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Bayesian inference based inverse analysis of the impact response of a rockfall protection structure: Application towards warning and survey

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Abstract

The viability of a rockfall protection structure is vital for the hazard mitigation of habitations and infrastructures. This article investigates the feasibility and potential of inverse analysis applied to data collected on on-site rockfall protection structures exposed to real events. As an application case, a rockfall protection wall made from interconnected concrete blocks which are piled up in a zig-zag pattern is considered. The corresponding numerical model is developed in a python-based open source software SICONOS which implements the Non-Smooth Contact Dynamics (NSCD) method. The numerical model was previously spatiotemporally calibrated from two real-scale impact experiments with 520kJ and 1020kJ projectile energy and used in this work to investigate the variability in wall mechanical response against different impact conditions. The simulation results served as input data to develop the Bayesian inference based inverse analysis method aided by the polynomial chaos expansion based metamodeling technique for two purposes. First, to aid in remote decision-making shortly after an event, based on real-time measurements and second, to retrieve the impact condition characteristics (energy, location) from data collected after the event is addressed. The proposed approach appeared efficient for back-analysing (*i.e.*, output to input) data related to the wall response for being used as a warning based on its displacement with respect to the protected element at risk and damage to the wall with root mean square error (RMSE) of 16 cm and 82 kJ respectively and for a rockfall site survey with RMSE of 71 kJ energy transferred to the wall and position of impact with 37 cm.

Keywords: rockfall, impact, meta-model, statistical learning, NSCD modelling, inverse analysis

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1. Introduction

Passive rockfall protection mitigation measures such as embankments [1], galleries [2] or flexible barriers [3] are exposed to severe loading when intercepting rock blocks threatening elements at risk. During their normal operation, these structures thus experience significant deformation, displacement, and damage and possibly fail to withstand the impact or to satisfactorily control the rock block's trajectory [4].

In this context, and similarly, as for other gravitational natural hazards, increasing use is being made of equipment for monitoring on-site rockfall protection structures, to collect the data upon the impact of a rockfall [5]. On-site monitoring of structures with accelerometers or force sensors, for example, in particular aims at serving as a warning system for supporting decision-making (*e.g.*, road closure) or for providing information regarding the loading amplitude or the structure response in real situations. On-site monitoring is becoming increasingly common in the field of landslides due to the improvement, miniaturisation and cost reduction of sensors, data acquisition and transmission systems [6, 7].

Numerical models are widely used for addressing rockfall protection structures' response as a forward problem. Published research demonstrates the accuracy of the model predictions as compared to experimental data (*e.g.* [8, 9, 10]) or addressing the structure response under some specific impact conditions (*e.g.* [11, 12]) or considering sets of realistic impact conditions (*e.g.* [13, 14]). By contrast, inverse analysis conducted (*i.e.*, finding input from the output) based on numerical models has rarely been used in this field. To the best of the authors' knowledge, the only exception concerns the work presented by Escallón et al. [15] who proposed an inverse optimisation process for determining the parameters of macroscopic FE models of steel wire-rope cables and steel wire-rings.

In this work, we investigate the feasibility of conducting an inverse analysis of the structure response to derive the information with added value for stakeholders and engineers. It is for instance proposed to analyse the measured data pertinent to the structure's performance to retrieve the impact conditions. The proposed inverse analysis presents means to correlate the data retrievable from an on-site structure during and after an rockfall event, with the corresponding impact response obtained from the numerical model simulation of that structure. This correlation relies on the use of statistical learning methods enhanced by meta-modelling tools. A statistically modelled series of different impact conditions and a learning-enabled link between input and output responses provide us with the necessary components to do

30 the inverse analysis. Further, the establishment of a mathematical link between the structure's response
31 and the corresponding impact condition is enabled through the use of meta-models having negligible
32 computation costs.

33 In this work, we focus on an innovative passive rockfall protection structure made of pile-up con-
34 crete blocks to form a wall with a zig-zag pattern, for which a Non-Smooth Contact Dynamics (NSCD)
35 method-based numerical model was previously developed. The calibration of this model was conducted
36 against experimental data following a complex method involving statistical learning, resulting in im-
37 proved confidence in the model's predictive capacities, reported in Gupta et al. [16]. In parallel, specific
38 instrumentation including sensors (*i.e.* accelerometers and inclinometers), remote data acquisition and
39 processing has been developed to equip these structures. In principle, the proposed approach for conduct-
40 ing an inverse analysis could be applied to any type of structure, and in particular structures exposed to
41 dynamic loading such as flexible barriers.

42 The article is organised as follows: First, the type of the protection structure considered in this study
43 is described followed by the presentation of its numerical equivalent developed in the non-smooth contact
44 dynamics (NSCD) framework - named the NSCD model. A brief description of the previously conducted
45 NSCD model calibration using the displacement data from the impact response for two full-scale struc-
46 tures is presented alongside. Then the mechanical response of the calibrated NSCD model wall to the
47 model projectile impact is addressed via an extensive campaign of simulations. An illustrative structural
48 response is first presented at three distinct sections of wall geometry followed by the generalised impact
49 assessment via varying the six parameters collectively describing the rock block trajectory, kinematics
50 and impact point on the wall. The impact simulation results highlight the intricacy of the structure
51 response and suggest the simulation outputs which best allow differentiating the impact cases. Then, a
52 method for conducting the inverse analysis from the acquired data is developed using a combination of
53 meta-modelling and Bayesian inference techniques to support the real-time decision-making and rockfall
54 activity monitoring purposes for a given site. A discussion on of predictive capability of the inverse
55 analysis method, its limitations and the perspective on improvements towards future research concludes
56 the work.

57 2. Experimental Structure and NSCD model

58 2.1. Presentation

59 The considered structure is a composition of concrete blocks, reinforced with internal rebars and placed
60 together in a staggered pattern to form a wall whose geometry can be adapted to specific requirements
61 (*e.g.*, linear or zig-zag conformation along its longitudinal axis). Each block weighs about 1800 kg,
62 is cuboid in shape with dimensions 1.56m×0.76m×0.8m having rounded extremities in the horizontal
63 plane and is traversed by two cylindrical holes of diameter 154 mm along the vertical axis. The blocks
64 are connected thanks to metallic tubes and cables passing through these holes, providing mechanical
65 continuity to the structure [17]. There exist mechanical plays between concrete blocks of the same row
66 as well as between the metallic tubes and the blocks.

67 This type of articulated structure constitutes an alternative to other massive passive rockfall protection
68 structures with reduced footprint [18, 19] with the advantages of high versatility in the design and
69 deformability under impact. For such an application where the structure is exposed to a localised dynamic
70 loading, tubes and cables increase the number of blocks involved in the structure's response proportional
71 to the impact loading.

72 The dynamic response of this structure is evaluated thanks to two full-scale impact experiments carried
73 out at the pendulum testing facility of the Université Gustave Eiffel test site (Montagnole, France). This
74 testing facility enables the control of the impact position and constraining the projectile incidence angle
75 and rotational velocity to zero. The blocks are arranged following a zig-zag pattern (at 45° angle) to
76 improve the structure stability against tilting. The wall is made up of 38 blocks and four half-blocks
77 stacked in four layers resulting in 3.2 m height and 14.1 m length, presented in Figure 1a. Notably,
78 the layers from the ground up are named 'base', 'second', 'third' and 'top' for all future mentions. The
79 projectile used for this purpose is 2600kg in mass and 1.1 m in dimension, corresponding to approximately
80 $1/3^{rd}$ the wall height, conforming with the requirements of flexible barrier testing [20]. The released
81 projectile impacted the wall at its mid-length and at a height of about 1.7 m from the ground. The
82 velocity at impact was 20m/s and 28m/s during the first and second impacts, corresponding to kinetic
83 energies of 520 kJ and 1020 kJ respectively.

84 The wall displacement evolution data is recorded at a couple of points on the impact axis (at points
85 Top and Base) and on the distant axis (at points *C* and *D*). Besides, the data from two points *A* and *B*

86 in the impact axis is also available which is used for the cross-reference purpose only. Measures along the
 87 impact axis were derived from video records while measures from cable extensometers were considered
 88 along the distant axis. Notably, due to the absence of this later data for the 520 kJ impact test at point
 89 *C*, the evolution obtained from simulations presented in Furet et al. [17] are considered. This exception
 90 is thought to have a minor influence due to the very small amplitude in displacement observed in this
 91 specific case. The experimentally recorded evolution of displacement with time at these four points for two
 92 impact tests can be referred to in Figure 2. Further information on the two real-scale impact experiments
 93 setup, instrumentation and data acquisition shall be referred to in Furet et al. [17].

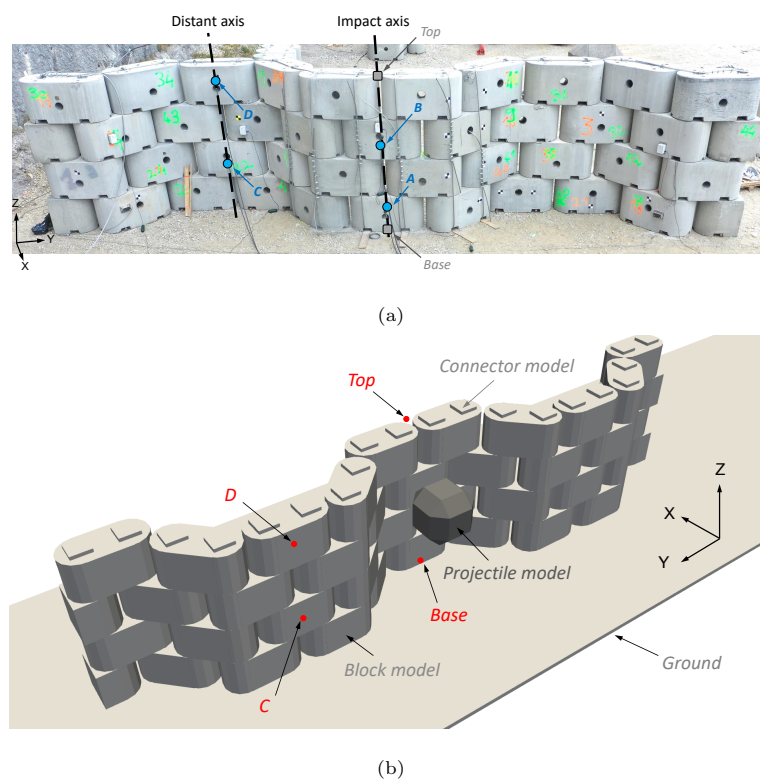


Figure 1: (a) The experimental real-scale wall structure and (b) its numerical equivalent developed using SICONOS software based on the framework of non-smooth contact dynamics (NSCD) method, hereby referred to as NSCD model.

94 Based on these impact experiments, a numerical model of the structure was developed under the
 95 Non-Smooth Contact Dynamics (NSCD) framework implemented in a python-based software package
 96 SICONOS [21]. The NSCD model of the structure is a collection of blocks and connectors, presented in
 97 Figure 1b. The detailed description of the model development and calibration is presented in Gupta et al.
 98 [16] and briefed hereafter.

99 The NSCD method was developed to solve multi-body multi-contact problems with rigid and/or

100 deformable bodies with rigid contact laws such as Signorini’s model of unilateral contact and Coulomb’s
101 dry friction without any kind of regularization (viscous friction) or compliance. It finds many modelling
102 applications in the field of civil engineering and geomechanics such as masonry and stone structures
103 exposed to static, cyclic, and dynamic loading, cohesive and non-cohesive granular materials and rockfall
104 propagation on slopes to name a few.

105 In the present work, the system is modelled as a collection of rigid blocks connected by unilateral
106 constraints with Coulomb friction. The finite-freedom dynamics of rigid bodies with unilateral constraints
107 are known to be non-smooth, in the sense that the velocities of the system possess jumps when a contact
108 is closing with a positive relative velocity. These velocity jumps are described through the introduction of
109 an impact law. Thereby, the NSCD method can perform the numerical time integration of the multi-body
110 system under impacts in a dynamic condition.

111 The NSCD model of the experimental structure is a collection of the model objects - *i.e.*, blocks,
112 connectors, projectile and ground, as shown in Figure 1b. The same block and projectile geometry is
113 considered in the model as that in the real structure and the tubes and slings are collectively modelled
114 as connectors. In the NSCD framework, these model objects are defined as a combination of different
115 contactors, collectively making the model equivalent to the real structure. These contactors are defined
116 with a uniquely assigned collision group to identify them and differentiate one from another. The inter-
117 action between model bodies is assigned through Newton impact friction non-smooth law [22]. This law
118 governs the interaction between a pair of contactors (identified through their respective collision groups)
119 via a user-defined coefficient of friction (μ) and coefficient of restitution (e).

120 2.2. Calibration

121 The model parameters governing the interactions between the various bodies of the system were
122 calibrated against the experimental database describing the spatio-temporal response of the wall during
123 the two impact tests. The calibration was based on the displacement measured with time (at three-
124 time instants) at the four locations previously mentioned. These three-time instances correspond to
125 the evolving displacement from the start of the impact at (1) the initial nearly linear slope with a
126 representative instance of 0.1 seconds for the impact axis and 0.25 seconds for the distant axis, (2)
127 maximum block displacement and, (3) displacement at rest *i.e.*, at 1.0 second.

128 The model calibration was carried out for five parameters. The first two take into account the imposed

129 constraints for the block-connector (d_z) and connector-connector (v_p) interaction which collectively con-
130 trols the relative flexibility of the wall and the relative looseness in the sling. The other three parameters
131 concern the interaction laws between contacting bodies in the NSCD framework. They are defined as
132 the friction coefficient between blocks *i.e.*, concrete-concrete (μ_{cc}) and between blocks and ground *i.e.*,
133 concrete-soil (μ_{cs}) and the restitution coefficient (e). The calibration was supported by the Bayesian
134 inference statistical learning method, improving the confidence in the derived set of model parameters as
135 6.8 cm, 7.1 cm, 0.316, 0.307 and 0.222 chronologically as mentioned above. Consequently, it enables the
136 replication of the structure response with time and space, over a range of impact energies up to 1 MJ.

