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Artificial intelligence techniques for prediction of the capacity of RC beams strengthened in shear with external FRP reinforcement

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ABSTRACT

The prediction of the shear capacity of reinforced concrete beams retrofitted in shear by means of externally bonded FRP is very complex as demonstrate the studies carried out up to date. As alternative to the conventional methods two approaches based on artificial intelligence are proposed for the first time. Firstly, the use of neural networks as a means of predicting shear capacity without the need of using complex models and, secondly, the use of genetic algorithms as a means of determining suitably how the shear mechanism works. Predictions obtained with both approaches are compared to experimental values.

1. Introduction

Artificial intelligence (AI) is a term that in its broadest sense would indicate the ability of a machine to perform the same kind of functions that characterize human thought. Several artificial intelligence techniques are used increasingly as alternatives to more classical or conventional techniques. They have been used to solve complicated practical problems in different sectors, such as engineering, economics, medicine, military, marine, etc., and are becoming more popular nowadays. Into the structural engineering field, they have been successfully applied to different areas such as structural analysis and design [1,2], damage assessment [3–5] and constitutive modelling [6].

On the other hand, it is well-known that the understanding of concrete structures designed for strengthening in shear using fibre-reinforced polymers (FRP) is still an area where uniform design rules do not exist or are treated very briefly. The cause of shear failure is a result of a complicated mechanism even for simple RC elements, so it would be even more complex when external FRP reinforcement is added to the concrete [7–9]. Because of this, the prediction of the ultimate shear strength of reinforced concrete (RC) beams is critical especially when the value is used in the design and, therefore, a lot of theoretical and experimental work is still in progress to solve open questions.

In contrast with the usual regression analysis of experimental data [7,9,10] and with the classical strut-and-tie models [11] employed to predict the capacity of an FRP shear-strengthened RC beam, this paper outlines an understanding of how artificial intelligence systems, in particular neural networks and genetic algorithms, can be used to improve the predictive capacity.

For it, firstly, sixteen reinforced concrete beams shear strengthened with FRP external reinforcement have been tested considering different configurations. These results together with other experimental results taken from the literature have been taken as a basis to construct an artificial neural network to predict the ultimate shear strength of this kind of repaired beams. Due to their unique features, the neural networks can be used to solve complex problems that cannot be handled by analytical approaches, even problems whose underlining physical and mathematical models are not well-known. From this point of view, they result suitable for determining the shear capacity of RC beams strengthened with FRP shear reinforcement as the results have demonstrated.

Other way of focusing the posed problem through artificial intelligence is by using genetic algorithms to solve an optimization problem. The shear mechanism of RC beams with FRP externally bonded reinforcements can be assumed to a variable angle truss model, also known as strut-and-tie model. However, in spite of its conceptual simplicity there is not a clear guide to define the geometry of the strut-and-tie model. Its major complexity is about how to transform a continuous structural domain to a strut-and-tie model. By using genetic algorithms, a simple automatic procedure for determining the optimal configuration of the strut-and-tie mechanism of an FRP shear-strengthened RC beam is developed. For it, the procedure is set out as an optimization problem based on the minimization of the total strain energy solved by using genetic algorithms. Unlike traditional gradient-based optimization

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methods, genetic algorithms use multiple points to search for the solution rather than a single point. Starting from an initial random generation of possible configurations of the strut-and-tie model for the reinforced beam subjected to study, new populations of possible configurations are generated iteratively using typical genetic operators with the purpose of improving the best individuals of the previous populations by the application of the principle of minimum strain energy. The algorithm progresses with successive generations to reach an optimum solution for the studied problem which corresponds to the optimal strut-and-tie configuration. Unlike the conventional truss approaches, in the optimal configuration, compressive struts are not enforced to be parallel, which represents more consistently the physical reality of the flow of forces.

The two proposed approaches are validated successfully against the results of the experimental tests performed. Furthermore, a comparison with the predictions of some design proposals has been also performed with the purpose of remarking the advantages of both proposals.

