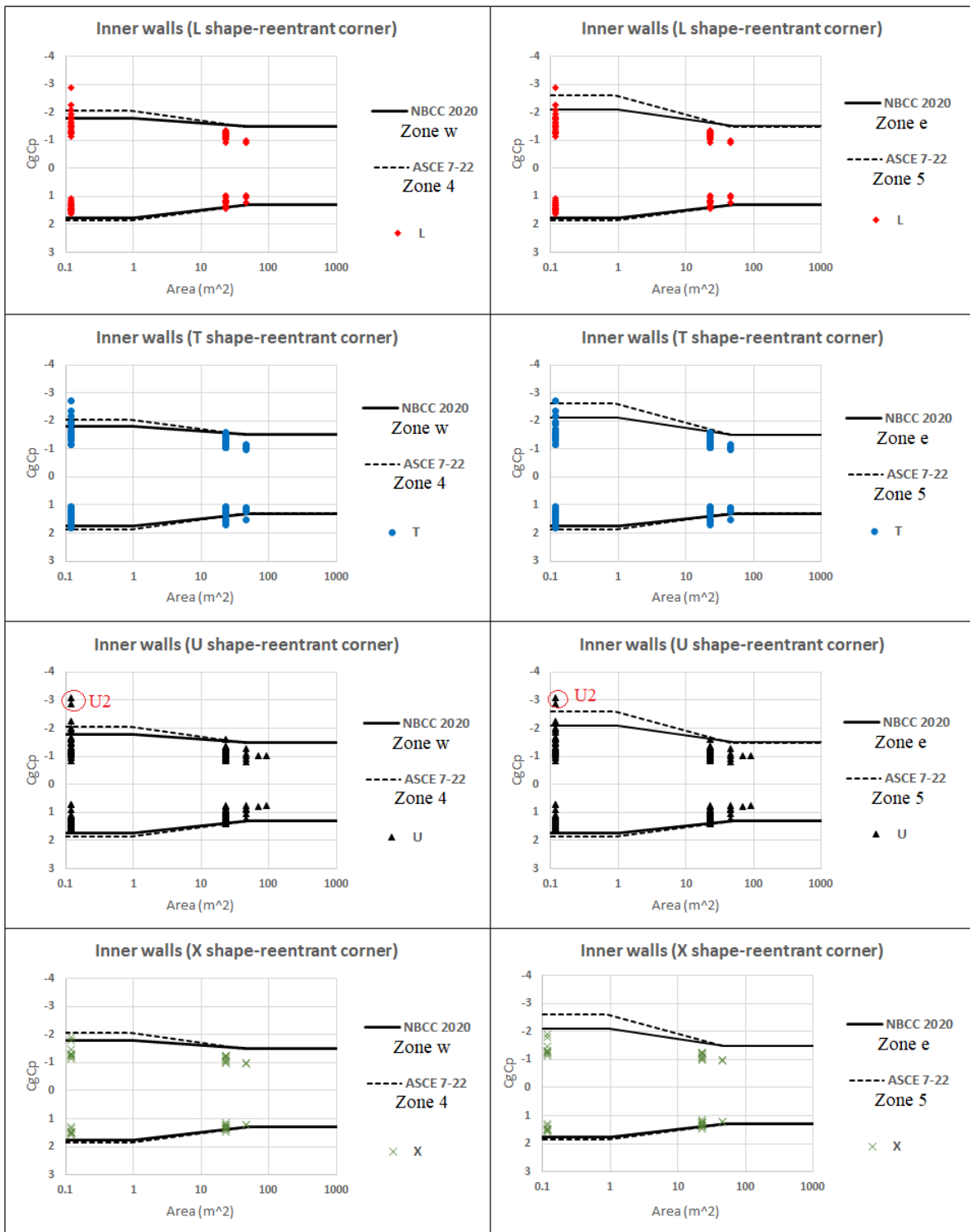


Figure 5.12: Comparison of wall pressures at the reentrant corners and those of NBCC 2020 and ASCE 7-22.

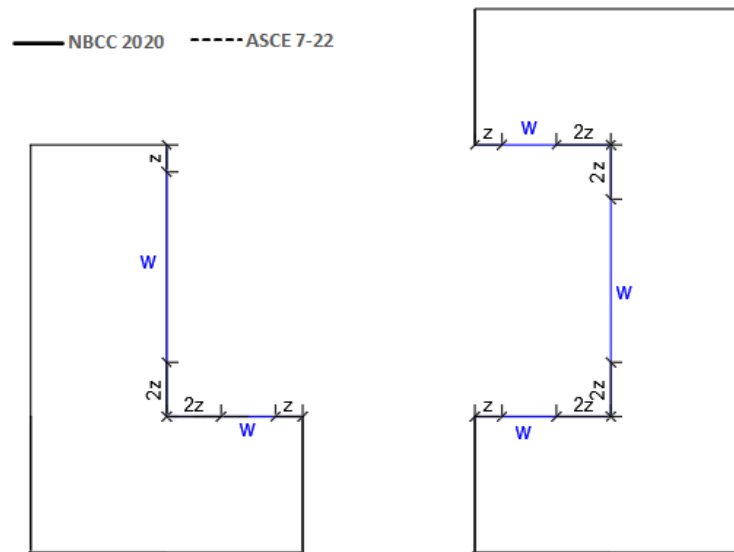
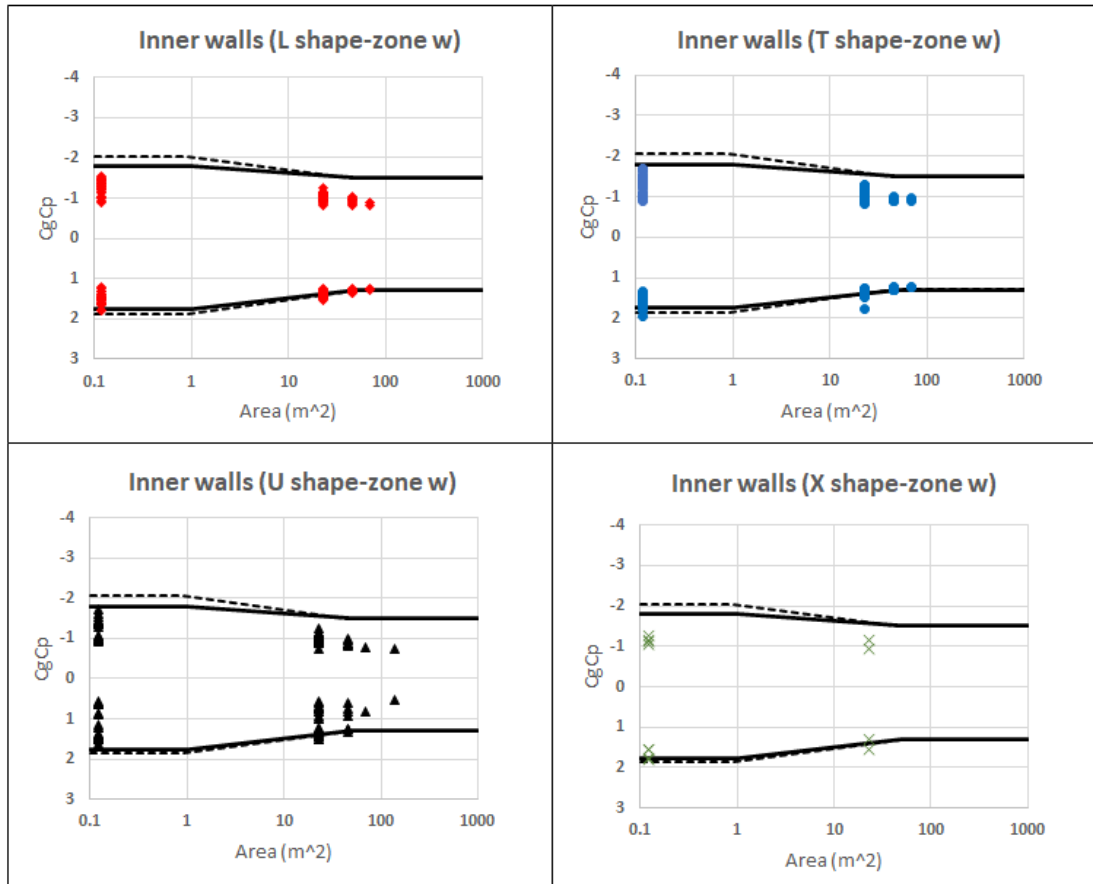


Figure 5.13: Comparison of pressure coefficients of the middle of the inner walls and those of NBCC 2020 and ASCE 7-22 (zone w/4).

Figure 5.14 shows the suggested provisions for the design of cladding and components of walls of nonrectangular buildings based on those of rectangular building provisions in ASCE 7-22 and NBCC 2020. The T shape plan is used as a reference, and the suggested provisions apply to the rest of the non-rectangular shapes. The summary and the rationale of the updates in Figure 5.14 are as follows:

- **Zone e/5:** This wall high suction zone applies at the corners (for a distance of z/a) and reentrant corner (for a distance of $2z/2a$) as indicated in Figure 5.14. Since the area-averaged peaks are sensitive to the density of pressure taps, it would be reasonable to suggest that the rectangular building negative provisions of ASCE 7-22 are applicable for the design of non-rectangular buildings. It would also be reasonable to suggest that the NBCC rectangular building negative peaks of zone e are appropriate for the design of non-rectangular buildings, with one exception for the short walls and reentrant corners, where the negative peaks of zone e of NBCC 2020 that correspond to an area less than 1 m^2 need to be increased by 30%.
- **Zone w/4:** This zone applies to the rest of the wall areas as indicated in Figure 5.14. it is suggested that the provisions of the rectangular buildings of both ASCE 7-22 and NBCC 2020 can be used for the design of walls of non-rectangular buildings after implementing two modifications. For the short walls, the negative peaks of zone w of NBCC 2020 that correspond to an area less than 1 m^2 need to be increased by 30%.

- Although the X shape reentrant corner suctions are comparable to peaks of zone w/4, the conclusion of the open wing shapes (L and T) needs to be applied to the X shape, because it shares aerodynamic similarities with open wings shapes, the fact that the X shapes was studied through a single configuration, and to provide simplicity in the suggested provisions. Further, the U shapes exhibited suction comparable to the provisions of the NBCC at short edges, and the suction of U1 and U3 is also comparable to peaks of zone e at the reentrant corner. However, it was decided to extend the conclusion of open wings shapes to the U shapes. this would provide simplicity in the suggested provisions and address the increased suction of U2 at the reentrant corner.
- **Positive peaks:** The experimental positive peak pressure coefficients are comparable to the corresponding ASCE 7-22 and NBCC 2020 provisions, except for the area-averaged peaks of the T shapes. Given that the area loads are sensitive to the density of pressure taps, it would be reasonable to suggest that the wall positive pressure coefficients of rectangular buildings in ASCE 7-22 and NBCC 2020 are applicable without modifications.

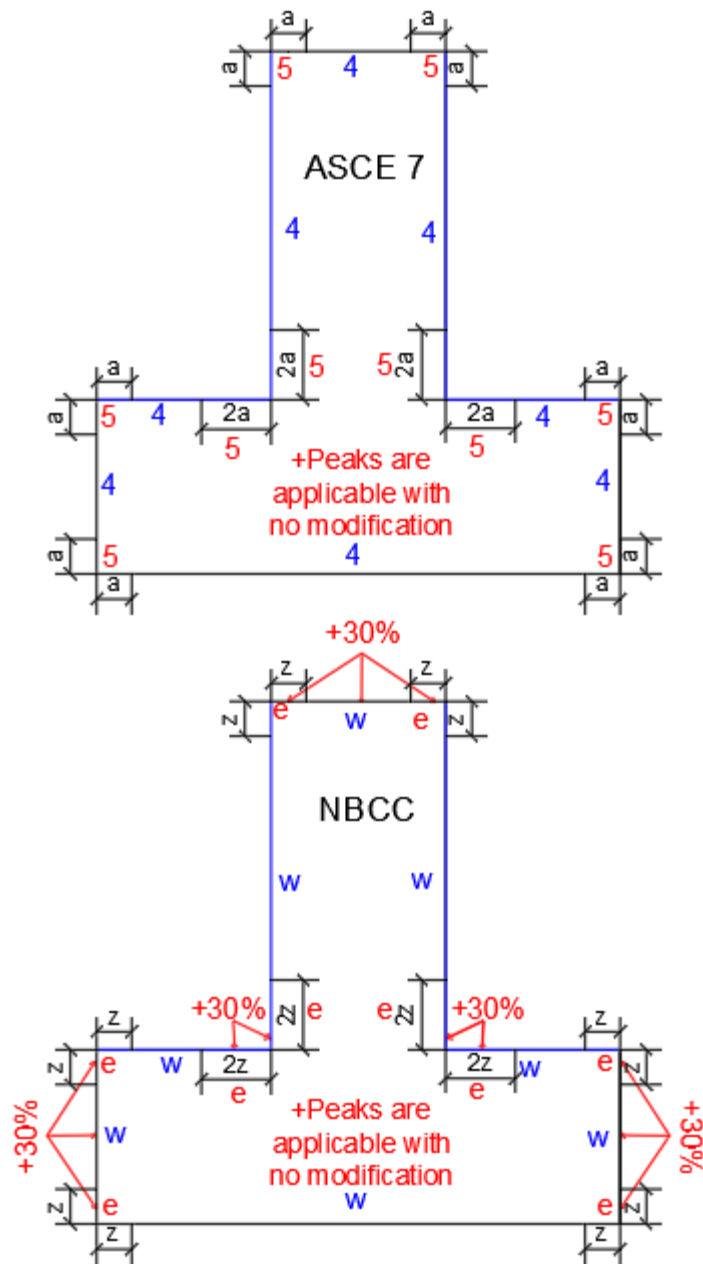


Figure 5.14: Suggested provisions for walls of non-rectangular buildings based on those of rectangular buildings (the T shape plan is a reference).

Chapter 6

Application of Machine Learning

Part of the materials presented in this chapter has been published in Wind and Structures (Aldoum and Stathopoulos 2025b) and presented at two conferences (Aldoum and Stathopoulos, 2023; Aldoum and Stathopoulos, 2024b).

6.1 Basic principles

Machine Learning (ML) is a powerful tool for performing multiple and multivariate regression of complex data. Given the variety of configurations and results presented previously and the accelerating advancement in Artificial Intelligence, ML may emerge as a potential approach for codification in the future. Therefore, it is important to implement ML techniques in wind engineering to configure the potential usage of ML in the codification process. ML was implemented in this study to perform multiple regression to forecast the wind pressure coefficients of non-rectangular buildings based on variables that were obtained from the experimental dataset. Several regression algorithms were used to generalize to the experimental dataset. This includes Random Forest (RF), externally randomized trees or Extra Trees (ET), Gradient Boosting (GB), Voting Regressor (VR), Stacking Regressor (ST), and Artificial Neural Networks (ANN). This section introduces those ML algorithms.

The child estimator of RF, ET, and typically of GB is a decision tree. The following includes details of those regressors based on the documentation provided by Scikit-learn (Pedregosa et al., 2011).