137 In addition, the model being simple and developed under the NSCD method framework provides on
138 average about 30 times faster computation times in comparison to conventional FE-based models [17]
139 and allows envisaging running a large number of computations.

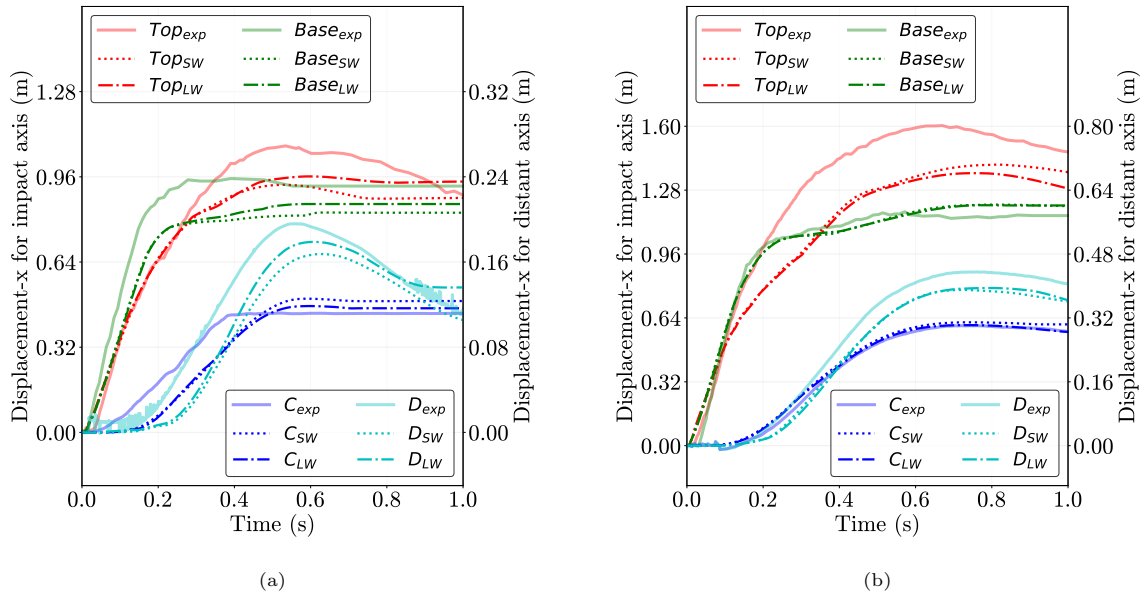


Figure 2: Comparison of the wall displacement response for (a) 520 kJ and (b) 1020 kJ impact tests at ‘Top’ and ‘Base’ points (for impact axis) and ‘C’ and ‘D’ points (for distant axis) recorded experimentally (exp) with its counterpart evaluated from the calibrated NSCD model of the short-wall (SW) and long-wall (LW).

140 In the present work, all simulations are conducted on a wall 3.2m high and about 28.2m long (Fig. 3).
141 The increase in length as compared to that in Gupta et al. [16] aims at avoiding any potential boundary
142 effects when varying the impact location along the wall longitudinal axis. For these simulations, the same
143 projectile is considered. Moreover, the comparison of spatio-temporal displacement response for both
144 small wall (SW) and large wall (LW) lengths (*i.e.*, 14.1 and 28.2m respectively) for the two calibrated

145 impact cases are reported qualitatively and quantitatively similar, as presented in Figure 2. Therefore,
146 the calibrated model constitution parameters as reported in Gupta et al. [16] are directly applied to the
147 long wall model. Notably, the SW displacements are quantitatively slightly different (up to 4cm) from
148 the one reported in Gupta et al. [16] due to the current computations in an updated version of SICONOS.

149 3. Impact response investigation

150 Due to its zig-zag conformation, discrete nature and complex design where concrete blocks are in-
151 terconnected thanks to metallic components and including mechanical plays, the structure response is
152 expected to be highly sensitive to impact conditions, for example varying the impact location or the
153 projectile pre-impact trajectory. Therefore, an extensive campaign of numerical simulations is carried
154 out on the NSCD model of the structure to understand, evaluate and exploit the response under different
155 impact conditions.

156 First, the structural response variability is illustrated by considering three impact cases in similar
157 conditions to that during the experiments but with different impact locations. Then the investigation is
158 generalised varying the six parameters describing the impact conditions.

159 3.1. Response for the illustrative impact conditions

160 The wall response is addressed by varying the projectile impact location to illustrate its complexity
161 and variability. The projectile with an impact energy of 520kJ is simulated where the point of impact
162 is located in the centre of each of the distinct sections of the zig-zag pattern. The 520kJ impact energy
163 is significantly below the wall nominal capacity of 1 MJ where severe block damage, loss of mechanical
164 continuity and very large wall displacements are observed. Therefore, the 520kJ is considered to represent
165 the structure's serviceable impact energy levels, for which the complexity of the wall response is hereby
166 illustrated. These sections are referred to as convex-wedge, angled-wedge and concave-wedge, when
167 viewed from the impacted side, as presented in Figure 3. The origin of the wall structure for the 'along
168 length position' (*i.e.*, $Y=0$) is assigned at the wall centre and for the 'wall movement due to impact' (*i.e.*,
169 $X=0$) at the rear face of the wall. The wall response is addressed in terms of block displacement, velocity,
170 deflection and plastic damage hereafter.

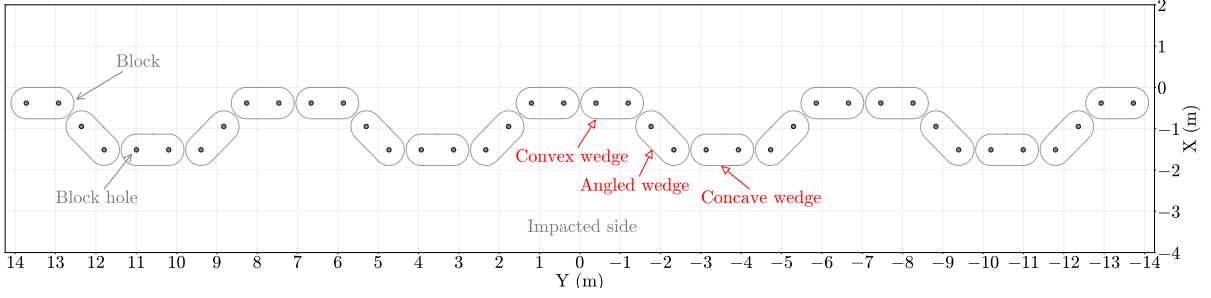


Figure 3: Top view of the wall model highlighting the repetitive pattern and an identifier for different sections. Here, the abscissa refers to the block position along the wall length where $Y=0$ is located at the wall centre. And, the ordinate refers to the direction of wall movement when a projectile hits the wall from the impacted side where $X=0$ is located at the wall's rear face.

171 3.1.1. Displacement

172 The displacement of the wall is extremely sensitive to the impact location, presented for three illustrative impact conditions (IC), via the top view of the wall in Figure 4. Here, the three simulated impacts one each at convex, angled and concave wedges are named IC-1, IC-2 and IC-3 respectively. The sensitivity to the impact location is particularly noticeable in terms of structure conformation. The impact on the concave-wedge results in aligned blocks (Fig. 4c), while an impact on the convex-wedge amplifies the amplitude of the zig-zag pattern (Fig. 4a). The length of the movement zone along the wall longitudinal axis varies from approximately 6 m in the case of an impact on the angled-wedge to 7 m for the two other impact cases, corresponding to four and six top-row blocks respectively. A significant difference in the displacement of the individual blocks is also observed in Figure 4, where the displacement is evaluated at the block's centre of gravity. Larger block displacement is observed for impacts on the concave-wedge in comparison to the other two ICs.

183 As this zig-zag patterned wall aims at protecting a given element at risk, it appears much more relevant to consider the residual distance to the so-called 'Safety line' shown in Figure 4 in addition to the displacement of the blocks. The safety line may be defined based on the position of the protected element at risk. It is here arbitrarily located at 1.5 m from the convex-wedge block's rear face. From Figure 4, it can be deduced that the minimum residual distance to the safety line is much smaller in the case of the impact in the convex-wedge (0.5 m. approx.), as compared to the two other impact cases (1.3 m approx.). With respect to this criterion, an impact on the convex-wedge thus reveals comparatively more critical than others.

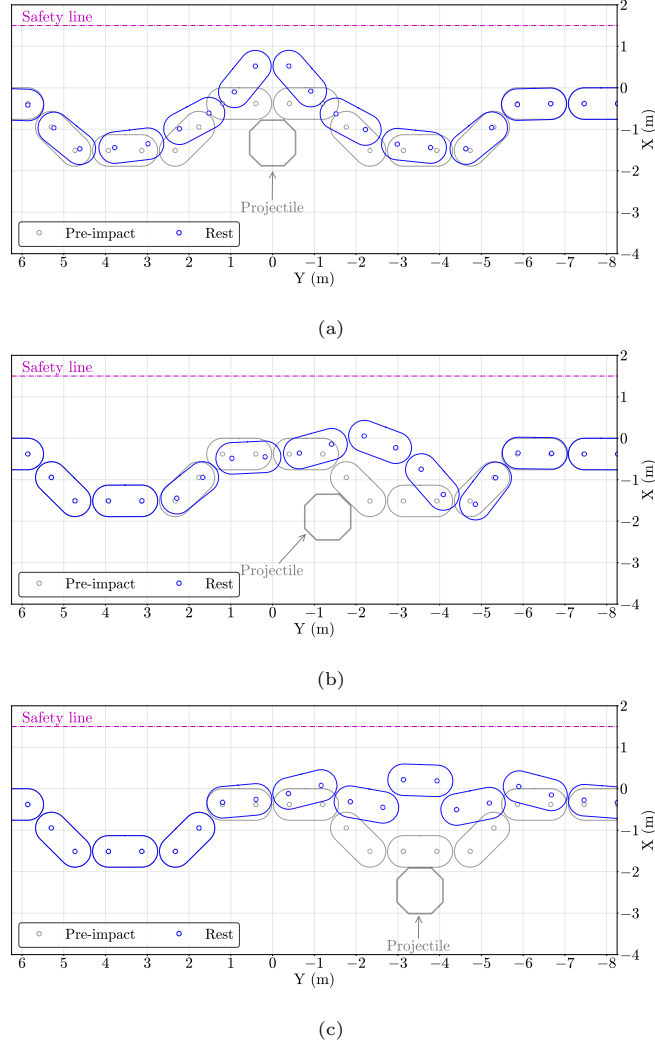


Figure 4: Top view of the displaced component of the whole length of the wall structure before and after a 520-kJ impact located in the centre of (a) the convex-wedge (IC-1), (b) the angled-wedge (IC-2) and (c) the concave-wedge (IC-3).

191 3.1.2. Velocity

192 The variability in the wall's response is here illustrated by the time evolution of the velocity of the
 193 concrete blocks during the impact. For this purpose, the velocity computed at the mid-bottom of the
 194 block rear vertical face ' v_{face} ' (*i.e.*, on the side opposite to impact) is considered which represents the
 195 potential position for the sensor deployment in the in-situ structure. In this position, the instrumentation
 196 shall likely be with 1D accelerometers to capture the time evolution of the acceleration normal to the
 197 block. For a simplified analysis, the desired velocity profile from the NSCD model shall also be computed
 198 normal to the block face at all time instances. For this, the ' v_{face} ' vector is projected onto the unit normal
 199 vector ($\hat{n}_{\mathbf{b}}$) to the block face. The computation process is presented in Equation 1.

$$v_{\text{face}} = v_{\mathbf{g}} + (p\Omega p^{-1}) \times q \quad (1)$$

$$v_{\text{nb}} = (v_{\text{face}} \cdot \hat{n}_{\mathbf{b}}) \hat{n}_{\mathbf{b}}$$

200 where $v_{\mathbf{g}}$ is the velocity at the block gravity centre, Ω is the rotational velocity, p is the quaternion
 201 (presenting block's 3D orientation) and q is the relative position vector of the block face (envisaged sensor
 202 location) to its centre of gravity. The time evolution of velocity normal to block face computed for all
 203 three cases is presented in Figure 5 (all left). In addition, the peak velocity of the blocks and the time to
 204 reach this peak are plotted in Figure 5 (all right).

205 A general trend where the peak velocity localises at the impacted block is observed. Besides, the
 206 number of blocks experiencing rapid displacement from the impact beginning is comparatively higher
 207 when the projectile impacts the concave-wedge (Fig. 5c). Indeed, three blocks close to the impact location
 208 experience very similar curves. The time for the wall to come to rest is smaller in case of an impact on
 209 the convex-wedge with a duration of about 0.5 as compared to 0.8 seconds after an impact on the angled-
 210 wedge in particular (Fig. 5a vs Fig. 5b). Overall, the velocity of all the blocks appears to provide rich
 211 information, with high amplitude as well as significant differences from one case to the other.

212 The blocks with significant maximum velocities are located within a distance along the wall length
 213 ranging from 8 to 12 m approximately depending on the impact location. This observation is in line with
 214 the observation made in Figure 4. The shape of the maximum velocity pattern significantly differs from
 215 one impact case to the other. These observations suggest that the distribution of peak velocity along the
 216 wall could be specific to an impact case in a rather univocal manner.

