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1 Genetic algorithm supported by influence lines and neural network for bridge 2 health monitoring

3 G. Marasco¹; G. Piana^{2,3*}; B. Chiaia⁴; and G. Ventura⁵
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5
6 ¹ Politecnico di Torino, Department of Structural, Geotechnical and Building Engineering, Corso Duca
7 degli Abruzzi 24, 10129 Torino, Italy. E-mail: giulia.marasco@polito.it

8 ² Politecnico di Torino, Department of Structural, Geotechnical and Building Engineering, Corso Duca
9 degli Abruzzi 24, 10129 Torino, Italy. E-mail: gianfranco.piana@polito.it

10 ³ Tongji University, Department of Bridge Engineering, 1239 Siping Road, Shanghai, P.R. China.
11 E-mail: gianfranco.piana@polito.it

12 ⁴ Politecnico di Torino, Department of Structural, Geotechnical and Building Engineering, Corso Duca
13 degli Abruzzi 24, 10129 Torino, Italy. E-mail: bernardino.chiaia@polito.it

14 ⁵ Politecnico di Torino, Department of Structural, Geotechnical and Building Engineering, Corso Duca
15 degli Abruzzi 24, 10129 Torino, Italy. E-mail: giulio.ventura@polito.it
16

17 **ABSTRACT**

18 The paper proposes a hybrid technique to solve the inverse problem of damage localization and severity
19 estimation in beam structures. The first phase of the method involves the use of influence lines (IL) to
20 extract information about the damage location. Then, a genetic algorithm (GA), representing the core of the
21 whole procedure, utilizes static parameters as displacements and rotations at few points to evaluate the
22 bending stiffness along the structure by updating a finite element model. The information obtained in the
23 first phase is used in the second phase for: (i) reducing the number of design variables of the GA and the
24 consequent computational time; (ii) improving the accuracy of GA solutions because it allows a suitably
25 trained neural network to select proper values for the coefficients of the proposed cost function inside the
26 genetic algorithm. The procedure is applied to a test problem, namely a simply supported, prestressed

27 concrete railway bridge, located in northern Italy. Numerical experiments are also conducted to test the
28 procedure when the beam length and geometric properties vary.

29 **Keywords:** PC bridge; damage detection; influence line; neural network; genetic algorithm.

30

31 **INTRODUCTION**

32 In the last two decades, the need to control the safety of civil infrastructure facilities has become
33 increasingly important. As proved also by recent happenings, the lack of knowledge of the actual structural
34 conditions of structures and infrastructures and the consequent underrating of their vulnerability can imply
35 severe problems. For example, structural damage due to corrosion, fatigue and aging can lead to significant
36 losses, both in terms of human lives and economic resources. On the one hand, the development of a
37 maintenance plan based on operations of detection, localization and quantification of damage is a complex
38 task for engineers and infrastructure owners. On the other hand, the necessity of infrastructure managers to
39 have a monitoring system that could be sustainable from an economic standpoint and able to point out the
40 structural criticalities needs answers.

41 The state of the infrastructural asset is in continuous change due both to gradual (e.g. fatigue, corrosion)
42 and shock (e.g. earthquakes, floods, and tornados) deterioration phenomena. Railway concrete bridges are
43 subjected to several types of degradation mechanisms. The taxonomy (Maksymowicz et al. 2006) of the
44 degradation processes and their classification highlight the main structural issues. They are due to
45 deformation, discontinuity, displacement, loss of material, and deterioration (Bień et al. 2007). In detail,
46 chemical (carbonation, salt, and acid actions) and physical (creep, fatigue, freeze-thaw action, overloading,
47 shrinkage) phenomena can change structural features. Significant benefits are obtained from the acquisition
48 of structural information to reduce the risk of human and economic losses. Some methods, e.g. Bayesian
49 decision analysis (Iannacone et al. 2021), are useful to estimate them. On the other hand it is now well-
50 known, and quantified by the De Sitter's "Law of five" (De Sitter 1984), the severe impact that a lack of
51 maintenance can have on the overall costs. The recent happenings (Bazzucchi et al. 2018), including the

52 collapse of the Polcevera Viaduct in Genoa, Italy, have shown the need for effective control strategies to
53 ensure safety in the infrastructural field (Clemente 2020).

54 Bridges structural evaluation based on non-destructive monitoring system (Kaloop et al. 2016) has been
55 performed using both dynamic and static measurements. The first approach involves the use of vibrational
56 measurements by means of operational modal analysis (OMA) and Experimental modal analysis (EMA)
57 (Schwarz and Richardson 1999) to estimate the modal parameters and to track their evolutions. OMA is the
58 most common procedure (Magalhães and Cunha 2011) as it does not require the use of any artificial
59 excitation with consequent interruption of the facility operation. Dynamic methods in Structural Health
60 Monitoring (SHM) have been investigated and developed for several decades and represent effective tools.
61 The literature on the subject is very vast. Examples of data analysis from ambient vibration recording are
62 reported in (Azzara et al. 2017)(Roselli et al. 2018)(Chiaia et al. 2020). At the same time, critical issues
63 arise when using them for in-situ monitoring. In fact, damage detection based on the response in terms of
64 frequencies (Salawu 1997), mode shapes (Allemang 2003), and damping ratios (Curadelli et al. 2008) has
65 highlighted as factors like data volume, monitoring time, uncertainty (Reynders et al. 2008), and
66 environmental effects have a significant impact on damage detection because they generate data variance
67 (Wu et al. 2020). As a matter of fact, many novelty detection methods are not able to distinguish between
68 frequency variations due to environmental/operational conditions and variations induced by a damage in
69 the structure. It is true that methods exist for filtering data from disturbances, but this is not an easy
70 operation and usually requires a long-term monitoring, and thus a lot of data to be stored. Progression to
71 real-world applications is delayed by the shortcomings still present in addressing the negative effects
72 produced by these factors (Moughty and Casas 2017). Furthermore, as in the case in matter, infrastructure
73 managers experience difficulties in storing dynamic data from continuous monitoring and they require
74 investigations that are able to exploit static data from periodic monitoring.

75 The second approach requires static load testing and collection of displacement (Nguyen et al. 2016), strain
76 (Sanayei et al. 2012), and curvature (Tonnoir et al. 2018) data. The advantage in their use lies in a more
77 direct achieving of the second level of the hierarchical structure into which the damage identification

78 problem can be divided, i.e. damage localization (Farrar and Worden 2012). In recent years, data-driven
79 algorithms have been implemented within the SHM framework due to their ability in analyzing data and
80 providing a real-time solution for decision making (Tibaduiza Burgos et al. 2020). Big data (BD) and
81 Artificial Intelligence (AI) are considered promising approaches for an effective structural assessment (Sun
82 et al. 2020). The applications of machine learning (Bao and Li 2020) and deep learning techniques (Toh
83 and Park 2020) (Azimi et al. 2020) have been having a rapid increase and have been garnering a growing
84 focus due to their better performance in a damage detection scenario (Flah et al. 2020). Therefore,
85 investigations in this direction are of interest and new methodologies can assist more traditional ones like
86 dynamic health monitoring, acoustic emission monitoring, etc.

87 The present work aims at investigating the possibility of using a reduced number of sensors/measure points
88 while achieving satisfactory results in terms of damage identification at the same time. Structural
89 assessment is designed as an outcome of a periodic (not continuous) monitoring in which few static
90 parameters are recorded when a given external load acts in different positions over the structure. Comparing
91 measurements made at different times under the same conditions can give information about possible
92 changes in the structural response. For this purpose, the paper proposes a hybrid technique to solve the
93 inverse problem of the damage localization and its severity estimation based on a genetic algorithm
94 supported by influence lines and a neural network. The first phase involves the use of influence lines to
95 extract information about the damage location (Chen et al. 2021). Then, a genetic algorithm (GA),
96 representing the core of the whole procedure, utilizes static parameters measured at few points, i.e. mid-
97 span deflections and end rotations, for estimating the bending stiffness along the discretized structure. The
98 use of a limited number of parameters, distributed to capture potential changes both in the middle of the
99 beam and near the supports, falls within an optimization perspective. Indeed, an increase in parameters
100 would imply redundancy and greater reliability in the damage identification problem resolution but
101 producing, on the other hand, an increase in cost and computational time. The information provided by the
102 first phase yields two advantages: (1) it allows reducing the number of design variables of the algorithm
103 and the consequent computational time; (2) it improves the accuracy of the solution given by the GA

104 because it allows a suitably trained neural network to find the best values of the coefficients of the GA's
105 cost function. The use of a cost function composed by parts having different sensitivities to the damage
106 locations gives the possibility to weight the different contributions by means of power coefficients.
107 To initially validate the overall approach (influence lines, genetic algorithm, and neural network) on an
108 elementary test problem, the method is applied to a simply supported beam with damage scenarios
109 characterized by localized reductions in the bending stiffness. To check the feasibility with actual values,
110 model data refer to an existing prestressed concrete railway bridge, located in northern Italy. In addition,
111 numerical experiments are conducted to test the procedure when the beam length and geometric
112 properties are changed. Obtained results look promising and encourage further developments for an
113 extension of the proposed method to more complex structural systems.