A decision tree regressor (Pedregosa et al., 2011) consists of nodes, branches and leaves, each node includes a number of samples, and each leaf includes a numerical value that represents the final output of the decision tree based on given inputs. The branches represent the rules of the decision tree to split the samples in the nodes based on a certain threshold. Scikit-Learn uses an improved version of the Classification and Regression Tree (CART). For a given dataset S that includes n samples and has X input (features) and y target, the decision tree starts allocating the dataset S in a root node and then split the samples into two smaller sets; left node S_L with n_L samples and right node S_R with n_R samples based on the split candidate $\Theta = (j, t)$, where j is a feature and t is a threshold. This can be represented as follows (Pedregosa et al., 2011):

$$S_L(\Theta) = S((X, y) | (X_j \leq t))$$

$$S_R(\Theta) = S((X, y) | (X_j > t))$$

To select the best split candidate, first, the split quality is computed through a loss function H , then the weighted average of H is calculated as follows:

$$\text{weighted average loss } (S, \Theta) = \frac{n_L}{n} H(S_L(\Theta)) + \frac{n_R}{n} H(S_R(\Theta))$$

Where H is calculated based on the selected criterion to measure the quality of split, for example, if MSE is selected as a criterion then:

$$H(S) = \frac{1}{n} \sum (y - y_{mean})^2$$

Finally, the best split Θ^* is determined using the following equation which represents the split candidate that minimizes loss:

$$\Theta^* = \operatorname{argmin}_{\Theta} (\text{weighted average loss}(S, \Theta))$$

The previous step is repeated until the tree reaches the specified maximum depth based on either the `max_depth` criterion or the minimum number of samples allowed to construct a leaf.

Random Forest (Breiman., 2001) is an ensemble of a huge number of decision trees that are trained independently and randomly based on the methodology explained previously for selecting the best split, the final output of the random forest is the average of the decision trees predictions.

Extra Trees (Geurts et al., 2006) is similar to Random Forest (i.e. the final prediction is the average of the decision trees outputs) but with increased randomness. The increased randomness in Extra Trees comes from selecting a random threshold, t , when looking for the best split, instead of ensuring that the selected threshold minimizes the loss. The extra randomness often increases the bias and reduces the variance of the model, which is why, sometimes, Extra Trees provides better performance than Random Forest.

Gradient Boosting (Friedman, 2001) uses several estimators (typically decision trees) in which each tree is constructed in a way to reduce the loss resulting from the previous one, in addition, the trees are fitted to predict the residuals instead of the target values. Further details can be found in the documentation provided by Scikit-learn (Pedregosa et al., 2011). The previously mentioned models are the base models in this study and will be combined through ensemble meta-estimators.

Voting regressor (VR) is a meta-estimator that combines the predictions of several models to output better predictions. For example, the base models RF, ET, and GB can be combined through VR to result in better predictions than the predictions of each of the base models. The VR averages the outputs of the estimators (base regressor) based on weights assigned to each estimator, the

best practice is to determine the weights of estimators based on a grid search; However, no efforts were made in optimizing the weights of the estimators in this study as it is computationally heavy, and the estimators were considered with equal weights.

Stacking regressor (ST) is an ensemble meta-estimator that implements the Stacked generalization method (Wolpert, 1992) to combine the predictions of several estimators. ST uses estimators and a final estimator to output predictions that outperform those of the best estimator used in the ensemble or at least result in a performance equal to that of the best estimator. The final estimator, typically RidgeCV, uses the stacked predictions of the estimators as an input, and then it is trained on the stacked predictions using cross-validation. It is also possible for the final estimator to be trained on stacked predictions and the original dataset used to train the estimators. Furthermore, the Stacking regression can be made with multiple layers. This can be implemented by creating a stacking regressor (ST) with certain estimators and appointing ST to the final estimator of another stacking regressor, the resulting stacking regressor can be referred to as ST_m. The details of Voting and the stacking regressor are demonstrated in Figure 6.1.

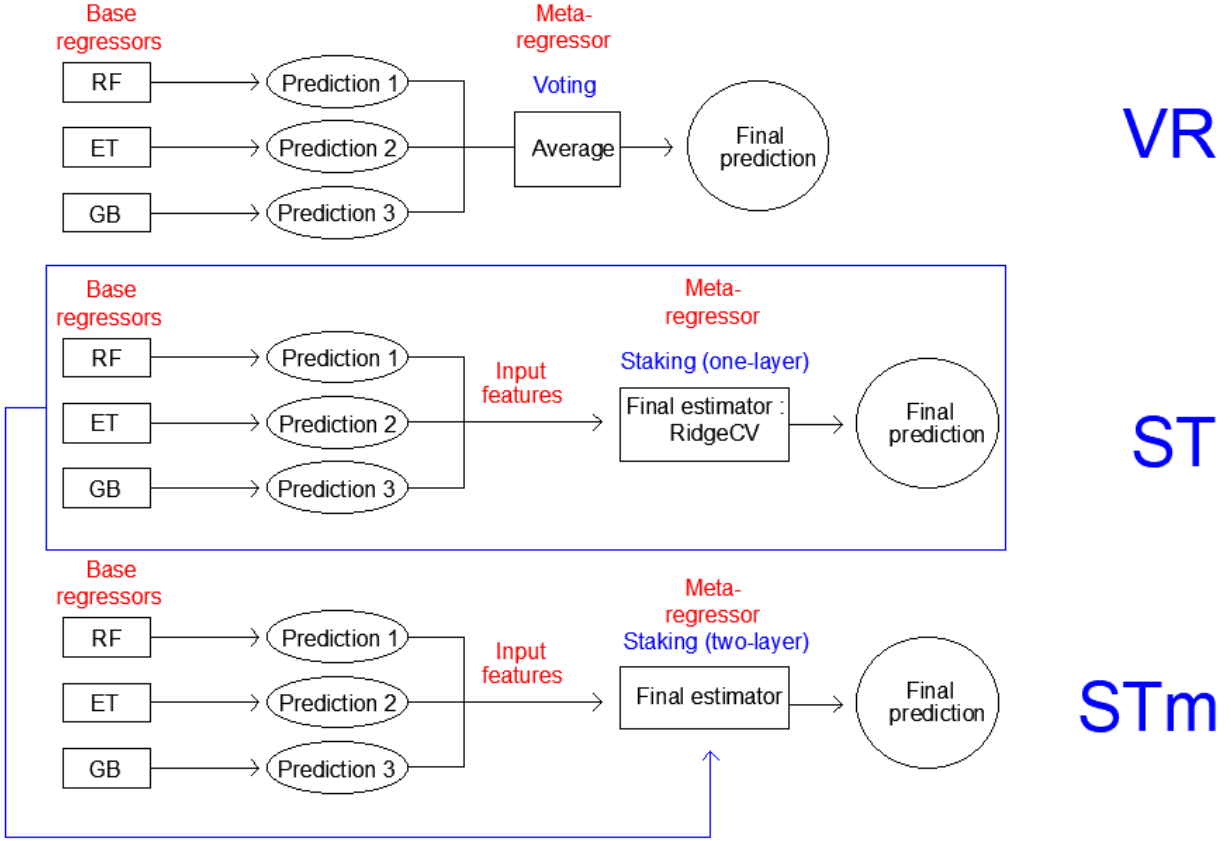


Figure 6.1: Demonstration of the meta-regression.

For the ANN, the study uses the TensorFlow Keras Sequential model (Abadi et al., 2015, Chollet, 2015) to fit the experimental data. Figure 6.2 shows a schematic of an architecture of an ANN of four hidden layers and a single output. In a fully connected sequential model, the neuron in a single layer receives an input, z , from the previous layer, the weighted sum of the outputs from all neurons in the previous layer plus a bias, which is represented as follows:

$$z = \sum_{i=1}^n (x_i w_i) + b$$

where n represents the total number of neurons in the previous layer, i denotes the order of the neuron in the previous layer, x_i , and w_i are the output and weight of the i th neuron, respectively, and b is the bias. The value z is then passed through an activation function to determine the final output value to the next layer.

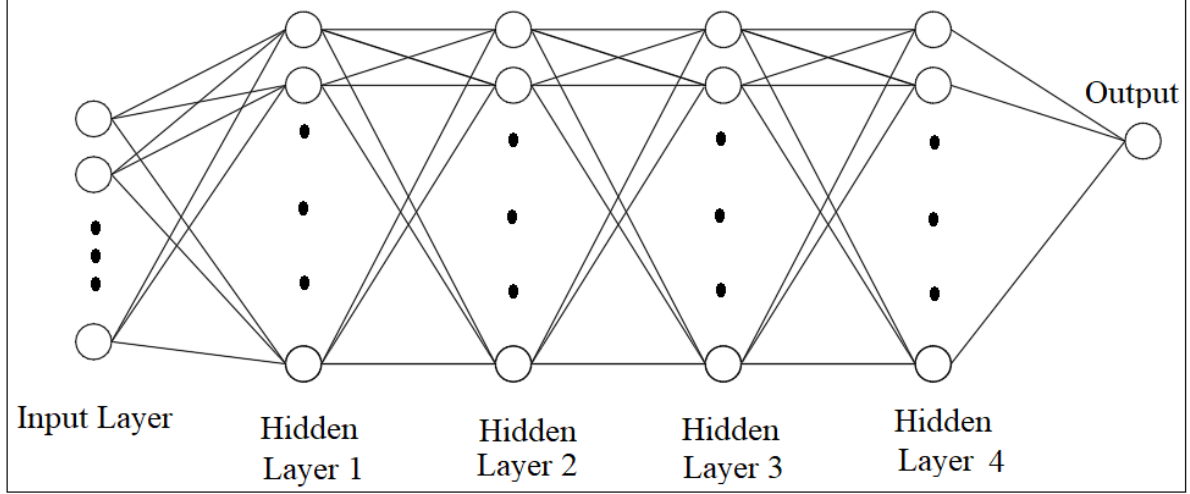


Figure 6.2: Architecture of the ANN.

A variety of metrics are employed to assess the performance of machine learning models. These include measures such as the coefficients of determination (R^2), mean square error (MSE), and other metrics to evaluate particular performance objectives of the model. This study utilized four metrics to evaluate the performance of the GBR and ANN: R^2 , MSE, mean absolute error (MAE), and mean bias error (MBE). The mathematical formulas of the four metrics are as follows

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - y_p)^2}{\sum_{i=1}^n (y_i - y_{mean})^2}$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - y_p)^2$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - y_p|$$

$$MBE = \frac{1}{n} \sum_{i=1}^n (y_p - y_i)$$

Where y_p is the predicted value, y_i is the actual value (evaluated based on the wind tunnel data), y_{mean} is the mean of y_i , and n is the number of samples within the selected set (e.g., training, validation, testing). R^2 reflect the proportion of variance in the target values (pressure coefficients) that is explained by the prediction of the ML model. MSE is used to quantify the mean squared difference between the target values and the ML model predictions. This metric squares the errors; thus, it signifies the large errors. MAE, on the other hand, calculates the average of the absolute values of errors; it is less sensitive to large errors compared to MSE. MBE is a reflection of the bias in the ANN predictions, a positive MBE indicates overestimation, and a negative MBE reflects underestimation of the wind tunnel pressure coefficients.

6.2 Input features, data preprocessing, and data split

6.2.1 Input features

As mentioned previously, four irregular shapes are included in this study: L, U, T, and X. In addition, each shape is characterized by a specific arrangement of pressure measurement points, different plan dimensions, and heights, and tested for several wind directions. The experimental dataset needs to be organized and translated into informative features (or variables) that can be input into the ML algorithm for training.

Figure 6.3 shows seven variables that could be read from the tested wind tunnel models and will be used as input features during training and testing. Feature 1 represents the shapes of the irregular buildings included in this study (L, U, T, and X). This is a categorical feature and needs to be converted to numbers through an encoder, as will be explained in the next subsection. Features 2 and 3 tell the pressure measurement point on the roof through a distance in x and y , respectively. In addition, the nine models have different plan dimensions, which can be described by the aspect ratio in x , feature 4 ($\beta_x = D/B_x$), and the aspect ratio in y , feature 5 ($\beta_y = D/B_y$). Finally, features 6 and 7 represent the wind directions and height of the building. It should be mentioned that the target variables are mean pressure coefficients (mean C_p), minimum pressure coefficients (or negative peak C_p), and maximum pressure coefficients (or positive peak C_p). Therefore, three different ML systems have been considered for the prediction of each target. It should be mentioned that only two configurations, L1 and L3, were tested for three heights which do not provide sufficient information regarding the effect of the building height on wind pressures for the rest of the irregular buildings; therefore, the experimental data collected for heights of 5 m and 20 m were excluded in this study. For walls, the same features were used, with the exception of the distances in x and y , a different coordinate system was adopted by unfolding the walls of the configuration as shown in Figure 6.4.

The experimental dataset includes a total of 195,000 samples for roofs pressure and 31,000 for walls, each sample represents a specific instance; for example, when the model L1 is tested for 30° wind direction (WD), and a height (H) of 10 m, the corresponding sample of the mean wind pressure coefficient at tap 1 can be specified using the seven prementioned input features and the target mean C_p as follows:

Feature 1: L (category)

Feature 2: 0.6 m (coordinate of tap 1 in x)

Feature 3: 0.6 m (coordinate of tap 1 in y)

Feature 4: 0.5 (aspect ratio of the model L1 in x)

Feature 5: 0.5 (aspect ratio of the model L1 in y)

Feature 6: 30° (WD)

Feature 7: 10 m (H)

Target: - 1.42 (C_p)

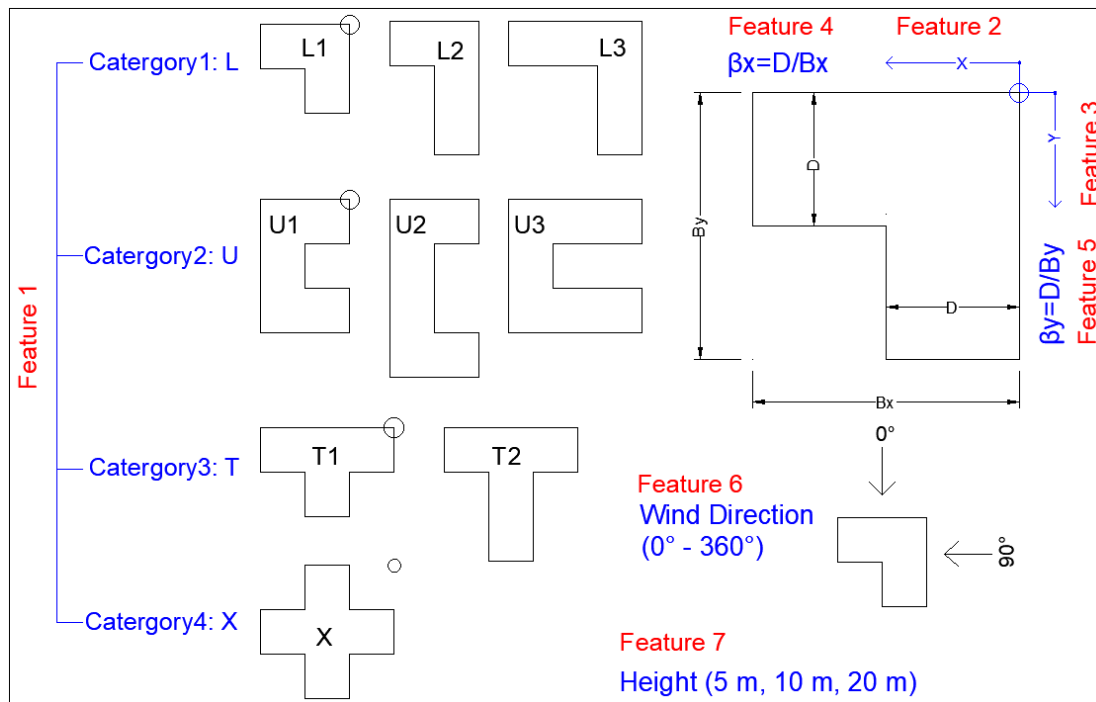


Figure 6.3: Input Features.