217 3.1.3. Deflection

218 In addition to the displacement and velocity, the deflection of the wall blocks, *i.e.*, their rotation
 219 around a horizontal axis, seems relevant to address as it relates to wall post-impact stability. In addition,
 220 deflection may be measured on-site with rather low-cost sensors. The post-impact deflection of all the
 221 blocks in the wall is presented in Figure 6. An impact on the concave-wedge results in block deflection
 222 over a wall length as large as 8 m. The maximum value of about 17° is observed at the upper row
 223 in the impact vicinity. Notably, the deflection results concerning the impact on the convex-wedge and
 224 angled-wedge are not presented as they induced nearly zero wall deflection.

225 Conclusively, the deflection doesn't provide sufficiently rich information to envisage relating it to the

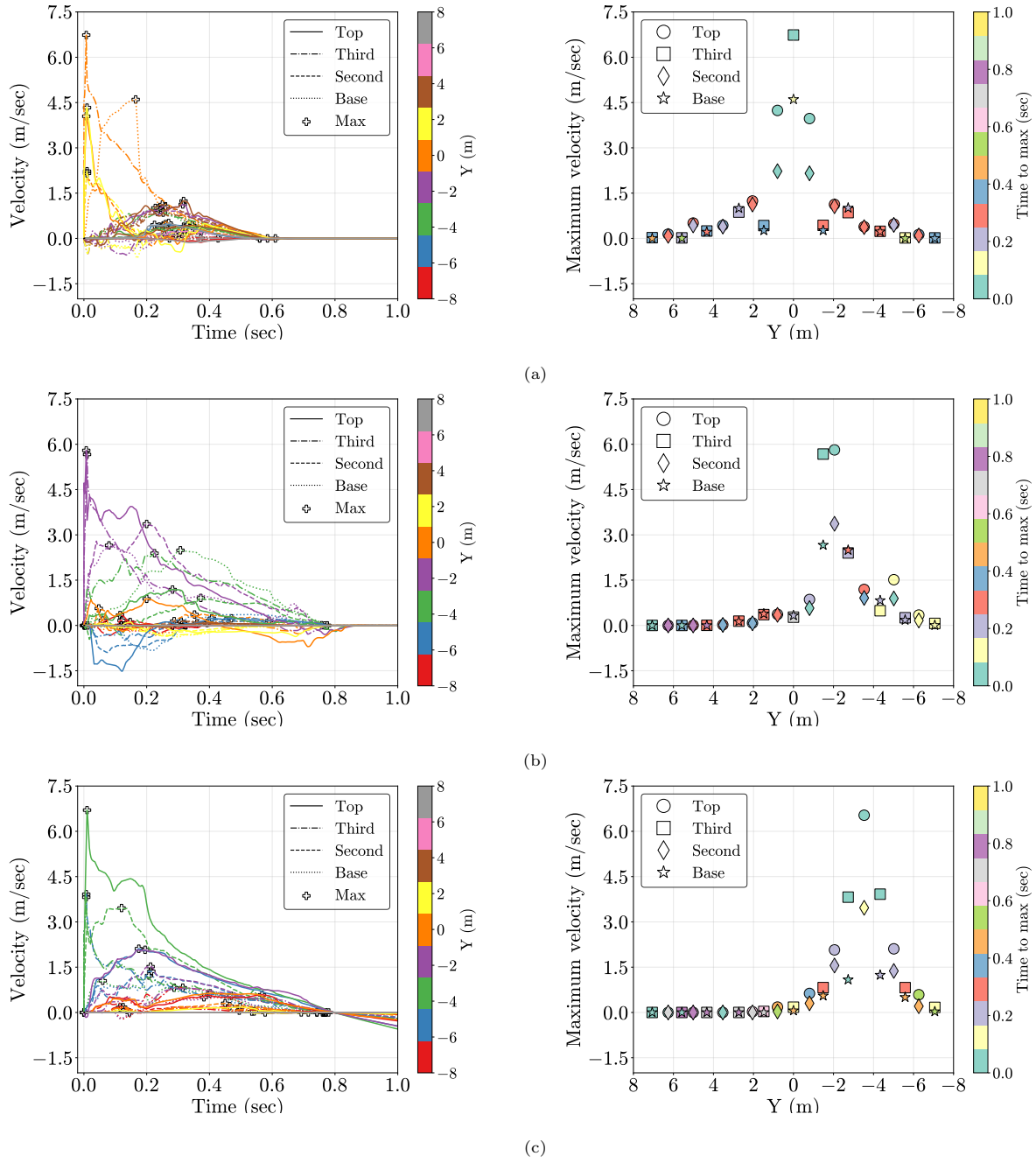


Figure 5: Evolution of the velocity of the concrete block in the movement zone (all left) and the corresponding mapping of the maximum velocity for blocks in all four rows *i.e.*, top, third, second and base (all right) for the illustrative impact cases at (a) convex wedge (IC-1), (b) angled wedge (IC-2) and concave wedge (IC-3) respectively. Here, ‘Y’ refers to the global position of the mid-bottom of the rear face of each block along the wall length.

226 impact conditions, in particular, because some impact conditions result in null deflection angle values
 227 and hence are not deemed appropriate to explore further.

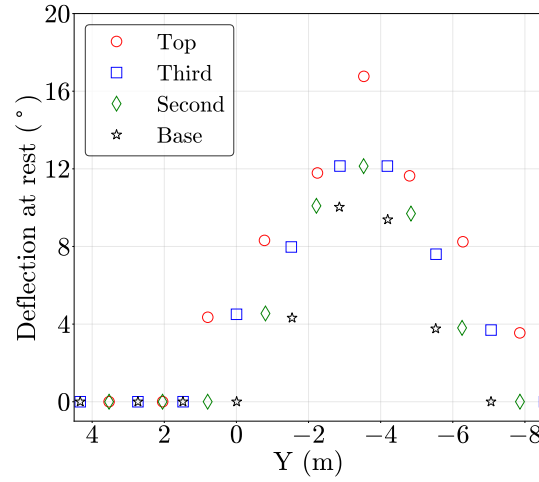


Figure 6: Deflection of all blocks in four layers of the wall (*i.e.*, top, third, second and base) with respect to the vertical at rest for the impacts at concave wedge (IC-3) under 520kJ energy impact. The results for the impact at the convex-wedge (IC-1) and angled-wedge (IC-2) are not presented because of their negligible magnitude.

228 3.1.4. Plastic damage

229 The rockfall impact on the structure causes plastic damage to the blocks, dissipating a portion of the
 230 incident projectile kinetic energy. Notably, the NSCD model is created as an accumulation of rigid bodies
 231 where the contact law controls the interaction. Despite that, the quantitative estimation of the energy
 232 dissipation mechanisms is possible following the work reported by Acary [23] in the NSCD framework.
 233 Subsequently, the relation presented in Equation 2 is implemented in the present work to compute the
 234 energy dissipation due to plastic damage (D_p).

$$D_p = \sum_{k=0}^N \sum_{\alpha \in I} \frac{1}{2} (v_{N,k+1}^\alpha + v_{N,k}^\alpha) P_{N,k+1}^\alpha \quad (2)$$

235 Here, v_N is the normal component of the velocity vector and P_N is the normal impulse at a given time
 236 step ' k ' (out of total N) at a contact point $\alpha \in I$. The details of velocity and impulse computations can
 237 be referred to at Gupta et al. [16].

238 The time evolution of D_p for the three illustrative cases with different impact locations is presented
 239 in Figure 7. A significant contribution of plastic damage is observed at the early time instance when the
 240 projectile impacts the wall. With reference to the zoomed-in window, the damage evolves relatively fast
 241 for the impact at convex-wedge (IC-1) and reaches a constant magnitude of about 380kJ in about 0.35
 242 seconds post-impact. The other two impact cases evolve for a relatively longer time (about 0.6 seconds)

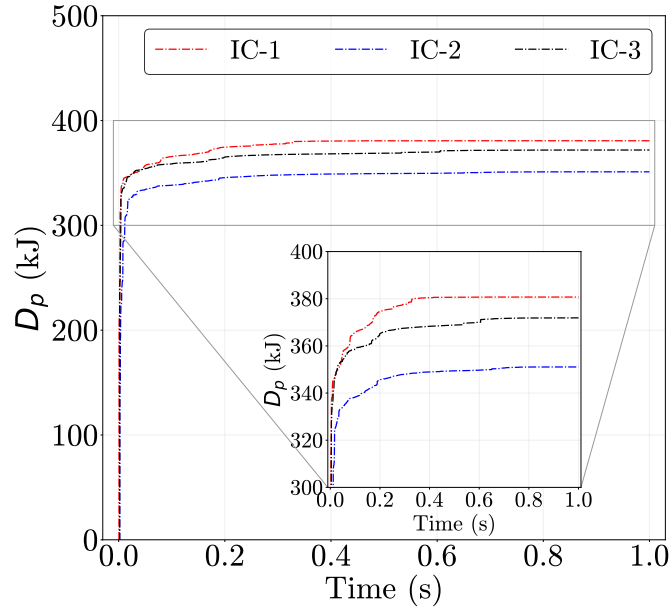


Figure 7: Time evolution of the energy dissipation due to plastic damage for the three illustrative cases, with impact at the convex-wedge (IC-1), the angled-wedge (IC-2) and concave-wedge (IC-3) and the zoom-in window between 300 and 400 kJ

243 before reaching a constant value towards the end of the one-second simulation time. This observation is
 244 in line with the duration over which the wall moves, as illustrated in Figure 5. Conclusively, the plastic
 245 damage is taken as a quantity of interest for structural response assessment as it presents the variability
 246 in response with different impact conditions.

247 Notably, the remaining part of the energy transferred by the projectile to the wall is dissipated
 248 by friction at the contacts, as detailed in Lambert et al. [24] where it is also demonstrated that the
 249 computation scheme complies with the fundamental principle of energy conservation.

250 3.2. Response to a large set of impact conditions

251 Following the illustrative structural response description in the previous section, the numerical sim-
 252 ulation framework is extended to address the response considering a large set of impact conditions. In
 253 a similar way as previously done for flexible barriers [13, 25, 26], the parameters describing the incident
 254 projectile trajectory, kinematics and location, hereafter referred to as ICPs (Impact Conditions Param-
 255 eters) are varied over realistic ranges to account for nearly all possible distinct impact conditions which
 256 may occur during natural rockfall event. The ICPs and their magnitude ranges are given in Table 1.

257 The first two parameters (*i.e.*, translational and rotational velocities) account for the incident kinetic

Table 1: Projectile model impact condition parameters (ICPs), their magnitude range and the probabilistic distributions for close-to-reality wall impact computations. Here, the Uniform (\mathcal{U}) distribution characterised by the minimum (a) and maximum (b) parameters, and Gaussian/Normal (\mathcal{N}) distribution characterised by mean (μ) and standard deviation (σ) parameters are used.

Parameter	Possible range	Unit	Distribution
Translational velocity (v)	10 - 25	m/s	$\mathcal{N}(\mu = 17.5, \sigma = 2.5)$
Rotational velocity (Ω)	0.0 - 5.6	rot/sec	$\mathcal{U}(a = 0.0, b = 5.6)$
Impact position - along length ‘offset’ (y)	0.0 - -3.53	m	$\mathcal{U}(a = 0.0, b = 3.53)$
Impact position - along wall height (z)	0.55 - 2.10	m	$\mathcal{U}(a = 0.55, b = 2.10)$
Impact inclination (α)	-60 - +60	°	$\mathcal{U}(a = -60, b = 60)$
Impact deviation (β)	-45 - +45	°	$\mathcal{N}(\mu = 0, \sigma = 15)$

258 energy of the projectile. Given the projectile geometric and mechanical characteristics considered in this
259 study, the translation velocity results in a kinetic energy ranging from 130kJ to 800 kJ. The rotational
260 velocity range is defined as per the work reported by Bourrier et al. [27] providing the rotational kinetic
261 energy up to 240kJ for the projectile geometry used in this work.

262 The impact location refers to the projectile’s centre of gravity at impact. The range for the impact
263 locations along the wall length (Y axis) is defined considering that the structure consists of the repetition
264 of a pattern. Thereby, the impact locations were restricted to a representative segment of the wall
265 conformation inclusive of all three wedges (*i.e.*, convex, angled and concave), defined as ‘ y ’ offset or
266 simply ‘ y ’ for future mentions. By definition, the response observed for this segment is extendable to
267 other parts of the wall, except for the wall extremities. Indeed, impacts at a close distance from the wall
268 extremities shall result in a different impact response, in particular depending on some design choice with
269 influence on the mobility of the blocks at the wall extremity (such as retaining cables or abutments).
270 The case of impacts close to the wall extremities is thus not considered in the present work. The impact
271 location along the vertical axis (z) is defined considering the wall height and the block size, which is 1.1m.
272 The minimum value for the impact location along the vertical axis is half the projectile dimension. The
273 maximum value corresponds to the distance between the projectile centre of gravity and the wall crest
274 equalling the projectile diameter.

275 The inclination and deviation angles are varied over the ranges reported by Toe et al. [25]. The
276 inclination angle (α) represents the relation of the z-component of projectile impact path with the normal
277 to the wall face [13]. Negative α values thus correspond to upward trajectories (*i.e.*, away from the
278 ground). The β angle accounts for the deviation in the horizontal plane of the incident rock block
279 trajectory with respect to the normal to the wall longitudinal axis (and not with respect to the impacted
280 block uphill face). The range considered for β implies that the wall longitudinal axis is considered
281 perpendicular to the line of the maximum gradient of the uphill slope. Also, β determines the planer
282 (x,y) components of Ω while the z-component is considered to have no magnitude such that the incoming
283 projectile spin is always in line with its trajectory. Notably, the sketch in the Figure 11 visually illustrates
284 the considered inclination and deviation angles.

