

## Optimizing the valorization of industrial by-products for the induction heating of asphalt mixtures

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# 1 **Optimizing the valorization of industrial by-products** 2 **for the induction healing of asphalt mixtures**

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14  
15 **Abstract** Self-healing within asphalt pavements is the process whereby road cracks can  
16 be repaired automatically when thermal and mechanical conditions are met. To accelerate  
17 and improve this healing process, metal particles are added to asphalt mixtures. However,  
18 this approach is costly both in economic and environmental terms due to the use of virgin  
19 metallic particles. So, even though the self-healing of asphalt mixtures has been widely  
20 addressed in experimental terms over the years, there is a lack of research aimed at mod-  
21 elling this phenomenon, especially with the purpose of optimizing the use of metal parti-  
22 cles through the valorization of industrial by-products. As such, the goal of this study was  
23 to develop a statistical methodology to model the healing capacity of asphalt concrete  
24 mixtures (AC-16) from the characteristics of the metal particles added and the time and  
25 intensity used for magnetic induction. Five metal particles were used as heating inductors,  
26 including four types of industrial by-products aimed at transforming waste products into  
27 material for use in the road sector. The proposed approach consisted of a combination of  
28 cluster algorithms, multiple regression analysis and response optimization, which were  
29 applied to model laboratory data obtained after testing asphalt concrete mixtures contain-  
30 ing these inductors. The results proved the accuracy of the statistical methods used to  
31 reproduce the experimental behaviour of the asphalt mixtures, which enabled the authors  
32 to determine the optimal amount of industrial by-products and time needed to make the  
33 self-healing process as efficient as possible.

34  
35 **Keywords** Asphalt mixtures; Cluster analysis; Industrial by-products; Multiple regres-  
36 sion analysis; Response optimization; Self-healing; Waste Valorisation.

## 37 38 **1. Introduction**

39

40 Self-healing technology has revolutionized the design, construction and maintenance of  
41 asphalt pavements, and can have great economic and environmental effects on the con-  
42 struction industry. The most efficient self-healing concept for asphalt pavements, is in-  
43 duction healing. Induction healing allows asphalt pavements to repair within 3 minutes  
44 of exposure to induction heating. However, the main drawback to this induction aided  
45 self-healing approach is the amount of metal particles required in the asphalt mixtures to  
46 enable efficient and effective asphalt repair [1].

47 To achieve induction healing, the amount of metal particles usually added to asphalt  
48 mixtures is 5-10% of the bitumen [2–4], which translates into 0.28-0.55% of steel parti-  
49 cles in the mixture. Currently, steel fibre costs €855-873 per tonne, a value which is ex-  
50 pected to increase in the future due to the growing demand for steel from the construction  
51 industry. The average cost of asphalt in the EU is €562 per ton [5]. If steel is added to  
52 asphalt mixtures in a percentage of 0.28-0.55%, the cost of asphalt mixtures per tonne  
53 would increase by between 50-100%. As such, these economic considerations make the  
54 adoption of this technology unaffordable for the road owners in the asphalt industry.

55 However, in line with previous studies on the incorporation of waste materials into  
56 asphalt pavements for different purposes [6–8], recent investigations have explored the  
57 use of metal by-products as a means of improving the resource and recycling efficiency  
58 of the self-healing process [4,9–11]. Research on self-healing for asphalt pavements have  
59 primarily focused on the experimental characterization of the healing capacity of asphalt  
60 concrete [12–14], porous asphalt [4,15,16] and stone mastic asphalt [17] mixtures through  
61 the addition of virgin metal particles.

62 A few studies have addressed the numerical modelling of asphalt self- healing using  
63 either mechanistic or discrete approaches. Qiu et al. [18] developed a cohesive zone  
64 model based on non-linear fracture mechanics with the support of finite element code to  
65 reproduce a monotonic loading-healing-reloading procedure. Although modelling and ex-  
66 perimental results were in acceptable agreement, they differed from each other in terms  
67 of long-term displacement. Magnanimo et al. [19] used a discrete element method to  
68 model the macroscopic self-healing response of asphalt mixtures when subject to uniaxial  
69 compression (tension) tests [20]. Again, the model captured the basic behaviour of asphalt  
70 mixtures; but they recommended further research into their strain-rate dependence. Yang  
71 et al. [21] applied the discrete element method to simulate the fracture strength recovery  
72 ratio of single-edge notched asphalt mixtures after induction healing. Their simulated re-  
73 sults qualitatively matched the experimental tests in terms of peak load and slope of load  
74 increase.

75 Other authors have approached the healing of asphalt mixtures as their recovery ca-  
76 pacity during mechanical tests. Chowdary and Murali Krishnan [22] tested the accuracy  
77 of a constitutive modelling framework to replicate healing experiments carried out  
78 through repeated triaxial tests. Luo et al. [23] used an energy-based mechanistic approach

79 to characterize the decrease of damage density during the healing process of asphalt mix-  
80 tures based on a step-loading recovery test. Levenberg [24] formulated a non-linear vis-  
81 coelastic constitutive model to simulate the healing capacity of asphalt concrete during  
82 recovery intervals of uniaxial compression and standard complex modulus experiments.  
83 They all reached a satisfactory graphical fit to their laboratory results.

84 All of these investigations assess the ‘goodness-of-fit’ of their models qualitatively,  
85 in other words, they lack any numeric measure to guarantee the validity of the simulated  
86 results. Moreover, some of these studies highlighted the complexity of modelling asphalt  
87 mixtures through numerical methods, due to their shape, size, distribution of aggregates  
88 and air voids or chemistry [22], while others highlighted the optimization of the healing  
89 process as an important step to ensure durable asphalt pavements [18].

90 As a result of these considerations, a research gap was identified in relation to the  
91 development of a simpler and more accurate method of optimising the self-healing be-  
92 haviour of asphalt mixtures. In comparison with numerical approaches, statistical meth-  
93 ods provide a more accessible means of modelling physical phenomena through the math-  
94 ematical combination of a set of contributing factors, with the added value of their capac-  
95 ity of testing significance hypotheses to verify the validity of the results achieved. Hence,  
96 this study aimed at designing a statistical framework to model the healing capacity of  
97 asphalt concrete mixtures, enabling the prediction of either the amount of metal particles  
98 or the heating time needed for achieving a certain road repair performance, depending on  
99 the preferences of the decision-makers. The underlying objective is the valorisation of  
100 metal waste through the optimization of the self-healing process in asphalt mixtures in  
101 terms of either resource or time efficiency.

102

## 103 **2. Methodology**

104

105 The proposed framework was intended to facilitate the modelling of the healing potential  
106 of asphalt mixtures containing metal additives as heating inductors, based on the coupling  
107 of experimental and statistical methods. A series of laboratory tests were designed in the  
108 first instance to enable the characterization of both metal particles and asphalt mixtures  
109 in terms of healing capacity. The experimental results were then modelled using a com-  
110 bination of statistical techniques including cluster analysis, regression analysis and re-  
111 sponse optimization.