2. Neural networks

2.1. Description

Neural networks are a very simple implementation of local behaviour observed within our own brains. Hopfield [12] provided the mathematical foundation for understanding the dynamics of an important class of networks. Kohonen [13] developed unsupervised learning networks for feature mapping into regular arrays of neurons. From 1986, many neural networks research programs have been developed in such a way that the list of applications that can be solved by neural networks has expanded from small test size examples to large practical problems.

A neural network is a collection of small individually interconnected processing units. Information is passed through these units along interconnections. An incoming connection has two values associated with it, an input value and a weight. The output of the unit is a function of the summed value. The main characteristic of ANNs is its ability to learn and generalize from experience and examples and to adapt to changing situations. For it, a previous training of the NN is needed. The training or learning process involves presenting a set of examples (input patterns) with known outputs (target output). The system adjusts the weights of the internal connections to minimize errors between the network output and target output. Data presented for training can be theoretical data, empirical data based on reliable experience or a combination of both. Once the NN has been trained, new patterns may be presented to them for prediction or classification. ANNs can automatically learn to recognize patterns in data from real systems or from physical models, computer programs, or other sources. The learning process avoids the need to use complex mathematically explicit formulas, computer models and impractical and costly physical models. In fact, neural network analysis can be conceived of as a black box approach and the user does not require sophisticated mathematical knowledge.

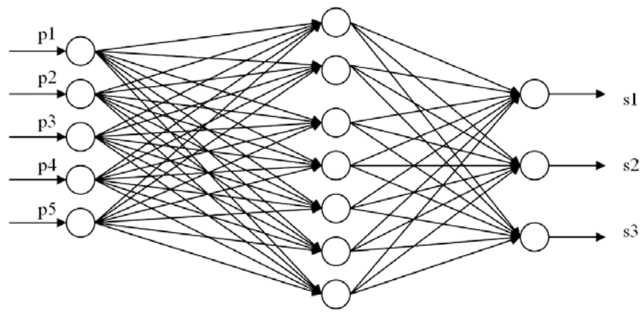

Fig. 1. Typical configuration of a three layer feed forward neural network.

In a typical configuration, the network has an input layer, an output layer and any number of hidden layers. Layers are fully interconnected (Fig. 1). The input layer receives inputs from the outside world, the output layer gives the predictions to the outside world and the hidden layer links the input layer to the output layer extracting and remembering the main features of the input patterns to predict the outcome of the network. The main difference between the network types lies in the type of activation function used by the hidden neurones. Common types of activation function include the sigmoid transfer function and the Gaussian radial basis function.

2.2. Application to FRP shear-strengthened RC structures

As commented above, ANNs are useful in solving problems where the algorithm or rules to solve the problem are unknown as is the case of the prediction of the shear capacity of RC beams shear strengthened with FRP composites. One of the keypoints to guarantee the success of the procedure is referred to the choice of the optimal configuration of the NN. Although the number of input parameters should be large enough to represent the system properly, a large number might reduce the efficiency and accuracy of the training process in case of using a small training set. For this particular problem, 46 U-wrapping beams [11,14,15] were used for the configuration and learning of the NN. The choice of the input parameters has been guided based on the predictions obtained with the shear capacity equations of different design proposals [16–19]. Those design equations whose predictions are closer to the experimental values have been taken as a basis to define the input variables. In particular, best predictions were obtained when the design guidelines contained in Fib Bulletin 14 [16] combined with Eurocode 2 [20] were used and, although this does not allow concluding that this guide is the most suitable for FRP strengthening design, has been adopted as a basis for selecting the input parameters to the ANN. After this previous study, the network was finally configured with nine input neurons, one output neuron showing the shear strength of the reinforced beam and one hidden layer with eleven hidden neurons. The variables associated to each one of the input neurons are the breadth of the beam (b_w; mm), the height of the beam section (h; mm), the ratio of the FRP transversal reinforcement (ρ_f), the angle between the principal fibre orientation and the longitudinal axis of the member (β), the elastic modulus of the FRP reinforcement (E_f; MPa), the ratio of the longitudinal steel reinforcement (ρ_l), the cross sectional area of transverse steel per length unit (A_{90}; mm^2/mm), the design yielding stress of the shear steel reinforcement ($f_{y90,d}$), and the characteristic compression strength of the concrete (f_{ck}; MPa).