285 In this study, the kinetic energy is considered sufficient for describing the projectile kinematics in view
286 of addressing the structure response. This obviously constitutes a simplification as it is evidenced that,
287 for a given projectile kinetic energy, the response of a rockfall protection structure may be significantly
288 influenced by the projectile mass-to-velocity ratio [28, 29]. Besides, the upper limit of the translational
289 kinetic energy is kept less than the wall nominal capacity as observed during the experiments, which is
290 above 1 MJ. This is motivated by two observations: (1) The representation of the model to correctly
291 model the structure displacement and damage is lower at impact kinetic close to the nominal value (*e.g.*,
292 due to loss of mechanical continuity in connectors [16]) and (2) The damage and displacement are severe
293 for translational kinetic energy at impact higher than 800 kJ, imposing visit and repair/maintenance
294 works without any doubts.

295 3.2.1. Statistical sample

296 A statistical set of 300 model computations, based on the Latin hypercube sampling (LHS) method [30]
297 is retrieved to represent the model response under different impact conditions. The created statistical
298 sample is presented in Figure 8, where the magnitudes of all parameters are in the range reported in
299 Table 1. Here, the filled input space assures that possible combinations of the input variables are well
300 considered in the finite set of ICPs. In general, 50-500 model runs are considered a ‘reasonable budget’
301 to create the metamodels of the NSCD model presented later on. The NSCD model computation time
302 is about 30-40 minutes for one projectile impact simulation and hence the computation cost of 300 runs
303 is deemed sufficient. Such sample size also enables the creation of all requisite metamodels to exploit

304 various response mechanisms without optimising the sample size for each mechanism separately.

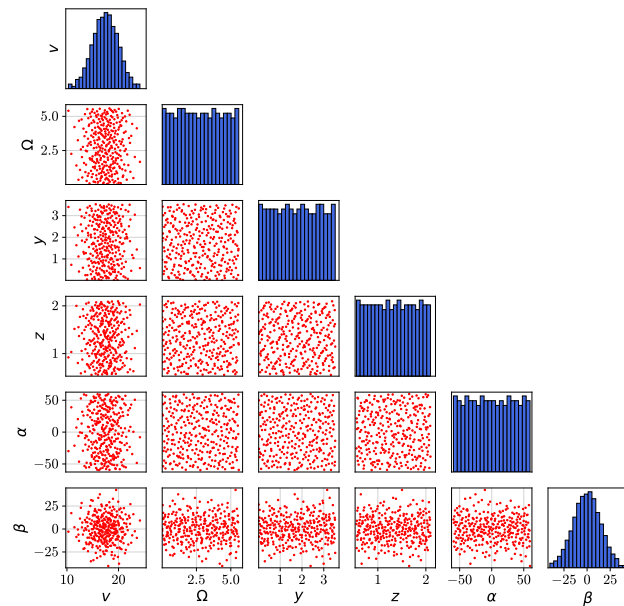


Figure 8: Input sample of size 300 (based on Latin hypercube sampling (LHS) sampling method) comprising six impact condition parameters (ICPs) and their probability distribution in the respective ranges of variability.

305 Moreover, a probability distribution is assigned to each parameter to account for the influence of
 306 rockfall trajectory, inspired by the work reported in Lambert et al. [14]. A Gaussian distribution is
 307 chosen for the translational velocity (v) and deviation angle (β) indicating that the extreme limits of
 308 both these parameters are less probable. The parameter β distribution abides by the idea that the
 309 structure installation on-site is such that the projectile is most likely to impact normally to its face.
 310 Similarly, the parameter v distribution takes into account the most likely impacting projectile energy
 311 and keeps the low and high-energy cases as rare events. The uniform distribution is assigned for all the
 312 remaining parameters as no prior information is available on their probability of occurrence.

313 It is worth highlighting that the ICPs were defined ignoring some correlations that may exist between
 314 the six parameters. For example, the velocity in the case of a downward projectile trajectory is higher
 315 on average than that for an upward trajectory. This results from the fact that a downward trajectory
 316 is associated with a rock block-free fall while an upward projectile trajectory immediately succeeds the
 317 rebound from the ditch which induces energy dissipation. This means that some combinations of param-
 318 eter values are not realistic (for instance, the lowest α value with the highest translational velocity, v).

319 A specific site-investigation-based ICP correlation can be established for a better representation of the
 320 input sample. However, this is out of the scope of the present work and hence we proceed further with
 321 the uncorrelated ICPs. Moreover, the Gaussian distribution for v and β parameters results in the repre-
 322 sentation of each ICP set as not equiprobable. Subsequently, it enables having less number of simulated
 323 cases corresponding to rare events.

324 3.2.2. Displacements under impact

325 The position of the top row blocks at the end of impact (*i.e.*, at rest) for all 300 simulations is
 326 presented in Figure 9. The hollow circles correspond to the location of the extremity of the vertical
 327 connectors position. The blocks represented in blue correspond to the impact case resulting in the least
 328 distance from the wall to the safety line. Impacts in the convex-wedge resulted in a lower distance to
 329 the safety line which is consistent with observations made based on Figure 4. The movement zone for
 330 all simulated cases stays within approximately 7m on either side from the centre of the wall (*i.e.*, $Y =$
 331 0). The cloud of points, together with the mean positions and the variability (estimated as twice the
 332 standard deviation), reveals that the amplitude of the displacement in the X- and Y-axis directions are
 333 much larger at a distance from the wall centre (*i.e.* at the concave wedge) and that it is significantly
 334 dependent on the impact location along the Y-axis.

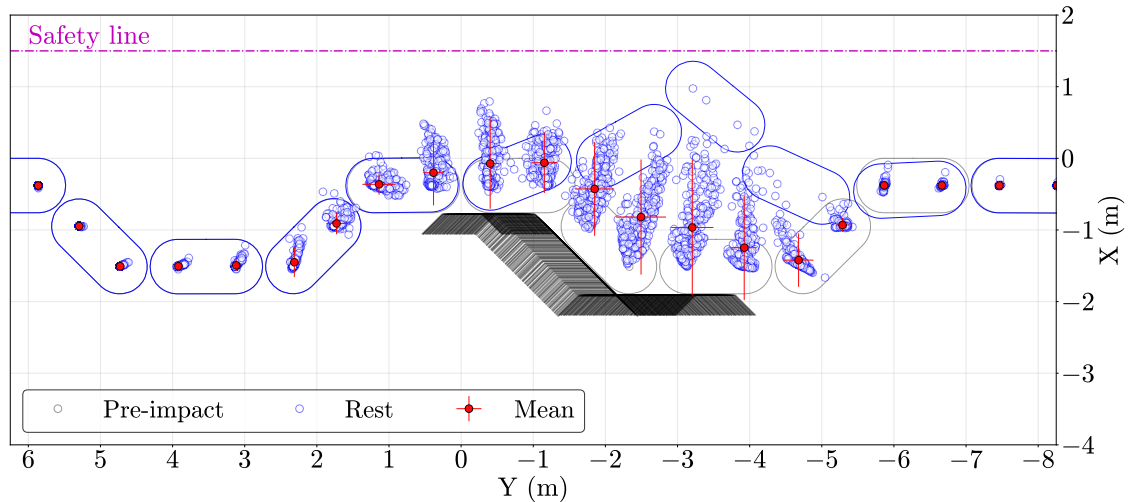


Figure 9: Top view of the displaced component of the whole length of the wall as per sampled 300 sets of projectile impact condition parameters. The position of the block holes position after impact is presented for each simulation and the impact case resulting in the least distance to the safety line is highlighted for better visibility.

3.2.3. Sensitivity analysis

The variability in structure response is further addressed by investigating the influence of each parameter on the different quantities of interest (QoI). In accordance with Section 3.1, the considered QoIs are the minimum distance to the safety line (u^{safety}), the maximum displacement of the wall (u_{max}), the maximum concrete block velocity recorded (v_{max}) during impact and plastic damage (D_p).

The influence of each parameter on the QoIs is investigated through the Sobol sensitivity method also known as analysis of variance [31]. This method decomposes the variance of the output parameters as the sum of the contributions of the different input parameters including the possible interaction between input parameters. Each contribution is characterised by the ratios of the partial variance to the total variance, called Sobol sensitivity indices.

The accurate computation of Sobol indices demands a large number of model computations (of order 10^6). This is highly impractical in the present study if the NSCD model is used directly. This limitation is circumvented with the help of the meta-modelling technique which enables to create a surrogate of the NSCD model, allowing direct computation of Sobol indices at zero cost [32, 33]. In this case, a meta-model (or surrogate) can be defined as a mathematical operator describing the response envelope of the wall in the 6D space corresponding to the six variables defining the impact conditions related to the rock projectile.

Here, a database of 300 model simulations is processed for each QoI to acquire the model output set and its corresponding ICPs. Then, the polynomial chaos expansion (PCE) based meta-modelling technique (as per UQlab PCE module [34], see Appendix A for details) is used to formulate a generalised link between the input ICPs and each output QoI. A total of four metamodels are created corresponding to four QoI, named Meta- u^{safety} , Meta- u_{max} , Meta- v_{max} and Meta- D_p . For each meta-model creation, a mathematical relation (as presented in Equation A.2), is established between the 300 distinct sets of input parameters and the corresponding displacement output set. The mathematical relation here can be analogically referred to as obtaining a regression for a 2D database. The accuracy of the PCE-based meta-model for each QoI is presented by the leave-one-out (LOO) error (Equation A.5), reported of order 10^{-2} for Meta- u^{safety} , Meta- u_{max} and Meta- D_p and of order 10^{-1} for Meta- v_{max} . Notably, these PCE-based meta-models are also used for the inverse analysis work, detailed in the section 4.

The UQlab sensitivity analysis module [35] is used for the computation of the Sobol indices. The first

364 and total order Sobol indices for the QoI are presented in Figure 10, computed to evaluate the influence
 365 of each of the six ICPs on the four aforementioned QoI.

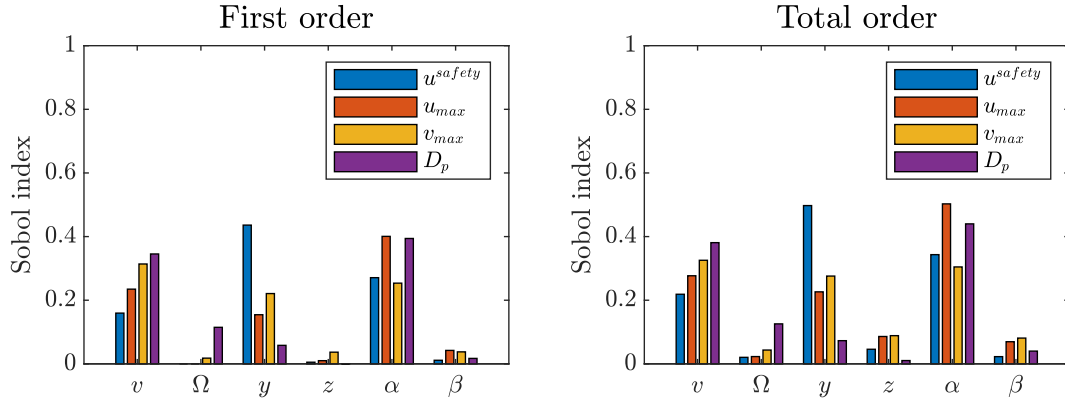


Figure 10: Sobol sensitivity analysis of the ICPs on different QoI towards the representation of the generalised impact assessment.

366 The first-order Sobol indices reflect the main effect of each ICP and the total order indices reflect
 367 the main effect plus the contribution from the interaction between different ICPs. Thereby, when there
 368 is no interaction between variables, the first and total index magnitudes shall be the same. However,
 369 the contrary is observed here which reflects the significant interaction between ICPs in terms of their
 370 influence on the QoIs. The main and the total effects of each ICP are briefly discussed as follows.

371 The main effect of the rotational velocity (except for D_p), the vertical position of impact (z) and
 372 deviation (β) are observed to have the lowest sensitivity to all QoIs. On the contrary, all QoIs are
 373 reported to be highly sensitive to the other three input ICPs. The y position of projectile impact is
 374 observed to be highly influential confirming the structural response variability from convex to angled to
 375 concave wedges, as reported in Figures 4 and 9. The v and α parameters collectively account for the
 376 projectile velocity component parallel to the ground (xy plane) and the component parallel to the wall
 377 face (z -axis) as presented in Equation 3.

$$v_z = v \sin \alpha$$

$$v_{xy} = v \cos \alpha \quad (3)$$

$$v_x = v_{xy} \cos \beta, \quad v_y = v_{xy} \sin \beta$$

378 It is thus evident that these three input ICPs influence all resulting QoI directly. Notably, the
 379 parameter β determines the further division of projectile velocity (v) in x - y plane (*i.e.*, v_x and v_y). Since

380 β is observed to have a low influence on the QoI, the collective effect of projectile velocity in xy-plane is
381 sufficient for further consideration. The negligible influence of ‘ z ’ infers the stability of the wall structure
382 throughout its height. Lastly, the negligible influence of ‘ Ω ’ on block displacement and velocity indicates
383 that the projectile spin induces a reaction from the block predominately in the vertical direction. A
384 relatively significant influence on D_p further emphasises this interaction inferring that Ω contributes to
385 the block damage with minimal induced displacement.