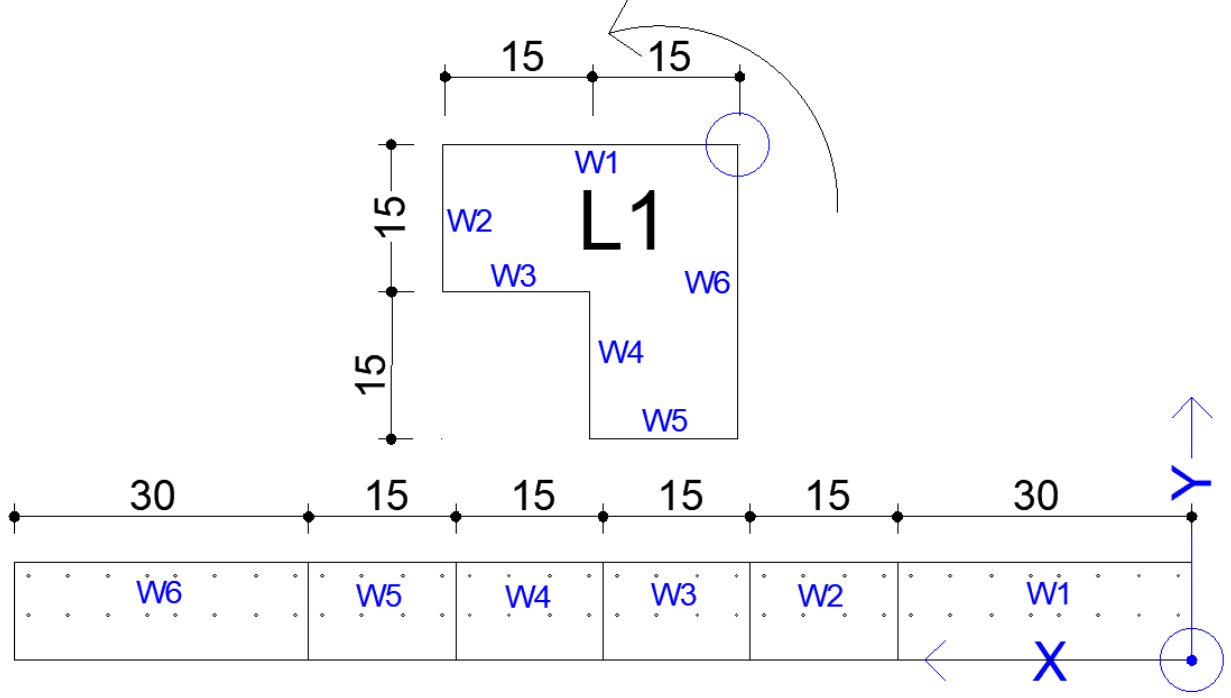


Figure 6.4: Illustration of X and Y coordinates for walls, L1.

6.2.2 Data preprocessing and data split

Data preprocessing is the most important step in ML as it enhances the ML model performance significantly. The input features are with different ranges and data types. Feature 1 includes four categories (texts) and needs to be transformed into numerical values using an encoder. Generally, the use of one-hot encoding is recommended if the categorical feature includes less than 10 categories (Géron, 2019). In this study, Feature 1 has four shapes, and consequently, a one-hot encoder was used, which transforms the text into one (1) when a certain category exists and zeros (0) elsewhere, as shown in Figure 6.5.

The remaining features describe the instances with numbers but are included with different scales and need to be brought to the same scale to improve the performance of the ML models (Géron, 2019). Having WD ranges from 0° to 360° , and x and y extend to up to 45 m and 60 m,

respectively, for roof and up to 240 m and 10 for walls; a scale from 0 to 1 is appropriate to make the features in the same range, this was performed by normalizing the features using the maximum values in each variable. It should be mentioned that features 4 and 5 are already between 0 and 1, and no scaling is required. Furthermore, the target values generally need not be scaled (Géron, 2019).

Figure 6.6 presents an example of feature transformation for one sample; the fourth and fifth features and the target remain unchanged, the first feature was transformed using one-hot encoding, and features 2, 3, 6, and 7 were normalized by the maximum values in each. It should be noted that the categorical feature was converted into four features after encoding, resulting in a total of nine input features.

One-hot encoding

Feature 1		Feature 1			
L	→	1	0	0	0
T	→	0	1	0	0
U	→	0	0	1	0
X	→	0	0	0	1

Figure 6.5: One-hot encoding of the four categories.

Original data									
Feature 1				Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Target (Cp)
L				0.6	0.6	0.5	0.5	30	-1.4203271



Transformed data									
Feature 1				Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Target (Cp)
1	0	0	0	0.02	0.02	0.5	0.5	0.083	-1.4203271



one-hot encoding



Normalization



No change



Normalization



No change

Figure 6.6: Example of features transformation (one sample).

The experimental dataset includes numerous instances for four building shapes, splitting the data into training and testing sets is crucial herein, as the type of data included in the testing set would decide the extent of generalization that the ML system can be claimed for in predicting the wind pressure coefficients on irregular buildings. In this regard, two possible scenarios could be set:

- Random split: Dividing the entire dataset randomly into training and testing units with a certain split ratio (e.g., 70% training to 30% testing). This allows having the four shapes in both training and testing sets. A satisfactory validation score positively confirms that the ML system provides predictions of wind pressure coefficients for building shapes of L, U, T, and U with sufficient accuracy.
- Structured split: splitting the data set based on an attribute such as wind direction.

6.3 Grid search

Each machine learning model has a set of parameters (hyperparameters) that control its performance on a given dataset, an exhaustive grid search with cross-validation (GridSearchCV)

(Pedregosa et al., 2011) was used to figure out the best parameters for each model and optimize its prediction performance. 4-fold cross-validation was applied to obtain the best parameters using a parameter grid and training set.

The parameter grid or space is a set of parameter ranges that includes a potential optimal value for each parameter. Constructing the parameter grid for hyperparameters optimization is challenging and could be time-consuming during running. Ideally, the parameter grid for a certain model should include all parameters associated with that model in all possible ranges. For example, RF, which uses a decision tree as a child estimator, has numerous hyperparameters, and the potential best value of each hyperparameter is available in the range applicable for each. Digging deep into RF, the first parameter to consider in the parameter grid is the number of decision trees (`n_estimators`) used in the random ensemble; the default value is 100 estimators but it could be higher or less than 100, therefore, a range between 50 and 2000 could include the potential best value but it could be above this range (e.g., 3000); however, expanding the search space is computationally heavy and requires long run time, also, increasing the number of estimators magnifies the model's complexity. Another hyperparameter is whether or not to use the bootstrap (i.e., training the estimators on different parts of the training set). Other parameters such as `max_depth` (the maximum depth of the child estimator), and `max_features` (the maximum number of features to make the best split) may also be considered.

Given the relatively huge number of hyperparameters, including every hyperparameter and with a wide range is impractical. Therefore, the best practice is to select a few hyperparameters with a limited range and implement the search, if the validation score on the testing set is acceptable, then the parameter grid is excellent, otherwise, the grid should be updated by increasing the range

of the hyperparameters or adding extra parameters to the grid (in some occasions, both actions should be applied). It should be mentioned that other grid search algorithms are available as well. For example, randomized grid search (`RandomizedSearchCV`) uses the same approach as in `GridSearchCV` but does not cover all parameters in the grid; rather, it selects parameter values randomly.

Figure 6.7 shows the Workflow of optimizing the ML models. The methodology starts with data preprocessing to obtain training and testing sets as presented previously. Then the training set, along with a parameter grid, is used for hyperparameter tuning (i.e., searching for the best parameters). Once the best parameters are obtained, an ML model is constructed using the best parameters and trained with the training set (the same set used for grid search) to end with a trained model. Afterward, the model performance is evaluated using the testing set (unseen by the model during training), if the evaluation score is greater than an acceptable value then the model will be retained as a final and optimized model, otherwise, the parameter grid needs to be updated by changing the space of the parameters, and the entire process will be repeated until a satisfactory score is obtained. It is important to mention that an acceptable value for an evaluation score takes a complicated definition as this value will be a threshold to stop the grid search and adopt a final model. In this study, the change in the grid stops when further modification will make the search computationally heavy. Nevertheless, most of the models presented in this study have scores of more than 0.94.

The flow chart shown in Figure 6.7 is applied to four ML models; RF, ET, and GB, once the optimized versions of the four models are obtained, Voting and stacking regressors (VR, ST) are

applied to combine the predictions and end with a more efficient ensemble. The optimization of ANN was similarly performed to achieve the highest possible performance of the ANN.

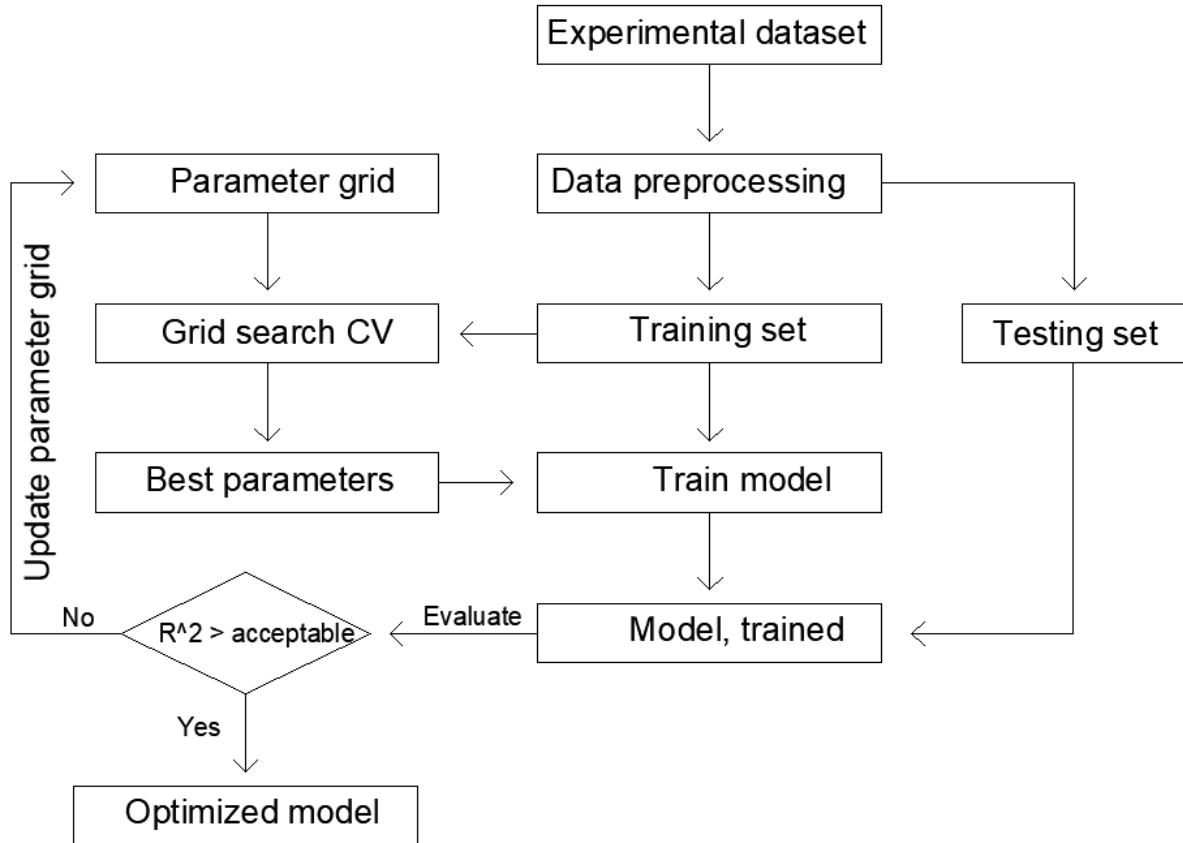


Figure 6.7: Workflow.

6.4 ML training and validation

6.4.1 Random split

This subsection involves the training and testing of the ML models using training and testing sets selected randomly. Six ML models were used in the random split approach: RF, GB, and ET, and the ensemble method was implemented using the VR and ST for roof pressure coefficients, and

VR, ST, and STm for wall pressure coefficients. The STm model was not used for roof pressures because the STm becomes computationally heavy for large datasets.

As mentioned previously, an exhaustive grid search with 4-fold cross-validation was implemented to optimize the ML models used in this study: RF, ET, and GB. Each model has a different set of hyperparameters, some hyperparameters exist in the three models (e.g., number of estimators).

To illustrate the effect of hyperparameters on the performance of the model, tuning the hyperparameters of GB on the roof dataset is discussed. The grid search was performed on four hyperparameters: number of estimators, max_depth, max_features, and min_samples_split, and the initial training/testing split ratio was 7:3, the split was performed randomly. The training set was then used for hyperparameter optimization and training of the GB algorithm, and the unseen testing set was dedicated as a validation set of the ML models and evaluate their performance and efficiency. The results of the grid search indicated that the optimal values of max_depth, max_features, and min_samples_split were 10, 6, and 8, respectively. Regarding the number of estimators, the optimal value was 1000 based on the grid search. However, further investigation was performed by evaluating the testing score for GB with different numbers of estimators in the range of 50 to 1000 at a step of 50, while the other hyperparameters were assigned to the optimal values. The variation of the GB prediction accuracy for the testing set was then plotted against the number of estimators, n , in Figure 6.8. It is evident that the accuracy is proportional to the number of estimators used in the GBR model; however, the R-squared value is marginally improving after $n = 500$ at which the coefficient of determination is about 0.960. This indicates that increasing the number of estimators beyond 500 will only add extra complexity to the model without gaining

a significant improvement in the prediction accuracy. Therefore, a value of 500 estimators was deemed optimal for GB.

The size of the testing set greatly influences the confidence in the validation and robustness of a machine-learning model. A larger testing set enhances confidence in the model's predictions. However, a larger testing set also means less data available for training the model to understand the dataset's patterns and relationships. Therefore, finding the right balance between the size of the testing set for validation and the size of the training set for model comprehension is crucial for effective machine learning model development. Searching for the balance requires trying several testing set sizes and adopting the optimal size for the testing data. The validation R-squared and MSE values of the peak C_p for a range of testing data sizes, 0.1- 0.9 at a step of 0.1, were calculated. It was found that the performance of the model on the testing set increases as the testing set size decreases. However, the performance was marginally improved when the size of the testing set was reduced from 0.3 to 0.2; the R-squared values increased by approximately 0.42%, changing from 0.957 to 0.961, and MSE changed from 0.02 to 0.018. Therefore, it was decided to use a test-to-train ratio of 3:7 as the resulting enhancement of the model outputs is small.

