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Towards an integrated computational method to determine internal spaces for optimum environmental conditions

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Abstract

Computational Fluid Dynamics tools and Response Surface Methodology optimization techniques were coupled for the evaluation of an optimum window opening design that improves the ventilation efficiency in a naturally-ventilated building. The multi-variable optimization problem was based on Design of Experiments analysis and the Central Composite Design method for the sampling process and estimation of quadratic models for the response variables. The Screening optimization method was used for the generation of the optimal design solution. The generated results indicated a good performance of the estimated response surface revealing the strength correlations between the parameters. Window width was found to have greater impact on the flow rate values with correlation coefficient of 73.62%, in comparison to the standard deviation 55.68%, where the window height prevails with correlation coefficient of 96.94% and 12.35% for the flow rate. The CFD results were validated against wind tunnel experiments and the optimization solution was verified with simulation runs, proving the accuracy of the methodology followed, which is applicable to numerous environmental design problems.

Keywords: Computational fluid dynamics (CFD); Response Surface Methodology (RSM); Optimization; Natural ventilation

23 **1. Introduction**

24 A successful building design improves the quality of life and facilitates the functional needs of the
25 users. However, the achievement of acceptable design solutions presupposes the contribution of
26 rational multidisciplinary decisions [1]. An important and mandatory step prior to every engineering
27 solution is the conceptual design phase that tends to establish the holistic integrity of the design. The
28 development of software tools has facilitated the decision-making process, by offering the
29 opportunity to evaluate the performance and efficiency of the initial design concept under numerous
30 objective parameters during the conceptual design phase.

31 Computational Fluid Dynamics (CFD) software is used to perform multiple types of analysis,
32 regarding a rational approach to design investigation that enables the simulation of air flow and
33 prediction of physical phenomena within building spaces [2]. This technique has been adopted by
34 numerous researchers, to study the thermal comfort of occupants in buildings [3], the positioning of
35 building services [4], natural ventilation [5], heat transfer effects [6], contaminant dispersion [7] and
36 the interaction between indoor and outdoor environments [8].

37 This study presents an integrated computational method to optimise design spaces in the built
38 environment. The work is based on simulation-driven optimisation techniques, using a CFD
39 simulation software integrated with Response Surface Methodology-based design optimisation
40 algorithms and validated against wind tunnel experiments. The method is applied to a generic cross-
41 ventilated building structure to investigate natural ventilation efficiency. Since 1992 [9] up to present
42 [10], studies on cross-ventilated buildings have been performed using CFD techniques and validated
43 with real scale measurements, wind tunnel experiments and flow visualization methods [11].
44 However, the increasing need for adopting integrated design solutions demands further information
45 beyond what it is offered by the investigation of the naturally occurring wind flow in buildings, and
46 it is this research gap under investigation here.

47 **2. Previous related work**

48 Stavrakakis et al. (2012) investigated the optimum window-opening configuration, to improve the
49 indoor thermal comfort in a naturally-ventilated building (NVB). Using a coupled CFD-ANN
50 (Artificial Neural Network) technique that enabled the evaluation of 126 data pairs to minimise
51 discomfort for 3 different activity levels. On the investigation of the influential behaviour of the air
52 speed and direction towards the ventilation rates in NVB, Shen et al., (2012) combined CFD and
53 Response Surface Methodology (RSM) optimization techniques. They evaluated different Design of
54 Experiment (DoE) methods for the generation of experimental models in a stand-alone software. The
55 obtained results were validated with CFD simulation cases.

56 In a more recent study, Shen et al., (2013) assessed the performance of different DoE methods on the
57 estimation of the ventilation rate in a naturally ventilated livestock. The parameters evaluated were
58 the window opening characteristics and wind conditions. The results indicated that the most accurate
59 response surface model was developed by the Box-Behnken design, followed by the central
60 composite rotation design (CCRD) method. The work also highlighted that the performance of the
61 DoE method may differ, depending on the case study. On the optimization of ventilation efficiency
62 and indoor homogeneous conditions in livestock buildings, Norton et al. (2010) employed CFD tools
63 and Box-Bohnken design methods for the generation of a response function based on the geometrical
64 characteristics of the building. The verified RSM method indicated that the environmental
65 heterogeneity is more correlated to the geometrical characteristics of the building and particularly
66 when the most restrictive eave opening conditions, regarding porosity and height, are applied.

67 Both ANN and RSM are well-recognised techniques that enable the approximation of the interrelated
68 nature of the independent design parameters and their design solutions [15]. However, the
69 aforementioned research topics within the NVB framework, generated the experimental case studies

70 in independent software and used CFD codes to perform parametric analyses and/ or validation of
71 the results.

72 In this study, a commercial CFD software integrated with RSM optimisation techniques is employed
73 to present a parametric simulation method for the analysis and optimisation of a simple cross-
74 ventilated building. The RSM technique is used to determine the interrelationships between the
75 design parameters and design responses. The Screening optimization technique is employed to
76 identify the optimum window opening dimensions that improve the natural ventilation efficiency in
77 terms of the air flow rate and flow homogeneity. The CFD results were validated against wind tunnel
78 experiments to establish the accuracy of the method.

79 In Section 3, the theoretical background of the RSM, which is used in the parametric-optimization
80 study, is briefly presented. In Section 4, the case study is introduced followed by the CFD
81 methodology, results and validation study. The optimisation methodology is presented in Section 5,
82 along with the interpretation and verification of results. Finally, the discussion and conclusions are
83 covered in Section 6 and 7 respectively.

84 **3. Response Surface Methodology (RSM)**

85 Pioneers in the exploration of the impact of the design parameters on several design responses were
86 Hotelling (1941) and Friedman and Savage (1947). In mathematical terms, the unknown functional
87 relationship between the design parameters (x) and their design responses (y) can be described by the
88 low-degree polynomial model given by the Eq. (1):

$$89 \quad y = f(x, \theta) + \varepsilon \quad \text{Eq. (1)}$$

90 where ε is treated as a statistical error. By employing mathematical and statistical methods, first-
91 order (Eq. (2)) and second-order (Eq. (3)) polynomial regression models are constructed, based on
92 physical or computer experiments [18].

93
$$\eta = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k \quad \text{Eq. (2)}$$

94
$$\eta = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i=1}^k \sum_{\substack{j=1 \\ i < j}}^k \beta_{ij} x_i x_j \quad \text{Eq. (3)}$$

95 where η represents a design solution (i.e. velocity, temperature, stresses, etc), x_1, x_2, \dots, x_k the
96 design variables (i.e. height, thickness, load, etc) and $\beta_0, \beta_1, \dots, \beta_k$ the unknown regression
97 coefficients.

98 Box and Wilson (1951) introduced a statistical tool that enables the evaluation of several design
99 parameters, targeting an improved design solution (or response) by satisfying specific requirements.
100 They defined the “experimental region” as the region within which the design parameters vary and
101 the optimum design solution is localized, with the minimum possible number of conducted
102 experiments. This method is known as Response Surface Methodology (RSM) and targets finding an
103 improved, if not optimum, response of given controllable variables.

104 The RSM calculates approximate values for the regression coefficients, based on the evaluation of
105 either experimental or simulation results generated for a specific number of sample design points.
106 Once the best fitted approximation function is found, several design combinations can be examined,
107 without the need to conduct deterministic response analysis that is an extremely time-consuming
108 process. It is therefore apparent that the performance of a fully accurate design study may necessitate
109 the simultaneous consideration of several independent design variables, resulting in complex
110 mathematical functions/systems.

111 RSM has been widely used in various projects and disciplines, due to its advantageous performance
112 in approaching mathematically the behaviour of multiscale phenomena, regardless of the nature of
113 the studied parameters [16]. The integration of this method with expensive computer simulation
114 codes has launched a new generation of research studies, which allows the optimization of designs
115 with either large or small number of input and output parameters.

116 Fegade and Patel (2013) studied a parametric finite element model of a rotor, by employing Design
117 of Experiments (DOE) techniques integrated in ANSYS simulation software. They performed 48
118 simulation runs, aiming at investigating the effect of different rotor diameters on the rotor's
119 frequency. For the purpose of this, two levels factorial design with eleven input parameters per
120 Plankett-Burman¹ design was considered and it two rotor diameters were found to have major
121 impact on frequency for the fluid film.

122 Mandloi and Verma (2009) employed Central Composite Design (CCD) experimental design in
123 order to improve the performance and efficiency of an in-cylinder engine intake port. Based on RSM
124 from ANSYS software, they established a goal-driven optimum design solution, determined by
125 independent geometrical characteristics.

126 Ng et al. (2008) evaluated the performance index of an air diffusion system integrated in a
127 displacement-ventilated office. With the aid of commercial statistical and CFD software, they used
128 RSM to predict the optimum position for the diffusers, the supply temperature and the exhaust
129 position, in order to provide optimum thermal comfort in the space. The results obtained from the
130 Box-Behnken design models were found to agree 95% with the CFD simulation results, indicating
131 the accuracy of the method, as well as the very promising benefits and results.

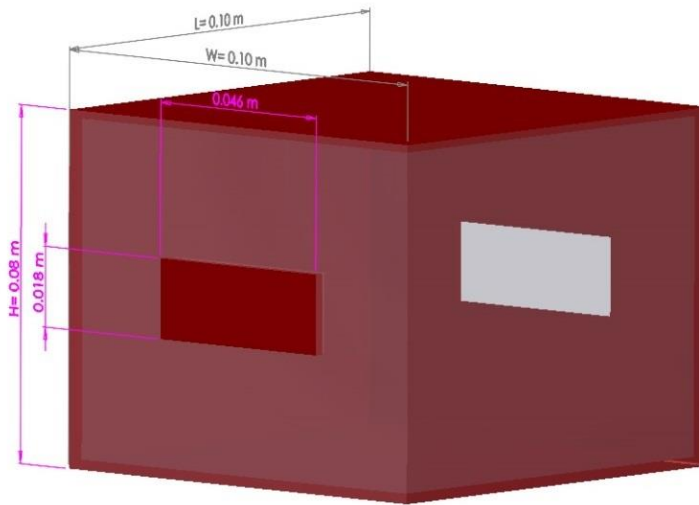
132 **4. Case study description**

133 The achievement of an accurate and reliable simulation research study requires full compliance with
134 the fundamental steps and in depth understanding of the CFD simulation and optimization processes.
135 For the purpose of this, a simple benchmark building model was designed, as illustrated in Figure 1.
136 The geometrical characteristics are based on a previously published research paper of Karava et al.
137 (2011). The scaled building dimensions are 0.1m x 0.1m x 0.08m (L x W x H), wall depth of 0.002

¹ Plankett-Burman experimental design is a fractional factorial design, which is mainly used for the identification of the most important variables of a partly known system with a large number of independent factors [21].

138 m, and two window openings of 0.018m x 0.046m (H x W), placed on the opposite sides at the
139 centres of the walls to promote natural airflow with the least resistance.

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141

142

Figure 1 Dimensional characteristics of the case study building model.