386 The total effect of each ICP is observed to reflect the interaction between them as their total Sobol
387 index is observed higher than the corresponding first-order index. It is an indication of the non-linearity
388 in the model response. The v and α parameters collectively account for the energy transferred to the
389 wall, which in turn influence all four evaluated QoIs. Thereby, an interaction between them is justified.
390 Similarly, the parameter y , despite being independent of the velocity parameter, accounts for the effect
391 of the wall pattern (i.e., convex, angled and concave wedges) on the wall response. Therefore, abiding
392 with the illustrative observations in Figure 4, the same energy impact at different locations results in a
393 different response, *i.e.*, sensitive to all four QoIs. The effect on D_p is observed least in comparison with
394 the other three QoI which indicates that the damage to the block is predominantly influenced by the
395 impact energy with a minor influence of the impact location. The reported D_p from the three illustrative
396 impact cases (see Figure 7) supports this observation. Lastly, similar to the main effect, the contribution
397 of Ω and z and β parameters in the total effect is observed relatively less.

398 3.3. Towards inverse analysis

399 The investigation of the structure response under close-to-reality conditions is of paramount impor-
400 tance, first, for evaluating its on-site efficiency and, second, for defining the best strategy for developing
401 the inverse analysis method.

402 The wall response to impact is revealed extremely complex, with a significant dependence on pa-
403 rameters describing the impact conditions (ICPs). Differences in response were revealed by the concrete
404 blocks’ kinematics, in terms of displacement and velocity. The sensitivity to the impact point location
405 along the wall’s longitudinal axis results from the wall’s zig-zag conformation and its discrete and ar-
406 ticulated nature. For instance, in the case of IC-1 (*i.e.*, an impact with a zero deviation and at a 520
407 kJ impact energy), the length of the wall experiencing significant displacement is about 12m (from -6
408 to +6), and similarly, it is about 8m for IC-2 and 9m for IC3 (see Figure 4). This is confirmed by the

409 distinct patterns of the peak concrete block velocity along the wall (see Figure 5). In addition, the wall
410 response depends on the projectile orientation with respect to the wall face (α and β) which is attributed
411 to the amount of energy that is transferred to the wall during impact (which will be further addressed in
412 see section 5.2).

413 The complexity of this response justified considering a specific approach for developing a relevant
414 inverse analysis method. In addition, it is concluded that the deflection of the wall is not relevant for
415 conducting an inverse analysis. On the contrary, the distribution of the concrete block's peak velocity
416 seemed to be impact-conditions-specific and is thus considered a good input data candidate for conducting
417 inverse analysis based on real-time measurements made on-site. These conclusions suggest that the
418 priority in terms of on-site structure instrumentation should be placed on accelerometers, from which
419 the concrete block velocity can be derived. By contrast, it is less relevant to install inclinometers for the
420 purpose of conducting inverse analysis.

421 In this work, it is proposed to conduct inverse analysis based on real-time measurements, during
422 impact, for the purpose of warning and decision-making upon impact. This requires installing sensors
423 in different locations on the structure, connected to data acquisition and transfer equipment. Then, it is
424 also proposed to conduct inverse analysis based on data collected on the structure after impact, such as
425 a cloud of points revealing the structure envelope obtained from scanning tools. These data sets may be
426 used for conducting post-impact inverse analysis in view, for example, of quantifying the consequence of
427 the impact on the structure or retrieving information related to the event.

428 In both cases, the inverse analysis consists of exploiting the data collected on-site to statistically
429 establish a link with the various impact conditions. The inverse analysis relies on meta-models created
430 based on a large set of NSCD model simulations of the structure response under close-to-reality conditions.
431 The Bayesian inference statistical learning method is used where the data collected on-site shall be fed
432 as evidence into the meta-models based forward model to find out the likelihood of obtaining the same
433 result (a single value or a pattern) from a particular set of input parameters. A brief description of the
434 Bayesian inference is presented in Appendix B and its implementation in the present work is detailed in
435 section 4.2.

436 4. Inverse analysis based on real-time measurements

437 4.1. General considerations

438 The instrumented protective structures *e.g.*, installed sensors, most often aim at warning the structure
439 owner or the protected infrastructure manager of any event. Real-time measurements could also be used
440 to improve decision-making over the next few moments after impact. Such a process could be based on
441 images from cameras, but sensors have the advantage of providing reliable information independently of
442 the light and scene conditions.

443 Two decisions could be taken remotely immediately after an impact on a structure protecting a traffic
444 line: traffic interruption and the need for structure inspection. Both are related to the consequences of
445 the impact on the structure, in terms of displacement and damage. An excess magnitude may be critical
446 to the safety of the traffic line or imply rapid repair or maintenance work. In this objective, the inverse
447 analysis is intended to rapidly and remotely indicate the magnitude of the consequences of the impact, for
448 example using consequence classes, rather than to provide a precise value of the displacement or damage.

449 The inverse analysis is based on measurements that shall be retrieved from the on-site structure
450 exposed to the natural rockfall impact event. The devices used for these measurements should con-
451 sider cost constraints to be of interest in an operational context. In particular, the number and type
452 of sensors should be optimised. The previous section suggested that a reliable inverse analysis could
453 be conducted from the block velocity, which can be derived from the on-site acceleration measurements
454 recorded during the impact. Based on this, the proposed inverse analysis is developed considering accel-
455 eration measurements from uniaxial sensors, because of their much lower cost compared to triaxial ones.
456 Also, it is developed to constrain the number of required data, meaning the number of measuring points
457 on the structure (*i.e.*, sensors). The number of measuring points is kept at a minimum while allowing a
458 sufficiently good prediction accuracy of the inverse analysis.

459 In this perspective, the sensor deployment scheme is defined for a representative wall length, in such a
460 manner it can be replicated along the full wall length. Considering the minimum length of the movement
461 zone observed in Figure 4, the choice is made to have at least 3 sensors per wall segment (*i.e.*, component
462 of the wall length comprising of one convex, angled and concave wedge each). More precisely, sensors
463 shall be located in the centre of the vertical face of concrete blocks experiencing significant displacements
464 whatever the ICPs. This number of sensors per representative length is presumed to be the minimum

465 number for allowing a reliable inverse analysis. It corresponds to 6 concrete blocks equipped with sensors
 466 over the maximum movement zone length, as shown in Figure 11. Here, the illustrative process of
 467 acceleration data acquisition followed by its integration to obtain velocity evolution with time for each
 468 sensor is also presented. The maximum velocity magnitude is identified and consequently, the pattern
 469 of maximum velocity for each sensor processed data is retrieved which is deemed unique for each impact
 470 condition.

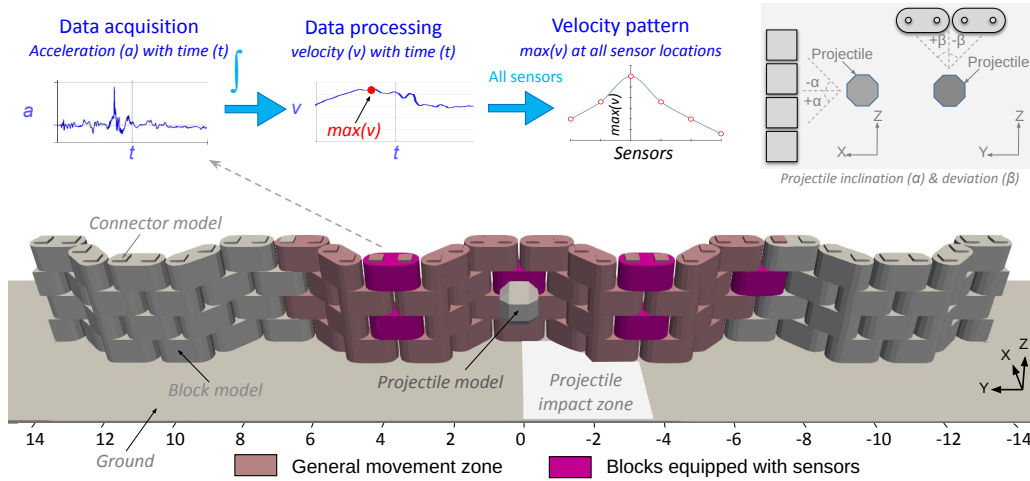


Figure 11: The schematics of the wall model indicating the blocks equipped with sensors for data acquisition. The sketch on the top right presents the notation of the impacting projectile inclination (α) and deviation (β)

471 The inverse analyses presented in the following make use of the maximum concrete block velocity along
 472 the direction normal to the block face at these 6 locations to represent the impact response corresponding
 473 to all possible sets of ICPs. The set of maximum block velocities recorded along the wall at these locations
 474 is in the following referred to as the maximum velocity pattern (MVP).

475 4.2. Inverse analysis method

476 The inverse analysis relied on the confrontation between the MVP that shall be obtained from an
 477 on-site measurements to that obtained from a large number of simulation-based results. The devel-
 478 oped method for conducting the inverse analysis comprised a combination of meta-models and Bayesian
 479 inference statistical learning methods. The flow diagram is presented in Figure 12 and detailed as follows.

480 The rich database of NSCD model simulations for 300 different ICPs (Figure 8) is processed (as per
 481 Equation 1) to obtain the maximum velocity normal to the block face for all blocks where a sensor is
 482 planned to be installed. This provides a database of MVP for 300 model computations. This database

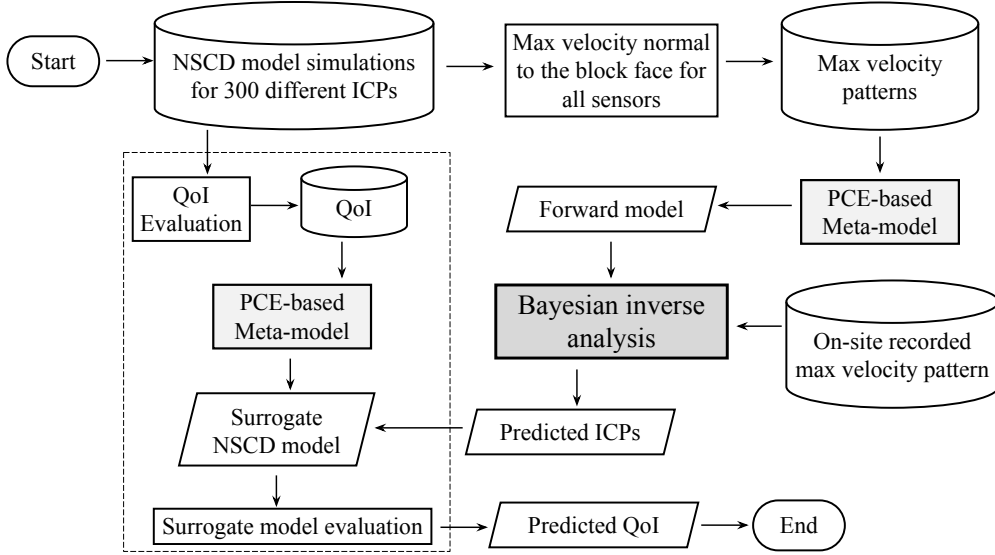


Figure 12: Computational workflow of the inverse analysis using a combination of meta-models, event data and Bayesian inversion methods

483 is processed to create a PCE-based meta-model, named Meta-MVP, associating each set of ICPs to a
 484 distinct MVP.

485 The accuracy of this meta-model is estimated via leave-one-out-error which is estimated of order 10^{-2}
 486 to 10^{-1} for 6 locations collectively making a MVP. Besides, the predictive capability of the Meta-MVP
 487 is presented by comparing the predicted vs true value from the NSCD model at all six sensor locations.
 488 For this, the same 300 simulations set complemented with an independent set of 300 simulations, where
 489 ICP sets generated using Halton sampling method [30] within the bounds reported in Table 1 are used.
 490 The collective outcome from a total of 600 simulations is presented in Figure 13.

491 The prediction accuracy of the Meta-MVP is quantified via the predictability coefficient (Q^2), esti-
 492 mated considering the results from the 600 simulations and 6 points, for a total of 3600 observations,
 493 as:

$$Q^2 = 1 - \frac{\sum_{i=1}^N (y_i^{\text{pred}} - y_i^{\text{true}})^2}{\sum_{i=1}^N (y_i^{\text{true}} - y_{\text{mean}})^2} \quad (4)$$

494 where y_i^{pred} is the meta-model predicted value and y_i^{true} is the value processed from the NSCD model
 495 for block (i) and y_{mean} is the arithmetic mean of all ‘true’ predictions. The interest of using the meta-
 496 models is to generalise the maximum concrete block velocity data obtained from 300 (*i.e.*, limited number
 497 of) simulations, to any possible ICP combination (*i.e.*, a large number), which is a prerequisite for the

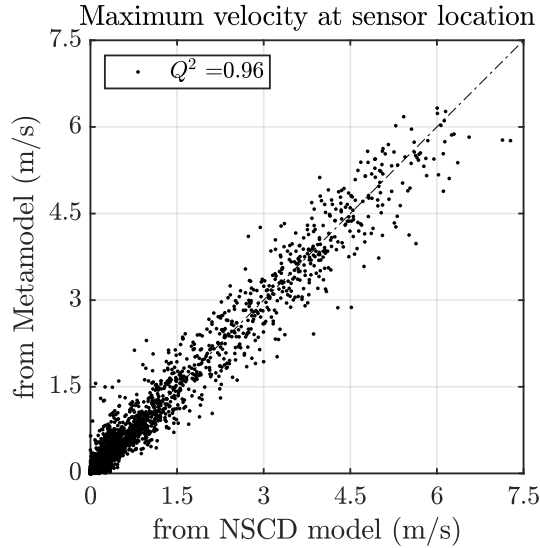


Figure 13: Validation of the PCE-based meta-model of the maximum velocity pattern (Meta-MVP) by comparison of the reported magnitude from 600 NSCD model simulations and the corresponding estimation by the meta-model.

498 next step.