114

115 **MOTIVATION AND PROBLEM DEFINITION**

116 The methodology, although included in a general framework, was focused on a simply supported
117 prestressed concrete railway bridge. Such choice is motivated by the fact that this type of viaduct represents
118 most railway viaducts built in Italy since the second half of the 20th century. They suffer from a lot of
119 damage phenomena, like transverse and longitudinal cracking, surface and internal humidity, water
120 infiltration, defects in concrete along the cable track, and defects in prestressing cables. Fig. 1 shows some
121 of the most important phenomena. As can be deduced, the severity of the deterioration can also be high,
122 therefore causing considerable variations of the effective geometric properties of the beam cross-sections
123 (e.g., bending rigidity).

124 The present work proposes a solution to address the damage detection problem in the framework of the
125 structural health monitoring based on static measurements. The analysis focused on a specific bridge. Figs.
126 2a and b display a general view of the viaduct and a bottom view of the deck, respectively. The deck has a
127 span of about 30 meters and is composed of four longitudinal prestressed beams, 2.5 meters deep, and five

128 diaphragms. The piers of the viaduct, having circular section with a diameter of 4 m, are connected at the
129 top to a pier cap on which the beams lean against (Fig. 2).

130 In the structural design, the simultaneous presence of the LM71 (static vertical load of normal railway
131 trains) and SW/2 (static load of heavy railway trains) on the two tracks was considered as the most severe
132 condition for traffic loads. Figs. 3a and 3b display the longitudinal distribution of vertical loads for LM71
133 and SW/2, respectively. In the transverse direction, the design load distribution factors of LM71 lying on
134 the left tracks are about 70% / 30% for the left inner / outer beam, respectively; and approximately 60% /
135 40% for the right inner / outer beam for SW/2 lying on the tracks on the right. Therefore, the left inner beam
136 is the most loaded one (see Fig. 4).

137 Only the longitudinal flexural behavior was considered in this preliminary study. The single longitudinal
138 beam-slab system (interior beam in Figure 4) was considered for the analyses. Its undamaged bending
139 stiffness is $EI = 9.407 \times 10^{10} \text{ Nm}^2$ (Young's modulus $E = 36.28 \times 10^9 \text{ N/m}^2$, area moment of inertia $I = 2.593$
140 m^4); the length is $L=27.8 \text{ m}$. From the design report, it results a cracking bending moment equal to 31693.38
141 kNm (acting moment at mid-span = 18209.80 kNm; safety factor = 1.7) and an ultimate resisting moment
142 equal to 46200.39 kNm (acting moment at mid-span = 18209.80; safety factor = 2.5).

143 In the calculations, we considered a vertical travelling force whose magnitude, equal to 294.2 kN, is
144 comparable to that of one of the concentrated loads in Figure 3a. It corresponds to the weight of a high-
145 speed train bogie, providing a plausible force value for the test. The method can easily be extended to a
146 series of travelling forces (train carriage).

147

148 **METHODS**

149 To analyze the damage scenarios, a finite element model (FEM) was used, with the beam discretized by NE
150 $= 27$ beam elements (Fig. 5). We solved the structural problem by the implementing the displacement
151 method based on the exact two-node beam stiffness matrix, which coincides with that of the two-node
152 Euler-Bernoulli beam finite element. The solution in terms of nodal displacements is exact since nodal
153 forces are considered; the deflection curve is sufficiently well described since element length is $1/27^{\text{th}}$ of

154 the total beam length. We selected 27 elements for considering damages extending for a length of 1 m
155 (which is realistic in some cases; see Figure 1). Considering more elements would only increase the
156 computational effort, which however is rather small for a simple problem as the one under discussion.

157 Static deflection was chosen to assess the structural state (Chou and Ghaboussi 2001) because it is more
158 locally sensitive to damage than dynamic response. Moreover, static measurements are often easier to
159 perform and more precise than dynamic ones (Jenkins et al. 1997). The mid-span deflection and the
160 rotations at the two supports were taken as the reference quantities. The values of bending stiffness along
161 the structure, considered as unknowns, are calculated based on the measured and model computed quantities
162 in order to evaluate the structural conditions. The “measured” quantities (mid-span deflection or end
163 rotation), which should come from in-situ measurements in practice, were derived from the FEM model
164 corresponding to the imposed damage scenario in this analysis; they are input data. The model computed
165 quantities (mid-span deflection or end rotation) were those produced by the FEM model which uses the
166 trial bending stiffness values coming from the genetic algorithm. Thus, the unknown quantities, expressed
167 in this context by the values of bending stiffness, can be determined (estimated) by comparing measured
168 and computed quantities and looking for those values which minimize the difference between the two sets
169 of data.

170 The structural assumptions and the main steps of the proposed methodology, that will be explained in detail
171 in the following sections, are summarized in the flowchart displayed in Fig. 6.

172

173 **Damage localization: influence line method**

174 As is well known, influence lines give the value at a *particular* point in a structure of entities such as shear
175 force, bending moment, support reaction, displacement and rotation for *all* positions of a travelling unit
176 load. The presence of damage in beams (Chen et al. 2014; Štimac et al. 2006) can be observed and localized
177 utilizing influence lines (Megson 2019). For example, let $\eta_m(x)$ and $\bar{\eta}_m(x)$ be the displacement influence
178 lines at mid-span of the damaged and undamaged structures, respectively, i.e., the mid-point displacement

179 in the two structures when a travelling unit transverse force is acting at section x . Thus, the difference
180 $\delta_m^\eta(x) = \text{abs}(\eta_m(x) - \bar{\eta}_m(x))$ will be larger at sections $x = x_d$ where a damage is present. Rotations or
181 curvatures influence lines may be used in the same way (Štimac et al. 2006). This allows identifying the
182 sections with possible damage, and also to investigate damage evolution by comparing measurements made
183 at different times.

184 As an illustrative example, let us consider a simply supported beam, 10 m long, with undamaged bending
185 rigidity $EI = 1 \text{ Nm}^2$. Assume that the beam is discretized into 20 elements, 0.5 m long each, and that a
186 damage is present in the fifth one (from the left) producing a 10% reduction in its bending rigidity, i.e. EI_d
187 $= 0.9 \text{ Nm}^2$. Influence lines can be calculated under the action of a travelling unit transverse force for the
188 undamaged and damaged conditions. Fig. 7a shows, from left to right, the mid-span displacement influence
189 line for the damaged beam, for the integer structure, and their difference as functions of the abscissa (load
190 position). Similarly, Fig. 7b shows, from left to right, the left-support rotation influence line for the damaged
191 beam, for the integer structure, and their difference as functions of the abscissa (load position). As can
192 easily be seen, the diagrams of the difference show a maximum in correspondence to the damaged element,
193 according with the discretization adopted.

