*RAI: R*apid, *A*utonomous and *I*ntelligent Machine Learning Approach to Identify Fire-vulnerable Bridges

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Abstract

Recent surveys have noted that the majority of bridges continue to serve for a prolonged period of time (+40 years) that far exceeds its intended operational lifespan. Given our limited resources to maintain and upkeep bridges, these structures become notoriously vulnerable to extreme events. Building upon the fact that bridges continue not to be specifically designed to withstand the adverse effects of fire, this study presents the development of a rapid, automated, and intelligent (*RAI*) approach that leverages machine learning to identify vulnerable bridges to fire hazard. This work also presents details on a comprehensive database comprising actual observations collected from 135 notable and international bridge fire incidents. This database was developed to train two machine learning techniques, deep learning and genetic algorithms, to quantify hidden patterns that govern the propensity of existing/new/historical bridges to undergo fire damage and/or fire-induced collapse via a multi-classification analysis. The proposed *RAI* approach also has the capability to pinpoint fire-vulnerable bridge components and to display its level of confidence in its predictions. As such, our approach can be of aid to bridge engineers and government officials (who may not be well-versed in fire design) with accuracy reaching 89.6%. This approach is implemented into a software (App) with optimized architecture and reduced computational complexity and hence is easily scalable and integratable into a user-friendly framework and

27   handheld devices. The outcome of this study shows that the *RAI* approach can be deployed to

28   arrive at an instantaneous assessment of fire vulnerable bridges.

29   *Keywords:* Bridges; Fire; Machine learning; Classification; Deep learning.

30   **1. Introduction**

31   Bridges are strategic transportation structures that offer commuters with a mean for ground

32   transportation and facilitate supply chain operations. As such, bridges are expected to withstand

33   day-to-day activities (i.e., traffic demands, etc.) and environmental conditions (wind, snow, etc.).

34   Similarly, bridges are also equally expected to endure extreme load conditions as well such as

35   impact and earthquake. Fortunately, bridge design codes provide guidance and provisions to

36   enable engineers to properly designing bridges against the aforementioned actions [1,2]. However,

37   there are still very limited provisions that cover the fire design of bridges [3]. In fact, the only

38   standard that contains some guidelines to mitigate bridge fires is the National Fire Protection

39   Association (NFPA) Report 502 [4]. Still, one should note that the NFPA 502 only lists general

40   and qualitative recommendations that apply to bridges with long spans (greater than 300 m); which

41   constitute a minute portion of total bridge population. In order to bridge this knowledge gap, a call

42   for action is being fostered by various researchers [5–8].

43   Bridge fires have been recognized as a critical problem given the rapid urbanization and the fact

44   that fires could break out anywhere and anytime due to natural causes (i.e., lightning, wildfires,

45   etc.) or human interventions (vehicle collision, arson, terrorism, etc.) [9]. Bridge fires are

46   associated with the burning of hydrocarbon fuels and unlimited ventilation, and hence these fires

47   are classified with high intensity (e.g., temperatures rapidly reaching 800-1000°C within the first

48   few minutes). Such fires release a significant amount of thermal energy and pressure, both of which

49   can adversely damage the integrity of a bridge infrastructure and develop thermally-induced forces

50   that can trigger significant damage or collapse [6]. This, when combined with the fact that bridges

51   lack fire protection measures or firefighting equipment, reflects the destructive nature of bridge

52   fires [10,11]. Knowing that the majority of bridges are poorly maintained, with many showing

53   signs of distress (e.g., cracking, exposed reinforcement, etc.) or being repaired with flammable

54   fiber-reinforced polymers (FRP) systems, further amplifies the adverse effects of fire hazard [12].

55   While it is true that bridge fires may burn out quickly (whether due to firefighting or burning out

56   of fuels), still such fires can induce large losses to physical properties of construction materials,

57   and this may eventually lead to partial or complete collapse [13]. Fortunately, most bridge fires do

58   not trigger a collapse but instead cause some level of damage. In such incidents, proper

59   investigation, inspection, and maintenance of the damaged bridge are required to be undertaken

60   by authorities. During this process, the bridge is either entirely or partially shut down as to serve a

61   reduced traffic volume, which imposes substantial delays to traffic flow and supply chain

62   operations [14].

63   Hence, identifying fire-vulnerable bridges can enable authorities and bridge engineers to take

64   appropriate actions to help minimize the: (1) vulnerability of such bridges and (2) enhance the

65   resilience of transportation networks. Given that there are more than 600,000 operational bridges

66   in the United States infers that identifying fire-vulnerable bridges can both be hectic and time-

67   consuming.

68   The open literature contains a few works that explored different solutions to identify vulnerable

69   bridges to earthquake and flooding, but little research has examined the problem of bridge fires

70   [15–18]. For instance, the authors have developed a fire-based importance factor approach similar

71   to that used for wind design in earlier works [19,20]. This importance factor is developed by

72   assigning weightage factors to reflect upon: (1) the vulnerability of a bridge to fire hazard, (2)

73   traffic usability of a bridge and (3) presence of any fire mitigation strategies. This importance

74   factor approach was validated against a number of actual bridge fire incidents and, despite its

75   iterative procedure, was shown to yield accurate predictions. In a similar manner, Peris-Sayol et

76   al. [6] carried out a statistical analysis on 154 bridge fires. The outcome of their analysis shows

77   that wooden bridges, as well as those built with steel I-girders, were shown to be most vulnerable

78   to fire. As such, similar bridges were recognized to have high vulnerability to fire hazards. Finally,

79   Gidaris et al. [21] proposed the use of multiple-hazard fragility and restoration models to identify

80   vulnerable bridges within a transportation network. However, the same researchers also noted the

81   lack of fragility models that can be applied to examine bridge fires.

82   This study hypothesizes that identifying fire-vulnerable bridges can be carried out with ease by

83   leveraging a modern form of analysis that utilizes machine learning. As such, this paper tailors

84   two machine learning techniques (namely: deep learning and genetic algorithm) to identify

85   bridges' vulnerability to fire hazards. These techniques are trained to analyze observations

86   collected from 135 international bridge fires. The outcome of the presented analysis led to the

87   development of a rapid, automated, and intelligent (*RAI*) approach that can be applied to identify

88   vulnerable bridges to fire hazard, as well as estimate the expected degree of damage an existing,

89   planned, or historical bridge could endure if exposed to a fire incident. The *RAI* approach is

90   developed with an optimized architecture, and reduced computational complexity and hence is

91   easily scalable and can be deployed to arrive at an instantaneous assessment of fire vulnerable

92   bridges.

93 **2. A Look into Recent Bridge Fires**

94 Statistical studies that examine bridge fires were conducted by Wardhaua and Hadipriono [22] and

95 Scheer [11]. These researchers reported that 3.2% and 4.9% of all bridges could experience some

96 degree of damage due to fire throughout their service life, respectively. Thus, bridge fires can be

97 classified under rare events [19,22]. Despite this small probability, Table 1 lists notable bridge

98 fires that occurred due to varying causes. This table also shows the devastating effect of bridge

99 fires in terms of structural damage and economic losses.