499 The Bayesian inversion process is deployed where the processed PCE-based meta-model is used as
500 the forward model (or ‘*prior*’, see Equation B.2). This approach is extensively used by many researchers
501 (*e.g.*, [36, 37, 16]) to accelerate Bayesian computations. The Bayesian inference is inspired by Bayes’
502 theorem [38] - a representation of the changing beliefs - simply demonstrating that the probability of a
503 ‘hypothesis’ being correct becomes more reliable with supporting ‘evidence’. In our work, the ‘hypothesis’
504 states that the 300 distinct sets of input parameters present a set of 300 distinct MVPs. The idea of
505 reliability increase in our hypothesis is that, if we have the on-site recorded MVP as ‘evidence’, then
506 there exists at least one set of ICPs (*i.e.*, ‘*posterior*’, see Equation B.3) such that the recorded evidence
507 is reproduced. The data that shall be obtained from on-site measurements for a real projectile impact
508 on the wall event shall provide the MVP which serves as evidence for inverse analysis. The Bayesian
509 process estimates the likelihood of this MVP amongst all possible MVPs recorded from the meta-models
510 and predicts the corresponding set of ICPs.

511 In the UQlab Bayesian inference framework [39], the uncertainty in the model prediction is assigned
512 via added Gaussian discrepancy (see Equation B.5) when correlated with the data that shall be recorded
513 from the real on-site event of the projectile impact on the wall. In the present work, as the inverse
514 analysis relies on a single MVP that shall be recorded on-site, deemed less precise, the discrepancy with
515 a known residual variance of order 10^{-3} is manually assigned.

516 The output from the Bayesian inference-based inverse analysis is a set of ICP values retrieved as point
517 estimates ‘*maximum a posteriori*’ and ‘*mean*’ (see Equation B.13). This predicted set of ICP values is
518 then used to estimate the QoI (in this case damage to the wall or distance to the safety line). As a
519 conventional approach, running a new NSCD model simulation with the predicted ICPs shall provide
520 detailed information on the wall response from which the QoI can be extracted as a subset. However,
521 this operation shall require about 30-40 minutes of computation time and added time for post-processing.
522 This added delay time between on-site observation and warning system activation is unfavourable.

523 A procedure by which the QoI is instantly computed is developed to reduce the reaction time. The
524 computational workflow components for this process are highlighted in the dashed box of Figure 12. The
525 database of NSCD model simulation results is processed to evaluate the QoI as outputs. The resulting
526 database of QoI is then used to create the PCE-based meta-model for each QoI. It serves as a surrogate
527 of the NSCD model where the input ICPs are processed to compute the corresponding QoI output.
528 The leave-one-out (LOO) error of order 10^{-2} is reported for the two PCE-based meta-models created
529 for the two QoI (*i.e.*, distance to safety and wall damage), named as Meta- u^{safety} and Meta- D_p (see
530 section 3.2.3). The predicted ICPs are then fed into this surrogate of the NSCD model as input which is
531 then evaluated to eventually predict the QoI and the whole computational process terminates.

532 Notably, in the absence of an exhaustive database of the MVP that shall be retrieved from the
533 structure exposed to the natural rockfall events, the essential ‘evidence’ database (*i.e.*, recorded MVP) to
534 test the inverse analysis process is not available. Therefore, the concrete block velocity patterns from the
535 same set of 300 model simulations and the new independent set of 300 simulations with different impact
536 conditions are used as pseudo-evidences to test the process as the realisation of the natural rockfall events
537 on the structure..

538 Each of these 600 known block velocity patterns is individually fed as input into the inverse analysis
539 using the multiple model output feature of Bayesian analysis in UQlab (demonstrated in Equation B.8),
540 providing the predicted ICP values set. The evaluation of the reliability of the inverse analysis is based
541 on the comparison between the QoI reported via the ICP set used for running the simulation and the one
542 estimated from evaluating the ICP set predicted by the inverse analysis onto the meta-model created for
543 the same QoI.

544 4.3. Inverse analysis for warning purpose

545 First, the inverse analysis addresses the traffic interruption issue for which the post-impact minimum
546 distance of the wall to the safety line constitutes the QoI. The higher the distance, the higher the safety.
547 The predictive capability of the inverse analysis workflow presented in Figure 12 is tested for the maximum
548 concrete block velocity database obtained from the 600 NSCD model simulations. The MVPs from the
549 three impact cases mentioned in Section 3.1 are also used to predict the minimum distance to the safety
550 line.

551 The comparison between the predictions from the inverse analysis + meta-model and the simulation
552 results is presented in Figure 14. The relative proximity of the predictions to the ideal diagonal reflects
553 the potential of the presented methodology. Points above the diagonal concern cases for which the inverse
554 analysis overestimates the distance to the safety line. On the contrary, the inverse analysis underestimates
555 the distance to the safety lines for points below the diagonal, which is on the safe side.

556 The root mean square (RMS) error of the deviation from the expected response for the 600 simulations
557 is 16 cm. About 58% of this RMS error is due to the surrogate of the NSCD model (*i.e.*, dashed box
558 component of the workflow). Besides, the presented process is also tested for the three illustrative impact
559 cases, reflecting a good prediction. In fact, in some sectors of the 6D space of the six ICPs, this surrogate
560 locally fails in precisely capturing the wall response, in particular due to the presence of non-linearities.
561 As an alternative, the reliability of the inverse analysis could be improved by running an NSCD model
562 simulation with the predicted ICPs in place of using the surrogate of the NSCD model, at the expense
563 of a longer reaction time upon event.

564 For practical purposes, it is proposed to classify the impact response into three classes depending on
565 the distance to the safety line: [0-0.75 m], [0.75-1.25 m] and [1.25-1.5m]. These classes correspond to
566 decreasing criticality concerning transport corridor safety, respectively high (H), medium (M) and low
567 (L) criticality. NSCD model simulation results indicate that 15%, 59% and 26% of the impact cases are
568 classified in class H, M and L respectively. Notably, the relatively high number of simulated cases are in
569 the middle category as a consequence of the Gaussian distribution of the magnitude of the velocity input
570 parameter. Predictions based on the inverse analysis + metamodel give values of 12%, 63% and 25% for
571 classes H, M and L respectively. Besides, the false negative predictions are estimated to be about 24%
572 and 10% among all in the H and M classes respectively. The remaining predictions *i.e.*, good and false

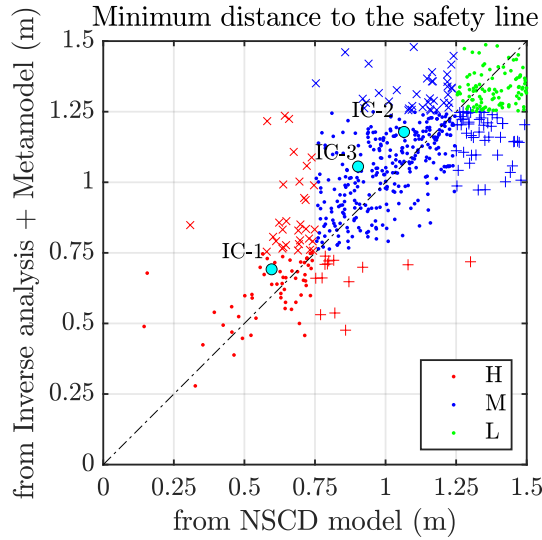


Figure 14: Comparison of the minimum distance from the safety line, estimated from the NSCD model and the corresponding prediction from the inverse analysis tool accompanied with *Meta-usafety*. Here, the predictions are divided into three zones reflecting high (H), medium (M) and Low (L) levels of severity inclusive of the corresponding zonal false positive (+) and false negative (×) predictions. Results are based on a set of 600 impact conditions complemented with the impact cases presented in section 3.1 (IC-1 to IC-3).

573 positives are in favour of the decision-making by the user, and hence are deemed acceptable.

574 In the end, the predictions are considered sufficiently good to be used in an operational context for
 575 estimating the consequences of the rockfall event in terms of structure displacement. The undeniable
 576 interest in this approach is that it automatically and remotely provides stakeholders with information of
 577 great value for decision-making upon impact. No quantitative evaluation would be derived rapidly from
 578 data measured on-site in the absence of such an approach.

579 4.4. Inverse analysis for structure damage quantification purpose

580 Second, the inverse analysis is used to remotely estimate damage to the wall. It is defined as the
 581 cumulative energy dissipated by the plastic damage of all the wall concrete blocks, D_p , after the wall is
 582 at rest. Damage to all concrete blocks of the wall is computed from NSCD model simulation results as
 583 per section 3.1.4. The approach considered for this inverse analysis is the same as that for the previous
 584 warning criterion. Figure 15 provides a comparison between D_p values obtained from NSCD model
 585 simulations and the predicted ones. The RMS error of the deviation from the expected response is 82 kJ,
 586 which may be considered acceptable when considering all uncertainties associated with the quantification
 587 of plastic energy dissipation due to real rockfall impacts. Similar to the previous prediction of distance,

588 about 35% of the contribution to the RMS error is attributed to the surrogate of the NSCD model.
 589 Besides, the process is tested for the three illustrative cases, reflecting a good prediction except for the
 590 impact at the angled-wedge (*i.e.*, IC-2).

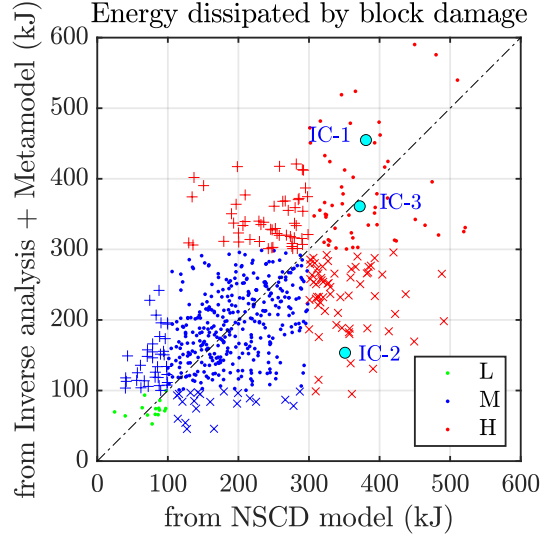


Figure 15: Comparison of the predicted damage to the wall, D_p , estimated from the NSCD model and the corresponding prediction from the inverse analysis tool accompanied with $Meta-D_p$. Here, the predictions are divided into three zones reflecting Low (L), medium (M) and high (H) levels of damage inclusive of the corresponding zonal false positive (+) and false negative (x) predictions. Results are based on a set of 600 impact conditions and impact cases presented in section 3.1 (IC-1 to IC-3).

591 The cases in the right upper corner constitute the most critical impact cases. Points above the diagonal
 592 concern cases for which the inverse analysis overestimates the damage, which is on the safe side. For
 593 practical purposes, it is proposed to classify the damage into three classes depending on the value of D_p :
 594 [0-100 kJ], [100-300 kJ] and [300-800 kJ] for low (L), medium (M) or high (H) damage. These limits are
 595 arbitrarily defined from the distribution of D_p over all cases.

596 The class limits refer to the level of damage to the wall corresponding to the fracture energy of one
 597 concrete block when a fracture propagates along a vertical plane in the middle of the concrete block.
 598 A classification based on the energy dissipation associated with the fracture of the considered concrete
 599 blocks following different patterns and mechanisms (compression or tension) and in different locations
 600 in each block (*e.g.*, middle of the blocks and corners) would be more appropriate for the practitioners.
 601 However, such specific estimations are not possible in the framework of the NSCD method used for the
 602 definition of the NSCD model in the present work. Also, the experimental estimation of these specific
 603 energy dissipation magnitudes through dynamic tests is not in the scope of the present work. Thereby, in

604 the absence of specific dynamic test results for these large and reinforced concrete blocks, results obtained
605 by Guo et al. [40] for a reinforced beam exposed to impact were extrapolated accounting for the difference
606 in block section and resulted in a value of 100 kJ approx. This value is a rough estimate of the first limit
607 for the considered concrete blocks.

608 According to NSCD model simulations results presented in Figure 15, 8%, 72% and 20% of the impact
609 cases result in damage classified as H, M and L respectively. Notably, the relatively higher number of
610 cases in the middle category are a consequence of the Gaussian distribution of the magnitude of the
611 velocity input parameter. Values of 6%, 76% and 18% for classes H, M and L are obtained from the
612 predictions respectively. Besides, the false negative predictions are estimated to be about 38% and 5%
613 among all in the H and M classes respectively. The remaining predictions *i.e.*, good and false positives
614 are in favour of the decision-making by the user, and hence are acceptable.

615 The differences between simulation results and predictions are associated with points at a large dis-
616 tance from the diagonal (Fig. 15). Further method developments could improve the accuracy of these
617 predictions. Nevertheless, the predictions following the described inverse analysis are considered suffi-
618 ciently good to be used in an operational context to aid in remote decision-making, the RMS error is 82
619 kJ.

620 4.5. Comments concerning the use of inverse analysis based on real-time measurements

621 The results presented in section 4.3 and 4.4 demonstrate the feasibility of conducting an inverse
622 analysis of data that shall be collected on-site during impact, focusing on two specific purposes.

623 The proposed method, making use of numerical modelling, meta-modelling and statistical approaches,
624 revealed rather efficient in providing useful information which could not be derived from the direct
625 observation of the data that shall be received from the site. The duration of the whole process for
626 treating the input data typically lasts about five minutes with the developed script making it compatible
627 with rapid reaction upon event. The analysis scripts are written in Matlab as per UQLab framework
628 [41] allowing running this complex process in two operations (one for inverse analysis and the other for
629 output of interest prediction). The accuracy of the predictions is considered sufficiently good for remotely
630 classifying the events and aiding in decision-making. If required for another purpose, this accuracy could
631 be improved further, for example by also accounting for other measure types, such as deflection, or by
632 improving the used methodologies for creating the meta-models.