194

195 **Estimation of damage severity: genetic algorithm**

196 The genetic algorithm (GA) is an optimization technique based on Darwinian principles (Mahalakshmi et
197 al. 2013; Mirjalili et al. 2020) that allows the generation of good solutions starting from a population of
198 individuals (often generated randomly) that evolve over time. After defining a set of possible solutions,
199 namely a population of $npop$ individuals, each solution is evaluated using a cost function. By using
200 crossover and mutation operators, the better individuals are chosen to create new individuals (offsprings).
201 Individuals' merge and sort operations are performed at this point, based on their cost function. The new
202 generation will be made up of the better $npop$ individuals. When the specified number of iterations is
203 reached or the quality of the better solution is considered to be acceptable, the process is complete. Only

204 the most "suitable" individuals survive and replicate, reducing the cost of future generations. A lot of
205 damage identification problems have been addressed in the scientific literature by exploiting this approach.
206 Most of the investigations have been based on the comparison between the computed and the measured
207 dynamic response (Au et al. 2003; Buezas et al. 2011; Hao and Xia 2002; Khatir et al. 2016; Meruane and
208 Heylen 2011; Nobahari and Seyedpoor 2011). They use the natural frequencies and mode shapes of several
209 vibration modes. Although effective, they imply the use of many sensors and a large volume of data. Studies
210 which combine both static and dynamic characteristics (Jung and Kim 2013) point out an improvement of
211 the results. The combination of modal parameters and static displacements (Jung and Kim 2013) (He and
212 Hwang 2006), as well as the use of static response exclusively (He and Hwang 2007), is less common.
213 For the particular issue, in the present study individuals are constituted by the bending stiffness of the
214 elements which were identified as damaged by the influence lines. Thus, the genetic algorithm, using the
215 available static measurements, calculates the bending stiffness of the damaged elements once their location
216 and number are known.

217 *Design of genetic algorithm*

218 The architecture of the GA requires the definition of several parameters, which are both "qualitative" and
219 "quantitative" (Eiben and Smit 2011). The selection, crossover, and mutation operators are examples of the
220 former type. The population size (n_{pop}), the crossover rate (CR), and the mutation rate (MR) belong to the
221 latter type. The first set of parameters, known as high-level parameters, defines the algorithm's key
222 structure: in this study, the Roulette Wheel Selection and the Uniform Crossover were the selected
223 operators. The second set of parameters, known as low-level parameters, are used to create a version of the
224 algorithm: they were determined as will be described later on.

225 *Cost function*

226 The GA's cost function is based on static parameters as mid-span displacement and support rotations. The
227 construction of a cost function based exclusively on static measurements, able to exploit only three

228 measured values thus eliminating the need to accumulate large volume of data, is one of the distinctive
 229 features of the proposed approach. It is made of the sum of five contributions:

$$230 \quad Cost = Cost_{Disp_{pol}}^{\rho} + Cost_f^{\varphi} + Cost_{RotA}^{\alpha1} + Cost_{RotB}^{\alpha2} + Cost_{RatioRot}^{\delta} \quad (1)$$

231 Power coefficients ρ , φ , $\alpha1$, $\alpha2$, and δ are introduced to weight the single contributions, which can be more
 232 or less sensitive to damage location. Their influence will be assessed in the following sections. Usually,
 233 they are initially set equal to one for preliminary analysis, and then computed at a later stage to improve the
 234 goodness of the solution, if necessary.

235 The expressions of each of the five contributions in Eq. (1) are the following (Eqs. (2-6)):

$$236 \quad Cost_{Disp_{pol}}^{\rho} = \left((NE - 2) \frac{\sum abs(Disp_a - Disp_m)}{\sum abs(Disp_m)} \right)^{\rho} \quad (2)$$

$$237 \quad Cost_f^{\varphi} = \left(abs \left(\frac{f_m - f_a}{f_m} \right) \right)^{\varphi} \quad (3)$$

$$238 \quad Cost_{RotA}^{\alpha1} = \left(abs \left(\frac{RotA_m - RotA_a}{RotA_m} \right) \right)^{\alpha1} \quad (4)$$

$$239 \quad Cost_{RotB}^{\alpha2} = \left(abs \left(\frac{RotB_m - RotB_a}{RotB_m} \right) \right)^{\alpha2} \quad (5)$$

$$240 \quad Cost_{RatioRot}^{\delta} = \left(abs(Ratio_m - Ratio_a) \right)^{\delta} \quad (6)$$

241 Eqs. (7) and (8) show the expressions adopted for $Ratio_m$ and $Ratio_a$, respectively:

$$242 \quad Ratio_m = abs \left(\frac{RotA_m}{RotB_m} \right), \quad (7)$$

$$243 \quad Ratio_a = abs \left(\frac{RotA_a}{RotB_a} \right). \quad (8)$$

244

245 The terms $Cost_f^\varphi$, $Cost_{RotA}^{\alpha1}$, and $Cost_{RotB}^{\alpha2}$ are directly linked to the measurements made
246 (displacement at mid-span and rotations at supports A and B). The first term, $Cost_{Disp_{pol}}^\rho$, is stemmed from
247 the displacements of the other structural nodes, which are estimated using the Vurpillot algorithm starting
248 from the measured quantities; the differences between computed and measured quantities which appear in
249 the numerator are normalized with respect to the average measured displacement. The last term,
250 $Cost_{RatioRot}^\delta$, is based on the ratio between the rotations at the supports. Subscripts m and a denote
251 measured and analytical (computed) quantities, respectively. The measured values were numerically
252 simulated using a FEM analysis, with the damaged elements having a reduced bending stiffness, as
253 previously mentioned; in real-world application, they should come from on-site measurements. The
254 analytical quantities, on the other hand, were determined using a FEM analysis in which the values of
255 bending stiffness of the damaged elements were picked-up from the GA individuals. The power coefficients
256 for each part of the cost function were set equal to 1 at the beginning.

257 Advantages coming from the use of such a cost function include: (i) utilizing few sensors/measure points
258 (thanks to the form of the cost function and information provided by influence lines); (ii) inclusion of
259 parameters as end rotations which are usually not considered; (iii) no need to save big volumes of data; (iv)
260 reduced computational time.

261 *Preliminary study: tuning of the numerical parameters of GA*

262 Each quantitative hyperparameter utilized within the genetic algorithm has a specific influence (Hassanat
263 et al. 2019) and a great impact on its performance. Consequently, it is not appropriate to recklessly proceed
264 with their selection.

265 Along with the previously described parameters ($npop$, CR , MR), there are three additional ones (β , γ , σ)
266 that depend on the chosen operators and deserve further exploration. The first one, β , allows the Roulette
267 Wheel method to select the parents by assigning probabilities ($probs$) to the individuals of the population.
268 This approach is carried out by defining a probability distribution over the population in a way such that
269 the better individuals of the population have a higher chance of being selected as parents.

270
$$probs = e^{-\beta c} \tag{9}$$

271 The symbol c , used in Eq. (9), represents the cost of the individual normalized with respect to the average
 272 cost of the population.

273 The second hyperparameter, γ , is related to the uniform crossover operator. It increases the exploration
 274 capabilities of the GA. A couple of offsprings y_j ($j=1,2$) with n genes (Eq. (11)) is built starting from a
 275 couple of parents x_j ($j=1,2$) with n genes (Eq. (10)). The i -th genes of the j -th offspring (Eq. (12)) is linked
 276 to the i -th gene of the corresponding parent (x_{ji}) and to the i -th gene of the other (x_{ji}) by means of the
 277 parameter α_i . The γ parameter is used to extend the classical dispersion range of α_i from $[0, 1]$ to $[-\gamma, 1+\gamma]$.
 278 In this way, it is possible to create offspring somehow different from their parents.

279
$$x_j = (x_{j1}, x_{j2}, \dots, x_{jn}) \tag{10}$$

280
$$y_j = (y_{j1}, y_{j2}, \dots, y_{jn}) \tag{11}$$

281
$$y_{ji} = \alpha_i x_{ji} + (1 - \alpha_i) x_{ji} \tag{12}$$

282 The third hyperparameter, σ , is related to the mutation operator. Such operation occurs by adding a random
 283 number with zero mean and variance σ^2 .

284 In the general context of a grid search strategy (Pontes et al. 2016; RAMADHAN et al. 2017; Shekar and
 285 Dagnew 2019), a complete search was performed on a subset of the space of hyperparameters defined in
 286 Tab.1. This latter gives details on the range values and step used for each of them.