143

4.1 CFD set-up

144

The CFD simulation analysis was performed with the commercial software ANSYS Workbench 15, since it comprises a complete interface for the implementation of the work. The study was conducted in three phases. The pre-processing phase included the creation of the building model and the domain geometry, and the generation of the computational mesh. The second phase comprised the solver, along with the selection of the transport equations, the physical models and the solver settings. Finally, in the post-processing phase, plots and graphs of the solutions were created and the results were interpreted.

150

151

4.2 Governing equations

152

The simulation of the natural ventilation phenomena was treated as steady and incompressible turbulent flow. The standard k- ϵ turbulence model was used with standard wall functions, since it is widely used in natural ventilation studies in buildings [11], [25], [26], [27], [28], [30] and it shows good performance when compared with wind tunnel experiments [29], [31], [32], [32][33]. Moreover, when empty rooms are studied, the standard k- ϵ and the RNG k- ϵ model have been

156

157 proven to behave similarly [34], [35]. The governing equations of continuity (4), momentum (5), as
 158 well as the transport equations of the standard k-ε turbulence model (6 & 7) are presented below:

$$159 \quad \frac{\partial \bar{u}_i}{\partial x_i} = 0 \quad \text{Eq. (4)}$$

$$160 \quad \frac{\partial \bar{u}_i \bar{u}_j}{\partial x_j} = -\frac{1}{\rho} \frac{\partial \bar{p}}{\partial x_i} + \frac{\partial}{\partial x_j} \left(\nu \left(\frac{\partial \bar{u}_i}{\partial x_j} + \frac{\partial \bar{u}_j}{\partial x_i} \right) \right) \quad \text{Eq. (5)}$$

$$161 \quad \rho \frac{\partial k}{\partial t} + \rho u_i \frac{\partial k}{\partial x_i} = \frac{\partial}{\partial x_j} \left[\left(\frac{\mu + \mu_t}{\sigma_k} \right) \frac{\partial k}{\partial x_j} \right] + P - \rho \varepsilon \quad \text{Eq. (6)}$$

$$162 \quad \rho \frac{\partial \varepsilon}{\partial t} + \rho u_i \frac{\partial \varepsilon}{\partial x_i} = \frac{\partial}{\partial x_j} \left[\left(\frac{\mu + \mu_t}{\sigma_\varepsilon} \right) \frac{\partial \varepsilon}{\partial x_j} \right] + c_{\varepsilon 1} \frac{\varepsilon}{k} P - c_{\varepsilon 2} \frac{\rho \varepsilon^2}{k} \quad \text{Eq. (7)}$$

163 where μ_t is the turbulent viscosity calculated by the equation $\mu_t = C_\mu \frac{k^2}{\varepsilon}$, with $C_\mu=0.09$, \bar{u} and \bar{p} are
 164 the mean (time-averaged) components of velocity and pressure, $P = \frac{\mu_t}{\rho} S^2$ represents the production
 165 of turbulence, $S = \sqrt{2S_{ij}S_{ij}}$ the shear stress magnitude and $C_{\varepsilon 1}=1.44$, $C_{\varepsilon 2}=1.92$, $\sigma_k=1.0$ and $\sigma_\varepsilon=1.3$
 166 [37].

167 4.3 Computational geometry and mesh generation

168 The size of the computational domain was set according to the wind tunnel's working section
 169 dimensions that would be used in sequence for a scaled validation study [39]. More specifically, the
 170 domain had dimensions of 0.5m x 1.0m x 0.5m (W x L x H) (Figure 2), allowing a blockage ratio
 171 ($\text{Area}_{\text{model}} / \text{Area}_{\text{tunnel}} \times 100\%$) of 2.8%, which lies within the recommended values for accurate
 172 simulation studies of air flow around buildings located in open flat terrains [40].

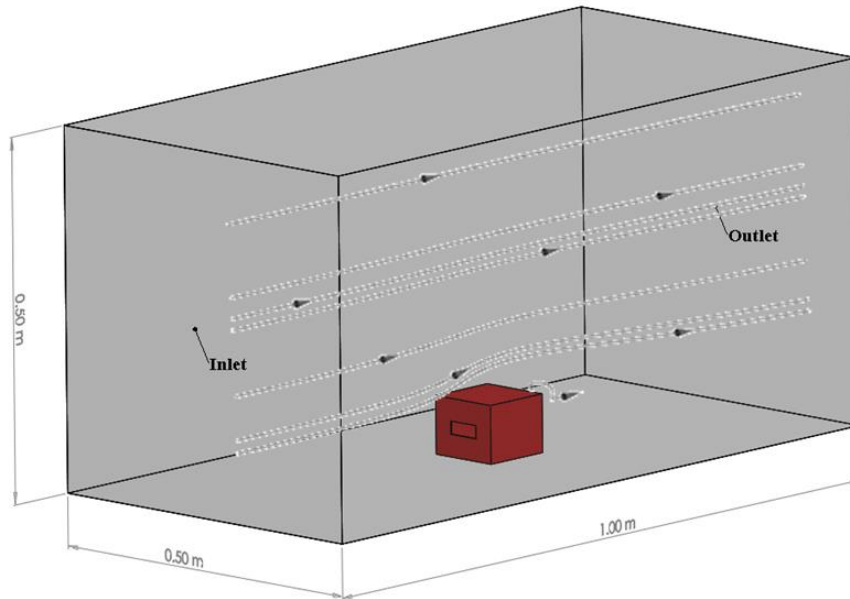
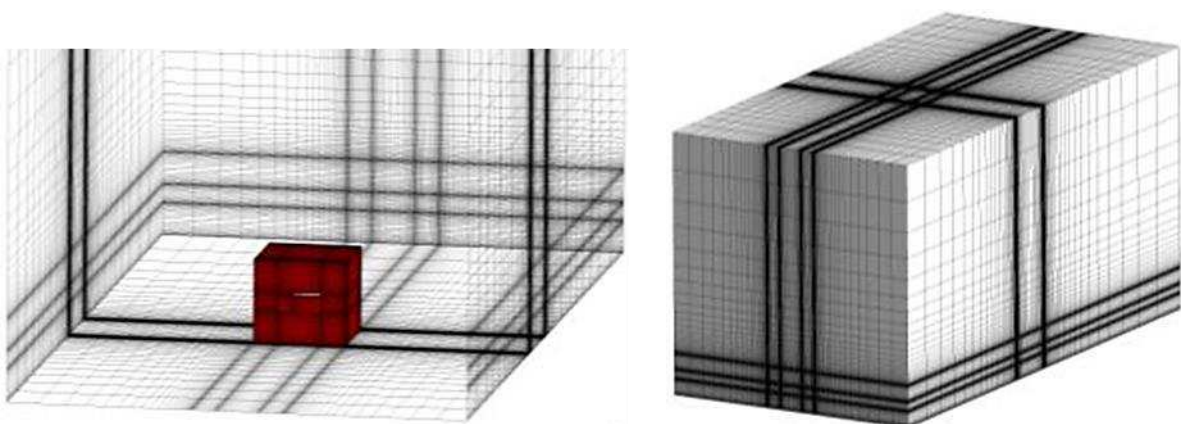


Figure 2 Computational domain and model positioning.

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174

175 The simplicity of the geometry allowed the creation of a fully hexahedral mesh that enables better
 176 convergence behaviour. A finer grid was generated around the critical areas of the model, including
 177 the building edges, the window openings, as well as, the front, back and lateral flow paths around the
 178 building block. The rest of the domain was developed with high-resolution on the connections along
 179 the critical areas, starting with height of the neighbour cell at 0.002 m and an increasing size
 180 thereafter till the edges of the domain with a ratio of 1.2, leading to a coarser grid size, as illustrated
 181 in Figure 3.



182
183

Figure 3 Computational surface grid of the simulation model (left) and the flow domain (right).

184 4.4 Grid Verification

185 In order to ensure grid independency, the volume adaptation method was used that enables the
 186 refinement and coarsening of the entire fluid volume. The initial mesh that was produced in ANSYS

187 Mesher, comprised of 1,071,790 hexahedral cells. The refinement and coarsening of the
 188 computational domain enabled the comparison of the average rates of air velocity in the two window
 189 openings. In the initial grid size of 1,071,790 cells, the average wind velocity value was equal to 1.88
 190 m/s. The coarsening of the domain led to 647,542 hexahedral cells, with a magnitude of average
 191 wind velocity equal to 1.79 m/s. After the refinement of the computational domain, 1,236,636
 192 hexahedral cells were produced, with an average wind speed equal to 1.92 m/s. The deviation of the
 193 average velocity magnitude from the medium grid was 4.8% for the coarse grid and 2.1% for the fine
 194 grid, as shown in Table 1. Thus, the medium size grid was selected for the simulation analysis,
 195 ensuring good performance, with reduced computational cost and without compromising the
 196 accuracy of the solution.

197 **Table 1. Estimated error of average velocity magnitude at the two openings of the building**
 198 **block**

Computational Grid Size	Average Velocity (m/s)	$\epsilon = (f_2 - f_1)/f_1$ 100%
Coarse: 647,542	1.79	4.8 %
Middle: 1,071,790	1.88	-
Fine: 1,236,636	1.92	2.1 %

199 **4.5 Boundary conditions and solution settings**

200 The boundary conditions set were similar to the one used in the research of Calautit and Hughes
 201 (2014), since the same wind tunnel facility was used. A constant wind profile was set at the inlet and
 202 zero static pressure at the outlet. At the side, top and ground walls of the domain, no-slip shear
 203 condition was applied with roughness height, $k_s=0.001$ m and roughness constant, $C_s=0.5$. The walls
 204 of the building block were set with similar roughness height of 0.001 m. The boundary conditions
 205 along with the solver settings are summarised in Table 2:

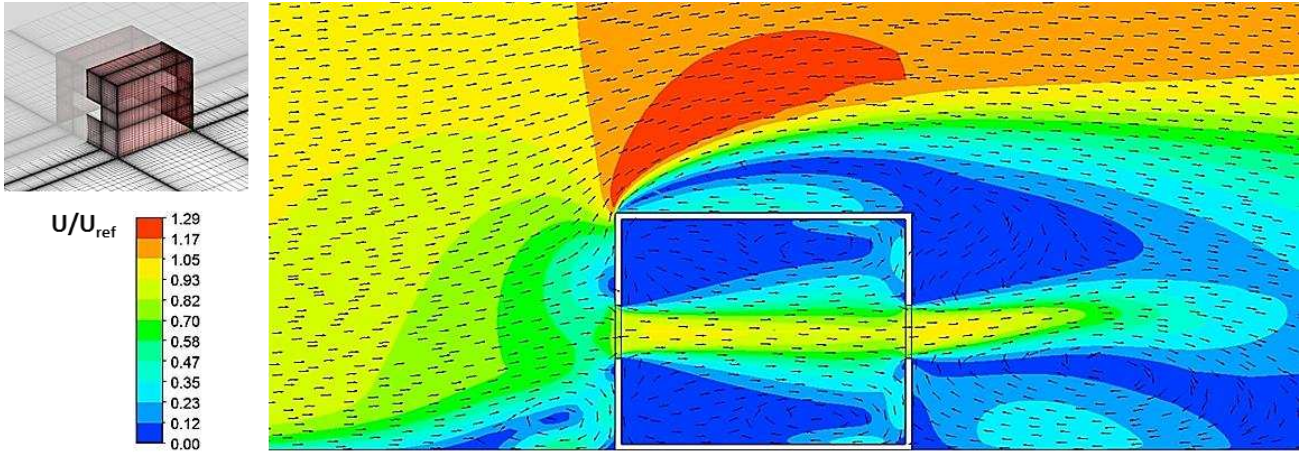
206

207 **Table 2. Boundary conditions and solver settings for the simulation model**