100 Table 1 Notable fire incidents in bridges

Bridge location	Year	Cause of fire	Bridge type	Description of damage/collapse
I-85, GA, USA	2017	Vandalism (burning of Polyvinyl chloride (PVC) pipes) that were stored under the bridge.	Concrete.	Major spalling and one span collapsed after 30 min of fire.
I-75, MI, USA	2015	Collision of a gasoline tanker carrying 9000 gallons.	Composite.	Concrete deck and steel girders were damaged.
I-15, CA, USA	2014	Blowtorching during construction.	Composite.	Bridge collapsed.
Freeway 60, CA, USA	2011	Collision of a tanker truck carrying 128 m^3 of gasoline.	Prestressed concrete.	Concrete girders were significantly damaged.
Zhuoshui Fengyu Bridge, China	2013	Unknown.	Wood.	Bridge collapsed.
I-75, MI, USA	2009	Collision.	Composite.	Bridge collapsed.

Big Four Bridge, USA	2008	Electrical short circuit within the lighting system.	Steel.	Minor damage which also resulted in large debris on the bridge.
Bill Williams River Bridge, AZ, USA	2007	Collision.	Prestressed concrete.	Concrete girders were severely damaged.
Rio–Antirrio bridge, Greece	2005	Lightning strike.	Prestressed concrete.	Cable failed after 40 minutes into fire.
Wiehltalbrücke Bridge, Germany	2004	Collision.	Steel.	Major damages that costed €7.2 million.
I-95, CT, USA	2003	Collision.	Composite.	Bridge collapsed.

101

102 Table 1 shows that most bridge fires break out due to spillage of highly flammable fuels or

103 hydrocarbon chemicals (with low flash point) in the aftermath of the collision of fuel tankers. The

104 same table also shows that bridge fires can occur due to natural causes (lightning strike), or

105 manmade accidents (blowtorching, etc.). Thus, despite the common public perception that it is

106 unlikely for a bridge to collapse as a result of a fire, as well as a low probability of fire break out

107 in bridges, the fact of the matter is that intense fires can indeed trigger fire-induced collapse. It is

108 worth noting that the New York state department of transportation reported that nearly three times

109 more bridges have collapsed due to fire than earthquakes in a national survey covering different

110 jurisdictions within the United States [23]. This survey emphasizes the importance of developing

111   proper measures to mitigate bridge fires. To further illustrate the adverse impact of bridge fires,

112   two incidents are described herein.

113   The first bridge fire broke out under the I-85 bridge near Atlanta, GA. The I-85 bridge was initially

114   built in 1953 with ten prestressed concrete girders resting on reinforced concrete piers. This bridge

115   was well maintained as it was refurbished in 1985 and scored a high sufficiency rating of 94.6%

116   in 2015. On March 30, 2007, a fire broke out underneath the bridge due to the ignition of stored

117   large Polyvinyl chloride (PVC) pipes. The burning of these PVCs has led to rapidly growing

118   temperatures in the range of 900-1100°C. Thirty minutes into this fire, a 30.3. m long span

119   collapsed, while adjacent piers and spans underwent significant fire-induced spalling damage. At

120   the time of the fire, this bridge was estimated to serve 243,000 per day, and the losses arising from

121   this incident were evaluated at $10 million.

122   The second bridge fire described here is one that broke out at the Wiehltal Bridge in 2004 in

123   Germany. The Wiehltal steel bridge measures 705 m in length and 31 m in width. This fire ignited

124   as a result of a collision between a speeding car and a fuel tanker that was transporting 8700 gallons

125   of gasoline. This collision has pushed the fuel tanker through the bridge's guardrail, letting it to

126   fall from a height of 30 m, thus exploding and killing the driver. As a result of this explosion,

127   intense heat was generated and reached temperatures of 1200°C [24]. This heat has severely

128   damaged the unprotected steel bridge and caused it to deform over 60 m. While the bridge did not

129   collapse, this fire has caused significant damages that required a 20 m × 31 m segment of the steel

130   bridge to be replaced. The overall damage in the aftermath of this incident was estimated at €32

131   million, and it took three tears to re-opened the bridge for traffic three years later. This incident is

132   considered to be one of the most expensive accidents in Germany.

3. Development of Bridge Fire Database

To effectively adopt machine learning to identify vulnerable bridges to fire hazards, one must develop a proper database that covers various bridges and fires. Hence, a literature review was first carried out to document notable bridge fires. During this process, a challenge arises that is related to identifying key factors (from a fire-vulnerability point of view) as a mean to attain a proper database that will lead to developing an optimally designed machine learning architecture with low computing complexity. Thus, the survey prioritized to document key factors that were noted in recent works, recommendations of departments of transportations (DoTs), and from consultation with practicing engineers [3,6,7,19,20,25–29]. These recent works have identified a number of key factors that were then divided into three domains; *physical features of bridges*, *traffic features served by the bridge*, *fire features of the incident*, as well as the *damage level* imposed upon the bridge resulting from fire*. Overall, this survey led to collecting 135 international bridge fires with nine different features, each of which will further be described below.

3.1 Physical Features

The physical features that are identified to govern the vulnerability of bridges against fire hazard encompass: *structural system* and *construction materials* used in load bearing, *span* length and *age* of the bridge. A look into these features reveals that these are also the same characteristics that govern the structural performance of a bridge. For instance, typical "structural systems, *S*" in bridges can be grouped under cable-type (cable-stayed and suspension), girder-type (box or I-shaped), and arch/truss-like. Cable-type bridges are often designed to span over natural obstacles

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* While the open literature contains much more bridge fires, the compiled database only opted to include bridges with full and reliable documentations on the aforementioned features.

153   or serve as landmarks, and hence these bridges have complicated construction and load pathing

154   [27]. On the other hand, traditional types of bridges are associated with relatively short spans and

155   easier design/construction. Figure 1 shows that the developed database contained 15 cable-type

156   bridges, 81 girder-type bridges, and 39 arch/truss-like bridges. As expected, there is a smaller

157   number of fires that occurred in cable-type bridges given that there is a smaller number of these

158   bridges in a given bridge population.

(a) Structural systems

(b) Construction materials

(c) Span (listed in vertical axis) – represented in meter

(d) Age (range shown in brackets) – represented in years

(e) Geographic/historical importance

(f) Number of lanes

(g) Location of fire break out

(h) Fuel type

Fig. 1 Statistics of the developed database

(i) Magnitude of damage

159

160   The aforenoted structural systems are often made from "construction materials, *M*" such as

161   concrete, steel, or timber. While these three materials can satisfy design requirements at ambient

162   conditions, each of these materials may still suffer from certain limitations under fire conditions.

163   For example, steel and timber structural members are prone to fire damage due to the poor thermal

164   properties of steel and the combustibility of timber. The same susceptibility may not be as apparent

165   in concrete bridges (i.e., reinforced or pre-stressed concrete), especially those that utilize novel

166   additives (steel and/or polypropylene fibers) to mitigate fire-induced spalling [30]. A blend

167   between steel and concrete bridges results in a composite construction that capitalizes on the

168   synergy between concrete and steel and hence achieves improved fire performance. Figure 1b

169   shows that the collected database contains 38 concrete bridges (24 reinforced concrete and 18 pre-

170   stressed concrete bridges), 41 steel bridges, 39 composite bridges, and 17 timber bridges[†].

171   The "span, *P*" of a typical bridge is mainly governed by the presence of any natural obstructions

172   (i.e., water bodies), selected structural system and material of construction, as well as expected

173   traffic demands. Hence, the span of a bridge is directly linked to the bridge's structural capacity

174   and performance. The average span of all bridges collected as part of this database is 108 m, with

175   a maximum of 737 m and a minimum of 5 m. The full distribution of spans in all bridges is shown

176   in Fig. 1c. As can be seen, most of the bridges have spans that are shorter than 100 m, as typical

177   of most highway bridges.

[†] Some modern bridges may solely use fiber-reinforced polymer (FRP) composites and/or special glasses as load bearing elements. Very limited works have examined these bridges and hence such bridges were not included in the developed database.