Once the NN configuration has been chosen, the network has been trained using the 46 beams specified above and back-propagation training algorithm with momentum factor of 0.9, learning rate of 0.15 and 3000 training cycles.

3. Genetic algorithms

3.1. Description

A GA is implemented as a computerized search and optimization procedure that uses the principles of natural genetics and natural selection [21]. The basic approach is to work with a population of candidate solutions that are encoded as chromosomes or strings of ones and zeros. Various portions of these bit-strings represent parameters in the search problem. From an initial population randomly generated, better populations will be generated iteratively through selection of fit chromosomes from the population and use of reproduction genetic operators. Selection is according to fitness of individual solutions, i.e. the best individuals are more often selected. Reproduction operators include crossover and mutation. Crossover produces offspring by exchanging chromosome segments from two parents. Mutation randomly changes part of one parent's chromosome. This occurs infrequently and introduces new genetic material. Although mutation plays a smaller part than crossover in advancing the search, it is critical in maintaining genetic diversity.

Unlike most stochastic search techniques, which adjust a single solution, GA keeps a population of solutions. Maintaining several possible solutions reduces the probability of reaching a false (local) optimum. Therefore GAs can be very useful in searching noisy and multimodal relations.

3.2. Application to FRP shear-strengthened RC structures

In all existing design proposals, the design shear strength, V_{Rd}, of an FRP-strengthened RC beam is evaluated from

$$V_{Rd} = V_c + V_s + V_f \tag{1}$$

where V_c is the contribution of concrete, V_s is the contribution of the steel stirrups and V_f is the contribution of the FRP. V_c may be calculated according to the provisions in existing RC design codes using the expressions for shear strength provided by concrete without web reinforcement which are based on empirical data. The contribution of vertical steel stirrups V_s and FRP external reinforcement V_f and, therefore, the evaluation of the shear strength in a cracked RC beam with external reinforcement can be carried out by using an ideal strut-and-tie model which approximates the stress fluxes in the material domain of the beam. The key idea of the equilibrated truss structure is that, after the formation of cracks, the transmission of forces to the supports is performed through a diagonal compression field linking in a proper way the bottom reinforced chord and the top compressed chord. The key point to idealize the beam as a truss structure is the solution of the local inclination of the compression struts approximating the real stress field. Usually, when the truss variable angle approach is used, the angle of inclination is considered constant for all the diagonal struts. This involves, undoubtedly, a simplification of the real forces flow. A more consistent approach to the physical reality would require the consideration of different angles of inclination for the different compression struts.

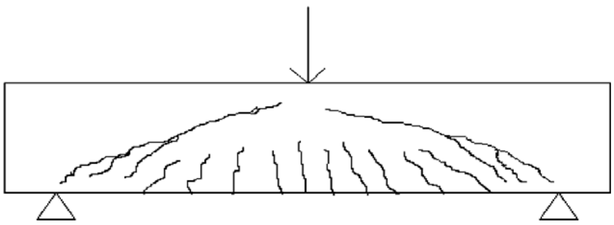

Fig. 2. Typical trajectory of stresses.

To generate the optimal two-dimensional strut-and-tie model for a beam structure allowing to evaluate Eq. (1), an optimization problem has been implemented in which as objective function the minimization of the total strain energy has been chosen, i.e.

$$\text{minimize} \sum F_i l_i \varepsilon_i \tag{2}$$

where F_i is the axial force and l_i and ε_i are the length and axial strain of the truss elements, respectively. The value of the strain energy for each configuration is dependent on the angles of inclination θ_i of the diagonal struts. These angles constitute the design variables of the procedure to be determined.