287

288 **Neural network: supervised learning for selection of cost function power coefficients**

289 A neural network, namely a supervised learning model nowadays successful in many scientific fields
 290 (Abiodun et al. 2018), was used to improve accuracy (and consequently decrease the error) of the solutions
 291 provided by the genetic algorithm. It was trained to select suitable power coefficients for the cost function,
 292 once the damaged elements were localized. Numerical simulations were carried out to associate the damage
 293 scenarios, characterized by some damaged elements, to the power coefficients. Several damage cases were
 294 investigated and, for each of them, numerical analyses considering 10,000 combinations of power

295 coefficients were performed. The minimum and the maximum values of the investigated variability range
296 for each power coefficient were set equal to 0.1 and 1, respectively; the step was set to 0.1. The only
297 exception was made for ρ . Since the corresponding term in the cost function is linked to computed
298 parameters rather than measured ones, this coefficient was set to 1. For each damage scenario, the
299 combination of power coefficients corresponding the least error was chosen among the 10,000 ones. In this
300 analysis, the error was defined as the absolute value of the difference between the genetic algorithm's
301 solution and the correct value of the variables. Further connections between other cases of damage and
302 power coefficients were built using a simplified method due to the high computational and time effort
303 involved in this procedure (Bergstra and Bengio 2012; Fayed and Atiya 2019; Huang et al. 2012; Shekar
304 and Dagneu 2019; Syarif et al. 2016). For damage cases similar to the ones already considered, where
305 similar means that the positions of the damages are near to the ones just analyzed, the power coefficients
306 previously calculated with the addition of a noise were utilized. The added noise ranges from 0.5% to 1.5%
307 based on the greater or lesser proximity to the previously investigated case. A neural network was trained
308 and tested using the 171 connections created. Its structure is depicted in Fig. 8. Every example fed into the
309 neural network has seven inputs. The first five are reserved for indicating damaged elements, which were
310 marked by a number ranging from 1 to 27. If the number of damaged elements, nd , is less than 5, the
311 remaining $5-nd$ inputs are given a zero value. The positions of the most affected elements are included in
312 the last two inputs. The targets, on the other hand, are made up of the four power coefficients.

313 The samples were subdivided into three parts: training (70%), validation(15%) and testing (15%). A two-
314 layer feedforward network, with a sigmoid transfer function in the hidden layer and a linear transfer
315 function in the output layer, was employed. The number of hidden neurons was set to 27, and the training
316 algorithm used Bayesian regularization. Regression value, R , and Mean Squared Error, MSE , were used to
317 evaluate the performance. R measures the correlation between outputs and targets. Values of R close to 1
318 indicate close relationship, whereas values close to 0 indicate random relationship. The Mean Squared Error

319 is the average square difference between outputs and targets. Low values of this index indicate a good
320 performance.

321

322 RESULTS

323 The influence lines of mid-span deflection and support rotations under the above-mentioned travelling force
324 were numerically computed for the undamaged and damaged structures for the problem in exam. This
325 allowed the damaged elements in the discretized structure parameter to be identified, providing information
326 for the genetic algorithm.

327 Fig. 9 shows three structural damage scenarios with two damaged elements. The upper part of the figure
328 displays the structural schemes. The most severely damaged element, and the associated flexural stiffness,
329 is highlighted in red. Orange color is used for the element with less severe damage. For example, the case
330 on the right has two damaged elements, one with a $0.9EI$ for element n. 7 ($de = 7$) and the other with a
331 $0.75EI$ for element n. 16 ($de = 16$). The squares of relative differences $\delta_m^{\eta,rel}$, $\delta_A^{\varphi,rel}$ and $\delta_B^{\varphi,rel}$ for the mid-
332 span displacement, the left (A) and right (B) support rotations (e.g. $\delta_m^{\eta,rel} = abs((\eta_m(x) -$
333 $\bar{\eta}_m(x))/\bar{\eta}_m(x))$) show peaks (diamonds) in correspondence to the damaged elements. The use of these three
334 indices also makes it possible to localize damage even in regions, like those near the supports, for which is
335 usually difficult (see the second case in Fig. 9).

336 It is worth noting that the selected bridge has a relatively high bending stiffness. Under the applied travelling
337 force, this resulted in very small variations in the values of displacement and rotation between the
338 undamaged and damaged states. However, high-sensitivity displacement transducers, such as LVDT
339 sensors, as well as modern techniques such as Digital Image Correlation (DIC) (Lacidogna et al. 2020), are
340 now available for micrometer measurements. Other damage-sensitive mechanical quantities, such as
341 strains, may also be used, the technique still being accurate and the above-described procedure remaining
342 unvaried in principle. The operation of damage localization performed by the influence lines results
343 effective for the subsequent estimation of damage severity. Performing these two operations simultaneously

344 would turn out to be a process with a high computational cost, especially for complex problems. In these
345 cases, in fact, the number of design variables is high and the accuracy of the solution decays. Influence
346 lines not only exclude from further analysis those elements with a low probability of damage, as it occurs
347 in grey relation analysis (He and Hwang 2007), but are also able to drastically reduce the number of design
348 variables by identifying damaged elements. The use of influence lines applied to the simple beam structure
349 is a simplification that has allowed a first validation of the procedure. To better describe the structural
350 behavior of the bridge, influence surfaces should be used on a 2D structural model (Štimac et al. 2006).

351 As previously pointed-out, a preliminary study was conducted for tuning the numerical parameters of the
352 GA. The goal of this preliminary analysis was not to find the best combination of hyperparameters, but
353 rather the combination that produce suitable results for subsequent studies. Thus, the comparison among
354 the performances in terms of cost, for each structural problem (case of damage) and each combination of
355 parameters, was carried out ignoring the stochastic nature of the problem. A total of 8400 combinations of
356 parameters were generated by using the range values and steps in Tab. 1.

357 The behavior of the cost function with respect to the combination of parameters was observed for each of
358 the four investigated damage cases (DC). For simplicity, in each case only one damaged element is present
359 in the structure. Therefore, the number of the variables within the GA was set equal to one. Tab. 2 reports,
360 for the four examined damage cases, the number de (comprised between 1 and 27, starting from the left
361 support A) that identifies the damaged element, and the corresponding bending stiffness, EI_d , expressed as
362 a fraction of the undamaged bending stiffness EI . Fig. 10 shows the cost as a function of the combinations
363 of parameters and damage scenarios DC₁ to DC₄. The cost resulted to be highly sensitive to the used
364 parameters, especially for DC₁. Thus, referring to DC₁ as the worst case, the combination of parameters
365 that corresponds to the minimum cost was chosen, i.e. combination 558; see Tab. 3.

366 For the examined damage scenarios, the results in terms of cost, accuracy, and error are collected in Tab.
367 4. The accuracy was computed as the ratio between the computed solution and the correct value. The error
368 was calculated as follows:

369
$$Error = \frac{GA_value - Correct_value}{Correct_value} \quad (13)$$

370 The findings might be deemed acceptable, but they are still subject of improvement. For this purpose, the
371 impact of the power coefficients φ , α_1 , α_2 , δ of the cost function, up to now considered unitary, was
372 investigated starting from the knowledge of the damage location. After having found the benefits obtainable
373 from the variation of these coefficients in the simplest damage scenario (only one damaged element), it was
374 considered appropriate to fully exploit the information related to the location of the damage to obtain better
375 results also in the most complex damage scenarios.

376 By exploiting the neural network as previously described, a value of regression R of about 0.92 for the
377 training set and about 0.88 for the test set were obtained. They may be judged as satisfactory, although of
378 course they can still be improved by increasing the number of sample cases used to train the network.
379 Recent studies focused on the investigation of the effects of varying the number of train samples for a fixed
380 model and a training samples have shown that by drastically increasing the number of training samples with
381 respect to the complexity of the model, it is possible to decrease the error on the test (Nakkiran and Yang
382 2018).

383 Fig. 11 (right) shows the value of MSE for the training and test sets vs. the variation of the epochs. The best
384 value of MSE was reached by the training set at epoch 1000 and it is fairly small. Besides, the downward
385 trend of the MSE index for the test set indicates that there is no overfitting of the training data. By
386 overcoming the overfitting process, an increase in the number of epochs could boost the network's
387 efficiency even further (Nakkiran and Yang 2018). Another method for measuring the network's goodness
388 is the error histogram shown in Fig. 11 (left). We can see that the error follows a Gaussian distribution with
389 a mean close to zero and a slight dispersion.

390 A series of validation tests were performed to verify the NN's robustness in generating power coefficients
391 that allow an accurate damage severity estimation. Starting from new damage cases, assumed known the
392 damage location from the influence line method, the neural network was used to produce the power

393 coefficients to be introduced into the genetic algorithm for the estimation of the bending stiffness of the
394 damaged elements. Tab. 5 contains the findings for one of the new damage cases tested. The error in
395 estimating the bending stiffness was calculated by Eq. (13).