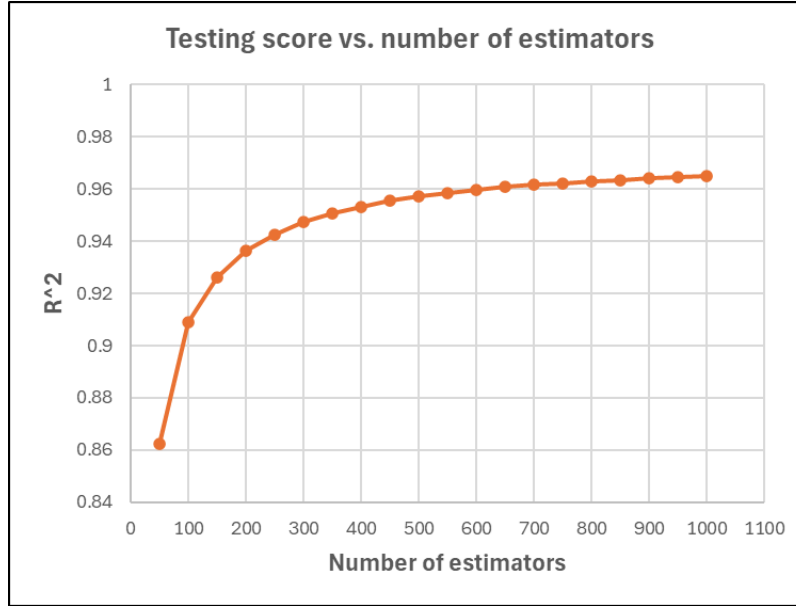


Figure 6.8: R-squared values versus number of estimators (GB), roof dataset.

Figure 6.9 presents ML predictions of roof mean pressure coefficients on the testing (unseen) set compared with those measured in the wind tunnel for five regressors. Among the five models, predictions of RF have the maximum MSE (0.003) and the Lowest R-squared (0.969). On the other hand, GB and ET models have R-squared values of 0.978 and 0.974, respectively, and slightly outperform RF. The three models were added up with equal weights using a voting regressor (VR) that takes the average predictions of RF, GB, and ET for each instance in the testing set, in other words, the voting regressor ensembles the three models. VR is more effective than each RF and ET, and almost the same as GB. ST output better prediction results, it provided predictions of mean values with better values of the adopted metrics; the R-squared was improved to 0.979, Although the improvement is small in the R-squared value, the prediction points are closer to the 45° line, which indicates a better prediction performance.

For the other two coefficients, minimum and maximum pressure coefficients, the same approach was implemented; each of the two parameters was fitted using the three regressors (RF, ET, and GB), and the voting stacking regressors were then applied to enhance the prediction accuracy.

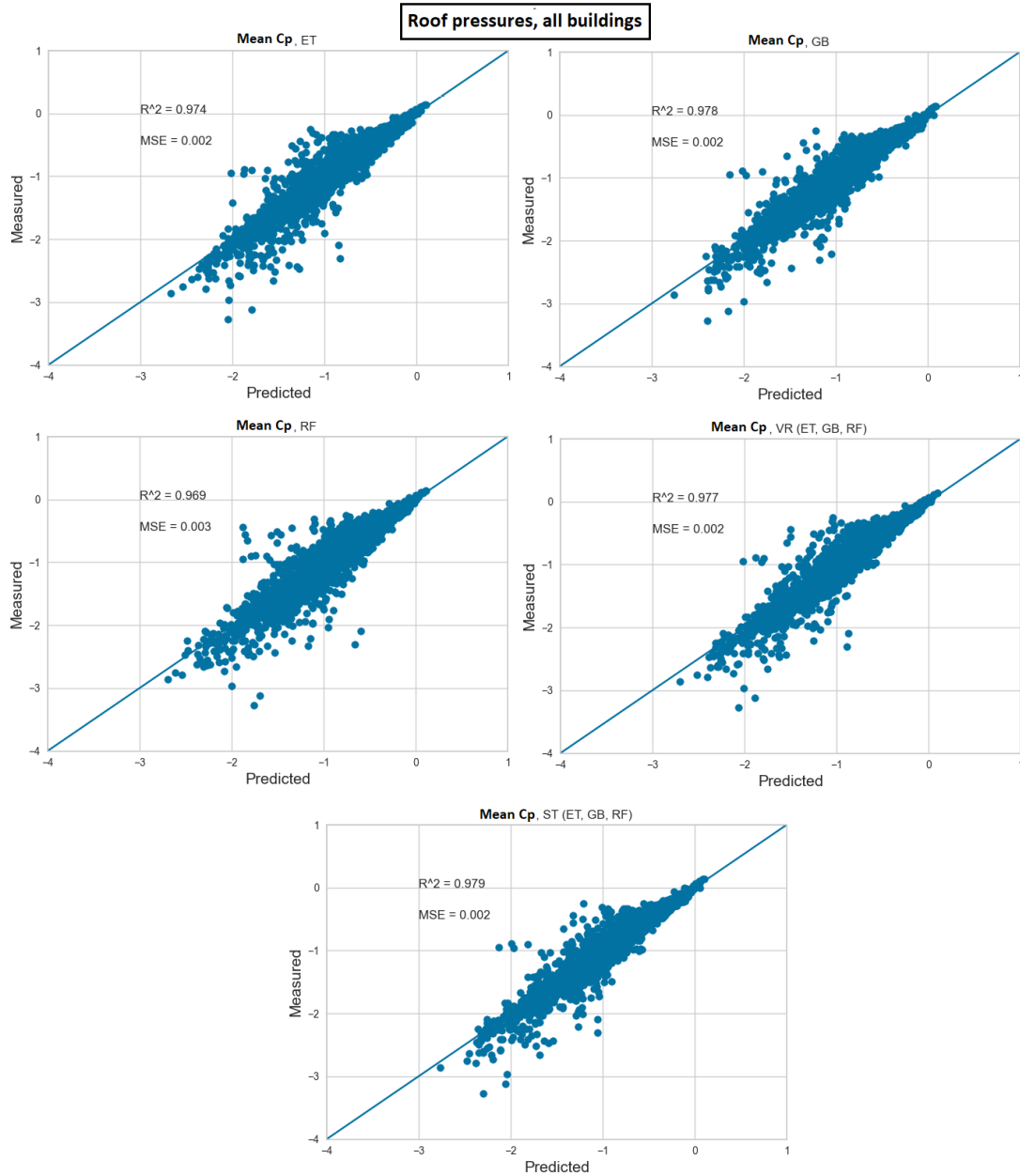


Figure 6.9: Comparison of predicted and measured roof mean pressure coefficients of five regressors, testing set.

Figure 6.10 shows the outcomes of the stacking regressors of minimum and maximum values compared with the WT values. The correlation of the minimum values is stronger than that of the maxima; this is an indication of the complexity of the distribution of the maximum values and is probably attributed to the fact that the maximum values include negative and positive values. The correlation of the minimum pressure coefficients is also lower than the correlation of mean pressure coefficients shown in Figure 6.9; however, the difference is small.

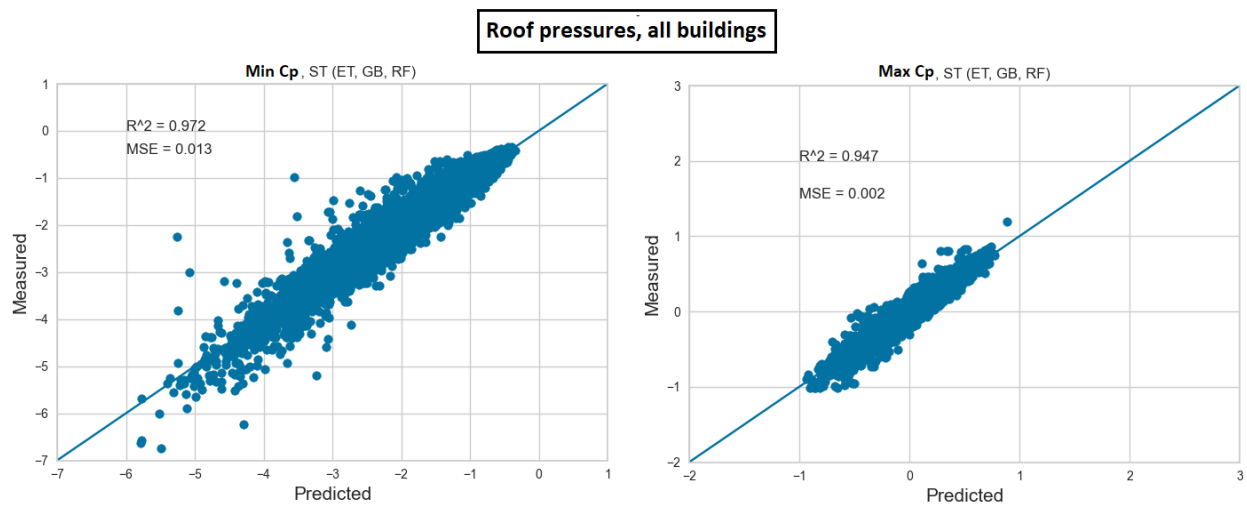


Figure 6.10: Comparison of predicted and measured minimum and maximum pressure coefficients of the ST, testing set.

As mentioned previously, the total number of samples collected for the irregular building walls is 31,000. 70% of the samples were used for training and the rest for testing. The mean, minimum, and maximum values were fitted using three base regressors, then the three base regressors were ensembled using one voting regressor and two stacking regressors.

The outputs of three base regressors and the stacking and voting regressors compared with the measured mean values are presented in Figure 6.11 for the walls of all shapes. ET and RF

exhibited almost the same prediction performance with a R-squared value of around 0.945, while the GB showed a better performance than ET and RF; this is clear from the higher score (0.965) and the tighter cluster of the plot points around the symmetry line. As the VR takes the average of predictions of the three base regressors, the performance of VR is better than that of ET and RF and somewhat less than the performance of GB. The predictions of the one-layer stacking regressor (ST) are almost identical to those of GB, the best base regressor. This is so because the GB is superior to the ET and RF in predicting the target values. On the other hand, the multiple-layer regressor STm outperformed GB and ST with a score of 0.969, in addition, the prediction outliers are significantly reduced. In other words, STm reduced the prediction errors for target points located outside the plot cluster in GB and ST.

Figure 6.12 compares the outcomes of the STm with the experimental maximum and minimum pressure coefficients for the walls of all buildings. The performance of STm is excellent for the maximum values with an MSE of 0.014 and an R-squared value of 0.97. For the minimum values, the prediction score of STm is 0.906; this is, as mentioned previously, an indication that the distribution of the wall minimum pressure coefficients is more complex than those of the mean and maximum. However, the residual for most of the data is around ± 0.5 .

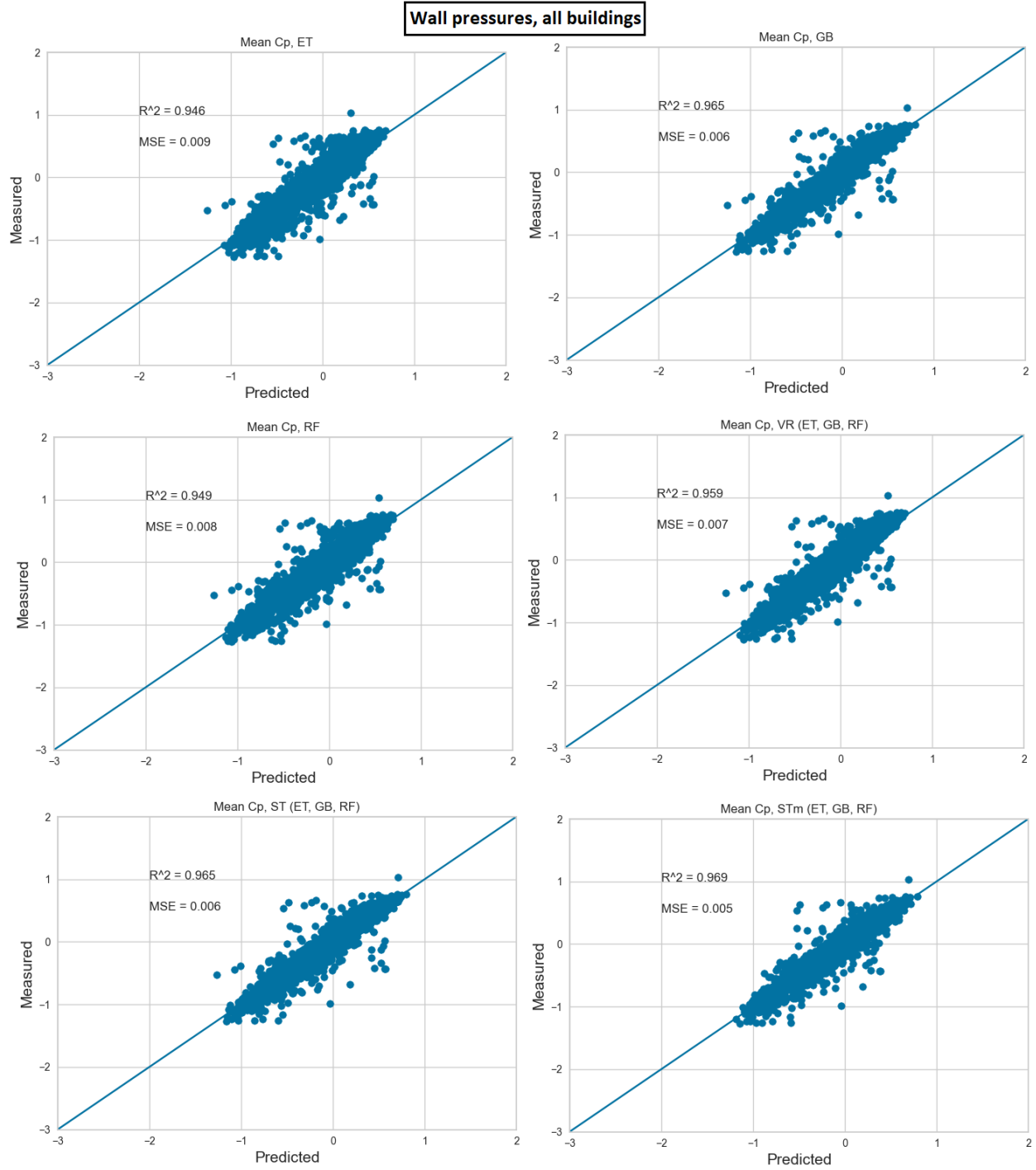


Figure 6.11: Comparison of predicted and measured mean pressure coefficients using six regressors for the walls of the six buildings, testing set.

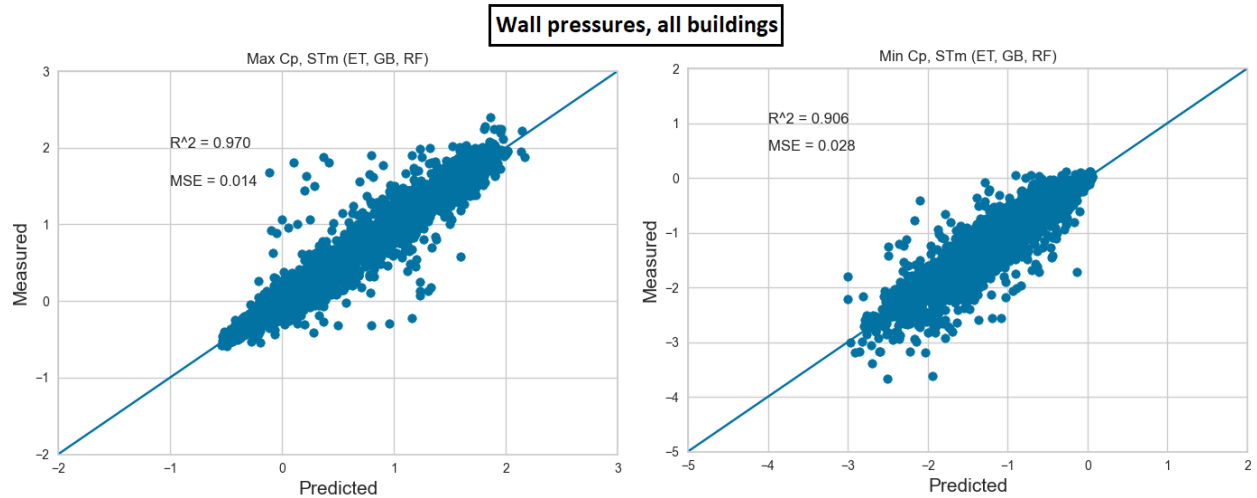


Figure 6.12: Comparison of predicted and measured maximum and minimum pressure coefficients using STm for the walls of the four buildings, testing set.