Inlet	Constant velocity $U = 3\text{m/s}$
Outlet	Zero pressure
Side, Top and Ground walls	$k_s = 0.001\text{ m}$ and $C_s = 0.5$
Building walls	$k_s = 0.001\text{ m}$ and $C_s = 0.5$
Turbulence model	Standard k- ϵ turbulence model
Scheme	SIMPLE
Spatial Discretization	Pressure: Standard, Momentum, Turbulence Kinetic Energy and Diss.Rate: Second Order

208 **4.6 CFD results**

209 The initial numerical simulation study generated results of the wind and pressure distributions inside
 210 and outside the building block. Figure 4 illustrates the dimensionless velocity patterns and the
 211 normalised vectors at the vertical cross section of the domain. The uniform velocity of 3 m/s (used
 212 also as reference velocity, U_{ref}) at the inlet resulted to a maximum velocity speed of 3.93 m/s and
 213 2.88 m/s at the exterior and interior areas of the building respectively. According to the results,
 214 recirculation zones are developed below the openings of the upwind and downwind walls, as well as
 215 across the roof due to flow separation at the top front edge of the building block. At the interior, the
 216 air is driven directly from the one side to the other, due to the pressure difference between the two
 217 opposite window openings. Recirculation zones are created at both top and bottom parts of the
 218 interior windward wall.



219

220

221

Figure 4 Dimensionless velocity contours and normalised vectors on the vertical plane in the middle of the building block; as U_{ref} was taken the inlet velocity magnitude of 3m/s.

222

In case of naturally ventilated buildings, the attainment of sufficient ventilation is important for the

223

provision of comfortable indoor environments, mainly counted in terms of air volume induced in the

224

occupied spaces and in terms of homogeneity, for equal flow distribution. Thus, the evaluation of the

225

results was focused on two parameters. The first one was the volumetric flow rate (Q), as an

226

indicator of the air volume passing through the windward window per unit time and the second one

227

was the standard deviation of velocities at the building interior, to assess the homogeneity of the

228

flow. These parameters can be calculated by the Eq. (8) and (9) below:

229

$$Q = \frac{\dot{m}}{\rho} \quad \text{Eq. (8)}$$

230

$$SD = \sqrt{\frac{\sum(U_i - \bar{U})^2}{n}} \quad \text{Eq. (9)}$$

231

where Q is the flow rate (m^3/s), \dot{m} is the mass flow rate (kg/s), ρ is the air density ($1.2 \text{ kg}/\text{m}^3$), SD is

232

the standard deviation of velocities, U_i is the velocity at interior location i (m/s), \bar{U} is the mean

233

velocity at the interior of the block (m/s) and n is the number of computational cells at the interior of

234

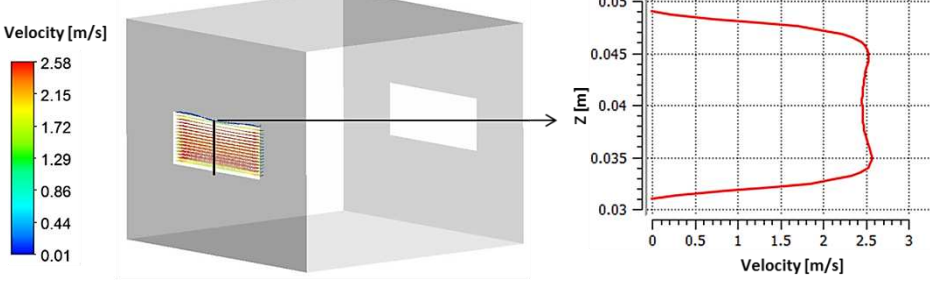
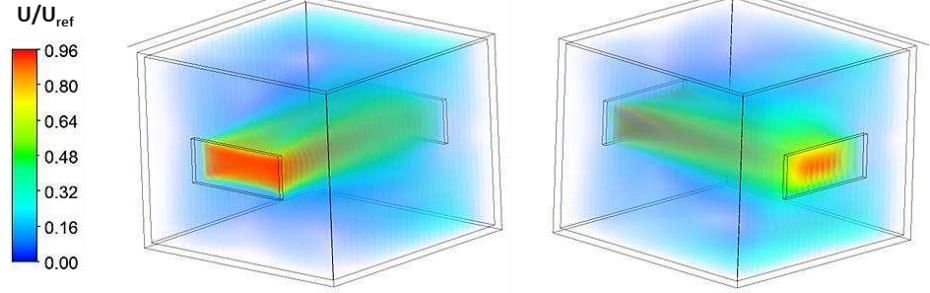
the block. The expressions were generated in ANSYS post processing and the graphical illustrations

235

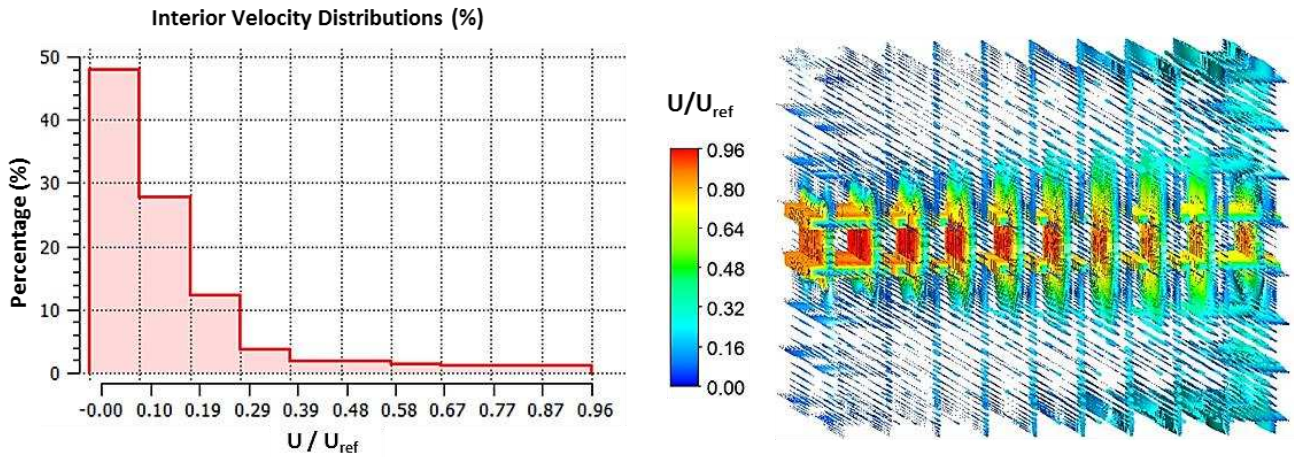
along with the obtained numerical values are presented in Table 3.

236

237 **Table 3. Graphical illustration of the CFD simulation results**

Expression	Value	Graphic Illustration
Flow Rate Q (m ³ /s)	1.81 x 10 ⁻³	 <p data-bbox="518 593 1452 672">Velocity vectors at the windward window opening (left) and vertical velocity distribution in the middle of the opening (right)</p>
St_Dev_Vel (m/s)	0.512	 <p data-bbox="518 1008 1452 1075">Dimensionless velocity magnitudes at the interior of the building block, on the windward (left) and leeward side (right)</p>

238 It was observed that the incoming air stream through the front window opening developed an almost
 239 symmetrical distribution of velocity magnitudes, with a maximum value of 2.58 m/. In the interior of
 240 the building block, the highest velocity magnitudes were recorded at the horizontal flow path
 241 between the two openings. The percentage distribution of velocity magnitudes are presented in
 242 Figure 5, indicating that around 48% of the internal points have velocity magnitudes lower than 0.29
 243 m/s. On the windward wall of the building model, recirculation zones were developed on top and
 244 below the window opening, creating intensively ventilated areas, compared to the leeward side of the
 245 building, where calm zones were observed, making the internal airflow relatively heterogeneous.



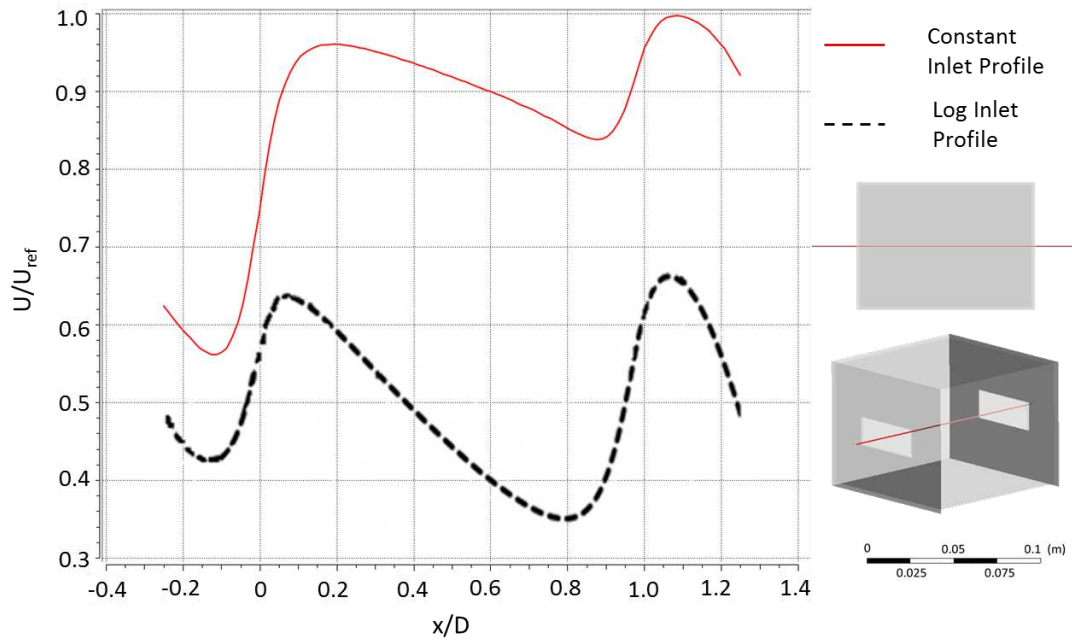
246
247 **Figure 5 Histogram of dimensionless velocity distribution (left) and dimensionless velocity**
248 **vectors (right) at the interior of the building block.**

249 **4.7 CFD validation**

250 **4.7.1 Inlet velocity profile**

251 For the current study a constant velocity profile was set as inlet boundary condition, in order to
252 match the one produced from the available wind tunnel facility, in the knowledge that it cannot
253 represent a realistic flow field. The generated velocity profile at the longitudinal direction in the
254 centre of the building block is illustrated in Figure 6, by the red line. The results are compared with
255 the one produced by the study of Ramponi and Blocken (2012) (see Figure 6 black dashed line), in
256 which a logarithmic velocity profile was applied at the inlet.