178   Bridges are open structures that are continuously exposed to weathering and environmental

179   conditions. Hence, such structures experience continuous deterioration, whether arising from

180   environmental factors (corrosion, humidity, etc.), loading factors (overstressing, fatigue), or

181   extreme events (earthquakes, hurricanes, etc.). While most DoTs require bridges to be inspected

182   regularly, the majority of bridges are not upgraded to current standards nor properly upkept due to

183   the limited resources. To consider such effect, the "age, A" of a bridge is identified as a key

184   character that falls under the physical features domain. The compiled database has an average age

185   of 50.6 years (with standard deviation = 36.8 years). The same database also has a maximum and

186   minimum age between 146 years and 1 year old, respectively.

187   *3.2 Traffic Features*

188   Two main features were found to be related to traffic demands in bridges; "geographical

189   significance, G" as well as "number of lanes, N". These features roughly represent the overall

190   expected traffic flow, closeness of a given bridge to population concentration, and availability of

191   nearby/alternative main routes. The geographical significance of bridges is grouped under three

192   classes: rural, sub-urban and urban – following a previous work by the authors [20]. *Rural* bridges

193   are those that serve small traffic and can be found in rural areas. *Sub-urban* bridges can be grouped

194   under those that present landmarks to a specific region. Finally, *urban* bridges present bridges with

195   high historical/national importance (i.e., Brooklyn Bridge, NY). Figure 1e shows that our database

196   contains a uniform spread of bridges wherein: 46 bridges were classified under the rural category,

197   and 44 and 45 bridges under sub-urban and urban categories, respectively. The number of lanes

198   reflects the magnitude of allowed daily traffic and in way, a bridge's traffic serving capacity.

199   Figure 1f shows the distribution of bridges' number of lanes wherein about half contains 1-3 lanes.

200   *3.3 Fire Features*

201   The magnitude of a bridge fire is governed by the type/size of available fuel and ventilation. While

202   the latter can be assumed to be similar in all bridge fires, given that bridges are open structures,

203   the type of fuel can vary from one incident to the other. As such, two features are identified to be

204   of importance: "type of fuel, T" involved in the fire and "closeness of fire break out, C" to the

205   bridge [31]. Three types of fuels were considered; those from vehicles in direct collision with other

206   vehicles (i.e., gasoline/diesel), or those from fuel tanker/barge crashes (hydrocarbon fuels), and

207   other types of flammables (i.e., stored materials, PVCs, wildfires, etc.) – see Fig. 1h. For

208   simplicity, three locations for fire break out were considered herein; near/in the vicinity of the

209   bridge, above the bridge, and under the bridge. Figure 1g shows that 4, 69 and 62 bridge fires

210   belong to the aforementioned locations.

211   The reader should note that while the bridge fires collected in this study may not share a similar

212   magnitude, still the harsh effects of a fire (whether by degrading material properties or imposing

213   thermally-induced forces) share a similarity. In fact, such a factor may not be readily available as

214   the size/intensity of a particular fire is not usually formally documented in a quantitative manner

215   (i.e., with details on the exact magnitude of burned fuel, maximum temperatures reached, etc.) but

216   instead is qualitatively described. As such, the magnitude of a bridge fire was not explicitly

217   accounted for as a key feature.

218   While the above discussed nine features cover three domains, one can also argue that other features

219   could also be considered (i.e., bridge rating, average daily traffic, last documented upkeep, etc.).

220   However, many of such features were not explicitly added to the developed database due to the

221   absence of evidence, especially in older or international bridges. On a more positive note, the

222   developed database can still be extended given that information on new features is provided. The

223   methodology presented herein is scalable and can include additional dependent, as well as

224   independent, features as shown in previous works [32–34].

225   *3.4 Damage Magnitude*

226   Contingent upon the fire incident, the magnitude of the damage the bridge experiences and any

227   possible stress to the surrounding transportation network can vary. On the one hand, if a bridge

228   does not undergo significant fire damage, then this bridge can be re-opened for traffic immediately.

229   On the other hand, major damage to a bridge is expected to be repaired. To enable timely repairs,

230   traffic can be either reduced or detoured. Thus, there are three classes of "damage magnitude, D"

231   that are to be considered herein; no/minor damage (does not necessitate shut down), significant

232   damage (necessitates shut down), and collapse.

233   It should be noted that a criterion to evaluate the goodness of a database was proposed by Frank

234   and Todeschini [35], who recommended data scientists to maintain a ratio of 3-5 between the

235   number of observations and input parameters. In this work, this ratio was satisfied.

236   **4. Description of Machine Learning Approach**

237   The development of the proposed *RAI* machine learning approach and two computing techniques

238   employed herein: deep learning (DL), and genetic algorithms (GA), are presented in this section.

239   *4.1 General Approach*

240   The proposed approach for identifying vulnerable bridges to fire hazards consists of two steps (see

241   Fig. 2). First, a database (or several databases) on bridge fires is compiled. This database is then

242   treated and processed via data structuring to handle outliers, missing data and/or apply feature

243   transformation operations (i.e., aggregations, feature engineering, etc.). Typically, such operations

244   rely on domain knowledge, intuition, and data manipulation and hence can be lengthy and hectic

245   to perform manually. Hence, feature transformation comes in handy, especially in large datasets

246   of varying features. Then, suitable machine learning techniques are selected, and then these

247   techniques are properly developed via a rigorous training and verification procedure. Such a

248   procedure trains the selected techniques via analyzing actual bridge fires. As such, compiling a

249   representative database that is uniformly and unbiasedly developed (such as that presented in Sec.

250   3.0) becomes of great importance. Once the selected techniques are adequately trained and

251   validated, then these techniques are deployed. This deployment will entail analyzing new bridges

252   (that were not used in the development stage) to evaluate their vulnerability against fire hazards.

253   Given the automated nature of the *RAI* approach, this approach can be easily integrated into bridge

254   population (i.e., from national (Federal Highway Administration (FHWA)/National Bridge