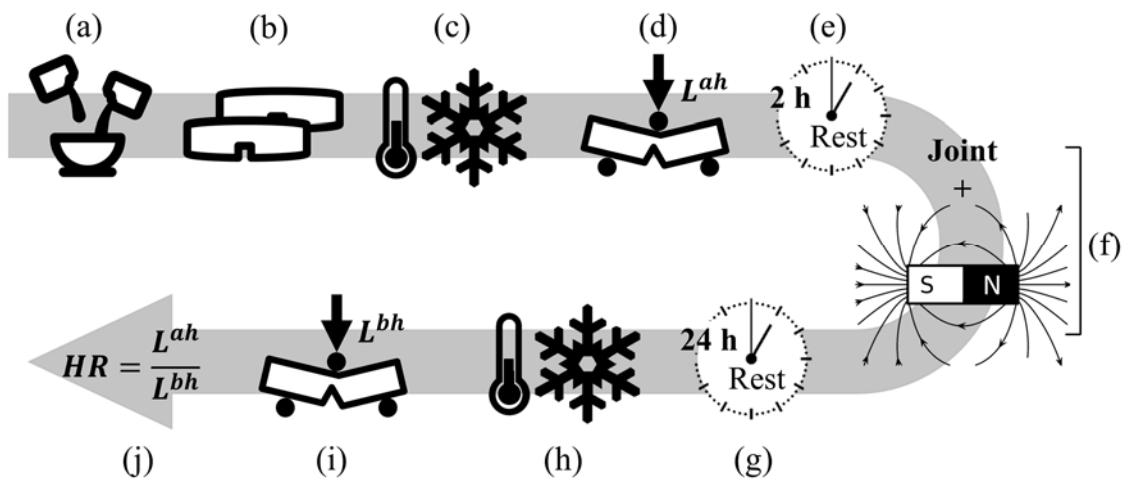
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### 113 **2.1. Experimental Setup**

114

115 The laboratory work focused on the determination of the Healing Ratio ( $HR$ ) of asphalt  
116 mixtures.  $HR$  is a measure that compares the strength of an asphalt mixture before and  
117 after a three point bending test [3]. All of the steps required to calculate  $HR$ , shown in  
118 Figure 1, are explained in detail below.

119



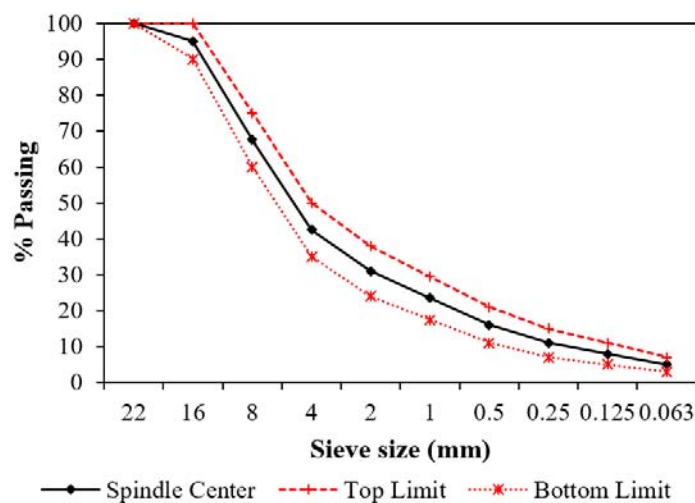
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121 **Figure 1.** Flowchart of the experimental steps (a to j) conducted in laboratory to determine the healing  
 122 ratio ( $HR$ ) of asphalt mixtures: (a) mixture dosage, (b) specimen manufacturing, (c) and (h) cooling-down  
 123 times, (d) breaking test after heating, (e) and (g) rest period times, (f) specimen joint and magnetic induction  
 124 tion, (h) three point bending test before heating and (j)  $HR$  calculation.

125

126 The first stage (Figure 1(a)) was the dosage of asphalt mixtures, which consisted of  
 127 the following components: ophite stone as coarse aggregate and limestone as fine aggregate  
 128 (from 0.063 mm to 2 mm), conventional bitumen 50/70 and metal particles of dif-  
 129 ferent nature to enable the healing process under magnetic induction. Up to 5 different  
 130 mixtures were studied by only changing this last component and then adjusting the dosage  
 131 to fit the particle size distribution of a dense asphalt mixture (AC-16), as depicted in Fig-  
 132 ure 2. To this end, both the particle size distribution (UNE 933-1) [25] and the specific  
 133 weight ( $\text{kg/m}^3$ ) of the mixtures were calculated through the pycnometer method following  
 134 the UNE 1097-4 [26] standard.

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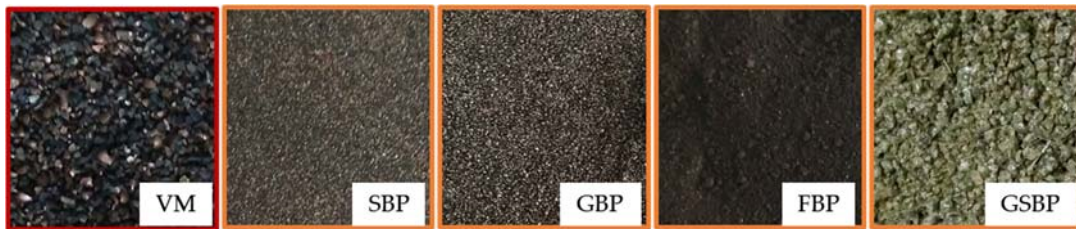
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138

**Figure 2.** Particle size distribution of a dense asphalt concrete mixture (AC-16)

139 The materials used as metal particles, which are shown in Figure 3, included virgin  
 140 steel grits (VM), by-products from blasting processes in the form of steel spheres (SBP)  
 141 and grits (GBP), dust by-products filtered from blasting processes (FBP) and green slags  
 142 from metal manufacturing (GSBP). In all cases, they were waste materials from metal  
 143 manufacturing processes. As such, they are potentially a valuable resource that can be  
 144 used in the design and production of asphalt mixtures to improve the healing process in  
 145 economic and environmental terms. These by-products were used as heating inductors  
 146 and/or supplementary aggregates either in isolation or in combination with each other.  
 147 Their heating capacity was measured by testing them under magnetic induction and reg-  
 148 istering the temperature they achieved, if any, using a thermal camera.

149



150

151

Figure 3. Metal Particles used in the study

152

153 The next step, represented in Figure 1(b), was the manufacturing of the mixtures, in  
 154 which ferromagnetic particles were added together with the fine aggregates. The distri-  
 155 bution of these particles into the specimens was assumed to be uniform, since no for-  
 156 mation of clusters was observed during their mixing. The sample size corresponded to  
 157 half-height Marshall specimens, which were compacted by 40 blows each side using an  
 158 impact compactor [11]. The reduced dimensions of the specimens were chosen with the  
 159 aim of saving resources, in line with the recycling aim of the research. After de-mold-  
 160 ing the specimens, they were pre-notched with a saw to produce a straight crack. Then, the  
 161 specimens were stored in a freezer for 24 hours, in order to ensure that the straight crack  
 162 remained unaltered when breaking (Figure 1(c)). In addition to experimental mixtures  
 163 manufactured using the by-products shown in Figure 3, a control asphalt mixture contain-  
 164 ing fresh steel grits was designed due to the innate ferromagnetic behaviour of these par-  
 165 ticles.