257 According to Chen and Srebric (2002) studies with significant level of accuracy are produced,
258 provided that the generated trends are consistent. It is also highlighted the fact that “very high
259 accuracy, while desirable, is not essential since most design changes are incremental variations from
260 a baseline”. Therefore, since our research is not directly focused on the ventilation performance of
261 the building block, but on the methodology to optimise the parameters that will improve the built
262 environment, a constant inlet velocity profile may be accepted.



263
264

Figure 6 Velocity profile at a longitudinal line in the middle of the building block.

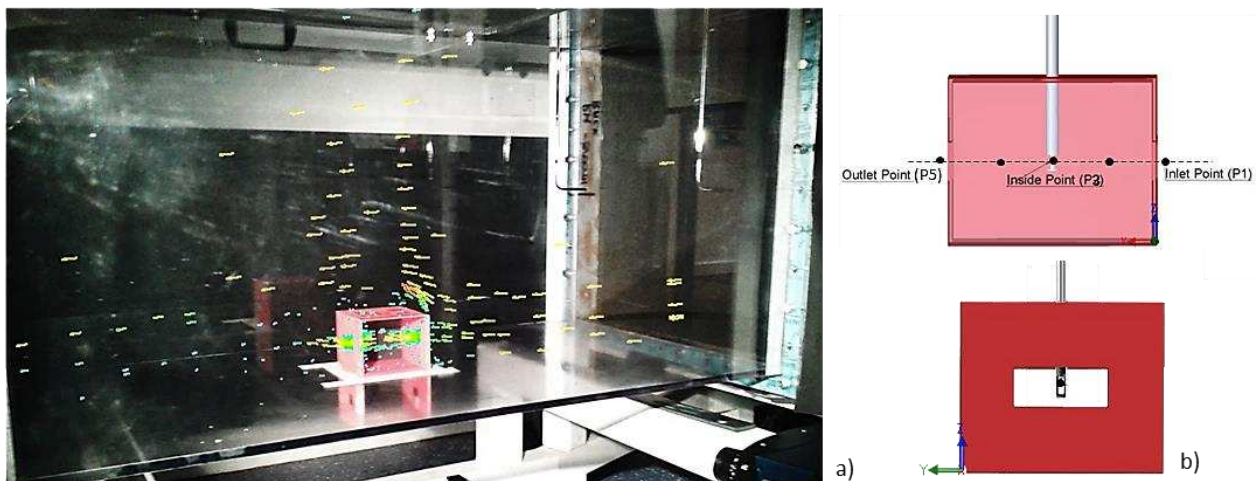
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4.7.2 Wind tunnel validation

266

For the validation of the numerical simulation, the wind tunnel facility of the Civil Engineering Department at the University of Leeds was used. The closed-loop wind tunnel is 5.6 m long, with test section dimensions of 0.5m x 1.0m x 0.5m (W x L x H) [39]. The performance assessment of the model was based on velocity measurements on specific locations inside the building block and outside the window openings, as illustrated in Figure 7.

270



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Figure 7 Model positioning in the wind tunnel test section and CFD velocity vectors indicating airflow distribution (a); hot wire measurement points of velocity speeds (b).

274

A uniform velocity profile of 3 m/s was achieved, identical to the one used for the numerical simulation. The speed measurements were conducted using a hot wire probe (Testo 425), obtaining

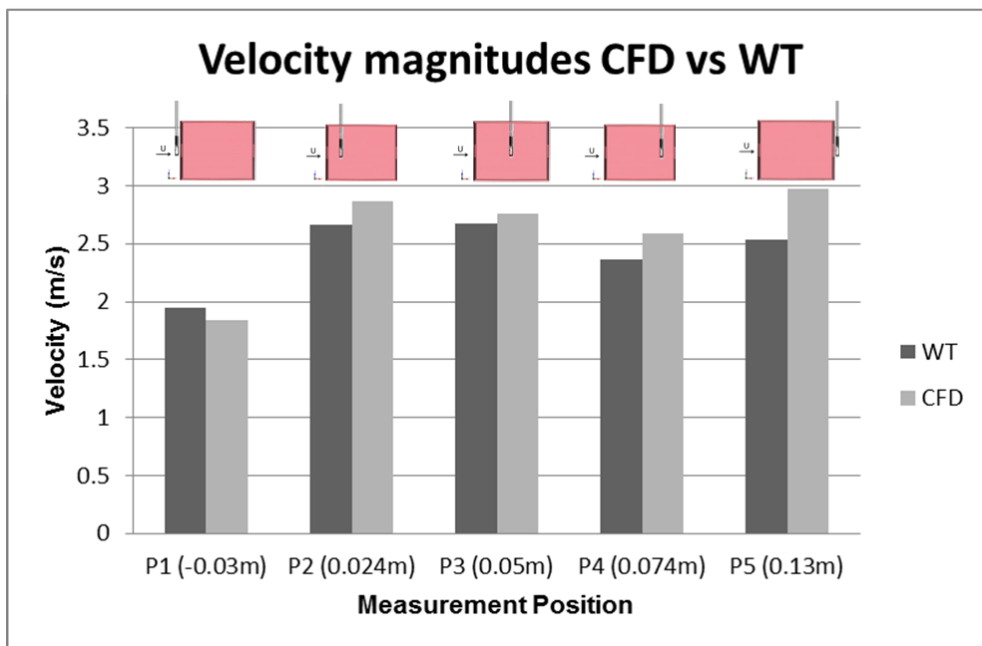
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276 results with $\pm 1.0\%$ rdg accuracy at velocity values of $\leq 8\text{m/s}$. For each measurement point, five
 277 repeated measurements of 2 min duration were performed to reduce the human error factor. The hot
 278 wire was placed on the exact proximity of the windward and leeward window openings and in three
 279 symmetric internal positions of the building model. The results obtained are presented in Table 4 and
 280 Figure 8.

281 **Table 4. Comparison of velocity magnitudes in five building locations from wind tunnel**
 282 **measurements and CFD simulation.**

Measurement Point	P1 (-0.03m)	P2(0.024m)	P3 (0.05m)	P4(0.074m)	P5 (0.013m)
W.T. Velocity	1.95 m/s	2.66 m/s	2.67 m/s	2.36 m/s	2.54 m/s
CFD Velocity	1.84 m/s	2.87 m/s	2.76 m/s	2.59 m/s	2.97 m/s
Error	5.9 %	7.3 %	3.3 %	8.9 %	14.5 %

283



284

285 **Figure 8 Graphical comparison of velocity magnitudes obtained by CFD and WT experiments**
 286 **in five measurement points.**

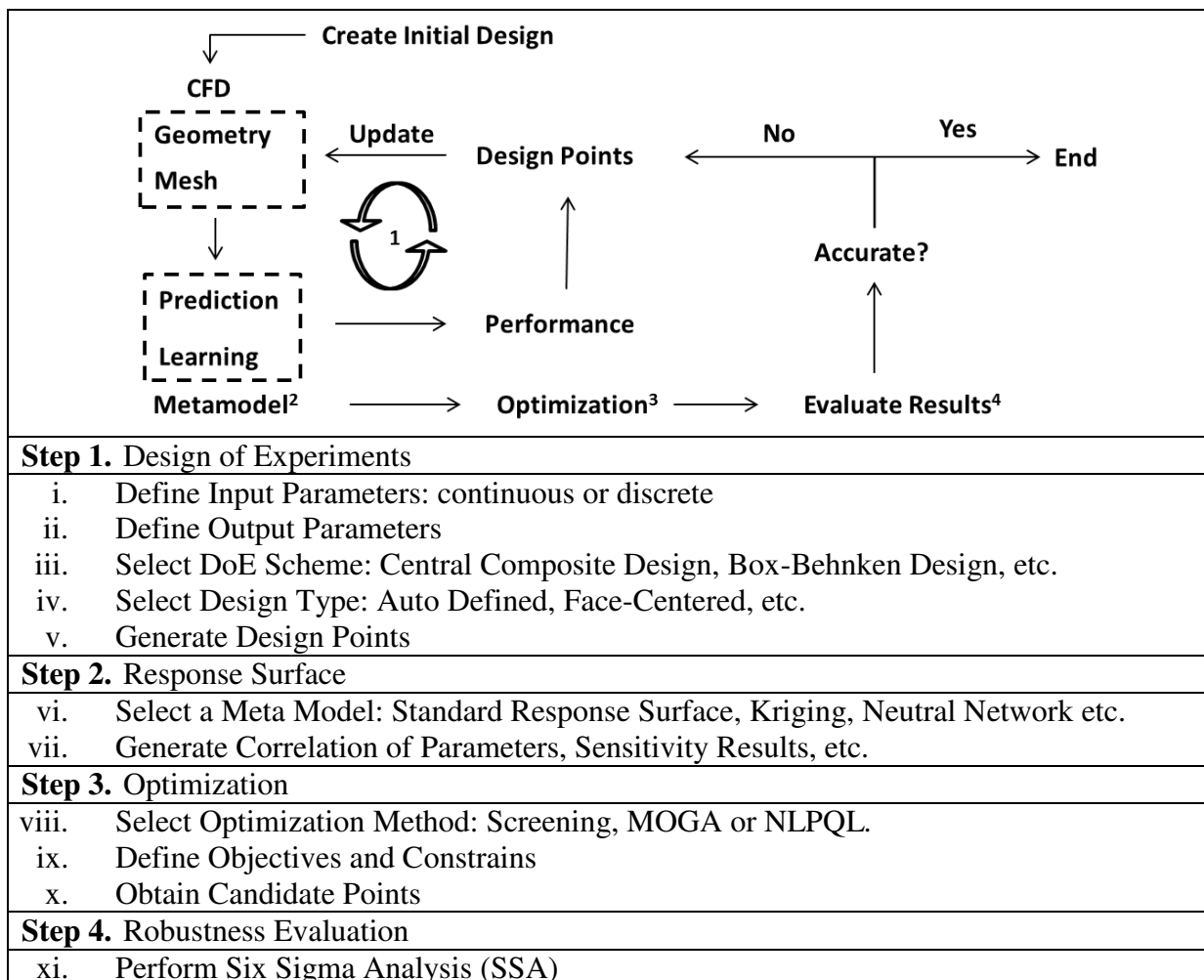
287 According to the velocity values obtained from the wind tunnel experiments, the k-ε model performs
 288 well, validating the CFD methodology followed for the wind flow simulation. The generated errors
 289 of 5.9% and 3.3%, at the inlet and the interior of the building, are within acceptable limits, if we take

290 under consideration the human, experimental and mechanical errors. The highest recorded error of
 291 14.5% at the outlet (P5) can be explained by the induced turbulence in the leeward underpressure
 292 region of the building block that increases the uncertainty of both numerical and experimental value.