255   Inventory (NBI)) or regional (DoT-based) databases) to identify fire-vulnerable bridges with ease.

256   *RAI* can also be deployed by design firms to analyze bridges being designed or retrofitted.
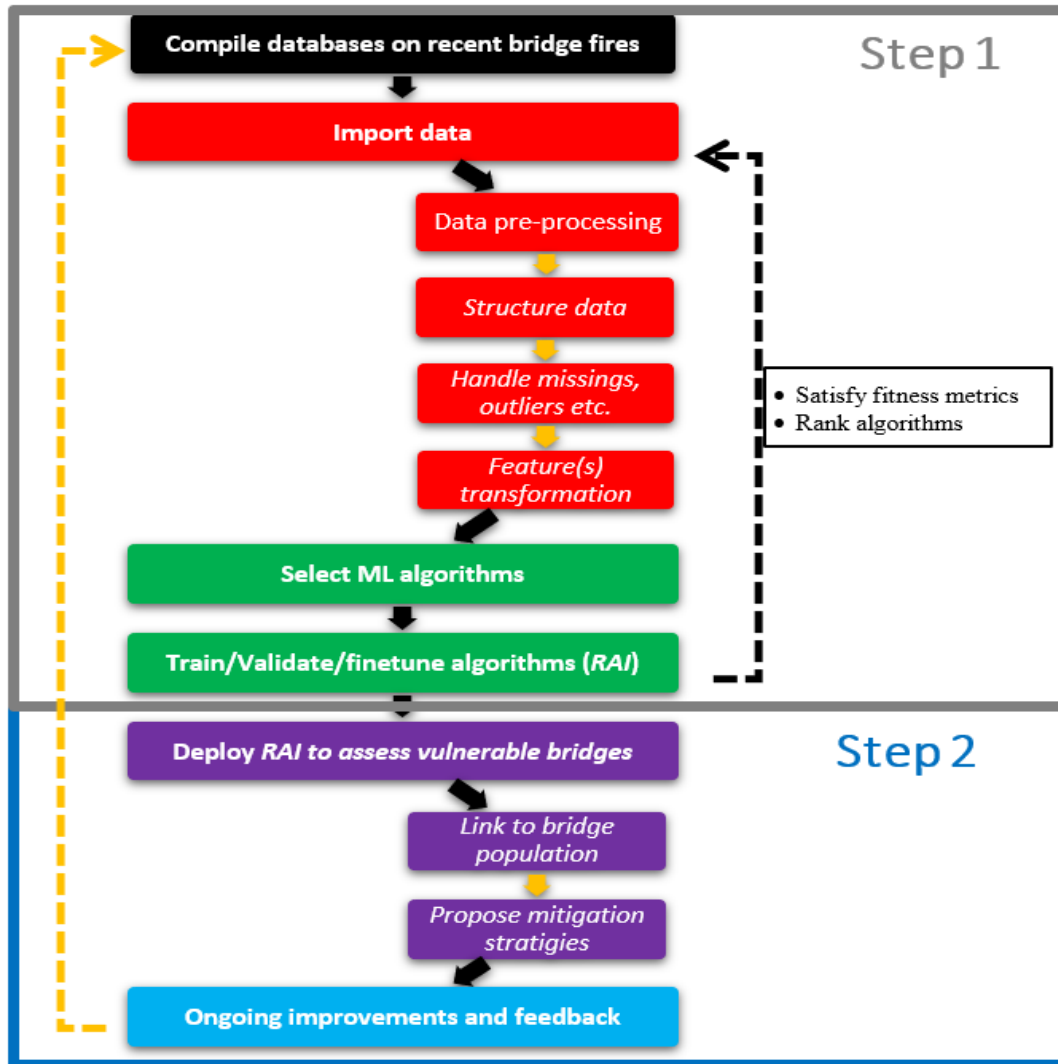
Fig. 2 A flowchart of the proposed *RAI* approach

Once the vulnerable bridges are identified, then these bridges are further examined to pinpoint the cause(s) of this vulnerability. For example, a bridge could be vulnerable to a fire that would break out beneath the bridge as opposed to a fire breaking out on top of the bridge. In such a scenario, measures can be put in place to minimize this vulnerability, i.e., insulate bridge girders, provide fire-proof shields to piers, install fire deluge systems, etc. In another scenario, say a cable-type bridge is found to be vulnerable to top bridge fires, then cables can be coated with intumescent

266 paints or fire-retardant materials etc. Other strategies could also be implemented, e.g., policy

267 changes can be put in place to minimize fire risk. Such policies may include: prohibiting storing

268 of flammable materials in the vicinity of vulnerable bridges, limit the speed of fuel tankers passing

269 through vulnerable bridges, detour large fuel tankers away from vulnerable bridges etc.

270 Once any of the above strategies are applied, the vulnerability of the bridge can be re-assessed in

271 a more fine-tuned manner (via importance factor or finite element simulation, etc.) as described in

272 previous publications [7,8,10,36,37]. For this purpose, load bearing members (i.e., girders) in a

273 given bridge can be analyzed under representative thermal and mechanical loading effects to

274 evaluate their fire resistance. If the fire resistance of girders is deemed inadequate, then such

275 girders are re-configured by providing fire insulation. The modified bridge is then re-analyzed in

276 an iterative procedure until an adequate insulation thickness (or any other possible solution for that

277 matter) that allows the girders to achieve a satisfying fire performance is arrived at.

278 *4.2 Deep Learning (DL)*

279 The DL technique is inspired by the topology of the brain. In this topology, a number of layers are

280 arranged in parallel (see Fig. 3). The first layer, also referred to as the input/receiver layer, receives

281 the observations to be analyzed which in this case cover those representing structural, traffic, and

282 fire features. These features are then processed to flow into subsequent layers. The next layers are

283 called the hidden layers. The hidden layers contain processing units (neurons) that analyze the

284 inputted features via specific weights (connections). During this processing procedure, the DL

285 technique learns relevant patterns of how the input features and outcome of bridge fire converge

286 and then maps such patterns through transformation operations. The training process continues

287 until a pre-defined fitness metric(s) (i.e., number of iterations and/or error tolerance) between DL-

288   based predictions and observations of bridge fires (e.g., magnitude of damage observed from

289   bridge fire incidents) is reached.

290   The DL network was developed herein using Keras library in Python [38]. First, we split the

291   compiled database into two parts (80% of the collected data were used for training purposes, and

292   the remaining data were used for testing the DL and improve its accuracy). Via a trial-and-error

293   process, we then used 5 hidden layers with 12, 10, 8, 5, and 3 neurons. In this DL network, the

294   weight and bias function for inputs are both selected to satisfy the *glorot_uniform initializer*. This

295   initializer draws samples from a uniform distribution within a range [-limit, limit]. The range

296   employed herein is *sqrt (6 / (fan_in + fan_out))* where *fan_in* is the number of input units in the

297   weight tensor and *fan_out* is the number of output units in the weight tensor [38]. The activation

298   functions for hidden layers were *relu*, *exponential*, *tanh*, *exponential* and *softmax,* respectively[‡].

299   Further, an optimization function is used to minimize the error. This function is *Adam* [39]. The

300   optimization function is used to improve the internal parameters of the model such as weight and

301   biased values. *Adam* is an adaptive learning rate method that is considered as a combination of

302   *RMSprop* and *Stochastic Gradient Descent* with momentum. This method uses squared gradients

303   to scale the learning rate like *RMSprop* and takes advantage of *Stochastic Gradient Descent* by

304   using a moving average of a gradient [39]. For error or loss function, we define

305   *categorical_crossentropy*. It is a *softmax* activation plus cross-entropy loss since this is a multi-

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[‡] *Relu* is often used in the most neural conventional network or deep learning problems with function and derivative are both monotonic. Other functions are also used; *Exponential* which is exp(x). *tanh* which is a hyperbolic tangent function. *Softmax* will calculate the probabilities of each target class over all possible target classes.

306   class problem. In order to improve accuracy, weight function needs to iterate several times. In this

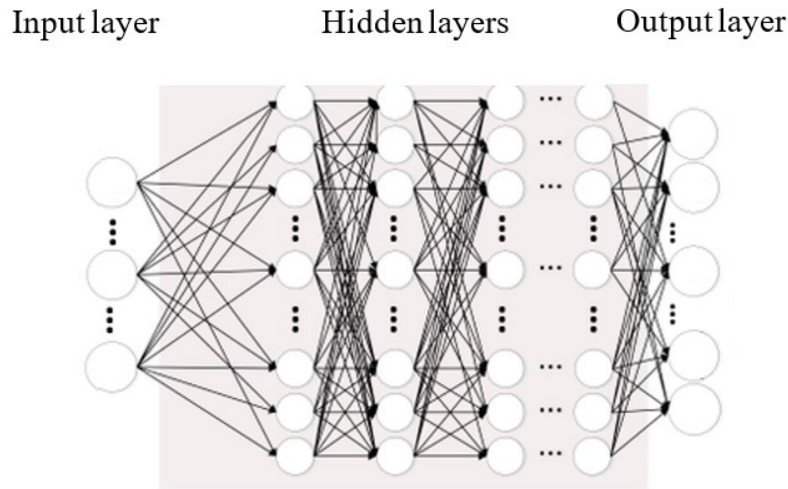307   study, the epochs or iterations for the model is set to 29.