In summary, the data was fitted using three base regressors and voting and stacking regressors, the R-squared values for all models and three pressure coefficients are provided in Table 6-1. The roof pressures were predicted efficiently with a minimum ST score of 0.947 for the maximum pressure coefficients. The minimum wall pressure coefficients, on the other hand, were predicted with a relatively low score of 0.906 using the STm. Table 6-1 shows that GB always outperforms ET and Rf, and RF and ET exhibited almost the same prediction performance. It can also be observed that the VR outperforms the best regressor when all models used in the voting are with comparable scores. Finally, the performance of staking regressors is always better or at least equivalent to the best regressor.

Table 6-1: R-squared values of all models and three pressure coefficients, testing set

	Roof pressures			Wall pressures		
	Min	Mean	Max	Min	Mean	Max
ET	0.966	0.974	0.932	0.844	0.946	0.94
GB	0.969	0.978	0.945	0.989	0.965	0.967
RF	0.96	0.969	0.928	0.842	0.949	0.945
VR	0.97	0.977	0.944	0.878	0.959	0.957
ST	0.972	0.979	0.947	0.899	0.965	0.967
STm	N/A	N/A	N/A	0.906	0.969	0.97

6.4.2 Investigation of the split approach

Although the random split approach indicates an excellent overall performance on the testing set using five regressors; however, the unseen set was selected randomly, resulting in high similarity between instances within the testing set and the training set, which suggests implicit data leakage. This can lead to an overestimation of the true performance of the five regressors to generalizing to the experimental data. In addition, the random split does not allow for efficient performance inspection. For example, if a pressure coefficient contours map (L1 roof) is presented for a certain wind direction, then the reader would rely on 30% of the contours to judge the model's efficiency, as the remaining 70% were seen by the model during training.

To investigate these issues, the methodology was changed, and the dataset was split based on WD, a structured split. The WD was selected as a criterion for the structured split because it is the independent variable that has the most influence on the target values. Twelve WDs (20°, 50°, 80°, 110°, 140°, 170°, 200°, 230°, 260°, 290°, 320°, and 340°) were set aside to serve as a testing set and the training set was formed by including the rest of the wind directions. This approach enables a comprehensive evaluation of the model's efficiency using full roof contour maps (and other

graphs) generated exclusively from the unseen set. Although the similarity between the training and testing sets still exists, the two sets are more divergent than in the random split.

GB, the best base estimator, was utilized again, using training and testing sets (split based on WD) and implementing the same grid search utilized previously. Its performance, however, on the new varied testing set yielded a decreased level of accuracy, with a maximum R-squared value of around 0.9 (for mean C_p), as shown in Figure 5.10. This confirms the implicit data leakage discussed above, which results in overestimation of the evaluation score of the GB. The decreased score of the GB suggests that a better model is required to enhance predictive performance and provide more accurate results. Consequently, a Feedforward Artificial Neural Network (ANN) was then implemented as presented in the following subsection. Further, the ANN was trained and tested using the roof dataset only.

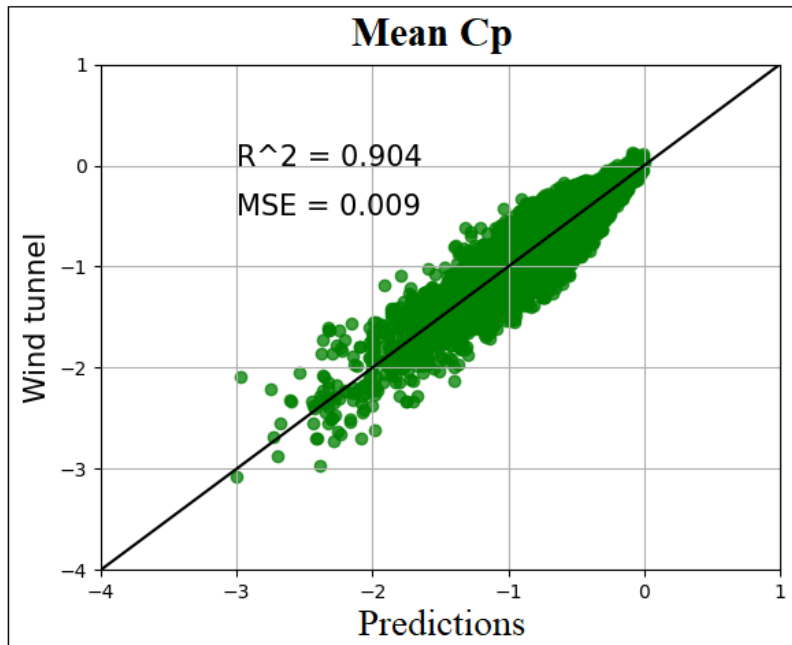


Figure 6.13: Comparison of wind tunnel pressure coefficients and predictions of GB on the testing set, WD-based split.

6.4.3 Structured split (Artificial Neural Network)

The TensorFlow Keras sequential model includes three types of layers: input, hidden, and output layers. The input and output layers consist of nine neurons and one neuron, respectively. This is so because the input and output layers are governed by the shape of the dataset, nine input features, and one target: mean C_p or negative peak C_p (i.e., Min C_p). The number of hidden layers and the number of neurons in each hidden layer were determined by experimentation; after evaluation of several configurations, it was found that four hidden layers with a number of neurons of 100, 500, 500, and 100 provide satisfactory results, and consequently, it was adopted.

The dataset was split into three sets: training, testing, and validation sets. The training and validation sets are dedicated to the training phase. First, the data was split into testing and training sets based on wind directions as described previously; the testing set was chosen to include 12 wind directions while the rest of the wind directions were chosen to be included in the training set, this results in a split ratio of about 26% (testing) to 74% (training). 10% of the training set was randomly selected to create a validation set, which is equivalent to about 7% of the entire dataset. Figure 6.14 presents a chart that includes the percentage of each set with respect to the entire dataset.

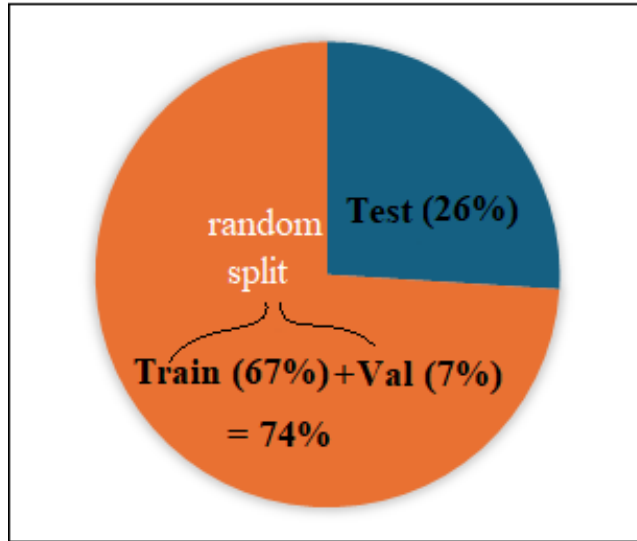


Figure 6.14: Splitting of the dataset into training, validation, and testing sets.

The optimal parameters for the ANN were determined using an extensive search. The search identified the following as the best parameters: the Adam optimizer with a learning rate of 0.001, batch size of 200, and 200 epochs for training. Rectified Linear Units (ReLU) activation functions, which output the input directly if it is positive and zero otherwise, were set for the hidden layers, while a Linear activation function was applied for the output layer. The Linear activation function passes the input through without any transformation.

The other hyperparameters of the sequential model were kept to their default values. The mentioned hyperparameter values were found to result in an excellent performance of the ANN model.

Figure 6.15 presents the learning curve of the sequential model used to predict the mean C_p values. The figure indicates rapid improvement in the model within the first 25 epochs, the learning process then continues improving at a gradual and slower pace until the maximum number of

epochs (200 epochs) is reached or is halted by the early stopping callback, which was set to prevent overfitting. For the peak C_p , a similar curve was achieved.

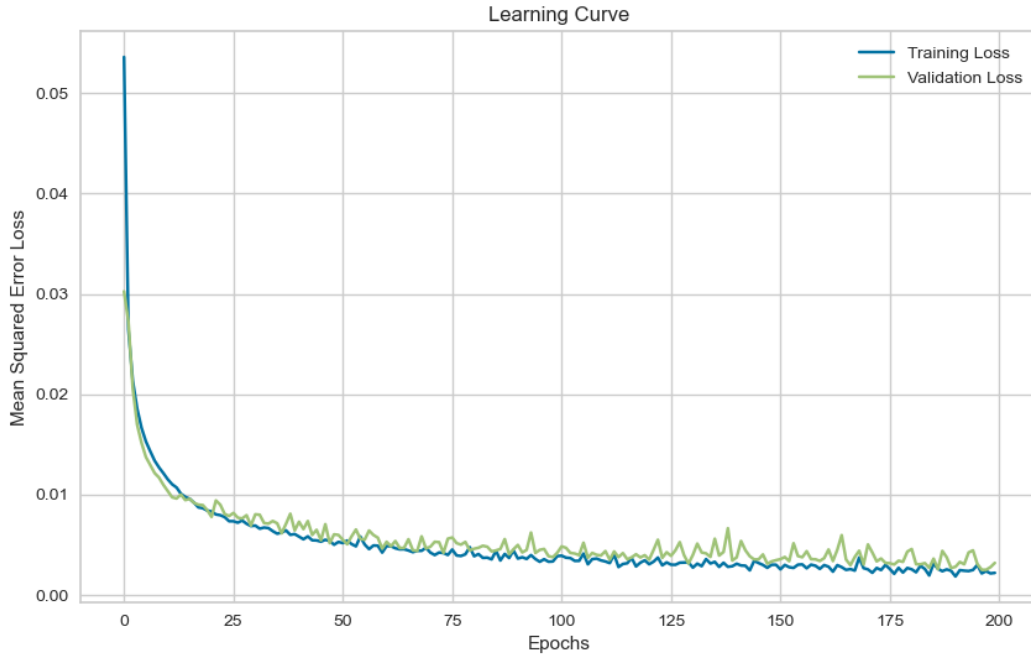


Figure 6.15: The learning curve of the mean C_p ANN.

Figure 6.16 compares the predictions of the ANN models (predicted, horizontal axis) and the wind tunnel mean and peak pressure coefficients (measured, vertical axis) for the training, validation, and testing sets, the corresponding R^2 and MSE values are included in each plot. The ANN models of mean and peak C_p 's exhibited an excellent performance on the testing set (unseen data). This is evidenced by the strong correlations between the measured and the predicted values, with R^2 values of 0.967 and 0.949 for mean and peak C_p 's, respectively. While a few instances from the unseen sets were predicted with relatively large errors, the majority of predictions exhibited high accuracy.

Further, the peak C_p predictions, despite excellent overall performance, demonstrated lower accuracy compared to the mean C_p 's. This is probably attributed to the inherent complexity and variability of the fluctuating components of the wind pressures. The scatter plots and R^2 values evaluated for the training sets of both mean and peak C_p 's demonstrated an excellent ability of the ANN models to fit the training data, making strong connections between the input and the target variables without overfitting, as indicated by the high performance on the testing sets. Similar accuracy was observed for the model's performance on the validation sets. The R^2 and MSE values evaluated for the three Mean C_p sets are comparable; however, those associated with the peak C_p sets exhibit a significant difference between training and testing errors, with testing MSE (0.024) nearly twice the training error (0.013).

This indicates that fitting and predicting the mean pressure coefficients was a simpler task compared to fitting and predicting peak pressure coefficients, confirming the complexity of the peak wind pressures.

Figure 6.16 provided an overview of the accuracy of the ANN models in predicting mean and peak pressure coefficients across the entire testing dataset, without focusing on specific details such as the ability of the models to capture the critical roof pressures at the corners and edge areas of the nonrectangular roofs where the flow separation occurs, causing high suctions and complex pressure fluctuations. Therefore, it is important to investigate the degree of accuracy of the ANN models to map pressures in such areas.

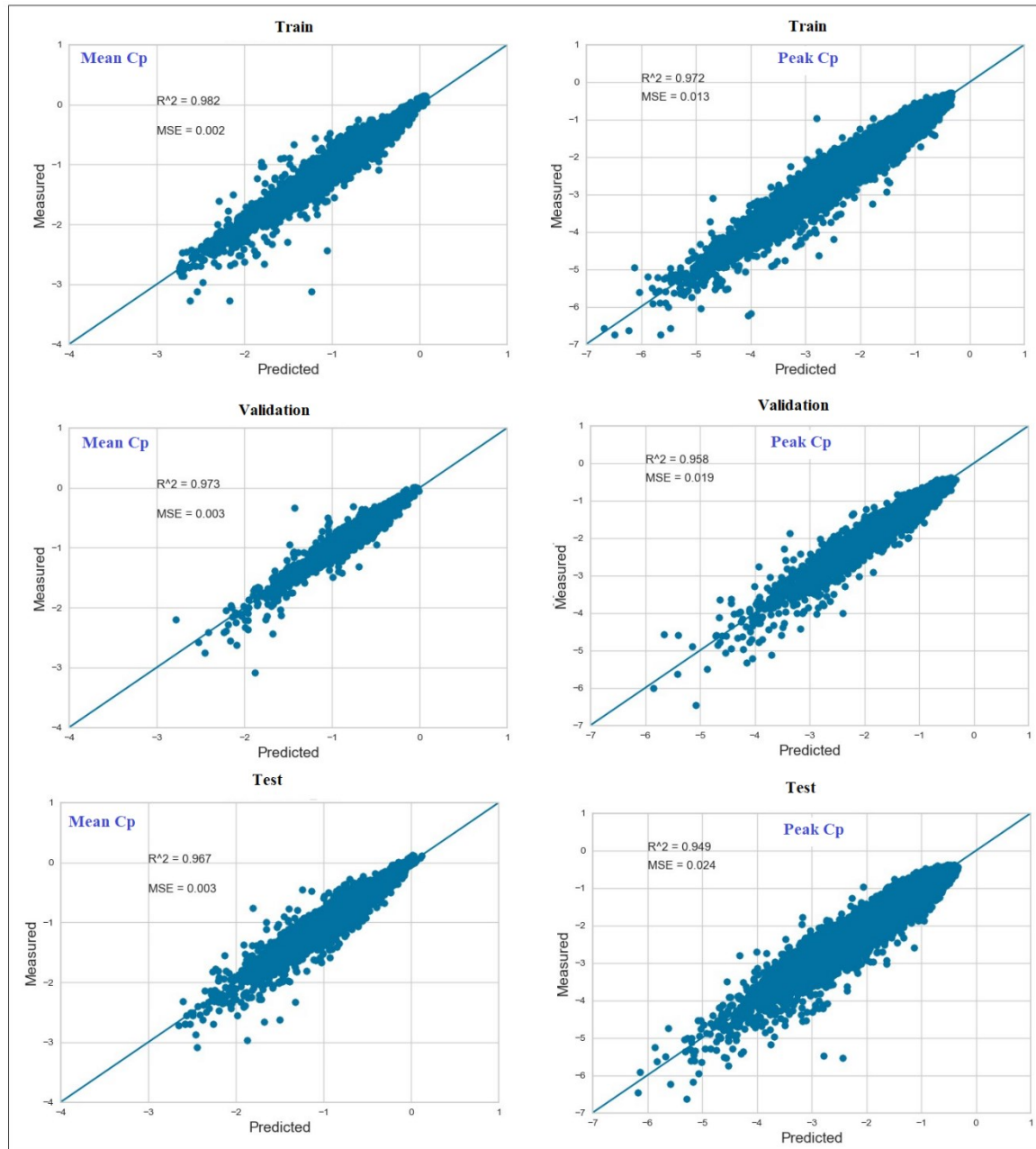


Figure 6.16: Predictions of the ANN compared with the corresponding wind tunnel mean and peak C_p 's for the training, validation, and testing sets.