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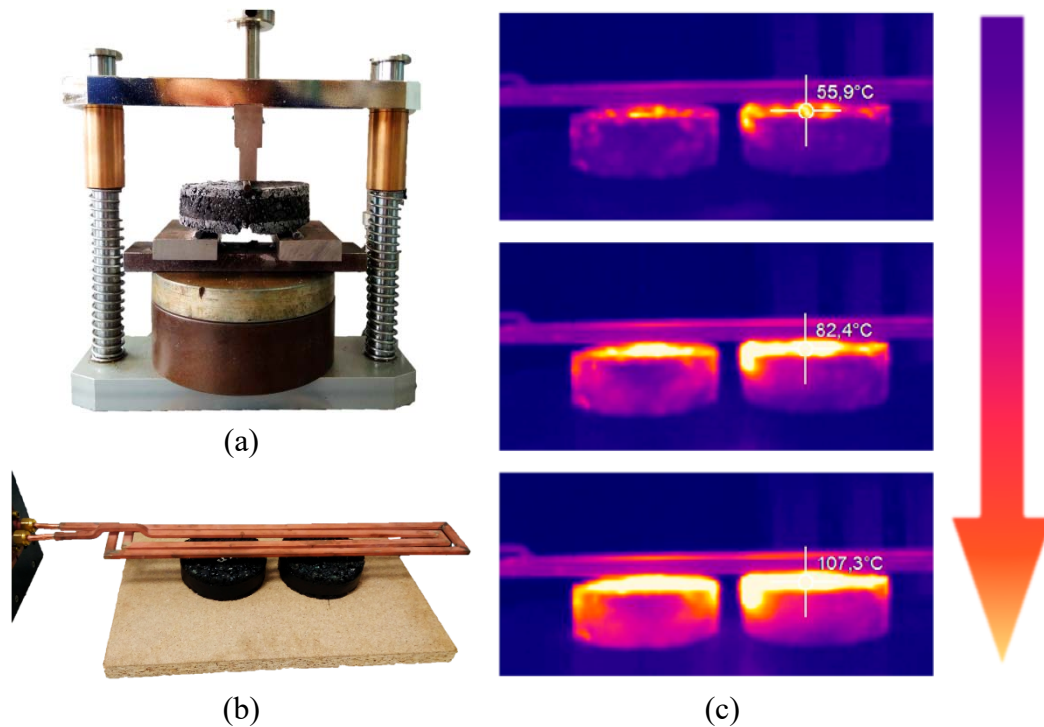
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Once the specimens were frozen, the breaking test (three point bending test as shown  
 in Figure 1(d)) was conducted using an ad-hoc manufactured cradle with a 7 cm separa-  
 tion between supports, as shown in Figure 4(a). This test yielded the max load resistance  
 by the mixtures before healing ( $L^{bh}$ ), which was the first parameter to include in the equa-  
 tion to obtain  $HR$ . This load was recorded by a cell inserted into the compression machine.

After the initial test (break), the specimens were left to rest for two hours (Figure 1(e)),  
 in a temperature controlled room (20°C) before the sixth and more complex stage, the  
 healing (Figure 1(f)). The healing was carried out using the magnetic induction using an  
 EASYHEAT machine (Figure 4(b)). The frequency of the test was set at 329 Hz, whilst

175 the values of intensity and time used varied between 200 A and 600 A and 90 s and 300  
 176 s, respectively. The temperature achievements during each test were recorded by an Op-  
 177 tical Pris Thermal camera, as shown in Figure 4(c).

178



179 **Figure 4.** Details of the break-heal-break test (a) Ad-hoc cradle manufactured to support the three-point  
 180 bending test (b) Position of the specimens under the coil during magnetic induction (c) Thermographic  
 181 images of the specimens when being increasingly heated

182

183 The penultimate phase consisted of letting the specimens rest for 24 hours before re-  
 184 peating the 24 hours freezing and then breaking them through the three-point bending test  
 185 previously described (Figures 1(g) and (h)). The second test (break) shown in Figure 1(i)  
 186 involved obtaining the load resisted by the specimens after healing ( $L^{ah}$ ), which allowed  
 187 the calculation of  $HR$  using Eq (1). Taking into account that the geometric characteristics  
 188 of the specimens were the same before and after healing, it can be assumed that the ratios  
 189 among the loads recorded before and after healing were the same that those corresponding  
 190 to the values of resistance achieved, as illustrated in Figure 1(j).

191

$$HR = \frac{L^{ah}}{L^{bh}} = \frac{R_t^{ah}}{R_t^{bh}} \quad (1)$$

192

## 193 2.2. Statistical modelling

194

### 195 2.2.1. Cluster Analysis

196

197 Cluster analysis is a term coined by Tryon in 1939 [27], who defined it as a set of algo-  
 198 rithms devoted to group different elements based on their similarity to each other. In terms  
 199 of this research, this technique enabled the partition of the initial types of asphalt mixtures  
 200 into a series of groups or clusters. According to the main premise of cluster analysis, this  
 201 implied that the specimens contained in the same group were alike, whilst they differed  
 202 from the mixtures belonging to other clusters.

203 The particular approach selected for this purpose was bottom-up hierarchical cluster-  
 204 ing. Unlike k-means clustering, this process does not require an aprioristic notion of the  
 205 desired number of clusters and involves fewer assumptions regarding the distribution of  
 206 the data. Its working principle consists of allocating a cluster to each item and then start  
 207 a repetitive procedure whereby the items are combined in larger and increasingly hetero-  
 208 geneous clusters according to their similarity, until they all are grouped into a single con-  
 209 glomerate [28].

210 Since hierarchical clustering is based on arranging the data as a distance matrix, the  
 211 number of groups to choose is determined by the similarity measure and linkage method  
 212 used. In this case, the Euclidean distance was selected as a similarity measure, since it is  
 213 one of the most adequate alternatives to deal with interval data [29]. The formulation  
 214 corresponding to this measure is provided in Eq. (2).

215

$$d_{ij} = \sqrt{\sum_k (x_{ik} - x_{jk})^2} \quad (2)$$

216

217 where  $d_{ij}$  is the distance between items  $i$  and  $j$ , such that  $x_{ik}$  and  $x_{jk}$  represent their values  
 218 across the  $k$  variables included in the analysis. As for the clustering algorithm, the ap-  
 219 proach taken was complete linkage, also known as the farthest neighbour method. In com-  
 220 parison with other hierarchical clustering techniques, this was the method proving to be  
 221 less sensitive to identify false clusters [30]. The distance between two clusters is com-  
 222 puted according to the maximum separation between the members within them, as ex-  
 223 pressed in Eq. (3).

224

$$D_{mk} = \max(D_{ik}, D_{jk}) \quad (3)$$

225

226 where  $D_{c_1c_3}$  is the distance between clusters  $c_1$  and  $c_3$ ,  $D_{c_2c_3}$  is the distance between clus-  
 227 ters  $c_2$  and  $c_3$  and  $D_{mc_3}$  is the distance between clusters  $m$  and  $c_3$ , such that  $m$  is the  
 228 merged conglomerate containing clusters  $c_1$  and  $c_2$ . Both distances and clusters are cal-  
 229 culated based on the values achieved by the items to compare across more than two vari-  
 230 ables. In this case, asphalt mixtures were clustered according to the density and content  
 231 of their metal particles, which represented the intrinsic properties of the heating inductors  
 232 used.



233 The interpretation of the output yielded by cluster analysis is supported with a den-  
 234 drogram, which is a tree plot indicating how the items are grouped into larger clusters  
 235 progressively. To this end, it measures the similarity level between the clusters at each  
 236 step of the process, facilitating the decision on where to cut it and determine the final  
 237 grouping.

238

### 239 **2.2.2. Multiple Regression Analysis**

240

241 The predictive modelling of the self-healing capacity of asphalt mixtures was approached  
 242 using Multiple Regression Analysis (MRA), which enabled exploring the relationships  
 243 between  $HR$ , which was the response to fit ( $Y$ ), and a series of variables involved in the  
 244 induction heating process, which served as predictors ( $X_i, X_j$ ).