308

309   Fig. 3 Representation of a typical DL network topology

310   *4.3 Genetic Algorithm (GA)*

311   Genetic algorithm is an evolutionary technique that utilizes supervised learning to arrive at

312   relations (i.e., expressions) that represent a particular phenomenon (which in this case refers to the

313   outcome of bridge fires). GA derives such relations by mimicking the natural selection process

314   (survival of the fittest) [40]. GA starts by assigning an arbitrary population of expressions (or

315   trees). Each tree houses mathematical symbols, functions, and operations – see Fig. 4. The analysis

316   procedure starts by re-arranging such functions and operations in an attempt to arrive at an

317   expression with high fitness (i.e., predictive capability). In this pursuit, GA employs refining

318   operations that are also inspired by the natural selection process (i.e., reproduction, mutation etc.)

319   to fine-tune a candidate expression. At the end of this analysis procedure, the fittest expression out

320   of all other expressions is selected. Finally, the fittest tree is converted into "Karva-expression"

321   form that is easy to input into a spreadsheet-like program, i.e., Matlab, Python, etc. In this analysis,

322   the notable works of [41, 42] (which were applied for classification problems and genetic

323   programming modeling) and [43–45] (which tackled structural engineering problems) were used

324   to identify suitable and commonly used mathematical, functional and genetic operators. An

325   examination of such works shows that commonly adopted mathematical operators include

326   addition, subtraction, multiplication, maximum, minimum, IF, and logical operators (such as and),

327   and hence these were used herein. In addition, Step, Logistic, Trigonometric functions (i.e., TAN,

328   COS) were also used as functions. For genetic operators, we used a mutation rate of 0.1, and a

329   crossover rate of 0.85. in general, we deployed a population size of 1000, and a generation of 1200.

330   The above was seen in very close to those used in the following references and hence proven

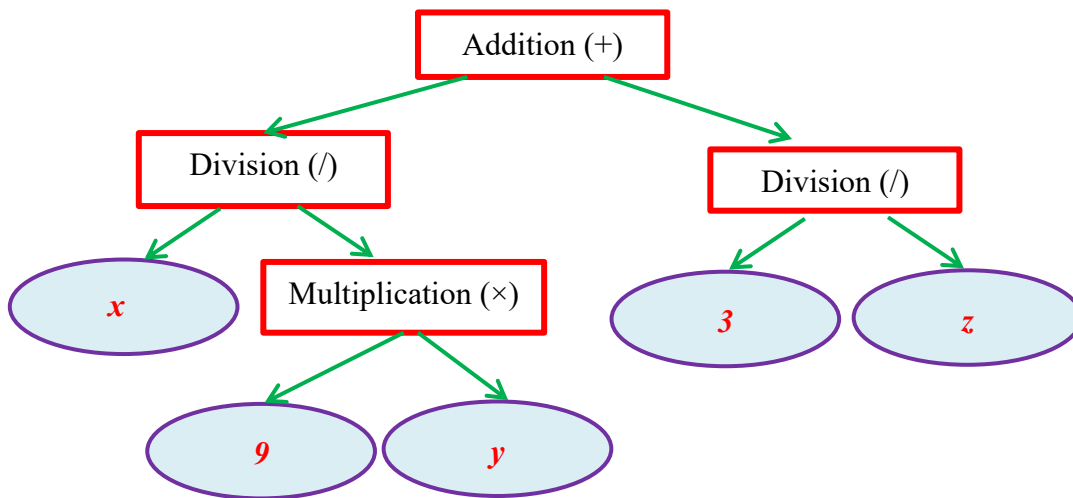331   effective herein. Further details on the development of a typical GA can be found elsewhere

332   [32,41].

Fig. 4 Karva-expression for a tree representation of $\frac{x}{9y} + \frac{3}{z}$

5. Machine Learning Model Validation and Deployment

Now that the machine learning techniques are developed, these techniques are to be trained and validated. For this purpose, the database was arbitrarily arranged to minimize biases that might arise from a particular feature (say, structural system, etc.). After that, the database was used to train the model via a 10-fold cross-validation method in which the dataset is randomly split up into test and training subsets, which is further divided into 10 groups. This cross-validation method allows the model to train and be validated on multiple train-validation splits, thereby resulting in a high model performance with less overfitting [42]. The model is validated on one of the groups and trained using the other remaining 9 groups. This process is repeated 10 times until each unique group has been used as the validation subset. Finally, the model's performance is examined on the test data not seen by the model during training.

Table 2 shows the results of the model examination by means of the confusion matrix and fitness metrics for both DL and GA techniques when applied to the whole dataset. In this table, one can see that the DL model performed well in the Recall metric, which shows the ratio of correct positive predictions to the total positives examples but struggled in the case of Major damage. The same model performed well on the precision (which shows the ratio of correct positive predictions to the total predicted positives) front in identifying No/minor damage class. On the other hand, the GA model performed in a better sense than the former model by attaining improved and consistent metrics across all classes. In addition, it is worth noting that the overall accuracy for these techniques on the whole database is 70% and 89.6%, with a Kappa metric (which measures inter-rater reliability) reaching 0.494 and 0.832, respectively. It is worth noting that a Kappa metric score within 0.41–0.60, and 0.81–1.00 implies "moderate agreement" and "almost perfect

21

363   agreement", respectively, as noted by Landis and Kochz [43]. All of the aforementioned metrics

364   reveal two observations, 1) both models seem to be of good standing, and 2) the accuracy of the

365   GA algorithm over the DL technique. Overall, the listed metrics show that the proposed *RAI*

366   approach can be used to classify fire damage in bridges with confidence (see Table 3).

367   Table 2 Confusion matrix of selected algorithms

		No/Minor	Major	Collapse	Precision[*] (%)
DL	No/Minor	63	15	5	75.9
	Major	5	18	8	580
	Collapse	2	5	14	66.7
	Recall[**] (%)	90.0	47.4	52.9	
GA	No/Minor	63	2	1	95.5
	Major	6	35	2	81.4
	Collapse	0	3	23	88.5
	Recall (%)	91.30	87.5	88.5	

368   *Precision $= \frac{TP}{TP+FP}$ and **Recall $= \frac{TP}{TP+FN}$ where TP (denotes true positives), FP (denotes false positives), and FN (denotes false*

369   *negatives).*

370   Table 3 GA-proposed expressions to evaluate expected damage to fire

No.	Case	Derived expressions[§]
1.	Collapse	$Collapse = step(69.5 \times M + 7.6 \times S + if(5.3 + 1.5 \times M \times C - 0.0062 \times P - 2.3 \times M - 3.07 \times C, tan(218.24 + if(0.39 \times N - 1.49, 0.39 \times N - 1.49, 0.85 \times M - 3.31)), 155.59 \times max(1.08 \times T - 2.19, 1.79 \times C - 2.73)) - 146.45 - 0.103 \times A - 1.12 \times N - 1.98 \times P - 3.04 \times T - 6.49 \times G - 6.8 \times C)$
2.	Major	$MJ = logistic(327.80 + if(0.39 \times N - 1.49, 27.30 \times cos(2.74 + 1.21 \times G - 3.08 \times P), 40.88 \times min(1.21 \times G - 2.42, 0.398 \times N \times tan(27.30 \times cos(2.74 + 1.21 \times G - 3.08 \times P)) - 1.49 \times tan(27.30 \times cos(2.74 + 1.21 \times G - 3.08 \times P))) + 30 \times min(0.85 \times M - 2.71, min(tan(0.39 \times N + cos(2.74 + 1.21 \times G - 3.08 \times P) - 1.49), 1005.52 \times cos(1005.52 \times tan(0.39 \times N + cos(2.74 + 1.21 \times G - 3.08 \times P) - 1.49)))) - 10.88 \times N \times min(1.21 \times G - 2.42, 0.39 \times N \times tan(27.30 \times cos(2.74 + 1.21 \times G - 3.08 \times P)) - 1.49 \times tan(27.30 \times cos(2.74 + 1.21 \times G - 3.08 \times P)))) - 0.21 \times P - 0.31 \times A - 6.71 \times N - 18.15 \times F - 18.25 \times M - 20.52 \times C - 21.42 \times G - 32.1 \times S)$