To be consistent with the physical reality, according to the typical trajectory of stresses for beams (Fig. 2), one constraint has been imposed over the design variables. This constraint implies assuming that the strut angles from the support to the midsection of the beam increase (Fig. 3), i.e.:

$$\theta_1 \leqslant \theta_2 \leqslant \theta_3 \leqslant \ldots \leqslant \theta_M \tag{3}$$

where M is the number of struts.

By implementing GAs in our problem, different strut-and-tie configurations are randomly generated and, then, by the application of the operators, crossover and mutation, new configurations are generate iteratively until reaching the optimal configuration minimizing the chosen objective function. The constraints are incorporated into the optimization problem through the inclusion of a penalty in the objective function whose value is dependent on the amount of each constraint violation present in a certain solution. More details can be found in [22].

The variables of the problem, the angles θ_i, are encoded in a binary form by assuming that only can take discrete values within a practical range (26–68°). Chromosomes grouping the binary strings associated to each one of the struts of the possible strut-and-tie mechanism represent the candidate solutions for the design problem.

Once the optima strut-and-tie mechanism has been determined by using the optimization procedure described above and assuming that the steel reinforcement yields previously to the failure, shear capacity corresponds with either failure of the external shear reinforcement or crushing of one of the truss struts. Therefore, according to the superposition hypothesis of the concrete and the reinforcement shear strength (Eq. (1)), the resisting shear force design value is

$$V_{\text{Rd}} = \min(V_{\text{strut}}, V_{\text{tie}} + V_c) \tag{4}$$

where V_{strut} and V_{tie} are evaluated by applying equilibrium conditions on the optimal strut-and-tie mechanism and are dependent on the design strength of the concrete and on the effective FRP strain ε_{fd}. Numerous predictions for ε_{fd} can be found in the literature and, in fact, the design guidelines adopt some of them [16–19].

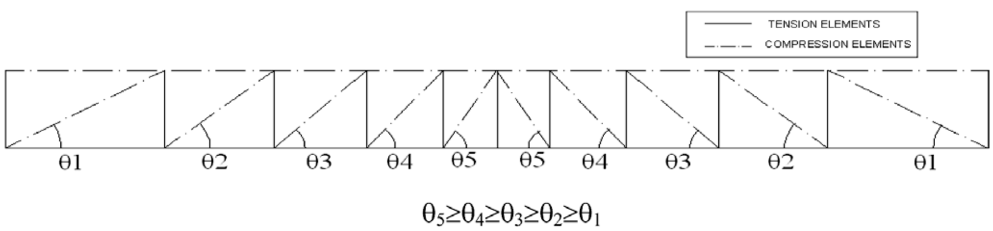

Fig. 3. Truss configuration used in this work particularized when $\alpha = 90°$.

Table 1
Test scheme.

SPECIMEN	Configuration	Fibre amount (g/m^2)	Spacing (mm)	Span (mm)	V_{test} (kN)
V2-U90-S530-L	U	530	200	4300	241
V2-U90-S530-C	U	530	200	3040	214
V3-U90-C530-L	U	530	0	4300	211
V3-U90-C530-C	U	530	0	3040	199
V5-U90-C530-L	U	530	0	4300	238
V5-U90-C530-C	U	530	0	3040	254
V8-U90-S300-L	U	300	200	4300	202
V8-U90-S300-C	U	300	200	3040	224
V9-U90-S300-L	U	300	200	4300	168
V9-U90-S300-C	U	300	200	3040	257
V11-U90-S530-L	U	530	200	4300	230
V11-U90-S530-C	U	530	200	3040	259
V13-U90-C300-L	U	300	0	4300	203
V13-U90-C300-C	U	300	0	3040	247
V14-U90-C300-L	U	300	0	4300	196
V14-U90-C300-C	U	300	0	3040	233