245 In particular, the predictors considered included the specific weight ( $X_1, \text{kg/m}^3$ ) and  
 246 content ( $X_2, \%$ ) of metal particles, as well as the time ( $X_3, \text{s}$ ) and intensity ( $X_4, \text{A}$ ) set for  
 247 the application of induction heating. The type of bitumen was not considered as a predic-  
 248 tor because it was the same in all the mixtures, whilst heating temperature was only rec-  
 249 orded at the surface of the specimens and, therefore, lacked enough representativeness.  
 250 Since the proposed variables were assumed to interact to each other, the MRA model was  
 251 expressed as shown in Eq. (4).

252

$$Y = B_0 + \sum_{i=1}^n \sum_{j=1}^n B_{ij} * X_i * X_j + E \quad (4)$$

253

254 where  $B_0$  is the constant of the regression equation,  $B_{ij}$  refers to the coefficients by which  
 255 the predictors are multiplied and  $E$  represents the residuals derived from the regression.  
 256 This model was built according to a significance level of 0.05 [31], such that those terms  
 257 demonstrating to be above that threshold were discarded for subsequent steps. To ensure  
 258 the pertinence of the terms included in MRA, their Variance Inflation Factors (VIF) were  
 259 determined to prevent any multicollinearity effect.

260 The quality of the model was assessed using two main goodness-of-fit measures: the  
 261 standard error of the regression ( $S$ ) and the predicted coefficient of determination (pred.  
 262  $R^2$ ).  $S$  indicates the distance between the observed and fitted values taken by the response,  
 263 whilst pred.  $R^2$  involves an evolution of the standard ( $R^2$ ) and adjusted (adj.  $R^2$ ) coeffi-  
 264 cients of determination. It is calculated by systematically removing each observation from  
 265 the model and then calculating how well the omitted values are predicted.

266 In addition to these general verifications, the validity of the regression model was  
 267 verified through a residual analysis. This consisted of evaluating the distribution of  $E$  in  
 268 terms of normality [32], homoscedasticity [33] and independence [34,35], thus preventing

269 the existence of type I and type II errors [36]. Table 1 compiles the graphical and analyt-  
 270 ical tests undertaken to test these assumptions.

271

272 **Table 1.** Graphical and analytical tests used to check the assumptions related to residual analysis

Assumption	Verification	
	Graphical	Analytical
Normality	Quantile-Quantile plot / Histogram	Ryan- Joiner test
Homoscedasticity	Standardized residual vs Fitted value plot	Levene's test
Independence	Standardized residual vs Observation order plot	Durbin-Watson statistic

273

### 274 2.2.3. Response Optimization

275

276 In the context of this investigation, response optimization was used to determine the com-  
 277 bination of factors leading to achieve a target value of  $HR$ , based on the MRA model built  
 278 in the previous step. This was accomplished using the desirability function approach,  
 279 which enables evaluating how well a combination of settings satisfies the purpose sought  
 280 by the response. In other words, response optimization was provided by the combination  
 281 of factors that best fitted the healing ratio desired for the mixtures, with the restriction  
 282 that the values obtained must remain within their upper and lower bounds.

283 Since there was only one response to optimize ( $HR$ ), the approach taken was limited  
 284 to the individual desirability ( $\delta_i$ ) of the settings established to target a fitted response  
 285 value  $\hat{Y}_i$ .  $\delta_i(\hat{Y}_i)$  ranges from 0 to 1, such that 1 represents an ideal solution. Eq. (5) formu-  
 286 lates the desirability function proposed by Derringer and Suich (1980) [37] to calculate  
 287  $\delta_i(\hat{Y}_i)$  when the response is target-based.

288

$$\delta_i(\hat{Y}_i) = \begin{cases} 0, & \text{if } \hat{Y}_i < L_i \\ \left(\frac{\hat{Y}_i - L_i}{T_i - L_i}\right)^s, & \text{if } L_i \leq \hat{Y}_i \leq T_i \\ \left(\frac{\hat{Y}_i - L_i}{T_i - L_i}\right)^t, & \text{if } T_i \leq \hat{Y}_i \leq U_i \\ 0, & \text{if } \hat{Y}_i > U_i \end{cases} \quad (5)$$

289

290 where  $L_i$ ,  $U_i$  and  $T_i$  are the lower, upper and target values desired for the response, whilst  
 291  $s$  and  $t$  represent how important is to achieve the target value. Hence,  $\delta_i(\hat{Y}_i)$  increases  
 292 linearly towards  $T_i$  in case  $s = t = 1$ , whereas the function becomes convex and concave  
 293 if  $s < 1$ ,  $t < 1$  and  $s > 1$ ,  $t > 1$ , respectively.

294

295 Given the values of specific weight and intensity of the metal particles to be modelled,  
 296 the application of response optimization was aimed at fitting the values of  $HR$  targeted  
 297 by making variations in the content of inductors and heating time, depending on whether  
 resource efficiency or quickness are a priority. These variations were restricted by the

298 maximum and minimum values of specific weight and intensity in the mixtures consid-  
 299 ered, which performed as constraints in the optimization problem. Variation were de-  
 300 tected among the collected data.

301

### 302 3. Results and discussion

303

304 This section displays and examines the main results obtained through the application of  
 305 the experimental and statistical approaches described in the methodology. To ensure the  
 306 cohesion between both sections, the results are presented according to the same structure  
 307 used above, whereby the experimental outputs lay the foundations required for the statis-  
 308 tical analyses.

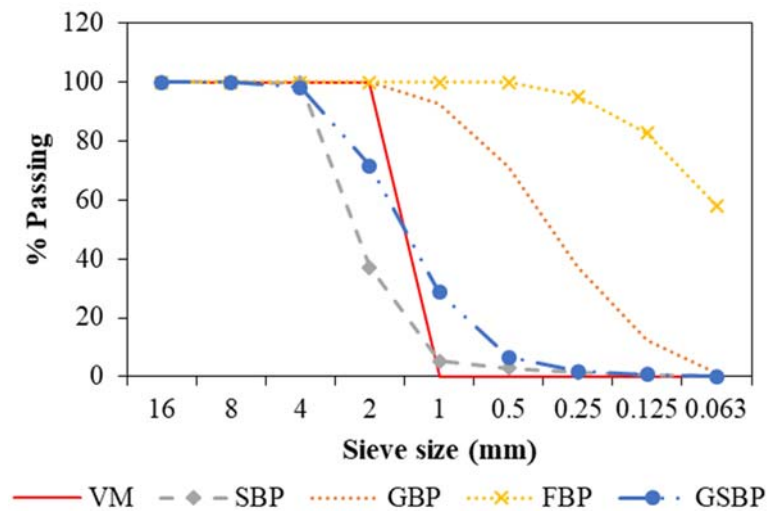
309

#### 310 3.1. Experimental Setup

311

312 Figure 5 illustrates the particle size distribution of the metal particles used. Their specific  
 313 weights, as well as the temperature they achieved (peak and average) when situ-  
 314 ated 2 cm beneath a coil under 100 A magnetic induction, are shown in Table 2.  
 315 Since 20 °C was the room temperature, the values in Table 2 indicated that GSBP  
 316 was almost completely insensitive to magnetic induction.derr

317



318

319

320

Figure 5. Particle size distribution of the metal particles tested

321

**Table 2.** Specific weight and temperature achieved by the metal particles tested

Metal particle	Specific weight (Kg/m <sup>3</sup> )	Heating test	
		Peak T <sup>a</sup> (°C)	Average T <sup>a</sup> (°C)
VM	7.850	79.8	59.4
SBP	7.465	87.4	45.4
GBP	7.639	73.8	39.2
FBP	3.585	53.2	32.0
GSBP	2.875	20.0	20.0