[§]All features were assigned an arbitrary numeric value such that:
- Structural systems: cable-stayed/suspension (1.0), truss/arch (2.0), box girders (3.0), and I-girders (4.0).
- Construction materials: prestressed concrete (1.0), reinforced concrete (2.0), composite members (3.0), steel (4.0) and timber (5.0).
- Geographic significance: rural (1.0), sub-urban (2.0) and urban (3.0).
- Closeness of fire break out to bridge: top of bridge (1.0), under bridge (2.0), and in the vicinity of bridge (3.0).
- Fuel type: gasoline/diesel (1.0), hydrocarbons (2.0), and other flammables/storage (3.0).

3.	No/Minor	$No/MN = step(17.57 \times M + 3.03 \times S + tan(if(0.006 \times P - 0.67, -1.53, if(1.37 \times and(0.31 - 0.0062 \times P, 1.8 \times C - 2.73) - 0.36 - 0.027 \times A \times and(0.31 - 0.006 \times P, 1.79 \times C - 2.73), 1.79 \times C + 0.91 \times S + 0.0028 \times P - 5.74, if(0.39 \times N - 1.49, -1.52, if(1.08 - 0.027 \times A, 1.79 \times C + 0.0061 \times P - 3.39, -1.525))))) - 39.98 - 0.024 \times P - 0.047 \times A - 0.19 \times N - 0.53 \times T - 3.12 \times C - 6.54 \times G)$

371

372 Since GA was found to have a superior predictivity, a sensitivity analysis was carried out on the

373 proposed GA-derived expressions. In this analysis, the relative impact of each feature within each

374 expression on the overall response to a bridge fire is examined and listed in Table 4. In this table,

375 the *% Positive* refers to the likelihood that increasing a specific feature leads to an increase to the

376 outcome (i.e., if % Positive = 75%, then 75% of the time an increase in a specific feature would

377 lead to an increase in the outcome). The *positive magnitude* quantifies the amount of positive

378 increase a specific feature can add to the outcome of the expression. Both, *% Negative* and *negative*

379 *magnitude* are equal opposites to the above. A look into Table 4 shows that the main three features

380 with the highest sensitivity (i.e., impact) are the span (P), age (A), and the number of lanes (N).

381 Table 4 Sensitivity analysis on the proposed expressions

Exp.	Feature	Sensitivity	% Positive	Positive Magnitude	% Negative	Negative Magnitude
No/Minor damage	P	1.84	100%	1.84	0%	0
	A	0.61	74%	0.61	26%	0.17
	N	0.44	60%	0.49	40%	0.35
	C	0.35	100%	0.35	0%	0
	S	0.32	100%	0.32	0%	0
	M	0.27	100%	0.27	0%	0
	G	0.16	100%	0.16	0%	0
	T	0.16	100%	0.16	0%	0
Major damage	P	44.2	45%	52.9	55%	37.21
	N	0.62	20%	1.52	80%	0.39
	S	0.40	0%	0	100%	0.40
	M	0.31	0%	0	100%	0.30
	T	0.24	0%	0	100%	0.24
	C	0.22	0%	0	100%	0.22
	A	0.21	0%	0	100%	0.21
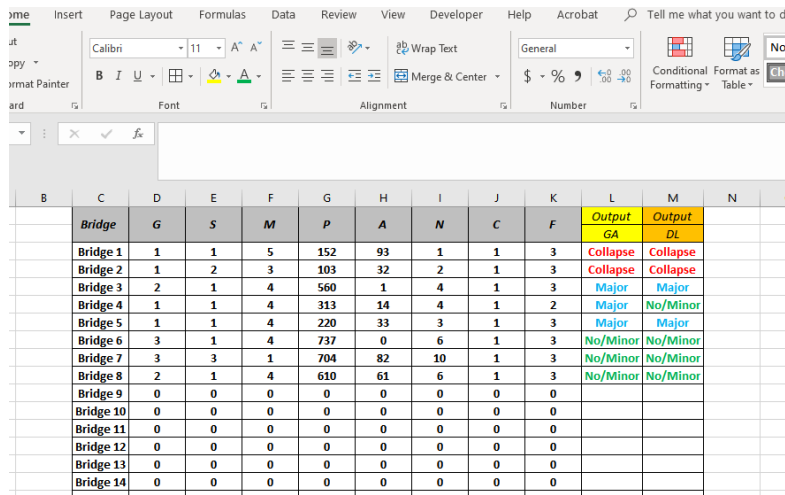
	G	0.20	0%	0	100%	0.20
	P	2.51	28%	0.18	72%	2.5
	M	0.69	100%	0.67	0%	0
Collapse	A	0.38	0%	0	100%	0.38
	C	0.18	50%	0.13	50%	0.22
	S	0.16	100%	0.16	0%	0
	G	0.16	0%	0	100%	0.156
	N	0.09	0%	0	100%	0.09
	T	0.01	0%	0	100%	0.015

382

383   A deeper look into the above three features shows interesting observations. For example, it is very

384   likely for a bridge to experience a high degree of damage (or to possibly collapse) if such a bridge

385   is made of steel or timber (e.g., an increase in M from $1 \rightarrow 5$ has a 75% likelihood of amplifying

386   the outcome and leading to collapse). An equally exciting observation can also be seen in the case

387   of P and $N,$ wherein an increase in these features (i.e., bridges with longer spans and/or a higher

388   number of lanes) is expected to minimize the possibility of collapse. While the latter may seem

389   counterintuitive, one should note that: (1) larger bridges are much more resilient and built to

390   achieve higher levels of performance, and (2) very few large bridges ever collapse due to fire [11].

391   The above approach can now be deployed into a bridge master database (say from FHWA etc.) to

392   identify vulnerable bridges. While the proposed approach was developed via complex machine

393   learning analysis, still this framework was successfully employed into a simple Excel-like

394   spreadsheet as well as software (App) that could be operated using a PC, tablet (i.e., iPad), or an

395   iPhone (see Fig. 5). As such, users of *RAI* approach do not need to have a background in coding

396   nor to be in need of a specialized software (i.e., Matlab) or device to evaluate the vulnerability of
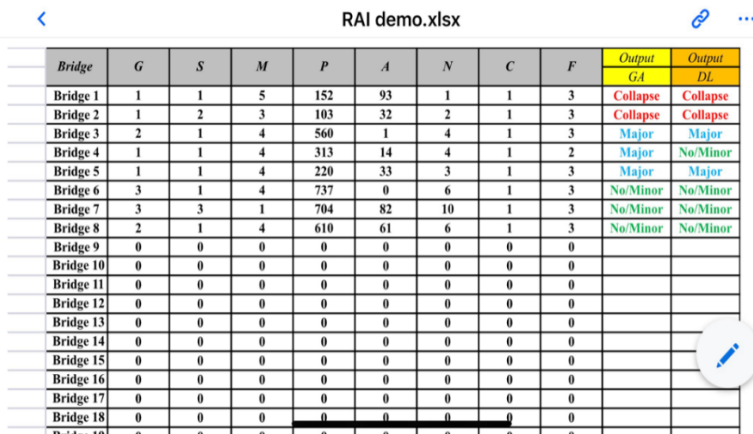
397   bridges to fires.