293 5. RSM metamodel methodology

294 The Response Surface Optimisation technique is a simulation driven optimisation tool that enables
 295 the exploration of various design parameters and displays the interactions among them and the
 296 resulting solutions. A DoE study was performed and combined with RSM, in ANSYS Design
 297 Exploration 15.0. The methodology followed for the identification of the optimum design solution
 298 can be summarised in steps 1 to 4, as shown in Table 5, and has doable extension to similar design
 299 exploration problems.

300 **Table 5. Workflow for optimization methodology**

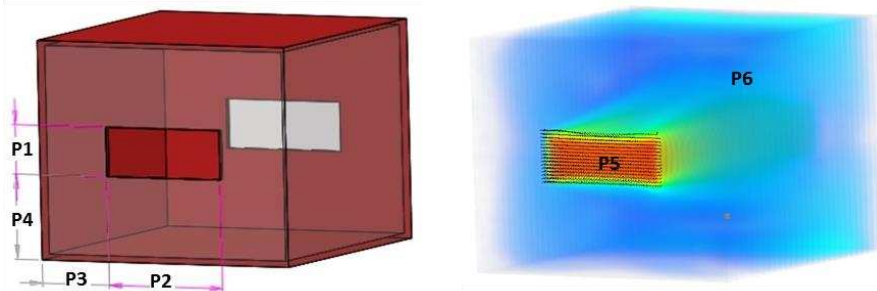


301 **5.1 RSM set up**

302 Once the input building design is created and the primary simulation run is completed (as presented
 303 in section 4), the optimization problem can be modelled. The first step concerns the identification of
 304 the input independent variables, their design space (or constraints), as well as the output dependent
 305 variables (Table 6). In the case of cross-ventilated buildings, the window positioning and window
 306 configuration has been found to play a determinant role in enhancing natural ventilation efficiency
 307 (Stavrakakis et al., 2012; Bangalee et al., 2013). Therefore, in consideration of the predicted results,
 308 the dimensional characteristics of the window openings, the width and height, were selected as the
 309 input continuous parameters. Additional derived input parameters were defined in order to keep the
 310 windows always centralised regardless configuration. The design space, within which the exploration
 311 of several design alternatives would be performed, was defined based on rational criteria. The range
 312 of the input variables was from 0.01 m to 0.018 m for the window height and from 0.023 m to 0.046
 313 m for the window width. Output parameters were set the flow rate through the front window opening
 314 and the homogeneity of the flow inside the room, represented by the standard deviation of velocities.

315 **Table 6. Quantification of input and output parameters**

Parameters		Name	Initial Value	Constrains
Input	P1	Window_Height	0.018 m	$0.01 \text{ m} \leq \mathbf{P1} \leq 0.018 \text{ m}$
	P2	Window_Width	0.046 m	$0.023 \text{ m} \leq \mathbf{P2} \leq 0.046 \text{ m}$
	P3	Horizontal_Dist	0.027 m	$\mathbf{P3} = (0.1 - \mathbf{P2}) / 2$
	P4	Vertical_Dist	0.031 m	$\mathbf{P4} = (0.08 - \mathbf{P1}) / 2$
Output	P5	Flow_Rate_Q	$1.81 \times 10^{-3} \text{ m}^3/\text{s}$	
	P6	St_Dev_Sensor_Vel	0.512 m/s	



Graphical representation of input (left) and output (right) parameters

316

317 After having defined the number of input and output parameters, the generation of the design points
 318 was performed using the Auto-defined Central Composite Design (CCD) scheme. The CCD consists
 319 of one central point, 2N star (or axial) points and a two-level full factorial design (2^N factorial points)
 320 [18]. The number of the design points can be determined by Eq. (10)

$$321 \quad DP = 1 + 2N + 2^N \quad \text{Eq. (10)}$$

322 where N is the number of input parameters (or factors).

323 The selected scheme enabled the creation of 9 rotatable and symmetrical designs, including the
 324 initial one. The calculation of their responses was the most time consuming part of the study, as they
 325 were solved sequentially to achieve convergence in every simulation run. The results obtained are
 326 listed in Table 7 and represent the design space within which the quadratic response surface was
 327 constructed.

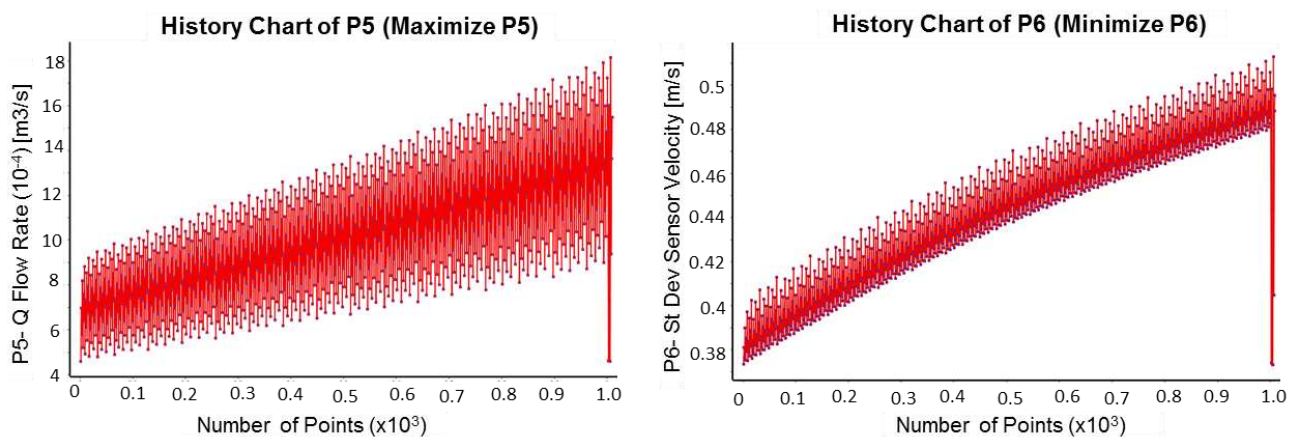
328 **Table 7. CCD-based Design Points and their obtained CFD solutions**

Design Point	P1 (m) Window_Height	P2 (m) Window_Width	P5 (m³/s) Flow_Rate_Q	P6 (m/s) St_Dev_Sensor_Vel
1 (DP 6)	0.014	0.0345	1.01×10^{-3}	0.443
2 (DP 2)	0.01	0.0345	0.69×10^{-3}	0.380
3 (DP 8)	0.018	0.0345	1.34×10^{-3}	0.491
4 (DP 4)	0.014	0.023	0.66×10^{-3}	0.438
5 (DP 5)	0.014	0.046	1.37×10^{-3}	0.469
6 (DP 1)	0.01	0.023	0.46×10^{-3}	0.374
7 (DP 7)	0.018	0.023	0.87×10^{-3}	0.477
8 (DP 3)	0.01	0.046	0.93×10^{-3}	0.402
9 (DP 0)	0.018	0.046	1.81×10^{-3}	0.512

329 The second step was the selection of a Response Surface Type algorithm. For the purpose of this, the
 330 Standard Response Surface was adopted, allowing the implementation of a regression analysis to
 331 generate a second-order fitted response for estimating the correlations among the selected
 332 parameters. The second-order models are commonly used for optimisation processes, due to their
 333 flexible nature and ability to perform better in complex problems (Myers et al., 2009). In this stage,

334 the relationships between the independent and dependent parameters can be investigated, by
335 providing a graphical insight into the design sensitivity analysis.

336 Next to the optimization problem was the selection of the objective function and the optimisation
337 algorithm. The objective of the optimization was to improve the natural ventilation efficiency. This
338 could be achieved by increasing the flow rate and also by promoting the flow homogeneity in the
339 area of interest. Thus, the resulting optimization aims were to maximise Flow_Rate_Q (P5) and
340 simultaneously minimise St_Dev_Vel (P6), within the restricted range values set for the window
341 height (P1) and width (P2). The Screening optimization algorithm was used, which is based on the
342 simple concept of sampling and sorting, identifying the most significant and influential variables,
343 regarding the predefined objectives and constraints [43]. 1,000 uniformly distributed sample sets
344 were generated for correlation, within the optimization domain, which constitutes one of the main
345 benefits of this method. Figure 9 illustrates the evolution of the sample sets by a red curve and the
346 location of the design sample points in the predefined design space by a blue dot.



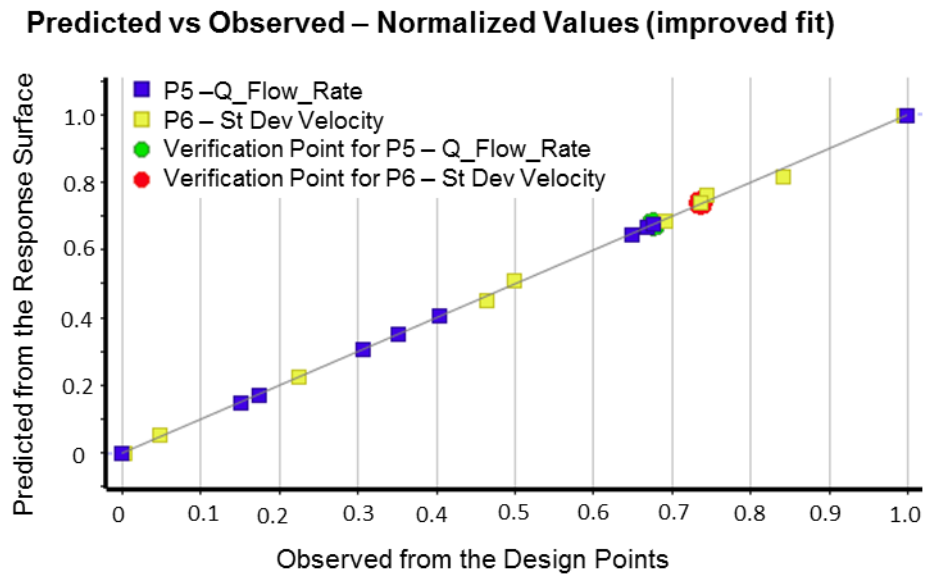
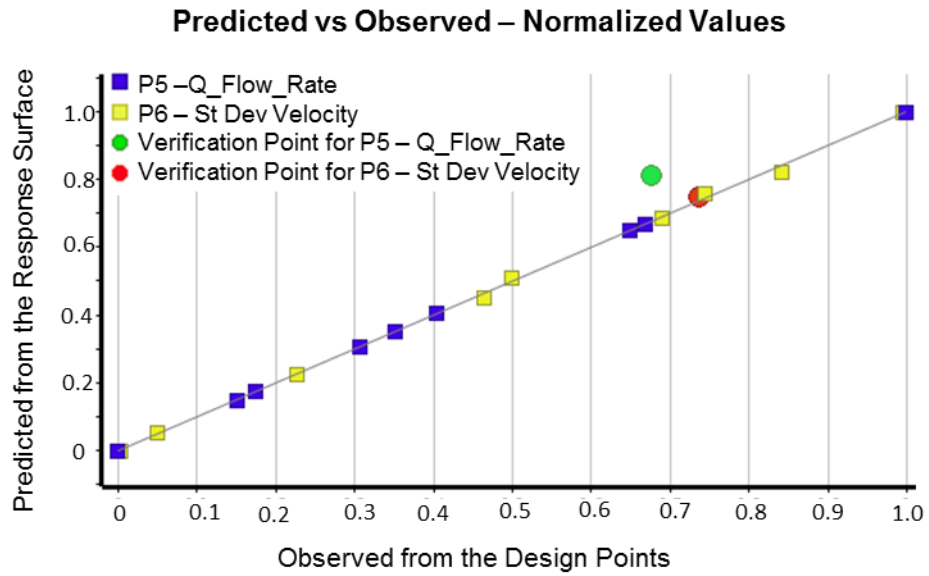
347
348 **Figure 9 History chart of the sampling design points for the two output parameters; Flow Rate**
349 **(left) and Standard Deviation of velocities (right).**

350 5.2 RSM results

351 The generated response surface was evaluated against its quality and accuracy by the response
352 surface's Goodness of Fit. Figure 10 (top) illustrates the fit of the regressed model on the response
353 function, by plotting the predicted response values versus the observed values from the design points.