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**Table 3.** Dosage of the experimental mixtures in comparison with the spindle center of that corresponding to dense asphalt concrete (AC-16)

Mixture	Sieve size (mm)										
	22.0	16	8	4	2	1	0.5	0.25	0.13	0.063	
AC-16*	100.0	95.0	67.5	42.5	31.0	23.5	16.0	11.0	8.0	5.0	
VM	0	+5.0	+2.8	+1.8	+3.1	-2.1	-1.7	-0.6		+1.6	
SB	0	+5.0	+2.9	+1.9	+1.3	+1.3	+0.7	+0.3	+0.4	+1.0	
JB1	0	+5.0	+2.4	+1.5	+1.1	+1.1	+0.6	+0.3	+0.3	+0.5	
JB2	0	+5.0	+1.7	+1.1	+0.0	-1.2	-1.0	+0.3	+0.7	+1.1	
JB3	0	+5.0	+3.4	+2.1	+1.3	+1.4	+0.8	-0.4	+0.4	+1.9	

\* Values corresponding to the spindle center

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All the experimental mixtures were subjected to the break-heal-break test as described in the methodology. Hence, the loads resisted before and after healing by each mixture under different pairs of induction intensity and time were recorded, in order to facilitate their comparison. The VM specimens were initially tested with intensities of between 400 A and 600 A and times above 120 s. For instance, the specimens tested for 240 s at 500 A reached a peak *HR* of 73%; nevertheless, they achieved temperatures (above 150 °C), which is not admissible to ensure the absence of changes in the bitumen. Thus, intensities were lowered to 400 A and 300 A, leading to healing ratios of up to 45 % and 47 % when heated during 120 s and 240 s, respectively.

347 Intensities between 300 A and 400 A were not sufficient to achieve good healing ratios  
348 in the SB mixture, to the extent that the specimens tested during 240 s at 300 A only  
349 reached values of *HR* of 7 %. Higher *HR* values started when applying 500 A during 240  
350 s (about 47 %). In this case, the surface temperature of the specimens was about 90 °C,  
351 which was considered a suitable value to soften the bitumen and let it flow to close any  
352 crack within the specimens. Two more groups of SB specimens were tested by increasing  
353 the intensity to 600 A with times of 240 s and 300 s. These two groups provided healing  
354 ratios of 47 % and 55 %, respectively, without exceeding a surface temperature of 130  
355 °C.

356 Again, currents of 300 A and 400 A were not enough to sufficiently heat and, there-  
357 fore, heal the JB1 mixtures. The coupling of a current of 500 A with healing times be-  
358 tween 180 s and 300 s yielded higher healing ratios, whilst the highest *HR* (31%) corre-  
359 sponded to a combination of 240 s and 600 A. Still, the results were not as good as those  
360 achieved in other mixtures. The lower amount of GBP by-products in JB1 in relation to  
361 SB explained why it resulted in an inferior healing performance. Furthermore, JB1 also  
362 contained FBP, which was found to be insensitive to magnetic induction (Figure 5).

363 To reduce the risk of overheating the JB2 specimens, the asphalt mixtures containing  
364 SBP and FBP were tested at currents of 400 A and 500 A and healing times between 120  
365 s and 180 s. The best performance was obtained by combining 180 s and 400 A, whereby  
366 the values of *HR* reached a maximum of 65 %. In general, the results of JB2 showed  
367 higher variability than other mixtures. This is probably due to the SBP particle size, which  
368 is substantially bigger than those of the other by-products tested and can result in either  
369 less homogeneous mixtures or boost the loss of aggregates when breaking the specimens.

370 The final mixture, JB3, contained two by-products: GBP and GSBP. Taking into ac-  
371 count that GSBP barely contributed to the heating of the mixture when applying magnetic  
372 induction, these specimens were tested using the maximum current intensity of 600 A and  
373 varying healing times between 240 s and 300 s. The highest values of *HR* reached were  
374 about 60%, suggesting that the longer the test, the higher the healing ratio when intensity  
375 remained steady.

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## 377 **3.2. Statistical modelling**

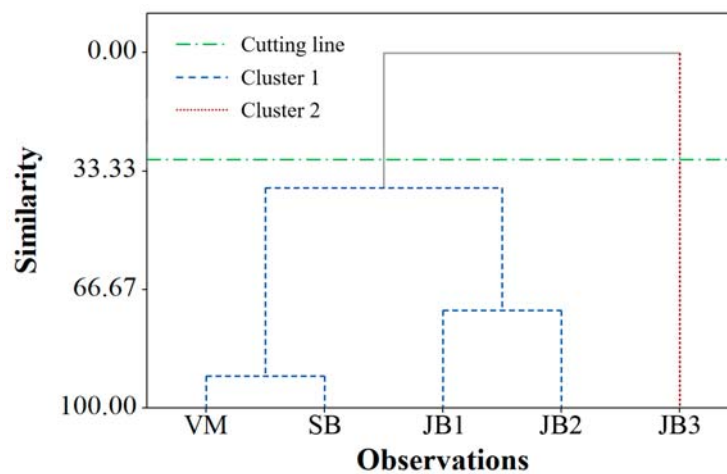
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### 379 **3.2.1. Cluster Analysis**

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381 The characterization and dosages conducted in laboratory enabled the determination of  
382 the specific weight and content of the additives included in the mixtures as heating induc-  
383 tors. These were the variables used for the cluster analysis, as representatives of the in-  
384 trinsic properties of the particles used. In mixtures with more than one single additive,  
385 specific weight was calculated as the weighted average of the individual values corre-  
386 sponding to each particle type, whilst content was computed as their sum.

387 As a result, the following pairs of values [specific weight ( $\text{kg}/\text{m}^3$ ), content (%)] were  
 388 obtained for the inductors included in the 5 asphalt mixtures under evaluation: [7.850,  
 389 5.0] (VM), [7.639, 4.4] (SB), [6.312, 5.5] (JB1), [6.041, 7.9] (JB2) and [5.405, 11.3]  
 390 (JB3). The application of Eqs. (2) and (3) according to these values yielded the dendro-  
 391 gram depicted in Figure 6. Although the density and amount of the metal particles added  
 392 to the mixtures were different in all cases, their dosage was adjusted to be coincident and  
 393 fit the gradation of an AC-16 specimen, thus making them comparable to each other.  
 394 Moreover, having a variety of combinations of specific weight and content was a require-  
 395 ment for building prediction models to optimize the valorization of by-products included  
 396 in asphalt mixtures with self-healing purposes, which was the ultimate objective of this  
 397 research.  
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**Figure 6.** Dendrogram indicating the clustering options to group the experimental mixtures according to their similarity

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The clustering algorithm began by yielding 5 groups, one per mixture, and then continued by producing increasingly heterogeneous conglomerates. Hence, the second possible cut involved 4 groups, whereby the only cluster formed included VM and SB constituents, whose content and specific weight are similar. The next step corresponded to the grouping of JB1 and JB2, leaving JB3 in isolation. Finally, the last meaningful level clustered all the mixtures except JB3. Since grouping definition is affected by the step where the values change more abruptly, the cutting line was drawn to result in 2 clusters, as represented in Figure 6.

Due to the low representativeness of the second cluster, JB3 was removed from subsequent steps. This line of action was consistent with the magnetic and thermal response observed in the particles used as inductors in this mixture, since GSBP was found to be very limited in those terms and made the application of high values of time and intensity necessary. Still, the low resistance of this by-product led to misleading results of *HR*. An

416 alternative path consisting of considering only GBP in JB3 for modelling would not pro-  
 417 vide added value to the final outcome of the study, reaffirming the decision to exclude  
 418 this mixture for prediction purposes.