398
399
(a) Excel application in a typical Desktop computer

400
401
(b) IPad tablet

(c) Demo App (the model also incorporates confidence intervals as per Brownlee [44] suggestions to showcase the model predictive decision across all classes)

Fig. 5 Deployment of *RAI* approach into a spreadsheet and software (App)

The user may also opt to start the vulnerability analysis using hand-calculation. In this case, it would be optimal to start by applying the first expression to check whether the bridge will collapse or not. If the first expression returns a value of unity, then the bridge is expected to collapse, and if not, then the second and third expressions will be applied to estimate the magnitude of the damage the bridge will experience[**]. In any case, the user must note that the derived expressions may not be genuinely aesthetic nor compact, and this is attributed to the complex nature of bridge

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[**] It is unlikely that the above expressions will agree on a specific outcome (i.e., all expressions yield an outcome of unity) for the same bridge. In any case, the designer might option to select the worst-case scenario outcome and/or try different approach such as bridge fire importance factor (which is based on weightage factors) [19] or finite element simulations [7].

413   fires these expressions reflect. In other words, mathematically representing the outcome of bridge

414   fires is hectic and requires a highly nonlinear form of expressions.

415   To further validate the proposed machine learning approach and software, the following three case

416   studies are carried out herein.

417   ***Brooklyn Bridge***

418   The first case study covers a fire that broke out at the Brooklyn Bridge, NY. This fire resulted from

419   a fuel tanker collision with another vehicle on top of the bridge. Given the following features listed

420   below, it is clear that this bridge could undergo a minor degree of damage due to such fire. It

421   should be noted that the Brooklyn Bridge has undergone a number of similar fires over the past

422   few years [45,46]. The outcome of these fires has been documented to be of insignificant/minor

423   magnitude.

424   Bridge features:

425   Physical features:

426   Structural systems, $S \rightarrow$ Suspension system = 1

427   Construction materials, $M \rightarrow$ Steel = 4

428   Span, $P \rightarrow$ 486 m

429   Age, $A \rightarrow$ 143 years

430   Traffic features:

431   Geographical significance, $G \rightarrow$ Urban = 3

432   Number of lanes, $N \rightarrow$ 6 lanes

433   Fire features:

434   Closeness of fire break out, $C \rightarrow$ Above bridge = 1

435   Type of fuel, $T \rightarrow$ Hydrocarbon fuels = 2

436   <u>Step 2:</u> Deploy machine learning techniques:

437   *Based on DL tool*

438   Predicts the bridge will experience no/minor damage.

439   *Based on GA-proposed expressions:*

440   $Collapse = step(69.5 \times 4 + 7.6 \times 1 + if(5.3 + 1.5 \times 4 \times 1 - 0.0062 \times 486 - 2.3 \times 4 - 3.07 \times$

441   $1, tan(218.24 + if(0.39 \times 6 - 1.49, 0.39 \times 6 - 1.49, 0.85 \times 4 - 3.31)), 155.59 \times max(1.08 \times 2 -$

442   $2.19, 1.79 \times 1 - 2.73)) - 146.45 - 0.103 \times 143 - 1.12 \times 6 - 1.98 \times 486 - 3.04 \times 2 - 6.49 \times 3 -$

443   $6.8 \times C) = 0.0$ (the bridge is not expected to collapse $\rightarrow$ check for expressions 2 and 3).

444   $No/MN = step(17.57 \times 4 + 3.03 \times 1 + tan(if(0.006 \times 486 - 0.67, -1.53, if(1.37 \times and(0.31 -$

445   $0.0062 \times 486, 1.8 \times 1 - 2.73) - 0.36 - 0.027 \times 143 \times and(0.31 - 0.006 \times 486, 1.79 \times 1 -$

446   $2.73), 1.79 \times 1 + 0.91 \times 1 + 0.0028 \times 486 - 5.74, if(0.39 \times 6 - 1.49, -1.52, if(1.08 -$

447   $0.027 \times 143, 1.79 \times 1 + 0.0061 \times 486 - 3.39, -1.525))))) - 39.98 - 0.024 \times 486 - 0.047 \times 143 -$

448   $0.19 \times 6 - 0.53 \times 2 - 3.12 \times 1 - 6.54 \times 3) = 1.0$ (this bridge is likely to undergo no/minor damage).

449   ***<u>Golden Gate Bridge</u>***

450   The second case study covers a bridge fire that broke out in a traffic jam upon the Golden Gate

451   Bridge, CA [47]. This fire resulted from a car collision. The bridge was reported to undergo a

452   minor degree of damage due to such fire.

453   <u>Bridge features:</u>

454   Physical features:

455   Structural systems, $S \rightarrow$ Suspension system = 1

456   Construction materials, $M \rightarrow$ Steel = 4

457   Span, $P \rightarrow$ 1280 m

458   Age, $A \rightarrow$ 82 years

459   Traffic features:

460   Geographical significance, $G \rightarrow$ Urban = 3

461   Number of lanes, $N \rightarrow$ 6 lanes

462   Fire features:

463   Closeness of fire break out, $C \rightarrow$ Above bridge = 1 (since the bridge crosses The Golden

464   Gate strait and has a 67.1 m

465   clearance above sea level).

466   Type of fuel, $T \rightarrow$ Hydrocarbon fuels = 2

467   Step 2: Deploy machine learning techniques:

468   *Based on DL tool*

469   Predicts the bridge will experience no/minor damage.

470   *Based on GA-proposed expressions:*

471    $Collapse = step(69.5 \times 4 + 7.6 \times 1 + if(5.3 + 1.5 \times 4 \times 1 - 0.0062 \times 1280 - 2.3 \times 4 - 3.07 \times$

472    $1, tan(218.24 + if(0.39 \times 6 - 1.49, 0.39 \times 6 - 1.49, 0.85 \times 4 - 3.31)), 155.59 \times max(1.08 \times 2 -$

473    $2.19, 1.79 \times 1 - 2.73)) - 146.45 - 0.103 \times 82 - 1.12 \times 6 - 1.98 \times 1280 - 3.04 \times 2 - 6.49 \times 3 -$

474    $6.8 \times 1) = 0.0$ (the bridge is not expected to collapse $\rightarrow$ check for expressions 2 and 3).

475    $No/MN = step(17.57 \times 4 + 3.03 \times 1 + tan(if(0.006 \times 1280 - 0.67, -1.53, if(1.37 \times and(0.31 -$

476    $0.0062 \times 1280 , 1.8 \times 1 - 2.73) - 0.36 - 0.027 \times 82 \times and(0.31 - 0.006 \times 1280, 1.79 \times 1 -$

477    $2.73), 1.79 \times 1 + 0.91 \times 1 + 0.0028 \times 1280 - 5.74, if(0.39 \times 6 - 1.49, -1.52, if(1.08 -$

478    $0.027 \times 82, 1.79 \times 1 + 0.0061 \times 1280 - 3.39, -1.525))))) - 39.98 - 0.024 \times 1280 - 0.047 \times 82 -$

479    $0.19 \times 6 - 0.53 \times 2 - 3.12 \times 1 - 6.54 \times 3) = 1.0$ (this bridge is likely to undergo no/minor damage).