633 In real situations, the probability of occurrence of an impact in given conditions is extremely variable.
634 By contrast, and as mentioned in section 3.2.1, the ICP sets considered in this work were defined by
635 not considering any possible correlation between the various parameters. The statistical assessment of
636 the inverse analysis predictive capacities is related to the considered ranges and distributions of the six
637 ICPs. It should thus be considered indicative at this stage. It should be improved by accounting for
638 the probability of each scenario considered in this evaluation, for example considering site-specific data
639 describing the rock projectile trajectory.

640 It is worth noting that, as the second step of the inverse analysis provides the set of ICP values
641 resulting in an MVP similar to the observed one, a preliminary estimate of the projectile velocity at
642 impact and consequently the impact energy can also be retrieved complementarily.

643 **5. Inverse analysis based on post-impact measurements**

644 *5.1. General considerations*

645 In addition to real-time measurements, the wall conformation after impact can be easily obtained by
646 employing techniques such as photogrammetry or Lidar. An accurate impact-induced displacements may
647 be obtained if the same type of data is collected before the impact. In such a situation, the number of
648 data that shall be from the site would be much larger than that for real-time response. Typically, the
649 position of the centre of gravity of all blocks can be derived from these data sets and will be considered
650 in the following.

651 In this context, the aim of an inverse analysis could be to retrieve information related to the rock
652 projectile kinematics at impact, such as its kinetic energy. This information could thus contribute to
653 better quantifying the rockfall hazard at the wall location.

654 The development of the inverse analysis method is based on the following considerations. In case there
655 is damage to concrete blocks, notably in the impact location vicinity, the determination of the blocks'
656 gravity centre will not be possible. This eventuality is accounted for in the development of the inverse
657 analysis method. In addition, it is considered that the rock projectile volume and the impact location
658 can be determined during the on-site visit. For the simplicity of executing the process, we assume that
659 the NSCD model which is calibrated for a unique projectile mass is also able to predict the structure
660 response for another rock projectile mass. In other words, this implies that for a given projectile kinetic

661 energy, the wall response is the same whatever the mass and velocity. Notably, this assumption is not
662 tested via the NSCD simulations of varying mass of the projectile and hence we acknowledge that it can
663 be considered a strong assumption. Under this assumption, the kinetic energy provided by the inverse
664 analysis combined with the observed rock projectile mass gives an estimate of its velocity at impact.
665 Thereby, the reliability of the prediction shall be relatively higher when the impacting rock mass in a
666 natural event is close to the simulated projectile mass.

667 The ICP comprise six physical parameters which describe the projectile kinematics and the point
668 of impact on the wall. The accurate prediction of all parameters is of limited interest for post-impact
669 measurements as the user is more focused on the estimation of the incident rock projectile kinetic energy.
670 Therefore, it is proposed to use a reduced dimension of the input parameters space to create the metamodel
671 from the 3D displacement database. The set of six ICPs is reduced to three by combining v , Ω , α and β
672 to calculate the total kinetic energy of the projectile (KE_{proj}) as per the Equation 5 below and keeping
673 position parameters y and z intact.

$$KE_{proj} = \frac{1}{2}m[v_{xy}]^2 + \frac{1}{2}m[v_z]^2 + \frac{1}{2}I[2\pi\Omega]^2 \quad (5)$$

674 Further, the total kinetic energy of the projectile can be divided into two components: one accounting
675 for the energy on the plane parallel to the ground (KE_p) and the other accounting for the rest of the
676 energy (KE_{np}). This is done by using only the planer component of the translational velocity (v_{xy})
677 component to compute KE_p and the remaining two components (*i.e.*, v_z and Ω) to compute KE_{np} .

678 This division is motivated by the observation that KE_p mainly governs the wall displacement, as it
679 is integrally transferred to the wall (except if the projectile rebound velocity is significant, which is not
680 the case here). On the contrary, the rest of the energy (which is associated with projectile rotation and
681 velocity along the vertical direction) is marginally transferred to the wall and thus has very little influence
682 on the wall response.

683 This proposition is qualitatively explored by the Sobol indices evaluated on reduced ICPs for the
684 maximum 3D displacement, presented in Figure 16. Here, KE_p is observed highly influential for the
685 resulting maximum displacement of the wall and as suspected, KE_{np} provides negligible influence. The
686 y-position of the projectile impact is observed as influential and supports the conclusion presented in the
687 previous section. The position-z is observed to have a negligible influence which supports the conclusions

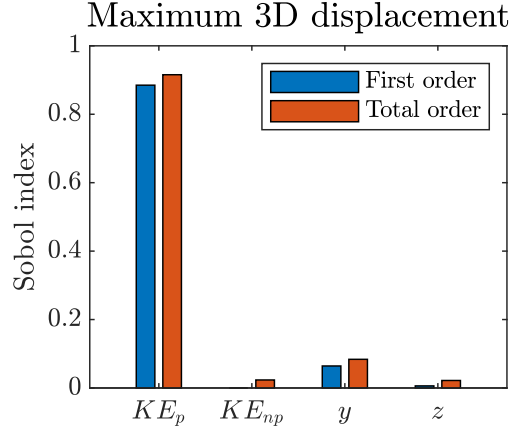


Figure 16: Sobol sensitivity analysis of the impact condition parameters (ICPs) of derived and reduced dimensions (*i.e.*, from 6 to 4) for the maximum 3D displacement

688 in the previous section as well. Thereby, observing from the Sobol indices, the inverse analysis is conducted
 689 taking into account the variability in the input KE_p and y parameters only hereby referred to as reduced
 690 dimension ICPs.

691 5.2. Inverse analysis method

692 The process of inverse analysis for displacement-based prediction of the impact conditions follows the
 693 same workflow as illustrated in Figure 12, however by replacing some components detailed hereafter. The
 694 recorded database from 300 NSCD model simulations is associated with the reduced dimension ICPs,
 695 instead of 6 ICPs. The 3D displacement post-impact is evaluated at all blocks in the movement zone
 696 and the database of the displacement pattern (as a replacement for the MVP mentioned in the previous
 697 section) corresponding to each set of reduced dimension ICPs is obtained. A PCE-based metamodel
 698 is created to associate each reduced dimension ICP set to a distinct 3D-displacement pattern, named
 699 Meta-3DP.

700 The accuracy of the Meta-3DP is estimated via the leave-one-out error, reported of order 10^{-1} for
 701 all 26 blocks in the movement zone collectively making a 3D-displacement pattern. Besides, the created
 702 meta-model for 3D displacement is validated by using the same simulation set and the independent set of
 703 300 simulations (presented in Section 4.2), thus a total of 600 simulations, and comparing the predicted vs
 704 true value (from NSCD model) at all 26 blocks in the movement zone, collectively presented in Figure 17.
 705 Here, the predictability coefficient (Q^2) presents the prediction accuracy, estimated for $N = 600 \times 26 =$
 706 15600 observations as per Equation 4.

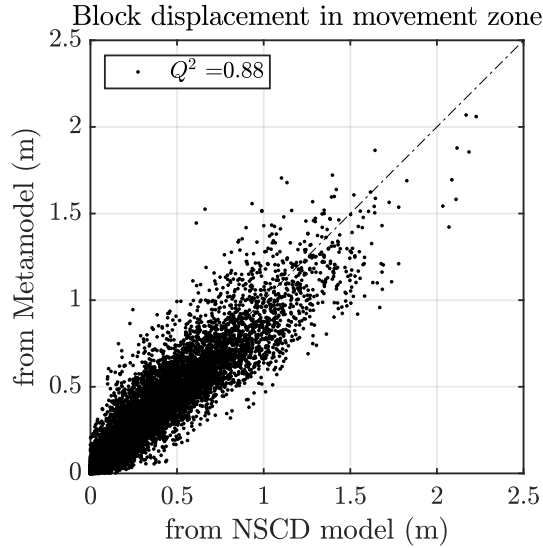


Figure 17: Validation of PCE-based meta-model of the 3D displacement pattern (Meta-3DP) of 26 blocks by comparison of the reported magnitude from 600 NSCD model simulations and the corresponding estimation by the meta-model

707 This created meta-model is used as a forward model for the Bayesian inference-based inverse analysis.
 708 The displacement data retrieved from real events shall serve as evidence for the inverse analysis, by
 709 replacing the ‘on-site MVP’ mentioned in the workflow of Figure 12. Notably, here, two threshold levels
 710 of displacement magnitude are considered at 0.2m and 0.05m based on the observation from processed
 711 displacement data from 300 simulations for all 26 blocks. The first threshold of 0.2m is assigned to limit
 712 the number of blocks in the displacement pattern to avoid overfitting. The second threshold of 0.05m is
 713 assigned to take into account a sufficient number of blocks for a small wall displacement situation where
 714 the first threshold limits the total number of moving blocks to a maximum of three.

715 The corresponding reduced dimension ICPs are predicted and the inverse analysis process terminates.
 716 Notably, the workflow (in the dashed box of Figure 12) corresponding to the evaluation of the QoI and
 717 the associated process to create a meta-model serving as a surrogate of the NSCD model is therefore not
 718 required.

719 5.3. Evaluation of the method

720 Following the guidelines of the previous section, the predictions of the energy transferred to the wall
 721 and the position of impact are compared with the corresponding NSCD model simulation results. These
 722 comparisons are presented in Figure 18 for the simulated 600 distinct impact conditions and the three
 723 illustrative impact conditions.

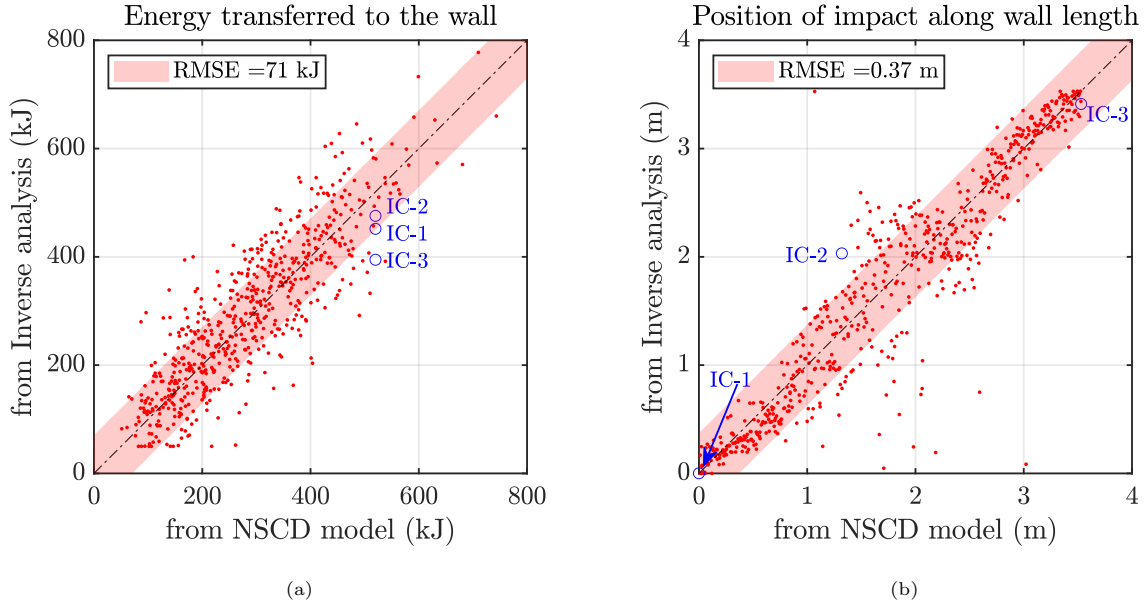


Figure 18: Comparison of displacement-scan inverse analysis-based predictions of (a) energy transferred to the wall and (b) position along the wall length with the corresponding magnitude deduced from 600 different sets of the impact condition parameters.

724 The energy transferred to the wall is predicted with an overall RMS error of 71 kJ (which is below the
725 fracture energy of the concrete block) based on 600 simulations. The overall prediction is satisfactory for
726 a wide range of energy magnitudes supporting the potential of the presented methodology. Nevertheless,
727 two out of three illustrative cases are badly predicted with up to 120 kJ difference from the expected
728 520kJ for all cases (IC-1 and IC-3).

729 Further, the position of impact along the wall length is rather well predicted for impacts at convex
730 and concave-wedges, including the illustrative impact tests in these two locations (IC-1 and IC-3). By
731 contrast, the predictions for the angled wedge zone (between 1.2 to 2.2 m approx.) are significantly less
732 accurate thereby contributing to the overall RMS error of 37 cm (which is about 24% of the length of a
733 block). This significant difference in prediction accuracy is attributed to the zig-zag conformation of the
734 wall, which amplifies the influence of the deviation angle (β) on the structure response depending on the
735 impact location, as illustrated by the Sobol indices. Considering a reduced ICPs input space dimension
736 suppresses the distinct contribution of β which in turn suppresses the variability of the impact at the
737 angled wedge.

738 Overall, the inverse analysis method based on the post-impact measurements is deemed acceptable
739 to retrieve the incident projectile impact position and the energy transferred to the wall. The presented

740 method well captures the variability in the retrieved information. Further efforts can be made to improve
741 the predictive capability of the inverse analysis method.

742 6. Conclusions

743 This work explored the potential of inverse analysis to obtain the information of interest in the opera-
744 tional context of a rockfall protection structure. The inverse analysis relies on simulation-based evaluation
745 of the structure response and makes use of the Bayesian inference and meta-modelling techniques. This
746 work in particular focuses on rockfall protection walls made of piled-up and articulated concrete blocks
747 for which an NSCD model was previously developed and calibrated against real-scale impact experiments.