419 The values of *HR* obtained for the remaining mixtures were arranged according to the  
 420 time and current intensity used. As the same combinations of values were applied to the  
 421 same specimens repeatedly until the results converged using Eq. (1), the data used from  
 422 this point were the mean values of *HR* obtained from such replicates, as specified in Table  
 423 4. To ensure the validity of subsequent prediction models, one randomly chosen sample  
 424 of each mixture was excluded from regression analysis for testing purposes. Under the  
 425 premise of using different values of heating time and intensity depending on the purity of  
 426 the metal particles, the healing ratios obtained were in the same order of magnitude in  
 427 most cases. The main exception to this line was found in SB\_3, which only recovered  
 428 6.9% of its initial resistance after the process due to its reduced content of metal particles  
 429 and the low intensity applied.

430

431 **Table 4.** Training and testing combinations of predictors used to model the healing ratio (*HR*) of asphalt  
 432 mixtures through multiple regression analysis

Purpose	Mixture	Metal particles		Time (s)	Intensity (A)	<i>HR</i> (%)
		Specific weight (kg/m <sup>3</sup> )	Content (%)			
Training	VM_1	7.850	5.0	120	400	28.331
Training	VM_2	7.850	5.0	240	500	67.039
Training	VM_3	7.850	5.0	240	300	45.850
Testing	VM_4	7.850	5.0	120	500	40.984
Training	SB_1	7.639	4.4	240	600	47.709
Training	SB_2	7.639	4.4	300	600	57.822
Training	SB_3	7.639	4.4	240	300	6.914
Testing	SB_4	7.639	4.4	240	500	42.041
Training	JB1_1	6.312	5.5	180	500	15.846
Training	JB1_2	6.312	5.5	120	600	14.976
Training	JB1_3	6.312	5.5	300	500	38.423
Testing	JB1_4	6.312	5.5	240	500	27.243
Training	JB2_1	6.041	7.9	240	300	38.556
Training	JB2_2	6.041	7.9	180	400	57.548
Training	JB2_3	6.041	7.9	120	400	36.300
Testing	JB2_4	6.041	7.9	120	500	40.789

433

### 434 3.2.2. Multiple Regression Analysis

435

436 The values of specific weight, content, time and intensity compiled in Table 4 were  
 437 used as predictors to model *HR*, which performed as response, through multiple regres-  
 438 sion analysis. The use of Eq. (4) led to obtain the model summarized in Table 5, which

439 demonstrated that the interactive effect of specific weight ( $X_1$ ) with the remaining pre-  
 440 dictors ( $X_2$ ,  $X_3$  and  $X_4$ ) was statistically significant (p-values  $< 0.05$  in all cases) and ex-  
 441 plained 90 % ( $R^2$ ) of the variability of the  $HR$  values around its mean. The model was  
 442 determined using the stepwise method, whose working principle consists of systemati-  
 443 cally adding the most significant term or removing the least significant term during each  
 444 step. The results of this procedure indicated that the most efficient model to fit  $HR$  was  
 445 based on the three interactions referred above, such that adding, replacing or removing  
 446 any term, either single variables or interactions, did not improve its quality.

447 All the coefficients associated with these terms were positive, which was logical ac-  
 448 cording to the physical relationships between the predictors and the response. Hence, the  
 449 percentage of resistance recovered after healing was proportional to the purity of the metal  
 450 particles and their content in the mixture, which favoured the fluency of the bitumen  
 451 through the rapid heating of the mixtures. The healing ratios also increased as long as the  
 452 values of time and the intensity applied during the process were higher, boosting the heat-  
 453 ing of the inductors. Furthermore, the p-value of the F-tests for the regression term was  
 454 also below the significance level, indicating that the model built provided a better fit than  
 455 the intercept-only model.

456

457 **Table 5.** Summary of the multiple regression model built for estimating the healing ratio ( $HR$ ) of asphalt  
 458 mixtures

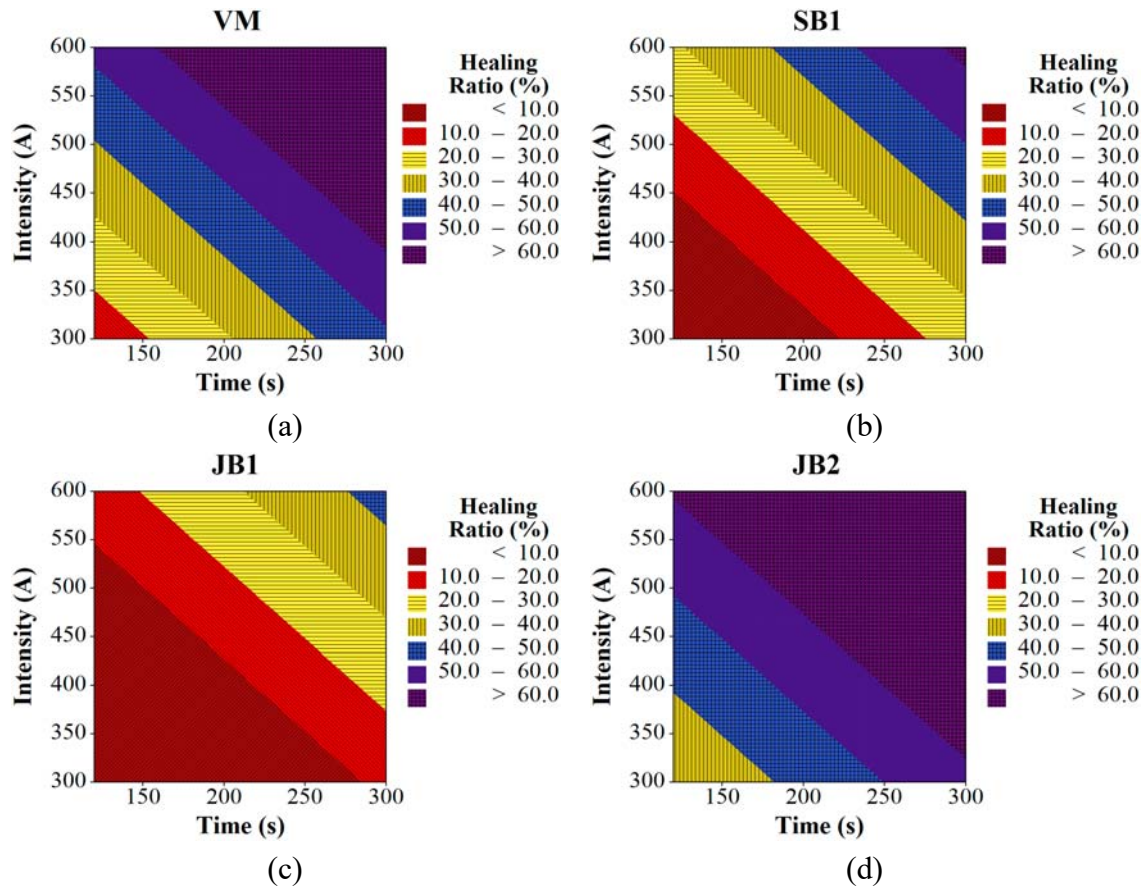
$S$	$R^2$	Adj. $R^2$	PRESS	Pred. $R^2$
7.025	0.90	0.86	962.164	0.75
Term	Coef	F-Value	p-value	VIF
Regression	-	23.40	0.000	-
Constant	-195.6	-	0.000	-
$X_1 * X_2$	3.739	53.65	0.000	1.95
$X_1 * X_3$	0.025	29.43	0.001	1.28
$X_1 * X_4$	0.017	30.25	0.001	1.73