The testing set was further divided into three groups, each corresponding to taps located in the corner, edge, and middle zones, as defined by NBCC 2020. Subsequently, the ANN models were used to predict the mean and peak pressure coefficients in these areas. The predicted values were then compared to the corresponding wind tunnel coefficients, as presented in Figure 6.17. The figure indicates excellent performance on the ANN models in predicting the pressure coefficients on all zones. The lowest prediction accuracy was for the corner zone with an R^2 of around 0.95 and MSEs of 0.01 and 0.05 for the mean and peak C_p 's, respectively. This was expected as the corner zone is associated with the highest turbulent flow marked with the propagation of vortices due to the upstream flow detachment at the roof edges. In addition, the testing set was selected with cornering wind (i.e., oblique wind directions) or $\pm 10^\circ$ from the perpendicular wind directions, which makes the nature of the turbulent wind flow excessively chaotic at the corner. Nevertheless, the overall prediction accuracy of the corner zone pressures is satisfactory.

The MAEs evaluated for the corner zone are 0.058 for the mean C_p and 0.153 for the peaks; these values are relatively higher than MSE's. This is so because most of the absolute differences between the WT C_p 's and predicted C_p 's are less than one. The MBE, on the other hand, are 0.006 (mean C_p) and 0.022 (peak C_p), these values are relatively small, particularly the mean C_p biased error. In addition, the MBEs are positive, suggesting a slight overestimation of both mean and peak pressure coefficients by the ANN models.

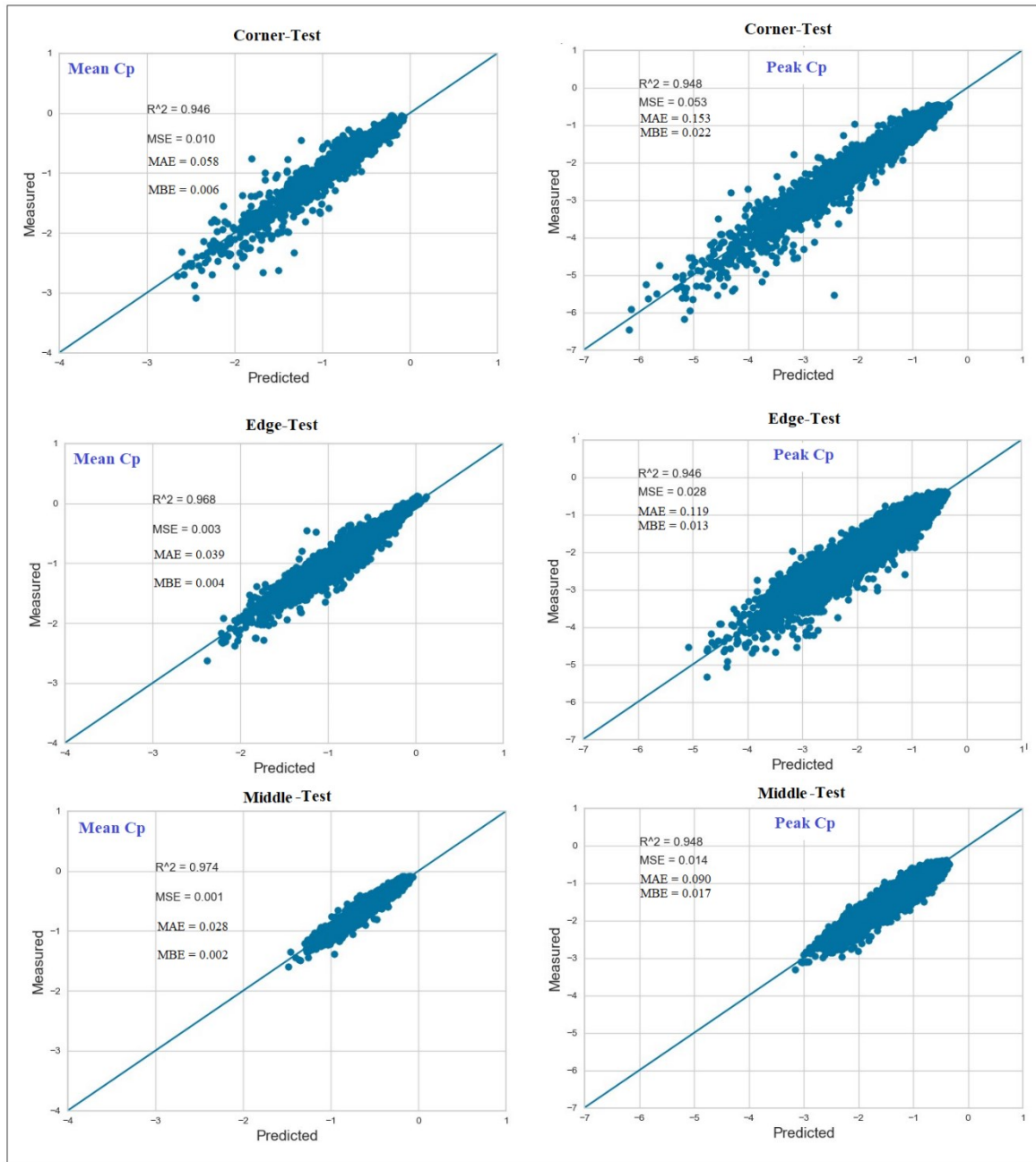


Figure 6.17: Predictions of the ANN compared with the corresponding wind tunnel mean and peak C_p 's on the testing set for the three roof zones.

The mean C_p ANN model demonstrated better performance in predicting coefficients within the edge zone compared to the corner zone, as evident in Figure 6.17, with a coefficient of determination of around 0.97 and a significant reduction in both MSE and MAE for the edge zone predictions. For the peak C_p , the R^2 values are comparable for prediction within the corner and edge zones; however, the other evaluation metrics demonstrated improved accuracy for predictions within the edge zone. This case highlights the importance of considering multiple metrics for the assessment of model accuracy, as relying on one metric would, sometimes, result in a misleading conclusion. ANN models exhibited the highest predictive accuracy for mean and peak C_p values within the middle zone. This superior performance is likely attributed to the nature of the middle zone as a flow reattachment area, characterized by relatively smoother flow conditions and lower variability in wind pressure fluctuations. It should be noted that the MBE is positive for the middle and edge zones, indicating, as mentioned previously, a slight overestimation of the pressure coefficients.

To further investigate the ANN's performance on the testing set, Figure 6.18 explores, in more detail, the ANN's performance on the testing set by visualizing the comparative distribution of mean and peak C_p values in contour plots for the L1 model at an angle of attack of 20° between the ANN predictions and the WT counterparts; the 20° angle of attack is one of the testing set wind directions. The dummy squares represent the areas that were not tested in the wind tunnel and can be concluded by symmetry. For the mean C_p 's, the ANN model mapped the entire roof area with minimal errors ($MSE = 0.025$), it also showed a slight overestimation of the bottom left area where the -1.5-contour line relatively covers a larger area compared to the WT mean C_p distribution, confirming the positive MBEs discussed and presented in Figure 6.17. The peak C_p 's exhibited similar trends; the overall accuracy is satisfactory and the overestimation, although

small, is more pronounced compared to the mean C_p 's, particularly, for contour lines of -3 and -2.5 at the bottom left part of the plan. It is also interesting to note that the ANN model effectively captured peak C_p 's of more than -3 in the bottom right corner, despite its very limited presence in the WT peak distribution.

Figure 6.19 shows a similar comparison but for the T-shaped model, T2, and 140° wind direction. The MSE is 0.14, which is slightly higher than the corresponding average error evaluated for the L1 model peaks; this is probably attributed to the wind azimuth; the inner edges of the T shape are upstream, unlike the L1 scenario, where the inner edges are present downstream. This potentially made the wind flow over the T2 roof more complex, resulting in relatively more challenging trends of peak pressures to generalize by the ANN model.

The general distribution of peaks within the two contours is comparable, indicating that the peaks were reconstructed with high accuracy by the ANN. However, peaks at the left reentrant corner, i.e., the inner corner at intersections between the T segments, show discrepancies; the wind tunnel contour lines indicate values with magnitude greater than -2.5, and the ANN predicted suctions are lower than -2.5.

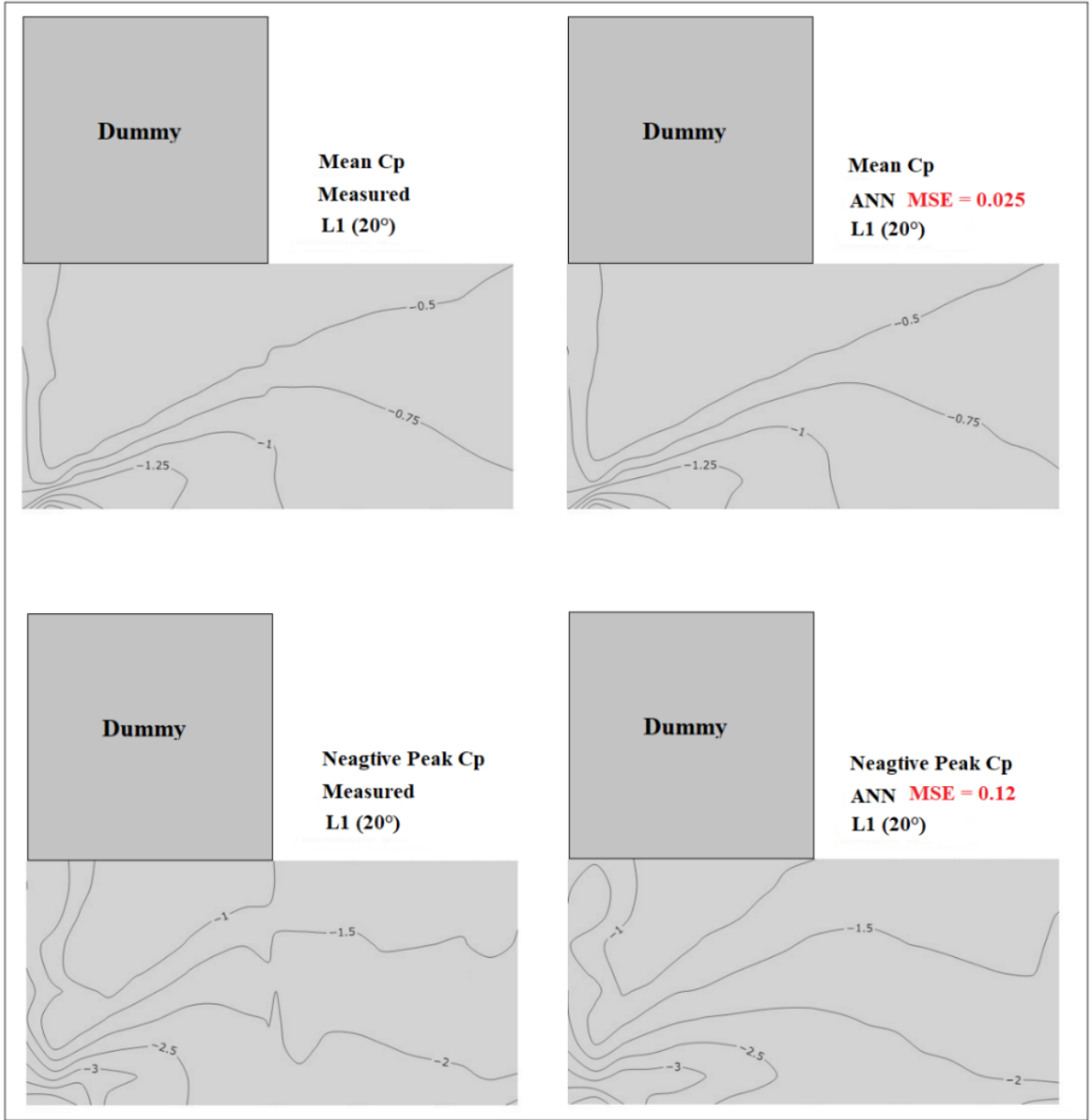


Figure 6.18: Contours of mean and peak pressure coefficients, comparison between WT coefficients, and predictions of ANNs for the L1 model and 20° wind direction (testing set).

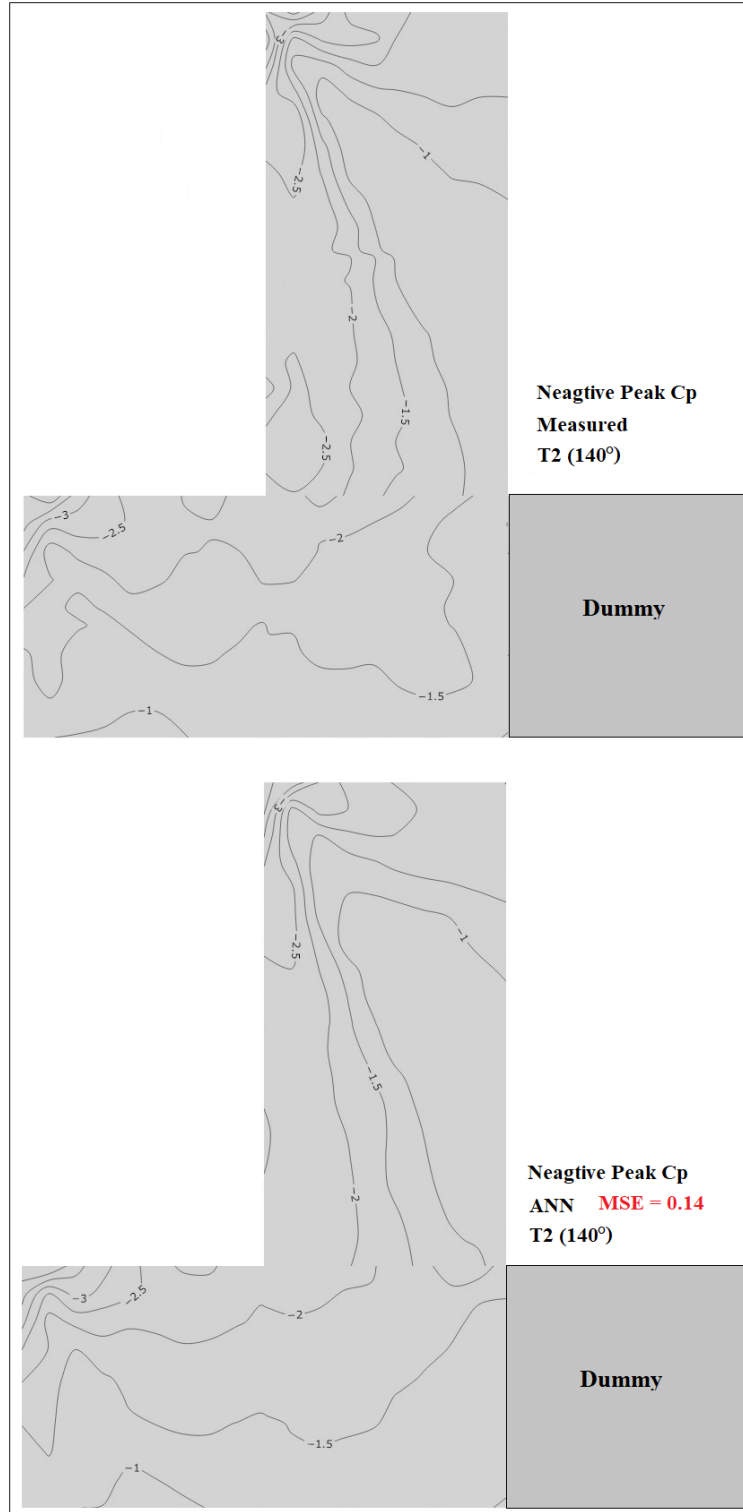


Figure 6.19: Contours of peak pressure coefficients, comparison between WT coefficients, and predictions of the peak C_p ANN for the T1 model and 140° wind direction (testing set).