748 The main conclusions drawn from this research are :

- 749 • Provided a well-calibrated model is available, it is possible to carry out reliable inverse analysis of
750 the response of complex structures subjected to localised dynamic loading.
- 751 • Investigating the structure response considering a wide range of impact conditions, representative
752 of those encountered in situ is a prerequisite in view of defining the strategy for developing the
753 inverse analysis method.
- 754 • The inverse analysis may be based on real-time or post-impact measurements and may serve various
755 purposes, in particular for remote warning upon impact or rockfall activity survey.
- 756 • The presented inverse analysis framework is transferable to other types of such structures (such
757 as flexible barriers) via the usage of the representative numerical model and the relevant recorded
758 database on-site.
- 759 • The inverse analysis process can be implemented to other wall configurations of the same constituent
760 blocks and connectors considering the same calibrated model parameters and following the workflow
761 presented in Figure 12.

762 The purpose of the two presented inverse analysis processes (*i.e.*, for real-time impact and post-impact
763 conditions) is different and hence a direct comparative assessment is not representative. Nonetheless, as
764 both analyses yield predictions of one distance-based parameter and one energy-based parameter, an
765 indirect comparative assessment is made that can be useful in future research. The displacement pattern
766 metamodel is about 8.3% less accurate than the velocity pattern metamodel accessed via the reported Q^2

767 values. The resulting energy-based prediction is 13% more accurate for the former whereas the distance-
768 based prediction relative to the corresponding block dimension (*i.e.*, length for position of impact and
769 width for minimum distance to the safety line) is reported 11% less accurate for the former when accessed
770 via the reported RMS errors.

771 As a perspective, the predictive capability of the proposed methodology shall be improved by focusing
772 on the accuracy of the individual components of the whole process. The improvement in the surrogate
773 model via an increase in the Q^2 coefficient and improvement in the inverse analysis method via (1)
774 reducing the RMS error of the predictions and (2) reducing the number of false indicators cases ‘especially
775 negative’ shall be adopted. As a supplementary outcome, the recorded concrete block velocity database
776 for different impact conditions can be further exploited towards the optimisation of the sensor location.
777 Moreover, the present method is limited to considering a single rock impact and therefore the assessment
778 of multiple rocks impacting the wall at the same time is subjected to future research.

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885 Appendix A. PCE based meta-model

886 Consider the articulated structure model represented by a $\mathcal{M}(\mathbf{X})$ as an equivalent mathematical
887 model. Here, $\mathbf{X} \in \mathbb{R}^M$ is a random vector with independent components described by the joint probability
888 density function (PDF) $f_{\mathbf{X}}$. Consider also a finite variance computational model as a map $Y = \mathcal{M}(\mathbf{X})$,
889 with $Y \in \mathbb{R}$ such that:

$$\mathbb{E} [Y^2] = \int_{\mathcal{D}_{\mathbf{X}}} \mathcal{M}(\mathbf{x})^2 f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x} < \infty \quad (\text{A.1})$$

890 Then, under the assumption of Equation A.1, the PCE of $\mathcal{M}(\mathbf{X})$ is defined as:

$$Y = \mathcal{M}(\mathbf{X}) = \sum_{\alpha \in \mathbb{N}^M} y_{\alpha} \Psi_{\alpha}(\mathbf{X}) \quad (\text{A.2})$$

891 where, the $\Psi_{\alpha}(\mathbf{X})$ are multivariate polynomials orthonormal with respect to $f_{\mathbf{X}}$, $\alpha \in \mathbb{N}^M$ is a multi-
892 index that identifies the components of the multivariate polynomials Ψ_{α} and the $y_{\alpha} \in \mathbb{R}$ are the corre-
893 sponding coefficients. In practical applications, the sum in Equation A.2 needs to be truncated to a finite
894 sum by introducing the truncated polynomial chaos expansion:

$$\mathcal{M}(\mathbf{X}) \approx \mathcal{M}^{PC}(\mathbf{X}) = \sum_{\alpha \in \mathcal{A}} y_{\alpha} \Psi_{\alpha}(\mathbf{X}) \quad (\text{A.3})$$

895 where, $\mathcal{A} \subset \mathbb{N}^M$ is the set of selected multi-indices of multivariate polynomials.

896 In this work, the least-angle regression (LARS) method is used to create the PCE meta-model trun-
 897 cated to the maximum polynomial degree (p) ranging from 1 to 20, and using hyperbolic truncation
 898 scheme (q) ranging from 0.5 to 1.

$$\mathcal{A}^{M,p,q} = \{\boldsymbol{\alpha} \in \mathcal{A}^{M,p} : \|\boldsymbol{\alpha}\|_q \leq p\}, \text{ where } \|\boldsymbol{\alpha}\|_q = \left(\sum_{i=1}^M \alpha_i^q \right)^{1/q} \quad (\text{A.4})$$

899 The accuracy of the constructed PCE is estimated by computing the leave-one-out (LOO) cross-
 900 validation error (ϵ_{LOO}). It consists in building N meta-models $\mathcal{M}^{PC \setminus i}$, each one created on a reduced
 901 experimental design $\mathfrak{X} \setminus \mathbf{x}^{(i)} = \{\mathbf{x}^{(j)}, j = 1, \dots, N, j \neq i\}$ and comparing its prediction on the excluded
 902 point $\mathbf{x}^{(i)}$ with the real value $y^{(i)} = \mathcal{M}(\mathbf{x}^{(i)})$ [34]. The leave-one-cross-validation error can be written as:

$$\epsilon_{LOO} = \frac{\sum_{i=1}^N \left(\mathcal{M}(\mathbf{x}^{(i)}) - \mathcal{M}^{PC \setminus i}(\mathbf{x}^{(i)}) \right)^2}{\sum_{i=1}^N \left(\mathcal{M}(\mathbf{x}^{(i)}) - \hat{\mu}_Y \right)^2} \quad (\text{A.5})$$

903 where, $\hat{\mu}_Y$ is the mean of the experimental design sample.

904 Appendix B. Bayesian inference for inverse analysis

905 Consider the computational model \mathcal{M} that allows the analyst to predict certain quantities of interest
 906 gathered in a vector $\mathbf{y} \in \mathbb{R}^{N_{out}}$ as a function of input parameters \mathbf{x} :

$$\mathcal{M} : \mathbf{x} \in \mathcal{D}_{\mathbf{X}} \subset \mathbb{R}^M \mapsto \mathbf{y} = \mathcal{M}(\mathbf{x}) \in \mathbb{R}^{N_{out}} \quad (\text{B.1})$$

907 The Bayesian inference for inverse analysis focuses on identifying the input parameters of a computa-
 908 tional model to recover the observations in the collected output data set. It comprises of a computational
 909 forward model \mathcal{M} , a set of input parameters $\mathbf{x} \in \mathcal{D}_{\mathbf{X}}$ that need to be inferred, and a set of experimental
 910 data \mathcal{Y} . Here, $\mathcal{Y} \stackrel{\text{def}}{=} \{\mathbf{y}_1, \dots, \mathbf{y}_N\}$ is a global data set of N independent measured quantities of interest
 911 (\mathbf{y}_i).

912 The forward model $\mathbf{x} \mapsto \mathcal{M}(\mathbf{x})$ is a mathematical representation of the system under consideration.
 913 The lack of knowledge on the input parameters is modelled by considering them as a random vector,
 914 denoted by \mathbf{X} which is assumed to follow a so-called prior distribution (with support $\mathcal{D}_{\mathbf{X}}$), as presented
 915 in Figure 8 in the present work.

$$\mathbf{X} \sim \pi(\mathbf{x}) \tag{B.2}$$

916 The Bayesian statistics combine this prior knowledge of the parameters with the few observed data
 917 points to obtain a statistical model called posterior distribution ($\pi(\mathbf{x} | \mathbf{y})$) of the input parameters, using
 918 Bayes' theorem [38], expressed as:

$$\pi(\mathbf{x} | \mathbf{y}) = \frac{\pi(\mathbf{y} | \mathbf{x})\pi(\mathbf{x})}{\pi(\mathbf{y})} \tag{B.3}$$

919 Now, considering the available data set (\mathcal{Y}) as independent realizations of $\mathbf{Y} | \mathbf{x} \sim \pi(\mathbf{y} | \mathbf{x})$, the
 920 collected measurements result in the definition of the likelihood function $\mathcal{L}(\mathbf{x}; \mathcal{Y})$, which is a function of
 921 input parameters \mathbf{x} :

$$\mathcal{L} : \mathbf{x} \mapsto \mathcal{L}(\mathbf{x}; \mathcal{Y}) \stackrel{\text{def}}{=} \prod_{i=1}^N \pi(\mathbf{y}_i | \mathbf{x}) \tag{B.4}$$

922 This implicitly assumes in/dependence between individual measurements in \mathcal{Y} . Intuitively the like-
 923 lihood function for a given \mathbf{x} returns the relative likelihood of observing the data at hand, under the
 924 assumption that it follows the prescribed parametric distribution $\pi(\mathbf{y} | \mathbf{x})$.

925 As all models are simplifications of the real world, a discrepancy term (ϵ) is introduced to connect
 926 real-world observations (\mathcal{Y}) to the predictions by the model. In practice, the discrepancy term represents
 927 the effects of the measurement error and model inaccuracy. The discrepancy term introduced here reads:

$$\mathbf{y} = \mathcal{M}(x) + \epsilon \tag{B.5}$$

928 Here, the ϵ is assumed as an additive Gaussian discrepancy [39] with a zero mean and given covariance
 929 matrix (Σ):

$$\epsilon \sim \mathcal{N}(\epsilon | \mathbf{0}, \Sigma) \tag{B.6}$$

930 Taking insights from the discrepancy term definition, a particular measurement point ($\mathbf{y}_i \in \mathcal{Y}$, is a
 931 realization of the Gaussian distribution with mean value $\mathcal{M}(x)$ and covariance matrix Σ . This distribution
 932 is named as discrepancy model and is expressed as:

$$\pi(\mathbf{y} | \mathbf{x}) = \mathcal{N}(\mathbf{y} | \mathcal{M}(\mathbf{x}), \Sigma) \tag{B.7}$$

933 In application, the discrepancy model defines the connection between the supplied data (\mathcal{Y}) and
 934 the forward model. In the present work, as the inverse analysis is conducted on the pseudo on-site
 935 measurement (as evidence), the discrepancy model with known residual variance is assigned.

936 Afterwards, the N independent available measurements (in our case, maximum velocity pattern and
 937 3D displacement databases) gathered in the data-set (*i.e.*, $\mathcal{Y} = \{\mathbf{y}_1, \dots, \mathbf{y}_N\}$) are used to define the
 938 likelihood function as:

$$\begin{aligned} \mathcal{L}(\mathbf{x}; \mathcal{Y}) &= \prod_{i=1}^N \mathcal{N}(\mathbf{y}_i | \mathcal{M}(\mathbf{x}), \Sigma) \\ &= \prod_{i=1}^N \frac{1}{\sqrt{(2\pi)^{N_{out}} \det(\Sigma)}} \exp\left(-\frac{1}{2}(\mathbf{y}_i - \mathcal{M}(\mathbf{x}))^\top \Sigma^{-1}(\mathbf{y}_i - \mathcal{M}(\mathbf{x}))\right) \end{aligned} \quad (\text{B.8})$$

939 Thereby, following Bayes' theorem, the posterior distribution $\pi(\mathbf{x} | \mathcal{Y})$ of the parameters (\mathbf{x}) given
 940 the observations in \mathcal{Y} can be written as:

$$\pi(\mathbf{x} | \mathcal{Y}) = \frac{\mathcal{L}(\mathbf{x}; \mathcal{Y})\pi(\mathbf{x})}{Z} \quad (\text{B.9})$$

941 Here, Z is a normalizing factor, known as the marginal likelihood or evidence, is added to ensure that
 942 this distribution integrates to 1:

$$Z \stackrel{\text{def}}{=} \int_{\mathcal{D}_{\mathbf{x}}} \mathcal{L}(\mathbf{x}; \mathcal{Y})\pi(\mathbf{x})d\mathbf{x} \quad (\text{B.10})$$

943 The closed-form solutions do not exist in practice, and therefore the posterior distribution is obtained
 944 through Markov chain Monte Carlo (MCMC) simulations. In the present work, among many proposed
 945 algorithms in [39], the Adaptive Metropolis (AM) algorithm is used and 100 parallel chains with 1000
 946 steps are assigned to the MCMC solver. The start of the covariance adaptation in AM algorithm is
 947 assigned at the 100th step (see Wagner et al. [39] for more details).

948 The output (\mathbf{y}) predictive capabilities of the Bayesian inference is assessed through the comparison
 949 of prior ($\pi(\mathbf{y})$) and posterior ($\pi(\mathbf{y} | \mathcal{Y})$) output distributions as:

$$\pi(\mathbf{y}) = \int_{\mathcal{D}_{\mathbf{x}}} \pi(\mathbf{y} | \mathbf{x})\pi(\mathbf{x})d\mathbf{x} \quad (\text{B.11})$$

$$\pi(\mathbf{y} | \mathcal{Y}) = \int_{\mathcal{D}_{\mathbf{x}}} \pi(\mathbf{y} | \mathbf{x})\pi(\mathbf{x} | \mathcal{Y})d\mathbf{x} \quad (\text{B.12})$$

950 Lastly, in the present studies, the purpose of the Bayesian inference is to obtain the ‘best set of impact
951 condition parameters (ICPs)’. Given the posterior distribution ($\pi(\mathbf{x} | \mathcal{Y})$), we are interested in finding a
952 suitable set among the posterior computed set *i.e.*, $\mathbf{X} | \mathcal{Y}$. This is done through a point estimator ($\hat{\mathbf{x}}$)
953 computed from:

$$\pi(\mathbf{y} | \mathcal{Y}) \stackrel{\text{def}}{=} \pi(\mathbf{y} | \hat{\mathbf{x}}) \tag{B.13}$$

954 This point estimator can be a mean or mode (maximum a posteriori ‘MAP’) [39] of the posterior
955 distribution as per the user’s choice.