354 The Goodness of Fit also enabled the evaluation of the performance of the selected meta-modeling
355 algorithm. The coefficient of determination (R^2) was equal to 1 (or 100%) for the flow rate and equal
356 to 0.9989 (or 99.89%) for the standard deviation, indicating a well-represented response surface by
357 the parametric model. However, the verification point for the flow rate showed a small deviation
358 from the diagonal line, indicating the need to refine the response surface. After taking under
359 consideration this point to the response surface, the updated Goodness of Fit (Figure 10 bottom)
360 resulted to an improved response surface with a reduction of the maximum relative residuals from
361 13.77% to 0.21% for the flow rate and from 0.42% to 0.19% for the standard deviation.

362 The RSM analysis produced estimations of the correlation between the independent and dependent
363 parameters, based on the input and output values of the Design Points, allowing the graphical
364 exploration of any design alternative within the constraint limits (Table 8 a). It also permitted the
365 quantification of the relationship between the input variables and their responses (Table 8 b, c). The
366 predicted coefficients of determination for every input variable indicated their impact effect on the
367 design responses and thus gave a first insight on the sensitivity of the design solution. Furthermore,
368 the results permitted the exploration of any design point within the design region, considering that
369 they were values obtained from the response surface and not from actual simulation runs.

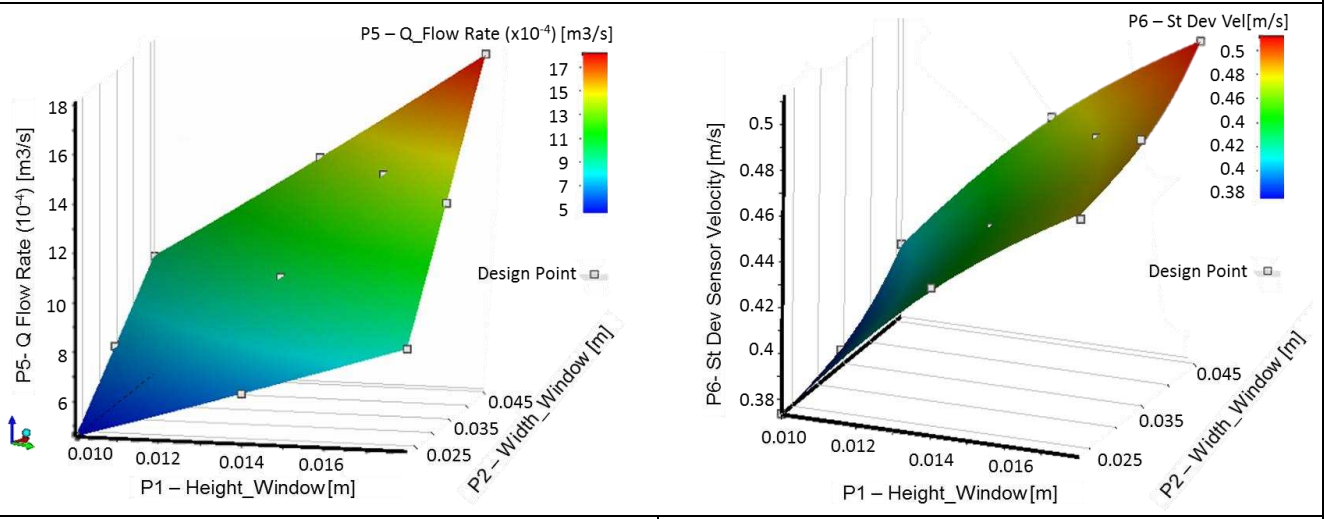


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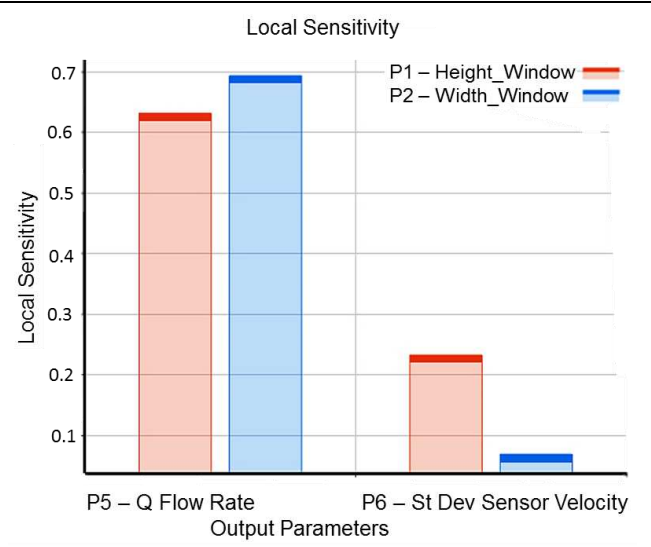
Figure 10 Goodness of fit for the estimated response surface function; initial prediction (top) and improved prediction (bottom).

Table 8. Results of Standard Response Surface algorithm

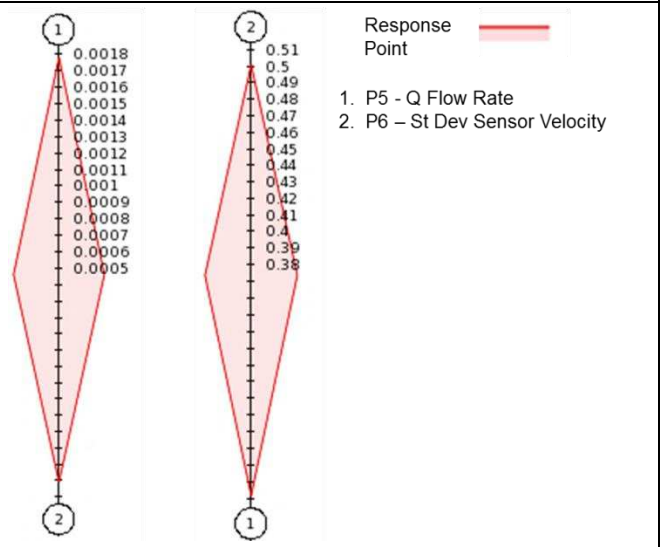
a) Response Chart – Graphical response exploration of any design alternative within the constraint limits



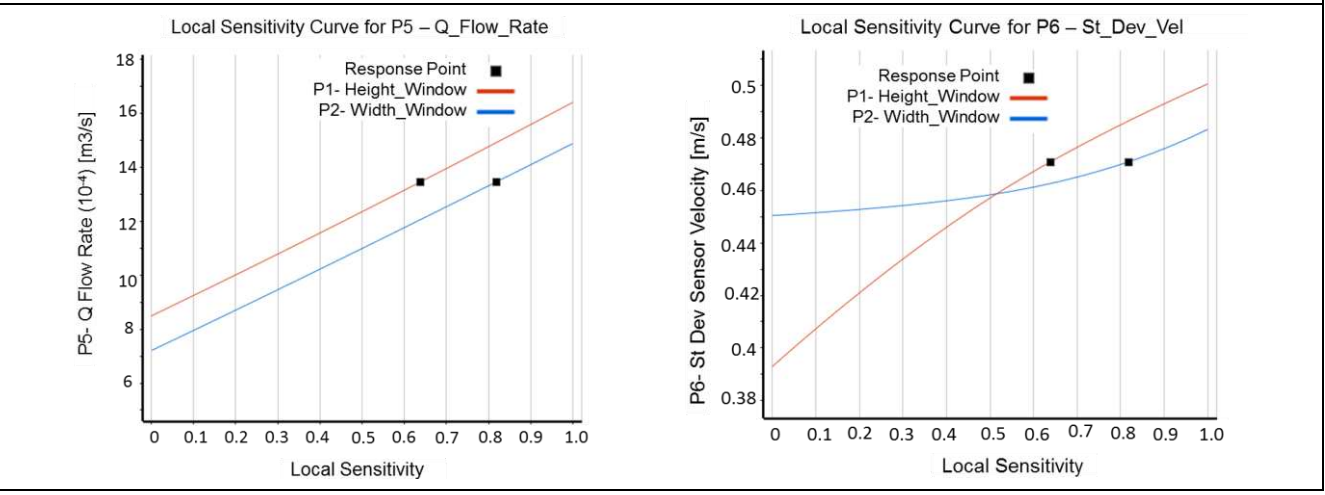
b) Local Sensitivity Chart – Impact chart of input on output parameters



c) Spider Chart – Impact of variable input parameters on all output parameters



d) Local Sensitivity Curves – Variation of design points response, based on the Local Sensitivity Chart

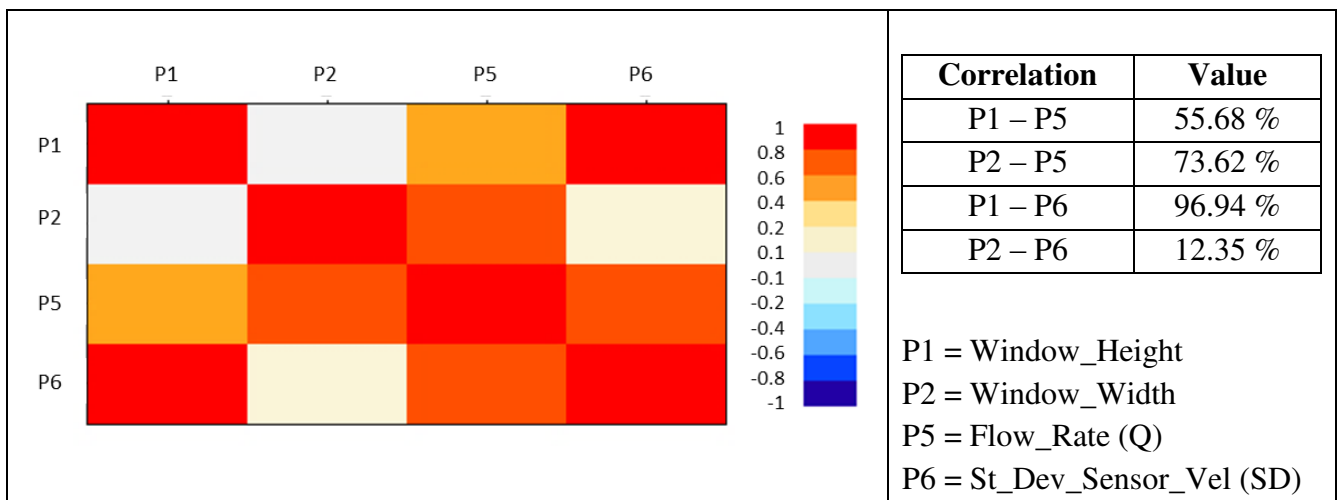


375 **5.3 Correlation of parameters**

376 A Parameters Correlation analysis was conducted, in order to assess the impact role of each input
 377 parameters on the design outputs and ascribe the degree of quadratic correlation between two
 378 parameters, with either a linear or quadratic trend, using the Spearman’s rank correlation². The
 379 implementation required the generation of 60 unique and randomly selected design sets, based on
 380 Latin Hypercube Sampling (LHS) method, according to which the input parameters have at least 5%
 381 deviation of correlations.