Figure 6.20 compares peak pressure coefficients predicted by the ANN and those evaluated based on the WT data for a line of taps on the roofs of L1 and U1, the figure includes the results of the 110° and 230° wind directions from the testing set, the peaks are plotted against a distance X normalized by the model width D . The peaks from the two sources exhibited an overall excellent similarity within L1 and U1 with few instances recorded errors of around 0.5 in the peak C_p values. These discrepancies appear on the windward side of the roof, as it is evident in the plot of the L1 peaks for X/D less than 0.1 when the wind azimuth is 110° and when X/D is between 0.8 and 1 for 230° wind direction. Similar results can be observed for the U1 model; however, the difference is smaller compared to the L1 model.

In summary, the ANN models exhibited excellent accuracy for predicting the mean and peak pressure coefficient, this was demonstrated by exploring the efficiency of the ANN models in predicting the mean and peak C_p 's across the entire testing set, the instances of the testing set within the roof pressures zones, the performance of the ANN models was also evaluated through roof pressure contours for wind directions within the testing set, and through a line of pressure taps along the roof. The predicted C_p 's were found to be highly correlated to the WT C_p 's with a coefficient of determination of up to 0.97, and negligible errors were observed across most of the samples on the testing set. Given the satisfactory predictive performance of the ANNs, the models can be utilized as a tool for estimating mean and peak pressures on roofs of nonrectangular buildings with the shapes of L, T, U, and X. This approach would significantly reduce the time, effort, and cost associated with testing nonrectangular models in boundary layer wind tunnels, providing a feasible tool for quantifying wind loads on roofs of such buildings. The proven excellent performance of the ML models would potentially encourage the wind code committees to incorporate ML in the codification. The ML models described in this chapter can be utilized by

the end-users to estimate the wind pressure coefficients. The input features (shape, coordinates of the desired point, aspect ratios, and WD) are needed to obtain the pressure coefficients at any point within the envelope of the non-rectangular building.

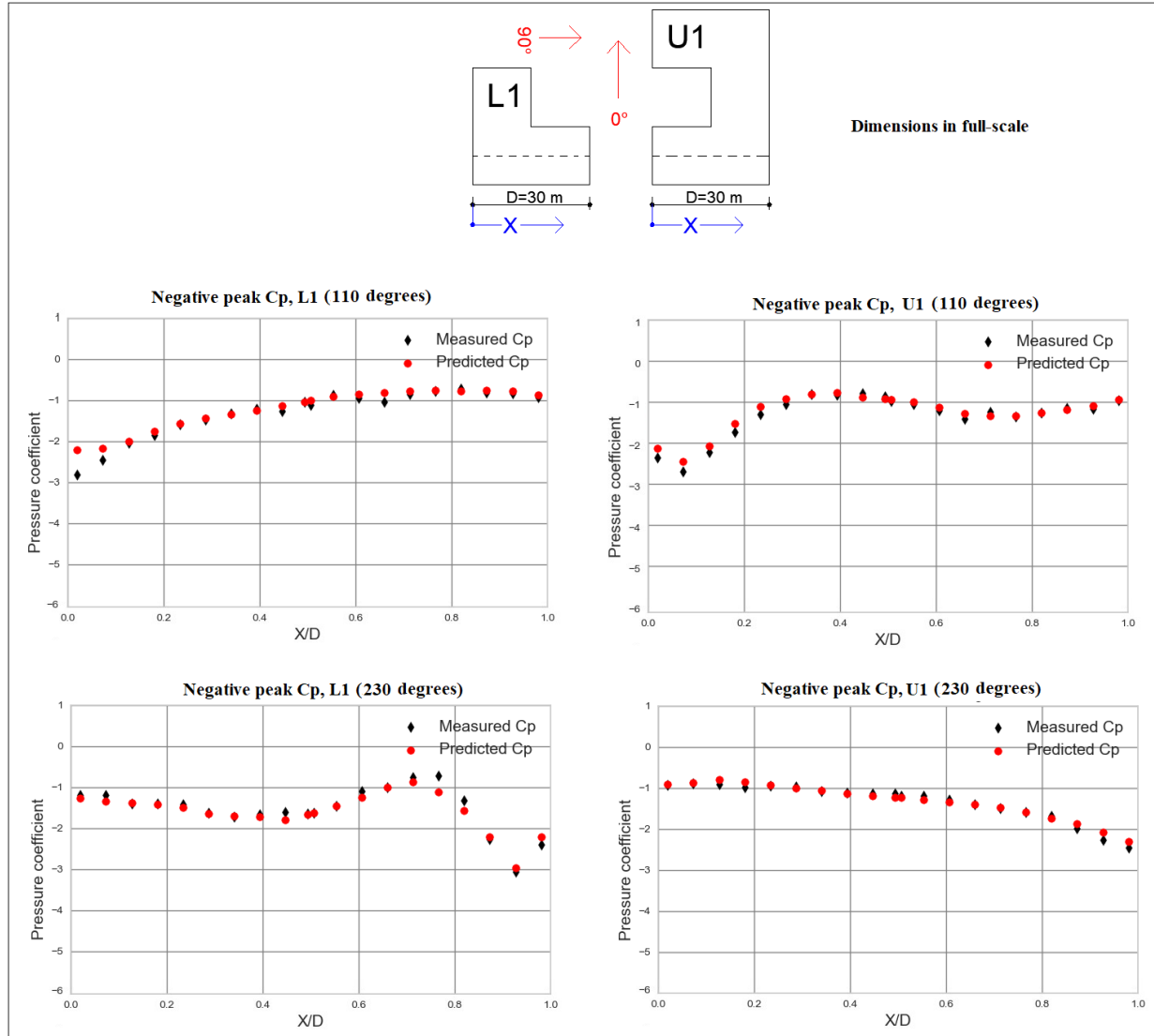


Figure 6.20: Comparison between the ANN predictions of the peak C_p and the WT counterparts for a line of taps on roofs of L1 and U1.

Chapter 7

Conclusion and recommendations

7.1 Conclusive remarks

The study investigated wind loads on roofs and walls of non-rectangular low-rise buildings through wind tunnel testing of nine non-rectangular models (three L, three U, two T, and one X models). The effects of height and plan dimensions were considered. The results were compared with wind loads on rectangular buildings. The experimental results were also compared with the North American wind codes and standards to propose a method for the design of cladding and components of non-rectangular buildings based on the rectangular building provisions in ASCE 7-22 and NBCC 2020. Further, the wind tunnel data were utilized to develop Machine Learning models for predicting wind loads on roofs and walls of non-rectangular buildings, employing Artificial Neural Networks and ensembles of Gradient Boosting, Random Forest, and Extremely Randomized Trees regressors through Voting and Stacking regressors. The following conclusive remarks are based on the experimental results and the application of Machine Learning:

Roof pressures

- Wind-induced pressures at the outer edges and corners of non-rectangular roofs are slightly affected by the plan dimensions. However, the plan dimensions affect the magnitude of wind suctions at the inner roof zone. The peaks on the short legs, compared to long legs, tend to be higher on the inner corners and lower on the edge near the reentrant corners. Additionally, the inner edges and corners experience higher suctions compared to those of the outer edges and corners and those experienced by rectangular buildings.

- The experimental results for different heights and plan dimensions indicate that the size of roof pressure zones is mainly a function of the building height and is almost independent of plan dimensions. The results also indicate that wind pressures rise in magnitude as height increases and extend on larger areas.
- Comparisons with NBCC 2020: the size of pressure zones was generally found insufficient to encompass the high peaks at the corners and inner edges of the L, T, U and X shapes. The comparison with peaks indicates that the corner provisions are comparable to the experimental results, while the NBCC peaks of the edge and interior zones are lower than the experimental results. Based on the results, the study suggests applying the NBCC rectangular building provisions to non-rectangular buildings after incorporating three key changes: packing the corners and edges as a single zone, increasing the NBCC provision of the interior zone by 40%, and referring the determination of the end-zone size to the building height for non-rectangular buildings.
- Comparison with ASCE 7-22: the design peak and roof pressure zones were found conservative when compared to the experimental wind pressure coefficients. Based on these results, it would be appropriate to recommend the application of rectangular building provisions to non-rectangular cases-applying the same edge/corner zones to the inner and outer roof areas.

Wall pressures

- The positive provisions of rectangular buildings in both ASCE 7-22 NBCC 2020 are comparable to the WT results. Consequently, the rectangular positive peaks can be used for the design of nonrectangular buildings.
- For negative pressure coefficients, the experimental results indicate that relatively high suction occurs on the wall areas at the corners and the reentrant corners (zone e/5), and lower suction on the rest of the wall areas (zone w/4).
- Comparison with NBCC 2020 (negative peaks): The study suggests that the NBCC rectangular buildings' wall peaks of zone e are appropriate for the design of non-rectangular buildings, with one exception for the short walls and wall areas at the reentrant corners, where the negative peaks of zone e that corresponds to an area less than 1 m^2 need to be increased by 30%. For zone w, it is suggested that the provisions of the rectangular buildings of NBCC 2020 can be used for the design of walls of non-rectangular buildings after implementing one update; the negative peaks of zone w that correspond to an area less than 1 m^2 need to be increased by 30%.
- Comparison with ASCE 7-22: The experimental results indicate that the rectangular building provisions of zone 5 are applicable for the design of non-rectangular buildings for the wall areas at the corners and reentrant corners. For zone 4, it is suggested that the provisions of the rectangular buildings can be used for the design of walls of non-rectangular buildings.

Machine Learning

- Ensemble ML, utilizing the stacking regressor, demonstrated excellent prediction capabilities for pressure coefficients of buildings with L, T, U, and X shapes. The Gradient Boosting regressor exhibited the best performance among the base regressors of the ensemble ML model.
- The Gradient Boosting regressor demonstrated excellent accuracy in predicting both mean and negative peak pressure coefficients, with evaluation scores of 0.97 based on the random split of the dataset. However, the GB showed a reduced evaluation score (0.9) when the split was performed based on wind directions. The results from the two splits indicate that the random split often causes implicit data leakage, resulting in an overestimation of the performance of the ML models.
- The ANN models, trained based on a structured split, demonstrated an overall excellent accuracy in estimating wind pressures on nonrectangular buildings, with a coefficient of determination of up to 0.97 evaluated for the testing set and minimal errors. The models were found to be biased toward overestimating wind pressure coefficients; however, the bias was very small.
- Predicting mean C_p 's was slightly more efficient than predicting peak C_p 's, but the ANN model performed satisfactorily for both.
- The efficiency of the ANN models in predicting the pressure coefficients on the corner, edge, and middle zones is satisfactory, with the best performance achieved for the middle zone pressure coefficients.

- These ANN models provide practical and cost-effective solutions for quantifying wind loads on roofs of non-rectangular buildings, saving a significant time and effort required for wind tunnel testing for non-rectangular buildings.

7.2 Contributions and Recommendations for future work

This study provided a methodology for the design of cladding and components of walls and roofs of non-rectangular low buildings. This was a gap in Wind Engineering for a long time and has been addressed by this study. ML was uniquely implemented to predict wind pressure coefficients on non-rectangular buildings of several plan shapes, addressing another gap in the existing implementation of ML in Wind Engineering. The study is limited to the wind design of cladding and components of the envelope of non-rectangular low-rise buildings with flat roofs; the wind load on the building main structure was not investigated. More research needs to be conducted to address the following points:

- Design of the main structures of non-rectangular buildings. This requires wind tunnel testing that provides simultaneous measurements of wind pressures on the roofs and walls of the testing models.
- Testing additional non-rectangular shapes (e.g., K, M, Y)
- Prediction of pressure coefficient time series using Machine Learning.
- Machine Learning can be further configured and expanded for the codification of building shapes.

References

- Abadi, M., and others (2015). *TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems*. *arXiv preprint arXiv:1603.04467*.
- Alanani, M., & Elshaer, A. (2023). ANN-based optimization framework for the design of wind load resisting system of tall buildings. *Engineering Structures*, 285. <https://doi.org/10.1016/j.engstruct.2023.116032>
- Aldoum M., 2018. Wind loads on low-slope roofs of low-rise and mid-rise buildings with large plan dimensions. Master thesis, Concordia university, Montreal, Quebec, Canada.
- Aldoum, M., & Stathopoulos, T. (2020). Wind loads on low-slope roofs of buildings with large plan dimensions. *Engineering Structures*, 225(October 2019), 111298. <https://doi.org/10.1016/j.engstruct.2020.111298>
- Aldoum, M., Stathopoulos, T., Chavez, M., & Baskaran, A. (2023). Wind loading on a stepped roof building: Comparison of field measurements, wind tunnel data, and standard provisions. *Journal of Wind Engineering and Industrial Aerodynamics*, 238(November 2022), 105441. <https://doi.org/10.1016/j.jweia.2023.105441>
- Aldoum M., Stathopoulos T., (2023) Prediction of wind loads on buildings with non-rectangular plans based on Machine Learning regression models. International Conference of Wind Engineering 16, Florence, August, 2023.
- Aldoum, M., Stathopoulos, T. (2024a). Wind Pressures on Non-Curved and Non-Rectangular Roofs. *SSRN 632 Electronic Journal*, August, 2–5. <https://doi.org/10.2139/ssrn.5038839>

- Aldoum M., Stathopoulos T. (2024b). Assessment of wind pressures on roofs of irregularly-shaped buildings. Proceedings of the Canadian Society for Civil Engineering (CSCE) 2024 Annual Conference, Niagara, Canada, June, 2024.
- Aldoum, M., and Stathopoulos, T. (2025a). Components and Cladding Wind Pressures on Flat Nonrectangular Roofs: Assessment and Comparison with Code Provisions. *Journal of Structural Engineering*, 151(11). <https://doi.org/10.1061/JSENDH.STENG-15082>
- Aldoum M., Stathopoulos T. (2025b). Wind pressures on roofs of nonrectangular buildings: Experimental and Machine learning approaches. *Wind and Structures, an International Journal*, approved.
- Alrawashdeh, H., Stathopoulos, T. (2015). Wind pressures on large roofs of low buildings and wind codes and standards. *Journal of Wind Engineering and Industrial Aerodynamics*, 147, 212–225. <https://doi.org/10.1016/j.jweia.2015.09.014>
- ASCE/SEI 7-22. (2022). Minimum design loads and associated criteria for buildings and other structures. In *ASCE Standard* (Issues 7–22).
- ASCE/SEI 49-21, 2021. Wind Tunnel Testing for Buildings and Other Structures. Structural Engineering Institute of ASCE, Reston, VA.
- AS/NZS 1170.2, 2011. Australian/New Zealand Standard for Structural Design Actions, part 2: Wind Actions. Sydney, New South Wales, Australia: Standards Australia and Standards New Zealand.