480

481

MacArthur Maze Bridge

483   The first case study covers the bridge fire that caused the collapse of MacArthur Maze in Oakland,

484   CA in 2007. This fire broke out once a fuel tanker carrying 8450 gallons crashed under the

485   MacArthur Maze interchange. This crash ignited the highly flammable fuel, which generated

486   intense heat and temperatures exceeding 1000°C. The intense heat severely degraded the strength

487   and stiffness of steel girders in this composite bridge, which had no fireproofing. As a result,

488   significant fire-induced forces were developed in the weakened girders. After 22 minutes of the

489   fire, the bridge collapsed. This collapse resulted in damages that were estimated at $9 million and

490   shut down traffic in all three lanes causing significant detours.

491   Bridge features:

492   Physical features:

493   Structural systems, $S \rightarrow$ I-girders = 4

494   Materials of construction, $M \rightarrow$ Composite (steel and concrete) = 3

495   Span, $P \rightarrow$ 24.5 m

496   Age, $A \rightarrow$ 37 years

497   Traffic features:

498   Geographical significance, $G \rightarrow$ Urban = 3

499   Number of lanes, $N \rightarrow$ 6 lanes

500   Fire features:

501   Closeness of fire break out, $C \rightarrow$ Under bridge = 2

502   Type of fuel, $T \rightarrow$ Hydrocarbon fuels = 2

503   <u>Step 2:</u> Deploy machine learning techniques:

504   *Based on DL tool*

505   Predicts the bridge will experience collapse.

506   *Based on GA-proposed expressions:*

507     $Collapse = step\Big(69.5 \times 3 + 7.6 \times 4 + if\Big(5.3 + 1.5 \times 3 \times 2 - 0.0062 \times 24.5 - 2.3 \times 3 - 3.07 \times$

508     $2, tan\big(218.24 + if(0.39 \times 6 - 1.49, 0.39 \times 6 - 1.49, 0.85 \times 3 - 3.31)\big), 155.59 \times max(1.08 \times 2 -$

509     $2.19, 1.79 \times 2 - 2.73)\Big) - 146.45 - 0.103 \times 37 - 1.12 \times 6 - 1.98 \times 24.5 - 3.04 \times 2 - 6.49 \times 3 -$

510     $6.8 \times 2\Big)$= 1.0 (the bridge is expected to collapse – a check for expressions 1 and 2 returns a "0" value).

511   It is worth mentioning that the above bridge is expected not to collapse (in this particular bridge

512   fire) has it been designed with reinforced concrete girders as opposed to a composite system with

513   steel I-girders. This infers the vulnerability of uninsulated steel girders to fire hazards. Other

514   observations can also be arrived at by examining variations in expression no. 3.

515   This outcome of this example shows that predictions from DL and GA may not always agree with

516   documentation and observations from the actual incident, given their accuracy, which falls short

517   of 100%. In this scenario, a designer may opt to select the worst-case scenario to be on the

518   conservative side or perhaps s/he may option to undertake a much detailed analysis, say via

519   complex FE analysis. Overall, the *RAI* approach is being improved to adopt ensemble (multi-

520   algorithms) machine learning technique to allow "majority voting". In this technique, a fire

521   vulnerability class will be assigned to a given bridge based on common class predictions from

522   different algorithms.

6. Considerations for Future Works

The proposed *RAI* machine learning approach seems to truly capture patterns of bridge fires and how such fires may adversely affect the integrity of bridges, and in some instances, may result in significant damage and/or collapse. This work could be regarded as a first step towards realizing a modern and automated identification of fire-vulnerable bridges. Still, the reader is to remember that a few burning issues continue to arise. For example, machine learning tools are best suited where there is a large number of observations. However, observations on bridge fires are: 1) very limited, 2) rarely documented or easily accessible, and 3) lack completeness in reporting common features such as (fire intensity, fire spread, quantitative damage assessment etc.). The above could also arise issues with regard to reliability, scalability, and public acceptance. Fortunately, these challenges will be overcome in future works [48–51].

For now, the presented approach can still be confidently applied as a raw assessment tool that has the capability to offer designers with qualitative insights into how to mitigate extensive fire damage in bridges [32]. For example, the proposed tool can be applied during the early stage of the design of a new bridge to assess its vulnerability to fire (given that we still lack codal guidance on design a bridge for fire hazards). As such, the proposed tool could identify possible fire-related weaknesses such as that with regard to selecting a structural system or construction materials, etc. Arriving at such information during the design stage could be both of merit and cost-effective. Overall, the proposed approach can be considered as an "expert system" that can supplement current design procedures and may in fact compensate for the deficiency that a number of bridge engineers might suffer from when it comes to fire hazards.

544   A promising and attractive feature of machine learning approaches is their ability to self-improve

545   with time and with the addition of new observations. As such, the proposed *RAI* approach could

546   theoretically undergo a more rigorous validation and calibration process before being formally

547   adopted into practice. Furthermore, effort should be made to develop machine learning tools that

548   can quantitatively identify the magnitude of bridge damage to various extreme events as well as

549   pinpoint how load bearing members will fail, and estimate expected cost of bridge restoration,

550   indirect cost of shut down/supply chain operations, etc. Additional considerations worthy of note

551   are those related to developing bug-free, user-friendly and aesthetic packages to allow scalable and

552   easily deployable frameworks. Such a tool can be fostered by a government-based organization

553   (i.e., DoTs) and can be linked to a computing cloud. Considerations with regard to security and

554   wrongful use need to be addressed. Finally, the use of active learning techniques or reinforcement

555   learning can help arrive at more optimal architecture of DL models, such as that developed herein,

556   and hence future works are invited to tackle such research areas.

557   **7. Conclusions**

558   This paper presents the development of a r̲apid, a̲utomated, and i̲ntelligent (*RAI*) approach that

559   leverages two machine learning algorithms DL and GA, to identify fire-vulnerable bridges. By

560   examining 135 actual bridge fire incidents, the proposed approach has achieved an accuracy

561   ranging between 70-89.6%. The proposed *RAI* approach also can quantitatively display its level of

562   confidence in its predictions which can become handy to bridge engineers and government

563   officials. This approach is implemented into freely available software (App) with optimized

564   architecture and is easily scalable into a user-friendly framework and handheld devices. The

565   following conclusions can also be drawn from this work:

566 • Recent years have noted a rise in bridge fires. Such fire incidents have led to damages and, in

567   some cases, collapse. These incidents clearly show the vulnerability of bridges to fire hazards,

568   given that these structures are not properly designed to withstand hazards.

569 • Machine learning can be successfully applied to develop bridge assessment tools that can

570   identify vulnerable bridges to fire hazard. These techniques can be specifically tailored to

571   account for varying features such as those related to physical characteristics, traffic demands,

572   fire intensity, etc., and can achieve 82.9-89.6% accuracy as noted in this study.

573 • The *RAI* approach has optimized architecture and reduced computational complexity and hence

574   is easily scalable and integratable into a user-friendly framework. This approach can be

575   deployed to arrive at an instantaneous assessment of fire vulnerable bridges.

576 • Future machine learning techniques can be enhanced given the addition of accurately

577   documented observations on bridge fires. The same techniques are expected to be able to arrive

578   at a quantitative assessment of expected damage and associated economic losses etc.

579 **8. Acknowledgment**

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