382 As indicated in Table 9, the window height emerges to be the most influential parameter when the
 383 standard deviation is evaluated, with correlation value of 96.9%, compared to 12.35% for the
 384 window width. While in the flow rate, the window width prevails slightly over the window height
 385 with correlation values equal to 73.6% and 55.7%, respectively.

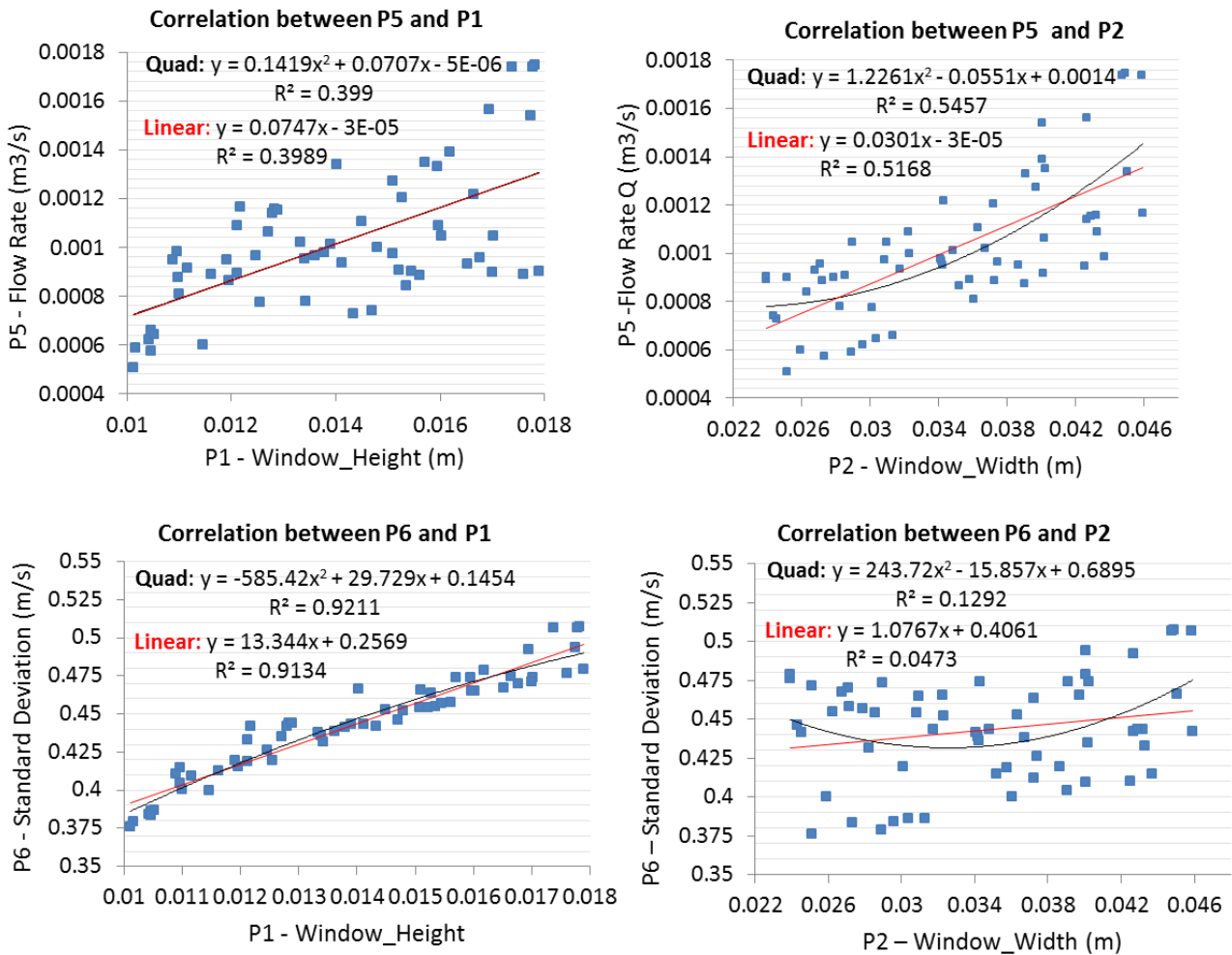
386 **Table 9. Linear correlation matrix and estimated correlation values between parameters**



387 Scatter plots were also produced to identify the degree to which the regression lines represent the
 388 model data. Figure 11 illustrates the generated linear and quadratic trend lines for each parameter
 389 pair. The multiple regression analysis showed that quadratic trend lines were a better fit for the input
 390 variables. The estimated coefficients of determination (R^2) showed that 39.9% and 54.6% of the
 391 Flow_Rate variation can be explained by the variation of the Window_Height and Window_Width,
 392 respectively. The variability of the Standard_Deviation can be strongly explained by the

²Spearman’s rank correlation is used to identify the relationship between parameters that belong in complex nonlinear data sets, without taking under consideration the outliers [44].

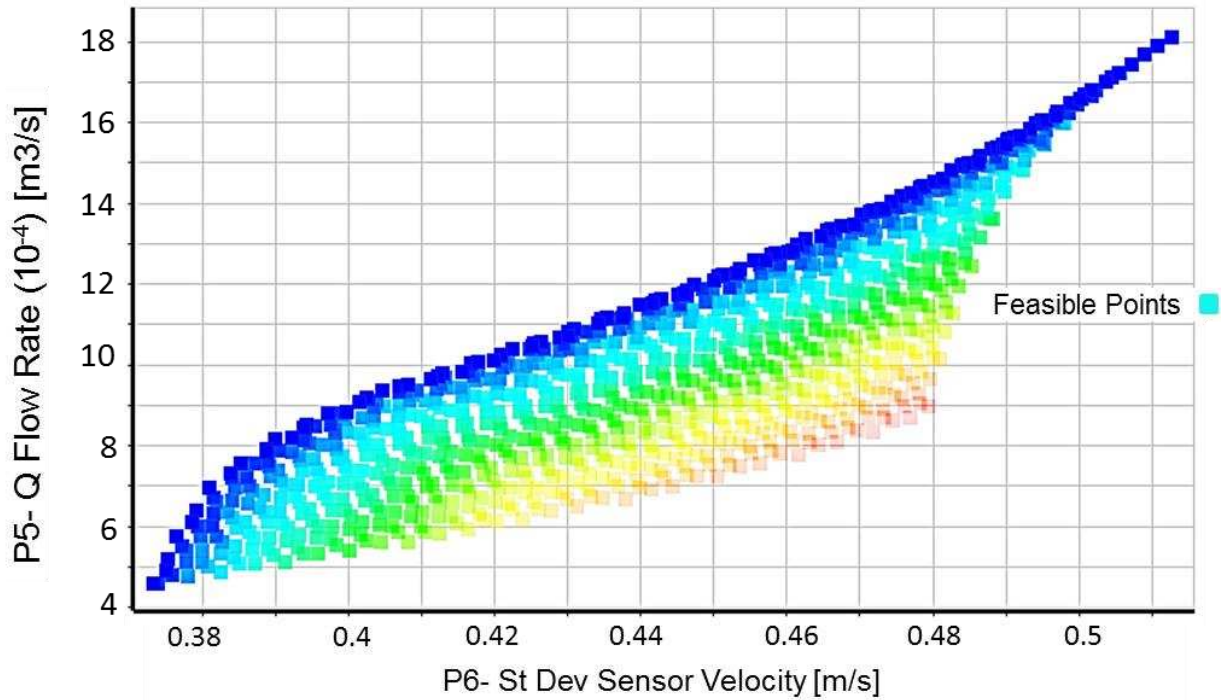
393 Window_Height with a percentage of 92.1%, as opposed to the Window_Width that gave a poor
 394 coefficient of determination equal to 12.9%.



395
 396 **Figure 11 Correlation charts with quadratic and linear trend lines for the Flow Rate (top) and**
 397 **the Standard Deviation of Velocities (bottom)**

398 **5.4 Optimization results**

399 On the improvement of the ventilation performance, the Screening optimisation method was
 400 employed that allowed the generation of 1,000 window design samples to be evaluated against the
 401 objective set. The optimisation results contained information about the candidate optimum design
 402 solutions, Pareto optimality and sensitivities analysis of the studied parameters. Figure 12 illustrates
 403 the generated design space, where feasible design solutions exist. Tradeoff charts, also known as
 404 Pareto fronts, enable the exploration of the best (blue), worst (red), feasible and infeasible designs.



405
406 **Figure 12 Two-dimensional Tradeoff chart displaying feasible design points.**

407 Table 10 shows the three generated candidate design points that show the best behaviour regarding
408 the predefined set of objectives and constraints. According to the results, all three candidate points
409 produced similar results for the standard deviation, with maximum variation of 3.64% between CP1
410 and CP3. On the other hand, the flow rate varied over 12.67% between these two points, which
411 makes the CP3 to satisfy most the established objectives for maximizing the flow rate and
412 minimizing the standard deviation.

413 **Table 10. Candidate Points generated from the Screening method**

Candidate Points	P1 (m) Window_Height	P2 (m) Window_Width	P5 (m ³ /s) Flow_Rate_Q	P6 (m/s) St_Dev_Vel
Candidate Point 1	10.03 x 10 ⁻³	40.26 x 10 ⁻³	0.818 x10 ⁻³	0.390
Candidate Point 2	10.06 x 10 ⁻³	43.14 x 10 ⁻³	0.882 x10 ⁻³	0.397
Candidate Point 3	10.00 x 10 ⁻³	46.00 x 10 ⁻³	0.937 x10 ⁻³	0.405

414 The dimensions of the optimum window opening are 0.01m height and 0.046m width. The values of
415 the output parameters over the initial design deviate -48% and -21% for the flow rate and the
416 standard deviation respectively. It is worth highlighting that the flow rate was not maximized, but
417 minimized in order to achieve local optimality.