- Bitsuamlak, G. T., Bédard, C., & Stathopoulos, T. (2007). Modeling the Effect of Topography on Wind Flow Using a Combined Numerical–Neural Network Approach. *Journal of Computing in Civil Engineering*, 21(6), 384–392. [https://doi.org/10.1061/\(asce\)0887-3801\(2007\)21:6\(384\)](https://doi.org/10.1061/(asce)0887-3801(2007)21:6(384))
- Bre, F., Gimenez, J. M., & Fachinotti, V. D. (2018). Prediction of wind pressure coefficients on building surfaces using artificial neural networks. *Energy and Buildings*, 158, 1429–1441. <https://doi.org/10.1016/j.enbuild.2017.11.045>
- BD (Buildings Department). (2019a). Code of Practice on Wind Effects in Hong Kong, Hong Kong.
- BD (Buildings Department). (2019b). Explanatory notes to the Code of Practice on Wind Effects in Hong Kong, Hong Kong.
- Chavez, M., Baskaran, A., Aldoum, M., Stathopoulos, T., Geleta, T. N., & Bitsuamlak, G. T. (2022). Wind loading on a low-slope gabled roof: Comparison of field measurements, wind tunnel data, and code provisions. *Engineering Structures*, 267(June), 114646. <https://doi.org/10.1016/j.engstruct.2022.114646>
- Chavez, M., Baskaran, A., Aldoum, M., Stathopoulos, T., Geleta, T. N., & Bitsuamlak, G. T. (2023). Wind pressure on a 45° gabled roof: verifying code provisions with field measurements and wind tunnel data. *Canadian Journal of Civil Engineering*, 50(12), 1017–1035. <https://doi.org/10.1139/cjce-2022-0351>

- Chen, F. B., Wang, X. L., Li, X., Shu, Z. R., & Zhou, K. (2022). Prediction of wind pressures on tall buildings using wavelet neural network. *Journal of Building Engineering*, 46(September 2021). <https://doi.org/10.1016/j.jobe.2021.103674>
- Chollet, F., and others (2015). *Keras*. GitHub repository, 2015. Available at: <https://github.com/fchollet/keras>.
- Cook, N.J., (1990). The Designer's Guide to Wind Loading of Building Structures. Part 2: Static Structures, Butterworths Press, London.
- Davenport, A.G. (1961). The spectrum of horizontal gustiness near the ground in high winds. *Quarterly 563 Journal of Royal Meteorology Society*. 87(372), 194–211.
<https://doi.org/10.1002/qj.49708737208>
- Ding, Z., Zhang, W., & Zhu, D. (2022). Neural-network based wind pressure prediction for low-rise buildings with genetic algorithm and Bayesian optimization. *Engineering Structures*, (April). <https://doi.org/10.1016/j.engstruct.2022.114203>
- Dongmei, H., Shiqing, H., Xuhui, H., & Xue, Z. (2017). Prediction of wind loads on high-rise building using a BP neural network combined with POD. *Journal of Wind Engineering and Industrial Aerodynamics*, 170(July), 1–17. <https://doi.org/10.1016/j.jweia.2017.07.021>
- Du, K., & Chen, B. (2023). A hybrid semi-supervised regression based machine learning method for predicting peak wind loads on a group of buildings. *Engineering Structures*, 275(PA), 115245. <https://doi.org/10.1016/j.engstruct.2022.115245>

- Elshaer, A., Bitsuamlak, G., & El Damatty, A. (2017). Enhancing wind performance of tall buildings using corner aerodynamic optimization. *Engineering Structures*, 136, 133–148. <https://doi.org/10.1016/j.engstruct.2017.01.019>
- Fernández-Cabán, P. L., Masters, F. J., & Phillips, B. M. (2018). Predicting roof pressures on a low-rise structure from freestream turbulence using artificial neural networks. *Frontiers in Built Environment*, 4(November), 1–16. <https://doi.org/10.3389/fbuil.2018.00068>
- Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5), 1189–1232. <https://doi.org/10.1214/aos/1013203451>
- Gavalda, X., Ferrer-Gener, J., Kopp, G. A., & Giralt, F. (2011). Interpolation of pressure coefficients for low-rise buildings of different plan dimensions and roof slopes using artificial neural networks. *Journal of Wind Engineering and Industrial Aerodynamics*, 99(5), 658–664. <https://doi.org/10.1016/j.jweia.2011.02.008>
- Geleta, T. N., Bitsuamlak, G., Chavez, M., & Baskaran, A. (2024). Wind loading on gable and multi-span roof buildings: Comparison between field monitoring, wind tunnel experiments, and design code provisions. *Journal of Wind Engineering and Industrial Aerodynamics*, 253(August), 105864. <https://doi.org/10.1016/j.jweia.2024.105864>
- Géron, A. (2019). Hands-on Machine Learning with Scikit-Learning, Keras and Tensorflow. In *O'Reilly Media, Inc.*
- Geurts, P., Ernst, D., & Wehenkel, L. (2006). Extremely randomized trees. *Machine Learning*, 63(1), 3–42. <https://doi.org/10.1007/s10994-006-6226-1>

- Gomes, M. G., Moret Rodrigues, A., & Mendes, P. (2005). Experimental and numerical study of wind pressures on irregular-plan shapes. *Journal of Wind Engineering and Industrial Aerodynamics*, 93(10), 741–756. <https://doi.org/10.1016/j.jweia.2005.08.008>
- Higgins, S., & Stathopoulos, T. (2021). Application of artificial intelligence to urban wind energy. *Building and Environment*, 197(April).
<https://doi.org/10.1016/j.buildenv.2021.107848>
- Ho, T. C. E., Surry, D., Morrish, D., & Kopp, G. A. (2005). The UWO contribution to the NIST aerodynamic database for wind loads on low buildings: Part 1. Archiving format and basic aerodynamic data. *Journal of Wind Engineering and Industrial Aerodynamics*, 93(1), 1–30.
<https://doi.org/10.1016/j.jweia.2004.07.006>
- Hu, G., & Kwok, K. C. S. (2020). Predicting wind pressures around circular cylinders using machine learning techniques. *Journal of Wind Engineering and Industrial Aerodynamics*, 198(January). <https://doi.org/10.1016/j.jweia.2020.104099>
- Hu, G., Liu, L., Tao, D., Song, J., Tse, K. T., & Kwok, K. C. S. (2020). Deep learning-based investigation of wind pressures on tall building under interference effects. *Journal of Wind Engineering and Industrial Aerodynamics*, 201(March).
<https://doi.org/10.1016/j.jweia.2020.104138>
- ISO (2009). Wind actions on structures. ISO 4354:2009, Switzerland, 2009.

- Jamieson, N. J., Carpenter, P., & Cenek, P. D. (1992). Wind induced external pressures on a tall building with various corner configurations. *Journal of Wind Engineering and Industrial Aerodynamics*, 44(1–3), 2401–2412. [https://doi.org/10.1016/0167-6105\(92\)90032-6](https://doi.org/10.1016/0167-6105(92)90032-6)
- Jin, Z., Shang, J., Zhu, Q., Ling, C., Xie, W., & Qiang, B. (2020). RFRSF: Employee Turnover Prediction Based on Random Forests and Survival Analysis. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 12343 LNCS, 503–515. https://doi.org/10.1007/978-3-030-62008-0_35
- Khanduri, A. C., Bédard, C., & Stathopoulos, T. (1997). Modelling wind-induced interference effects using backpropagation neural networks. *Journal of Wind Engineering and Industrial Aerodynamics*, 72(1–3), 71–79. [https://doi.org/10.1016/S0167-6105\(97\)00259-6](https://doi.org/10.1016/S0167-6105(97)00259-6)
- Kim, B., Yuvaraj, N., Sri Preethaa, K. R., Hu, G., & Lee, D. E. (2021). Wind-induced pressure prediction on tall buildings using generative adversarial imputation network. *Sensors*, 21(7). <https://doi.org/10.3390/s21072515>
- Krishna, P. (1995). Wind loads on low rise buildings-A review. *Journal of Wind Engineering and Industrial Aerodynamics*, 54–55, 383–396. [https://doi.org/10.1016/0167-6105\(94\)00055-I](https://doi.org/10.1016/0167-6105(94)00055-I)
- Lamberti, G., & Gorlé, C. (2021). A multi-fidelity machine learning framework to predict wind loads on buildings. *Journal of Wind Engineering and Industrial Aerodynamics*, 214(April), 104647. <https://doi.org/10.1016/j.jweia.2021.104647>

- Mallick, M., Mohanta, A., & Kumar, A. (2020). Multivariate adaptive regression spline approach to the assessment of surface mean pressure coefficient on surfaces of C-shaped building. *Scientia Iranica*, 27(6 B), 2967–2984.
<https://doi.org/10.24200/SCI.2020.51377.2142>
- Matus, M., & Zisis, I. (2021). *Investigation of irregular-shaped buildings and their pressure distribution*. 14–17.
- Meddage, D. P. P., Ekanayake, I. U., Weerasuriya, A. U., & Lewangamage, C. S. (2021). Tree-based regression models for predicting external wind pressure of a building with an unconventional configuration. *MERCon 2021 - 7th International Multidisciplinary Moratuwa Engineering Research Conference, Proceedings*, 257–262.
<https://doi.org/10.1109/MERCon52712.2021.9525734>
- Meddage, D. P. P., Ekanayake, I. U., Weerasuriya, A. U., Lewangamage, C. S., Tse, K. T., Miyanawala, T. P., & Ramanayaka, C. D. E. (2022). Explainable Machine Learning (XML) to predict external wind pressure of a low-rise building in urban-like settings. *Journal of Wind Engineering and Industrial Aerodynamics*, 226(May).
<https://doi.org/10.1016/j.jweia.2022.105027>
- Meddage, D. P. P., Mohotti, D., & Wijesooriya, K. (2024). Predicting transient wind loads on tall buildings in three-dimensional spatial coordinates using machine learning. *Journal of Building Engineering*, 85(January), 108725. <https://doi.org/10.1016/j.jobbe.2024.108725>
- Morse, S.M. (2003). Wind pressures Fields around non-rectangular buildings. Texas Tech University, Texas, USA, Master's Thesis.

NBCC. (2020). National Building Code of Canada: 2020. In *Government of Canada* (Vol. 1).

Parackal, K. I., Humphreys, M. T., Ginger, J. D., Henderson, D. J., Humphreys, M. T., Ginger,

J. D., & Wind, D. J. H. (2016). Wind loads on contemporary Australian housing.

Australian Journal of Structural Engineering, 7982, 1–15.

<https://doi.org/10.1080/13287982.2016.1229375>

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M.,

Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D.,

Brucher, M., Perrot, M., and Duchesnay, É., 2011. Scikit-learn: Machine Learning in

Python. *Journal of Machine Learning Research* 12(85):2825–2830. [http://scikit-](http://scikit-learn.sourceforge.net)

[learn.sourceforge.net](http://scikit-learn.sourceforge.net).

Ploton, P., Mortier, F., Réjou-Méchain, M., Barbier, N., Picard, N., Rossi, V., Dormann, C.,

Cornu, G., Viennois, G., Bayol, N., Lyapustin, A., Gourlet-Fleury, S., & Pélissier, R.

(2020). Spatial validation reveals poor predictive performance of large-scale ecological

mapping models. *Nature Communications*, 11(1). [https://doi.org/10.1038/s41467-020-](https://doi.org/10.1038/s41467-020-18321-y)

[18321-y](https://doi.org/10.1038/s41467-020-18321-y)

Sang, J., Pan, X., Lin, T., Liang, W., & Liu, G. R. (2021). A data-driven artificial neural

network model for predicting wind load of buildings using GSM-CFD solver. *European*

Journal of Mechanics, B/Fluids, 87, 24–36.

<https://doi.org/10.1016/j.euromechflu.2021.01.007>

- Sanyal, P., & Dalui, S. K. (2022). Forecasting of aerodynamic coefficients of tri-axially symmetrical Y plan shaped tall building based on CFD data trained ANN. *Journal of Building Engineering*, 47(October 2021). <https://doi.org/10.1016/j.jobbe.2021.103889>
- Sarma, H. D., Zisis, I., & Matus, M. (2023). Effect of roof shape on wind vulnerability of roof sheathing panels. *Structural Safety*, 100(August 2022), 102283. <https://doi.org/10.1016/j.strusafe.2022.102283>
- Shao, S., Stathopoulos, T., Yang, Q., & Tian, Y. (2018). Wind Pressures on 4:12-Sloped Hip Roofs of L- and T-Shaped Low-Rise Buildings. *Journal of Structural Engineering*, 144(7), 1–20. [https://doi.org/10.1061/\(asce\)st.1943-541x.0002077](https://doi.org/10.1061/(asce)st.1943-541x.0002077)
- Shao, S., Tian, Y., Yang, Q., & Stathopoulos, T. (2019). Wind-induced cladding and structural loads on low-rise buildings with 4:12-sloped hip roofs. *Journal of Wind Engineering and Industrial Aerodynamics*, 193(15), 103948. <https://doi.org/10.1016/j.jweia.2019.103948>
- Søgaard, A., Ebert, S., Bastings, J., and Filippova, K. (2021). We need to talk about random splits. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 1823–1832, Online. Association for Computational Linguistics. 10.18653/v1/2021.eacl-main.156
- Stathopoulos, T., & Zhou, Y. S. (1993). Numerical simulation of wind-induced pressures on buildings of various geometries. *Journal of Wind Engineering and Industrial Aerodynamics*, 46–47(C), 419–430. [https://doi.org/10.1016/0167-6105\(93\)90308-B](https://doi.org/10.1016/0167-6105(93)90308-B)

- Steadman, P. (2006). Why are most buildings rectangular? *Architectural Research Quarterly*, 10(2), 119–130. <https://doi.org/10.1017/S1359135506000200>
- Tian, J., Gurley, K. R., Diaz, M. T., Fernández-Cabán, P. L., Masters, F. J., & Fang, R. (2020). Low-rise gable roof buildings pressure prediction using deep neural networks. *Journal of Wind Engineering and Industrial Aerodynamics*, 196(June 2019). <https://doi.org/10.1016/j.jweia.2019.104026>
- Tong, B., Liang, Y., Song, J., Hu, G., & Kareem, A. (2024). Deep learning-based extension of wind pressure time series. *Journal of Wind Engineering and Industrial Aerodynamics*, 254(October), 105909. <https://doi.org/10.1016/j.jweia.2024.105909>
- Van Den Heuvel J., Kopp G.A., (2024). Evaluation of methods to determine wind loads on irregular low-rise building shapes. Canadian Society for Civil Engineering (CSCE) 2024 Annual Conference, Niagara, Canada, June, 2024.
- Von Karman, T. (1948). Progress in the statistical theory of turbulence. *Proceedings of National Academy Sciences*, USA. 34, 530–539.
- Weng, Y., & German Paal, S. (2022). Machine learning-based wind pressure prediction of low-rise non-isolated buildings. *Engineering Structures*, 258(February), 114148. <https://doi.org/10.1016/j.engstruct.2022.114148>
- Wolpert, D. (1992). Stacked Generalization (Stacking). *Neural Networks*, 5, 241–259.