396 The error distribution is depicted in Fig. 12. The normal distribution, with a mean equal to -0.011 and a
397 standard deviation equal to 0.06 , points out that about the 70% of damage cases has an error less than 6%.
398 In the same figure, the logistic distribution is also used to fit the data. With a mean of -0.0026 and a standard
399 deviation of 0.025 , it seems to fit the data even better. The damaged cases in Fig. 12 are those showing the
400 largest errors. In general, the findings are thus considered satisfactory and still improvable by training the
401 NN with more cases in order to remove the tails of the probability distribution.

402 The same damage cases were used to test the actual improvement in results which can be obtained, with
403 the approach described so far, by using power coefficients extracted from the neural network. Using unitary
404 coefficients, a normal distribution of the error was obtained with a mean of -0.015 and a standard deviation
405 of 0.48 , i.e. a less accurate solution compared to the above results. The approach is therefore valid.

406 Moreover, the same damage scenarios were used to test the validity of the methodology as the geometric
407 properties of the beam are changed. For example, if a beam length of 50 meters is considered, the error
408 distribution remains essentially unchanged. Also, even by varying the value of the moment of inertia I , the
409 distributions undergo very slight changes. Results for moment of inertia values of 2 and 1.5 m^4 were
410 investigated. In these cases, the mean of the normal distribution is about -0.01 , with a standard deviation
411 of about 0.08 . These results are encouraging about the validity of the methodology as the geometric
412 properties of the beam vary.

413 Lastly, we underline that the methodology results sustainable also from a computational point of view. The
414 required computational time is in fact equal to about 2.5 seconds for each analysis involving the genetic
415 algorithm.

416

417 **CONCLUSIONS**

418 The paper aimed at exploring the potential of a hybrid technique based on static measurements which can
419 help a genetic algorithm to identify and quantify damage in structures using a reduced number of variables.
420 A simply supported beam problem was selected to initially test the method, with data taken from a real
421 bridge structure for checking its effectiveness with actual values. The proposed hybrid technique for the
422 inverse problem of damage identification (detection, localization and estimation) has proven to be
423 successful and promising. The main new features and the associated advantages can be summarized as
424 follows:

- 425 • The use of influence lines with the three associated indices – namely, the square of relative
426 differences between undamaged and damaged stages for the mid-span displacement, $(\delta_m^{\eta,rel})^2$, and
427 the left (A) and right (B) support rotations, $(\delta_A^{\varphi,rel})^2$ and $(\delta_B^{\varphi,rel})^2$ – makes it possible to identify
428 damaged regions (beam elements), either along the span or near the supports.
- 429 • The use of influence lines sharply reduces the design variables of the genetic algorithm by
430 overcoming the concept of excluding unlikely damage locations (e.g. grey relation analysis). In this
431 way the computational time drops.
- 432 • The use of a cost function expressed as the sum of five addends, more or less influenced by the
433 damage according to its location, allows to associate a specific weight to each of them by means of
434 power coefficients and to improve the accuracy (decrease the error) of the solution. Results show
435 that, in the analyzed case, very good predictions are obtained adopting three measure
436 points/sensors. Displacements at any node used in the cost function are calculated starting from the
437 values of the mid-span displacement and the two end rotations only.
- 438 • The trained neural network turns out to be an effective support to set the power coefficient of the
439 cost function. Its architecture can also encompass cases with more than two damaged elements.

440 • Here, the approach was positively tested on a simply supported beam with damage scenarios
441 defined by localized bending stiffness reductions. The same damage scenarios were used to test the
442 validity of the methodology when the beam length and geometric properties are varied: good results
443 were obtained without changing the coefficients in the algorithm.

444 Summarizing, the obtained advantages are in terms of computational time, location of critical elements
445 using few measure points, and versatility of the approach. The satisfactory results obtained for the analyzed
446 case make this approach appealing and worthy of further deepening. Although further work is to be done
447 before moving to real-world application, the proposed method is amenable to generalization. In this
448 direction, planned future developments go toward the use of more refined structural models (grillage) as
449 well as the use of influence surfaces for damage localization, other damage indicators, and the analysis of
450 different damage scenarios.

451

452 **Data Availability**

453 Some or all data, models or code that support the findings of this study are available from the corresponding
454 author upon reasonable request.

455

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Table 1. Grid search for hyperparameter optimization.

Parameter	Range	Step
n_{pop}	[10-50]	20
CR	[0.5-1]	0.15
MR	[0.01-0.1]	0.02
β	[0.8-2]	0.2
γ	[0.1-0.5]	0.1
σ	[0.1-40]	10

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Table 2. Damage scenarios.

	DC₁	DC₂	DC₃	DC₄
<i>de</i>	14	14	2	2
<i>EI_a</i>	<i>0.5EI</i>	<i>0.8EI</i>	<i>0.5EI</i>	<i>0.8EI</i>

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Table 3. Chosen combination of parameters.

Combination 558					
n_{pop}	CR	MR	β	γ	σ
50	0.8	0.03	1.4	0.2	0.1

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Table 4. Cost and accuracy with combination 558.

	DC₁	DC₂	DC₃	DC₄
Cost	0.59	0.30	0.24	0.29
Accuracy	1.00	0.91	1.00	1.00
Error	0	-0.09	0	0

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Table 5. Example of new case of damage.

Damage case			
<i>de</i>	<i>EI_d</i>	<i>de</i>	<i>EI_d</i>
10	<i>0.8EI</i>	27	<i>0.95EI</i>
Power coefficients			
<i>φ</i>	<i>α₁</i>	<i>α₂</i>	<i>δ</i>
0.75	1.07	0.36	0.52
Error			
1.32×10^{-3}		1.8×10^{-2}	

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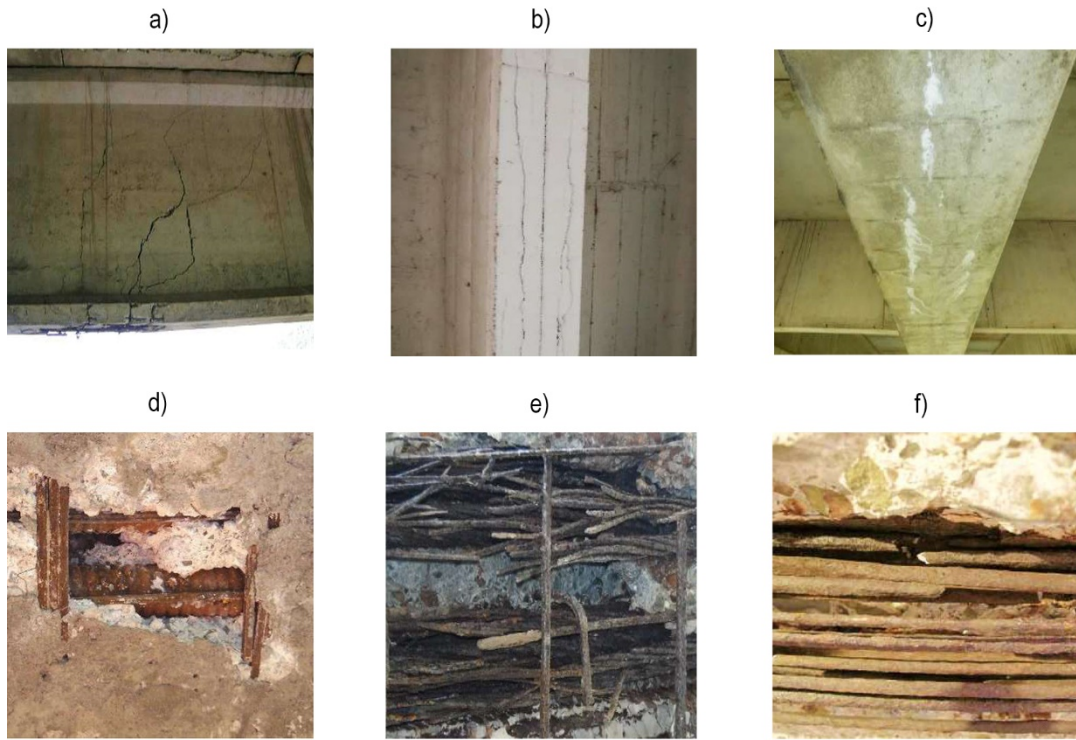
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Figure 1. Damage phenomena in PC bridges: a) transverse cracks, b) longitudinal cracks, c) traces of humidity with efflorescence on the intrados, d) cavity located on the intrados, e) cables with strands interrupted at the intrados, f) corroded and broken wires.