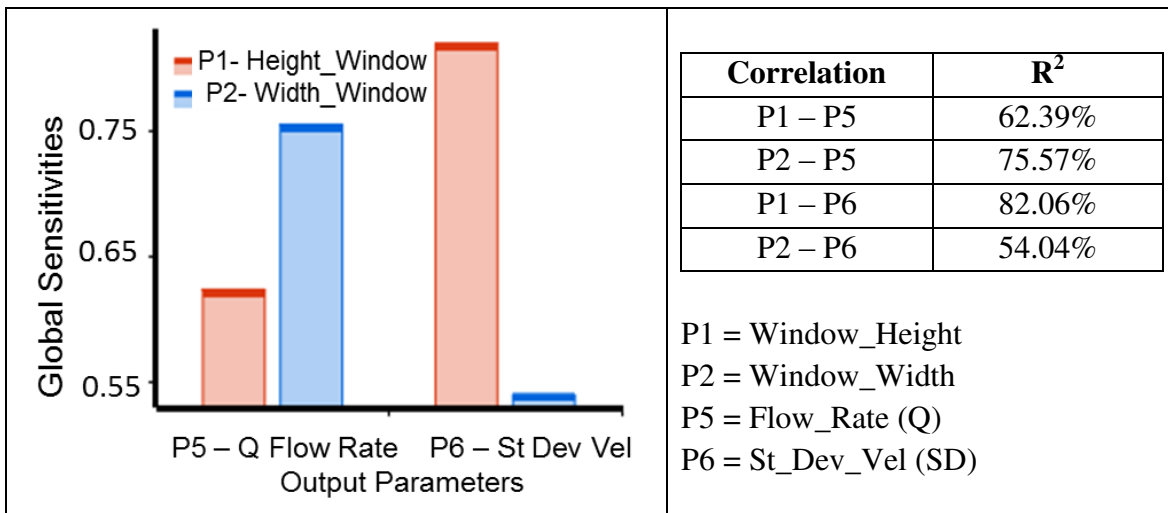
418 **5.5 Robust Analysis**

419 On the impact identification of the uncontrollable parameters on the design response, a robust design
420 analysis was performed. The robust design consists of a Six Sigma Analysis that investigates the
421 performance of the predicted response surface, by incorporating factors, uncertainties and
422 assumptions that are not taken under consideration during the RSM analysis. Thus, the robustness of
423 the model presupposes an unattained design, regarding the possible biases due to model
424 misspecification and misstatements and the distribution of the error [45].

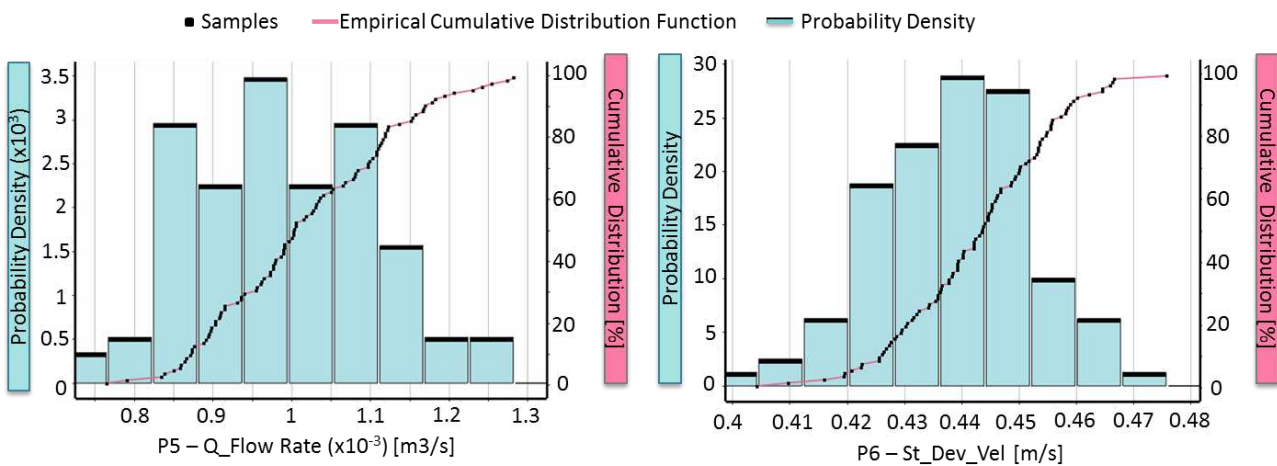
425 The Six Sigma Analysis followed the same steps and settings used in the Design of Experiments and
426 the Response Surface (refer to Table 5); with the main difference being that the inputs variables were
427 treated as uncertainty parameters. The LHS method was adopted for the generation of 100 samples
428 and the obtained results were focused on the sensitivities of output variables with respect to the input
429 parameters and the statistical distribution of the samples responses.

430 The sensitivity graph produced was not representative of the local sensitivities (such as in Table 9),
431 but of the global statistical sensitivities, irrespective of the values of input parameters. As illustrated
432 in Table 11, the sensitivity correlation coefficients highlighted the window width to affect most the
433 flow rate with a value of 75.57% and the window height to maintain the highest impact role on the
434 Standard Deviation response, with a correlation coefficient equal to 82.06%. It is worth mentioning
435 that when the factor of the Standard Deviation was assessed, the window width appears to have an
436 increased strength of correlation (54.04%) when compared with the one obtained from the RS
437 analysis (12.35%) (see Table 9).

438 **Table 11. SSA statistical sensitivities for the output parameters**



439 In order to prove the robustness of the model, the Six Sigma quality criterion needs to be satisfied.
440 According to this, the output parameters should lie within the lower and upper specification limits of
441 a Gaussian distribution. According to Figure 13, in the flow rate distribution the highest probability
442 density is in the range of $0.97 \times 10^{-3} \text{ m}^3/\text{s}$. The distribution is positively skewed and slightly flat, with
443 a skewness value of 0.22 and a kurtosis value of -0.55, approximating the graph of the normal
444 distribution. The standard deviation distribution shows a negative skewness of -0.23 and a small
445 kurtosis of -0.007, with the maximum probability density to lie in the range of the mean value (0.44
446 m/s) that gives the image of normal distribution.



447 **Figure 13 Statistical distribution functions for P5_Flow_Rate (left) and P6_St_Dev_Vel (right).**
448

449

450 **5.6 RSM optimization verification**

451 The verification of the optimization method concerns the comparison of the values estimated for the
 452 output parameters by the RSM metamodel and those obtained by the CFD simulation runs for the
 453 three candidate points. The calculated design solutions from the numerical simulation are presented
 454 in Table 12.

455 **Table 12. Verification of the optimization-generated Candidate Points**

Candidate Points	Candidate Point 1 RSM CFD		Candidate Point 2 RSM CFD		Candidate Point 3 RSM CFD	
Window Height (m)	10.03 x 10 ⁻³		10.06 x 10 ⁻³		10.00 x 10 ⁻³	
Window Width (m)	40.26 x 10 ⁻³		43.14 x 10 ⁻³		46.00 x 10 ⁻³	
Flow_Rate (x 10 ⁻³ m ³ /s)	0.818	0.837	0.882	0.901	0.937	0.9362
St_Dev_Vel (m/s)	0.390	0.406	0.397	0.414	0.4047	0.4049

456 According to the results, the values of both flow rate and standard deviation for the CP1 and CP2
 457 were underestimated over a maximum of 4.8%. The CP3 seems to be the optimum one for our case
 458 study, since it maintains the lowest value of standard deviation and the highest flow rate, satisfying
 459 the set of optimisation objectives.

460 The verification of the results enabled the production of two different error indicators. As shown in
 461 Table 13, the maximum error for the flow rate was equal to 4.28% and the one for the standard
 462 deviation equal to 2.32%, proving the high quality optimization results, verifying at the same time
 463 the Response Surface Methodology study.

464 **Table 13. Error between CFD and RSM results for the three candidate points**

Candidate Point	Error Flow_Rate	Error St_Dev_Vel
Candidate Point 1	2.32 %	4.10 %
Candidate Point 2	2.15 %	4.28 %
Candidate Point 3	0.03 %	0.07 %

465

466 **6. Discussion**

467 The RSM metamodel-based optimization technique allows the determination of the response of
468 several design variables after approximating a response function, averting the need for time-
469 consuming parametric studies [46]. It is a valuable tool when the relationship of the independent
470 variables needs to be assessed, regarding multiple design responses. However, the RSM method
471 should be carried out with extreme caution, when targets to the identification of those conditions that
472 will achieve the maxima or minima of the response function.

473 The arbitrary selection of the independent (input) variables is pre-dominantly user-based, and the
474 optimization of one response criterion does not always presuppose the optimization of other criteria
475 of the model and vice versa. Also the number of the selected parameters is of great importance, since
476 it determines the number of the studied design points, upon which the response surface function will
477 be based. Thus, the type and the number of the input parameters should always be selected after
478 rational consideration, in order to maximise the quality of the results within reasonable
479 computational time.

480 Moreover, the conduction of the DoE study, within a certain design space, bounded by dimensional
481 constraints, can only conclude to improved design solutions, or local optimal, which sometimes may
482 abstain from the global optimal solution.

483 The current investigation conducted a RSM metamodel-based optimization technique, using the
484 ANSYS commercial platform. The main aim was the presentation of a validated analysis of
485 experiments for the identification of improved (or locally optimal) conditions in the building's
486 interior environment, based on a set of controllable variables. For this purpose, a CCD design was
487 adopted for fitting a second order response surface regression model. The problem set was a two
488 response optimization, including the maximization of the flow rate from the frontal window opening

489 and the minimization of the standard deviation of internal velocities, deeming to a homogeneous
490 ventilation rate inside the building block.

491 In the first step a CFD simulation study on the wind distribution inside and outside the building
492 block was performed, followed by wind tunnel velocity measurements that validated the
493 methodology and the k- ϵ turbulence model used.

494 In the DoE study, nine design points were generated and the produced response function revealed the
495 estimated relationships and correlations of input and output parameters. The flow rate was more
496 influenced by the window width, rather than the window height with correlation coefficients of
497 73.62% and 55.68% respectively, as compared to the standard deviation, for which the window
498 height was the predominant factor of the response with a correlation coefficient of 96.94%, as
499 opposed to 12.35% for the window width.

500 The robust assessment, performed by the Six Sigma Analysis, revealed a reliable curve-fitted model
501 and arising extrapolation errors due to unrepresentative samples' selection or sampling error were
502 small to make the analysis imprecise.

503 Finally, the multi-objective optimization highlighted three candidate points with the most favourable
504 behaviour for the improvement of indoor airflow conditions. Their verification was valuable, because
505 even if the deviation of the results was small, it was important to prove the accuracy of the
506 methodology.

507 **7. Conclusion**

508 The verified solution of the optimal design for the window opening indicated that improved indoor
509 airflow condition inside the building block, as described by the ventilation rate and the airflow
510 homogeneity, was obtained by a 0.046 m wide and 0.01 m height opening characteristics. It was also
511 concluded that both dimensional parameters were influencing the design solution on a different level.
512 Coupled CFD and optimizations techniques were found to be important tools for the analysis and

513 evaluation of multiple parameters and responses, producing comparative results that may assist
514 decision-making process towards improved (if not optimum) design solutions. Finally, it was
515 deduced that the presented methodology can be successfully used in studies of the built environment,
516 allowing users to select throughout a plethora of parameters that are relevant to the equivalent case
517 study.

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