459

460 The value of Adj.  $R^2$  reached (0.86) suggested that the accuracy of the model was not  
 461 compromised by the number of predictors used, since it did not differ much from the  
 462 standard  $R^2$ . This was corroborated by the Variance Inflation Factors (VIF), which were  
 463 very close to the lower bound of this measure (1) for all predictors, suggesting that mul-  
 464 ticollinearity was not an issue. Although the Pred.  $R^2$  slightly decreased in comparison  
 465 with these two coefficients, it was high enough to validate it for making new predictions.  
 466 The standard error of the regression ( $S$ ) was strongly affected by JB2, which was respon-  
 467 sible for almost half of the distance between the values measured in laboratory and the  
 468 regression line. This was mainly attributable to the size of SBP and its combination FBP  
 469 in large quantities (Table 4), which hindered the modelling of this mixture and led it to  
 470 reach the highest values of  $HR$  under all the combinations of time and intensity, as demon-  
 471 strated in the contour plots in Figure 7. On the contrary, the limited purity and amounts



472 of by-products contained in JB1 explained its poor healing performance in comparison  
473 with the remaining mixtures (Figure 7(c)).  
474



475 **Figure 7.** Contour maps representing the relationship between the values time (s) and intensity (A) with  
 476 the healing ratio (HR) achieved by asphalt mixtures (a) VM (b) SB (c) JB1 (d) JB2

477

478 The reliability of the regression model built was first checked in analytical terms, as  
 479 shown in Table 6. The Shapiro-Wilk and Levene's tests yielded p-values above the sig-  
 480 nificance level (0.05), guaranteeing the normality and homoscedasticity of residuals.  
 481 Their independence was checked through the comparison of the Durbin-Watson statistic  
 482 ( $D$ ) with the lower ( $D_L$ ) and upper ( $D_U$ ) bounds established by Savin and White (1977)  
 483 [38], such that  $(4 - D) > D_U$  indicates an absence of serial correlation,  $D < D_L$  suggests  
 484 a positive correlation and  $D_L < D < D_U$  involves that the test is inconclusive. For a sam-  
 485 ple size of 12 (Table 4) and a number of terms equal to 3 (Table 5),  $D_L$  and  $D_U$  are 0.812  
 486 and 1.579, respectively. Since  $(4 - D) = 1.467$ , the test was found to be inconclusive.

487

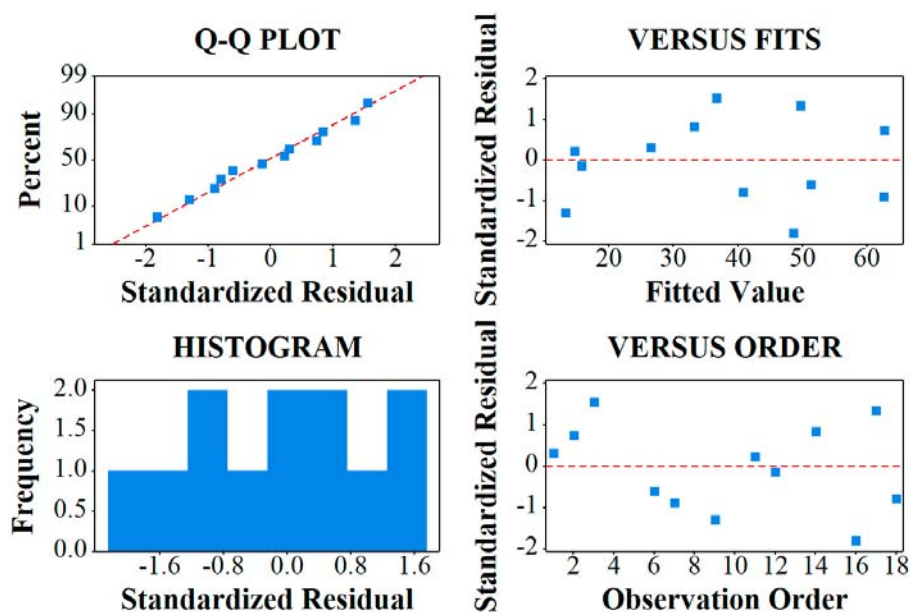
488 **Table 6.** Analytical verification of the assumptions involving the residuals of multiple regression analysis

Normality		Homoscedasticity		Independence
Shapiro-Wilk	p-value	Levene	p-value	Durbin-Watson
0.970	0.915	0140	0.931	2.533

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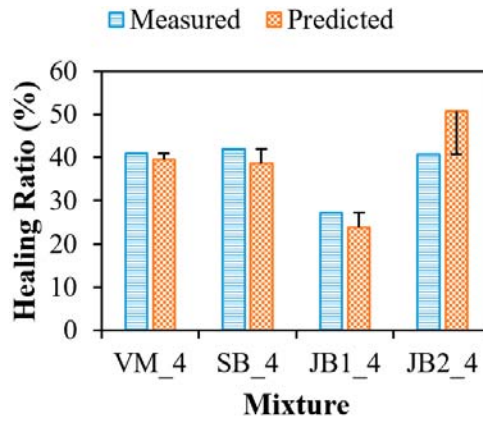
490 To further ensure the robustness of the model summarized in Table 5, the assumptions  
 491 concerning its residuals were also verified graphically, as illustrated in Figure 8. The re-  
 492 semblance of the residuals to the reference line of the quantile-quantile (Q-Q) plot, as

493 well as the approximate bell-shape of the histogram, confirmed that the assumption of  
 494 normality was met. The unbiased distribution of the residuals in the versus fits plot also  
 495 ensured the homoscedasticity of the model. Finally, the lack of clear patterns and the  
 496 random location of the residuals around the reference line in the versus order graph indi-  
 497 cated that they were not correlated to each other, which enabled assuming their independ-  
 498 ence too.  
 499  
 500



501  
 502 **Figure 8.** Residual plots used to test the assumptions of multiple regression analysis graphically  
 503

504 As a final step to prove the validity of the regression analysis conducted, the model  
 505 summarized in Table 5 was used to estimate the healing capacity corresponding to the  
 506 specimens reserved for testing, as indicated in Table 4. Figure 9 illustrates the fit between  
 507 the values of *HR* measured in laboratory and the regression model. The results proved to  
 508 be very accurate for the VM, SB and JB1 mixtures, to the extent that the errors between  
 509 measured and predicted values were less than half *S* in all cases (Table 5). However, the  
 510 estimate for the JB2 mixture resulted in an error of 10.016, which ratified the singularity  
 511 of this mixture, as a result of its uneven combination of low specific weight and high  
 512 content of by-products.  
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**Figure 9.** Fit between the values of healing ratio (*HR*) measured in laboratory and predicted through multiple regression analysis for the specimens reserved for testing

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### 518 3.2.3. Response Optimization