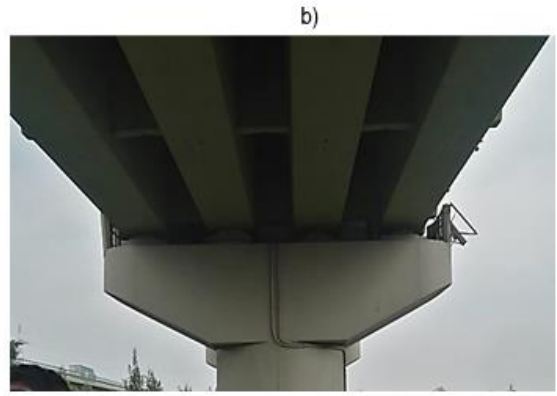


Figure 2. a) General view of the viaduct, b) bottom view of the deck.

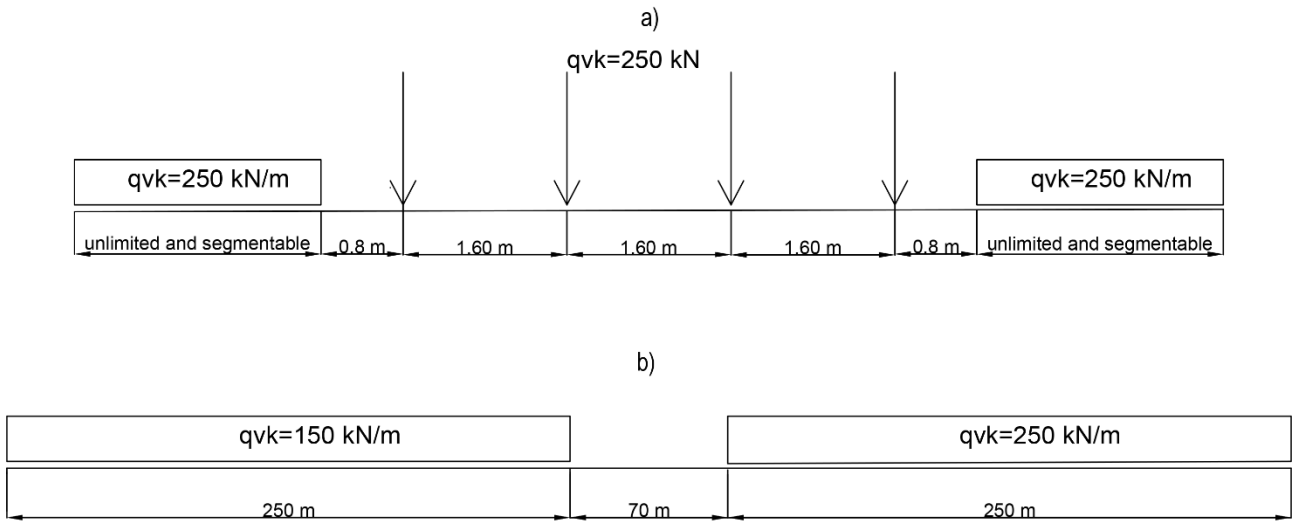


Figure 3: Design live loads: a) LM71, b) SW/2.

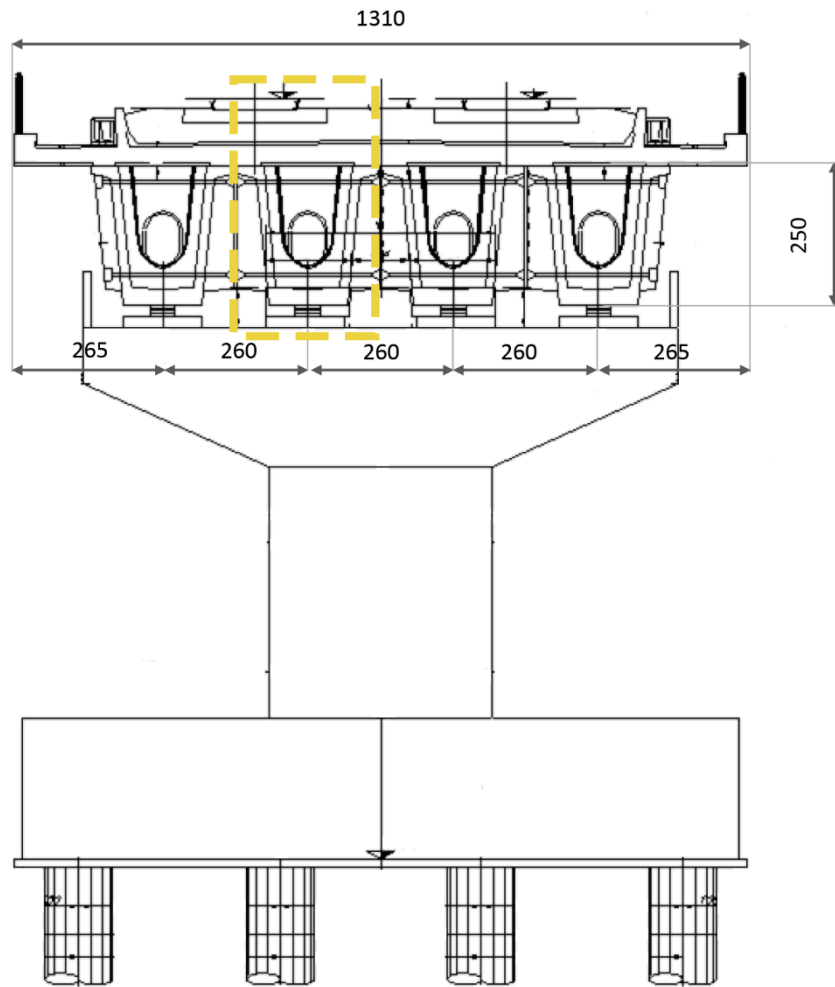


Figure 4. Pile elevation and bridge cross-section with indication of considered beam (dimensions in centimeters).

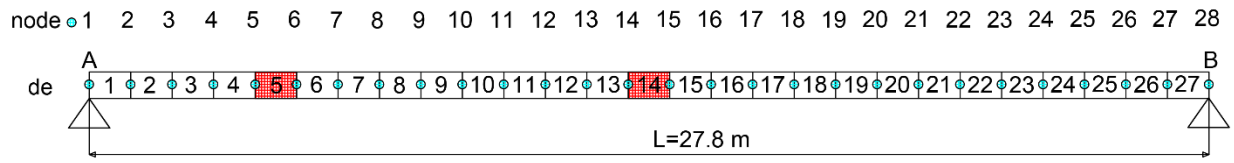


Figure 5. Simply-supported beam discretized by 27 elements. Red color identifies a generic couple of damaged elements.