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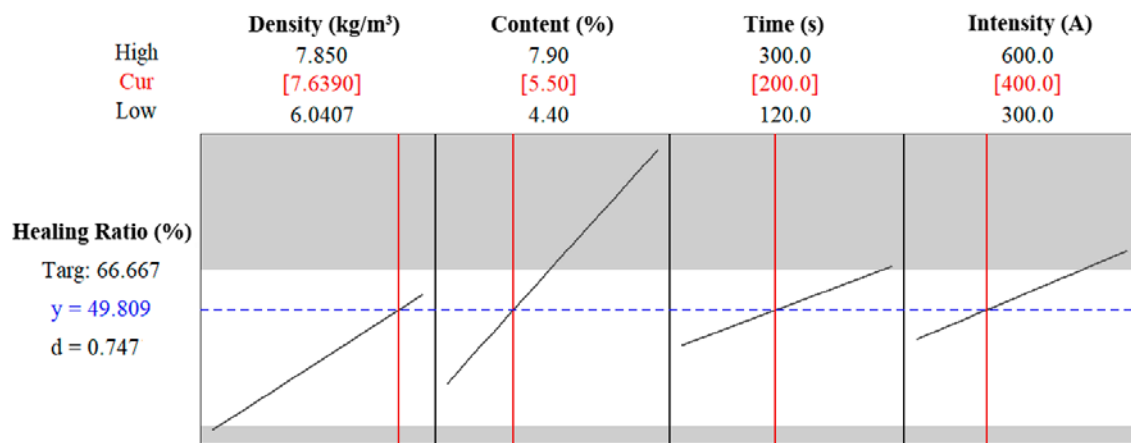
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Based on the multiple regression model built in Table 5, the application of the response optimization framework enabled the calculation of the minimum amount of time and resources required to achieve *HR* targeted values. Figure 10 depicts the working principle of this approach, indicating the extent to which changes in the variables used as predictors produced variations in the healing ratio. Hence, the variations derived from the displacement of the vertical lines associated with the predictors with respect to the horizontal axis can be combined to reach desired healing ratios. This is exemplified for a mixture containing 5.5 % of GBP and subject to induction during 200 s at 600 A, which resulted in a value of *HR* of 49.8 %.



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**Figure 10.** Optimization plot produced to target a healing ratio (*HR*) of 66.667 % by changing the values taken by the predictors

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In this case, a healing ratio of 66.7 % was set as a target, representing a recovery of two thirds of the original resistance of asphalt mixtures after breaking. This value was considered to be representative for a reasonable degree of healing capacity under real conditions. Since the underlying objectives sought were saving resources and be as time-

538 efficient as possible, intensity was a restricted parameter established according to the  
 539 heating susceptibility of the metal particles. Therefore, this parameter was set at 500 A in  
 540 VM and JBP1, which proved to be more likely to produce alterations in the bitumen, and  
 541 was increased to 600 A for SBP1 and SBP2. The implementation of the desirability func-  
 542 tion synthesized in Eq. (5) according to these conditions yielded the results compiled in  
 543 Table 7.

544

545 **Table 7.** Optimized values of content (%) and time (s) obtained for the resource efficiency and quickness  
 546 scenarios using the desirability function approach

Mixture	Objective	Content (%)	Time (s)	Intensity (A)	Healing Ratio (%)	$\delta_i(\hat{Y}_i)$
VM	Resource efficiency	4.760	297.119	500.000	66.667	1.000
	Quickness	5.926	120.000	500.000	66.667	1.000
SBP1	Resource efficiency	4.563	297.006	600.000	66.667	1.000
	Quickness	5.728	120.000	600.000	66.667	1.000
SBP2	Resource efficiency	6.474	300.000	600.000	66.667	1.000
	Quickness	7.658	120.000	600.000	66.667	1.000
JBP1	Resource efficiency	7.418	300.000	500.000	66.667	1.000
	Quickness	7.900	120.001	500.000	50.805	0.735

547

548 Overall, all the mixtures were found to be capable of achieving the target established  
 549 ( $\delta_i(\hat{Y}_i) = 1$ ), except JBP1 for the quickness scenario, which resulted in a desirability of  
 550 0.735. This low value of  $\delta_i(\hat{Y}_i)$  was due to the content of the metal particles used to man-  
 551 ufacture this mixture, which was the upper bound taken by the optimization problem for  
 552 this variable. Reaching a value of  $\delta_i(\hat{Y}_i) = 1$  in this scenario would involve increasing  
 553 the by-products to approx. 10 % ; however, this course of action may result in an exces-  
 554 sively dense asphalt mixture, which would cause transportation and installation prob-  
 555 lems.

556

557 Otherwise, the remaining mixtures reached the value of  $HR$  sought under both sce-  
 558 narios. Beyond the limitations of the regression model ( Table 5), the values of content  
 559 and time ( Table 7) show how the self-healing of asphalt mixtures can be optimized in  
 560 terms of either resource or time efficiency. In particular, the first course of action would  
 561 be to maximize the valorization of metal wastes in the road industry, where the construc-  
 562 tion and maintenance of pavements traditionally involve large amounts of raw material.  
 563 However, since the metal particle contents yielded by the optimization process differed  
 564 from those used to manufacture the specimens in laboratory to resemble an AC-16 dense  
 565 asphalt mixture (Figure 2), the practical application of these values would require rede-  
 566 signing their dosage, in order to ensure that they meet the mechanical and technical pa-  
 567 rameters required for their implementation.

567

## 568 4. Conclusions

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570 This study was concerned with the statistical modelling of the self-healing capacity of  
571 asphalt mixtures containing different combinations of metal particles, focusing on the use  
572 of industrial metal by-products to reduce economic cost and environmental impacts of  
573 road materials. A methodology integrating cluster algorithms, multiple regression analy-  
574 sis and response optimization was designed, applied and validated using the results ob-  
575 tained in laboratory regarding the healing potential of five experimental asphalt mixtures  
576 heated through magnetic induction. The analysis of these results led to the following con-  
577 clusions:

- 578 • The experimental tests highlighted the suitability of the metallic by-products used as  
579 heating inductors in the self-healing process of asphalt mixtures. The only exception  
580 to this trend were the green foundry slags, whose thermal and magnetic response was  
581 almost null. In general, the values of heating time and intensity required by the exper-  
582 imental mixtures were higher due to the lower purity of the by-products, although the  
583 steel shot wastes from sandblasting resulted in healing ratios similar to those of the  
584 control specimens with virgin metal particles.
- 585 • In line with the inferences extracted from the laboratory results, cluster analysis led  
586 to discard the mixture type containing green slags, due to its almost null heating po-  
587 tential and high fragility. The regression model built to replicate the laboratory results  
588 for the four remaining mixtures reached high coefficients of determination and met  
589 all the assumptions regarding its residuals, guaranteeing its reliability to make new  
590 predictions. In fact, the application of the model to the specimens excluded from the  
591 analysis for testing purposes yielded estimates in the order of magnitude of the stand-  
592 ard error of the regression, which further corroborated its validity.
- 593 • The desirability function approach used for response optimization showed that the  
594 amount of metal particles to include in the mixtures and the time of magnetic induc-  
595 tion required to achieve targeted healing ratios. This step was intended to increase the  
596 viability of the self-healing of asphalt mixtures. On the one hand, it can help to max-  
597 imize the recycling of industrial by-products as a valuable resource in asphalt design  
598 and road conservation. On the other hand, it can also limit the traffic disruptions as-  
599 sociated with conventional road maintenance practices by designing asphalt mixtures  
600 that minimize the time required to apply magnetic induction.

601 Although the results produced in this study proved to be valid and meaningful, further  
602 work is needed. Future work should focus on testing the proposed framework using more  
603 specimens with different values of specific weight and content of metal particles, as well  
604 as new asphalt mixture dosages to verify how generalizable the optimized results are. In  
605 this vein, another area of research to develop in the future concerns the incorporation of  
606 additional mechanical tests conducted in laboratory into the statistical modelling, in order  
607 to provide a more comprehensive characterization of the experimental behaviour of self-  
608 healing asphalt mixtures.

609

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611

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