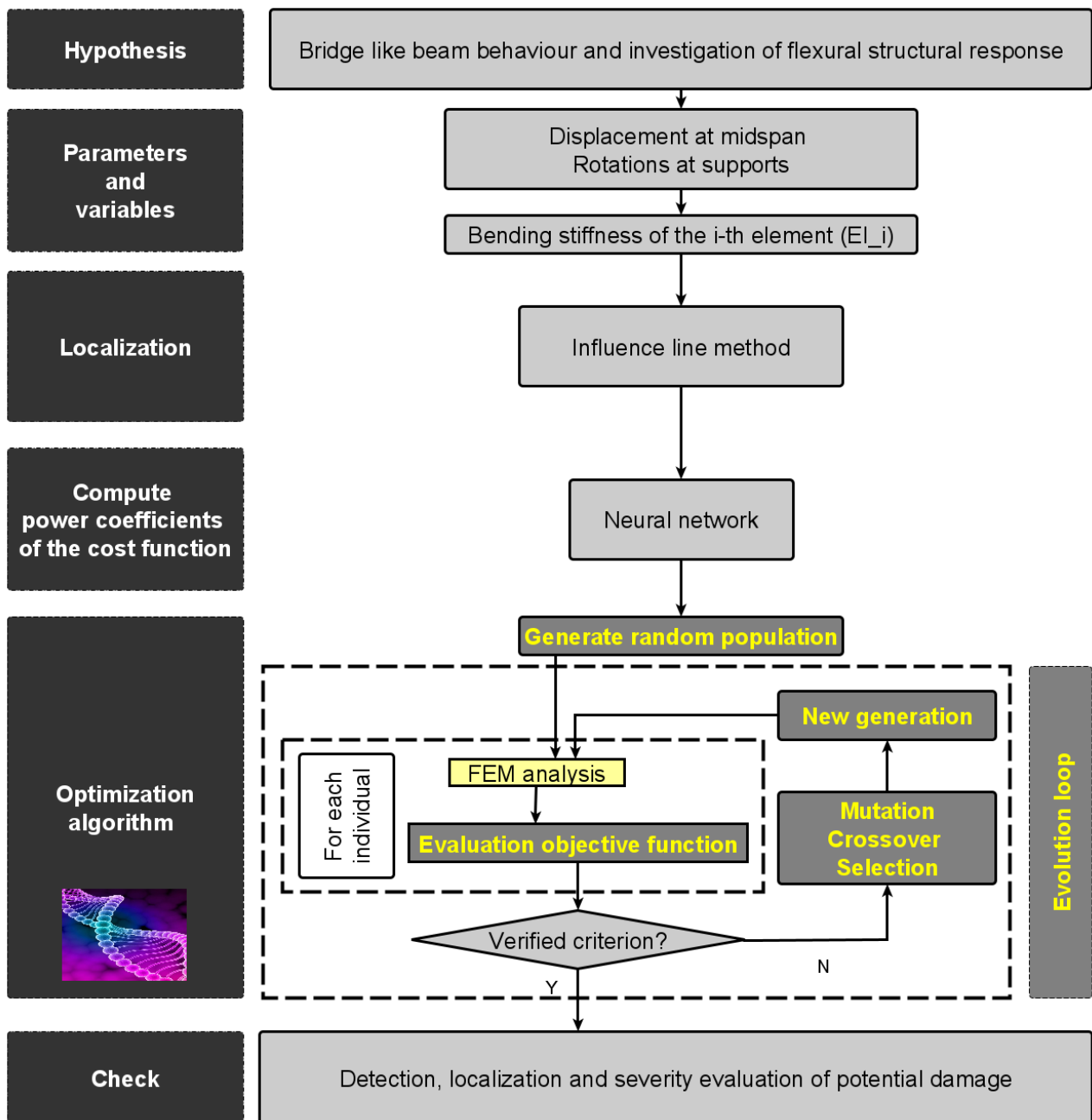


Figure 6. Flowchart of damage identification process.

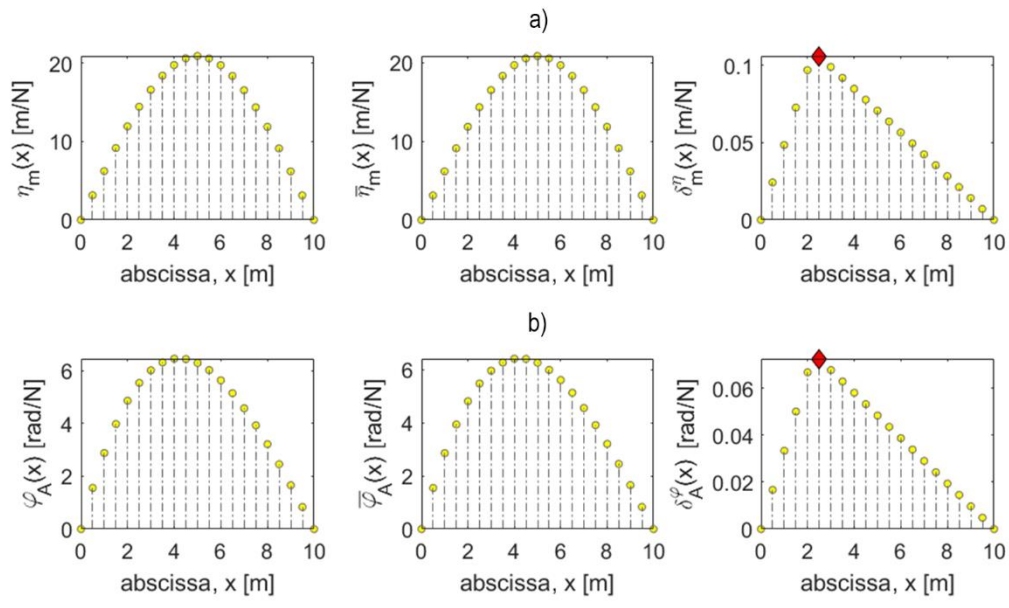


Figure 7. Damage identification by influence line method: illustrative example. a) mid-span deflection, b) left-support rotation.

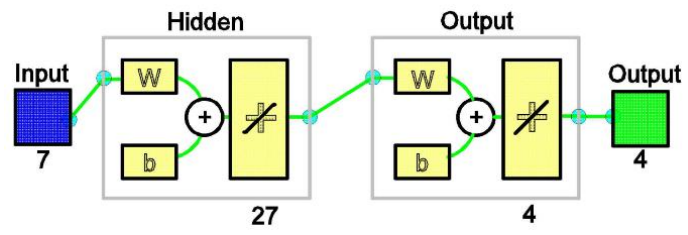


Figure 8. Neural network architecture.

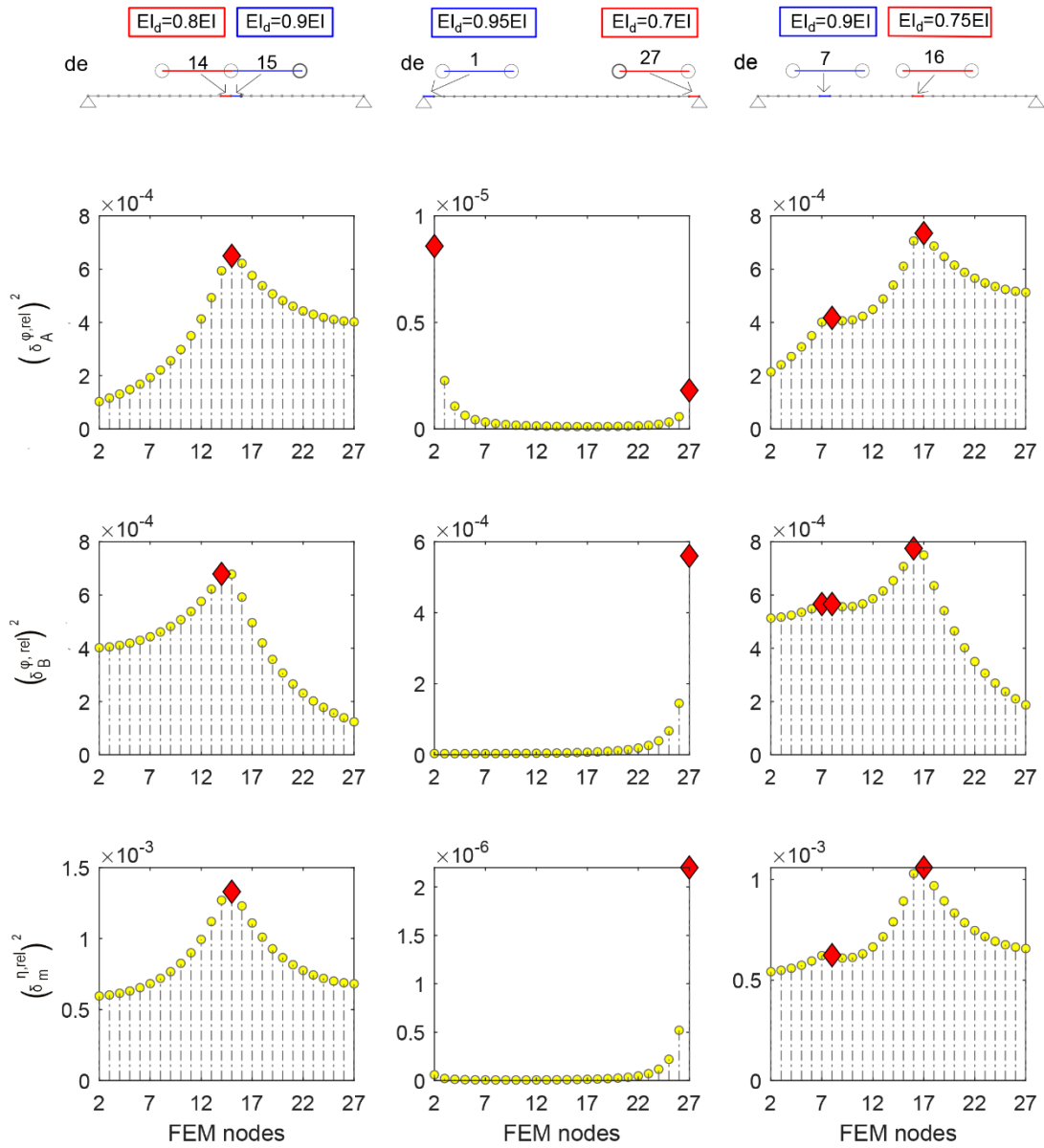


Figure 9. Three damage scenarios identified by influence line method.

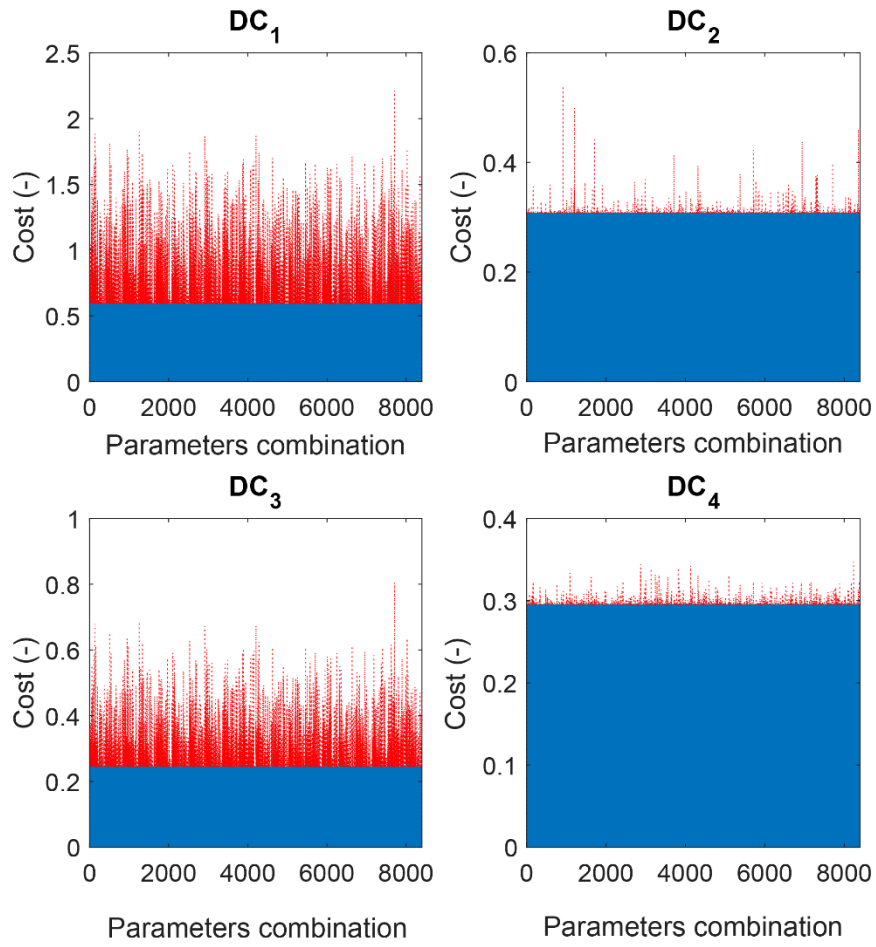


Figure 10. Cost as a function of the combinations of parameters and damage scenarios.

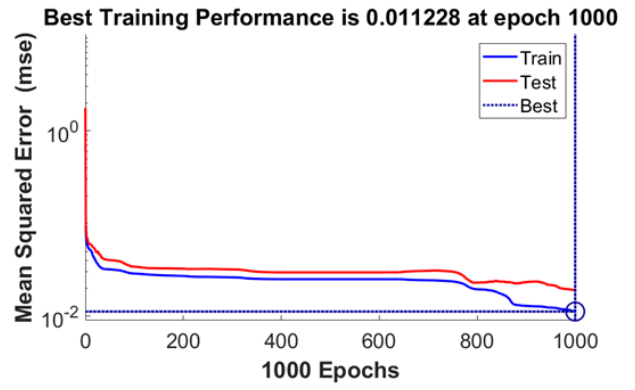
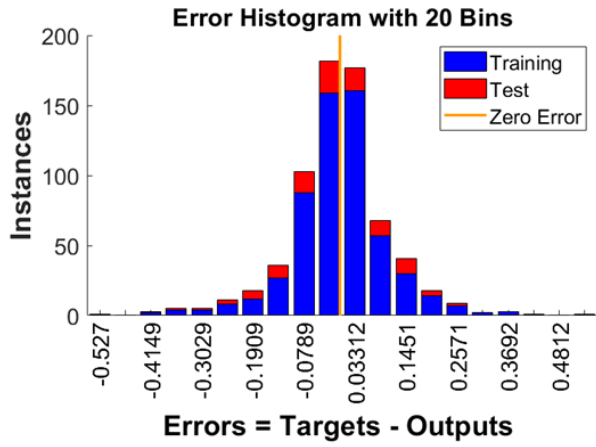


Figure 11. Error histogram and performance of neural network.

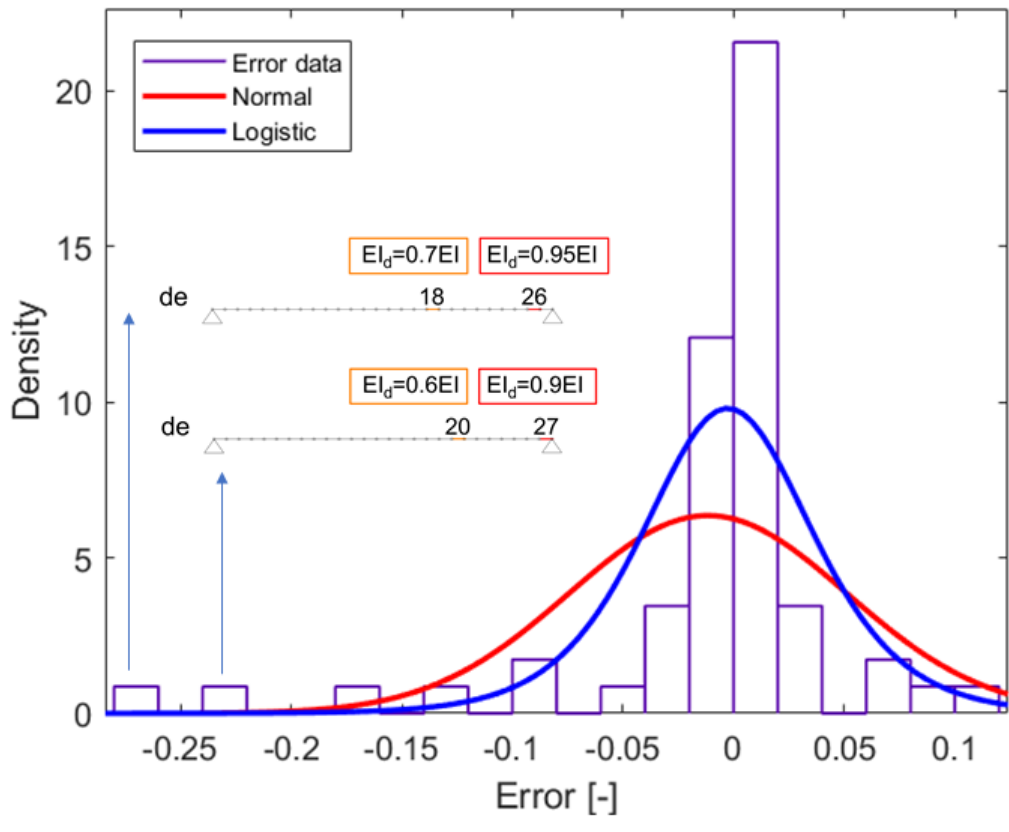


Figure 12. Distribution of the errors.