4. Experimental tests

The experimental program includes the testing of sixteen RC beams with insufficient shear capacity. The experimental tests were performed in the Eduardo Torroja Institute for Construction Science (Spain). The dimensions of the beams are as follows: length, 4500 mm, width, 250 mm and height, 420 mm. The bottom longitudinal reinforcement consists of 6$\varnothing$20 mm bars arranged in 2 layers with 4 bars in the first layer and 2 in the second one, the top longitudinal reinforcement is made of 2$\varnothing$10 mm and the shear reinforcement consists of $\varnothing$8 mm stirrups, placed at a spacing of 380 mm. The beams have been externally shear reinforced with unidirectional carbon fibre sheets adhered to the beam my means of epoxy resin using the configurations shown in Table 1. Each laminate has 300 mm wide and 1 mm thick. Two different types of laminate were used. One with a fibre amount of 530 g/m^2 and the other with 300 g/m^2. The properties of the fibre in the first case are: elastic modulus equal to 240 GPa and tensile strength equal to 4000 MPa. For the second type, these values are 227 GPa and 3800 MPa, respectively.

In order to avoid the early FRP failure, the beam has rounded corners with a 25 mm radius, which was achieved during manufacturing by placing concave wooden wedges in the frameworks.

Before bonding the sheet, the beam surface is prepared, removing the top cement layer by using a sand jet and cleaning the resulting waste in order to guarantee a greater bonding between the concrete and the FRP.

In accordance with the above table, the following nomenclature is adopted: the first two characters indicate the reference of each beam; the third letter indicates the configuration of the external reinforcement, in this case U-jacketing for all the specimens; the main orientation angle of the fibres with respect to the longitudinal axis of the beams is denoted by the number written after the type of configuration; the following character indicates whether the strengthening is placed with spacing (S) or it is continuous (C); after that the weight for square meter of FRP is indicated and finally the last letter indicates whether the beam at issue is a long (L) or short (C) span one.

For the tests carried out on long span beams, a single load was applied at a distance from the support that equals three times the beam depth. Tests on short span beams were performed over the long span beams, once they were previously tested, by shifting the support to the point where the load was placed in the first test and by applying the load at a distance from the support that equals 2.5 times the beam depth. Experimental values of shear capacity reached for each beam are shown in Table 1.

5. Application of NNS and GAs to evaluate shear capacity of FRP shear-strengthened RC beams

Predictions of the experimental results were performed with the two proposed approaches, NNs and GAs, in order to evaluate their performance. The estimation of the shear capacity using the first proposal, NN, requires only the introduction of the corresponding input parameters of each beam into the trained neural network. As commented above, this procedure is very simple since it does not require of the application of any formula or expression. On the contrary, the application of the second proposal requires evaluating Eq. (5) from the optimal strut-and-tie mechanism obtained by solving the proposed optimization problem by using GAs. To perform this, the estimation of the FRP effective strain of the experimental beams collected in the previous section has been calculated with three design proposals, those proposed by the International Federation for Structural Concrete (FIB14) [16], the American Concrete Institute (ACI 440) [17], and the Italian National Research Council (CNR-DT 200) [19]. Furthermore, in accordance with the different proposals, the following design rules were used to calculate the contribution of concrete V_c in Eq. (4): (a) Spanish code for concrete EHE [23]; (b) Eurocode2: Part 1 [20]; (c) ACI 318-02 [24].

By suitably combining the values of FRP effective strains given by the different design guidelines for strengthening using FRP with the different codes for concrete, four predictions of the shear capacity were obtained with the proposed model by using GAs. Furthermore, the following parameters were chosen for the application of the proposed genetic algorithm: (a) size of population = 100; (b) crossover probability = 0.6; (c) mutation probability = 0.03; (d) maximum number of generations = 50. These values are typical in GAs and were chosen after some previous numerical tests. Furthermore, taking into account the stochastic nature of GAs, twenty independent runs were performed per GA and test problem in order to decrease the influence of random effects.

Comparisons of all predictions with experimental results are shown in Table 2. The statistical performance of all predictions upon the whole of the experimental data is also shown in Table 2. For comparison, in Table 2, all strength reduction factors in the equations used for design have been set equal to one.

In the same way, predictions with the two proposed approaches have been compared with those 'theoretical' predictions calculated directly from the concrete codes and the FRP guidelines. To apply ACI 318 codes in the 'theoretical' estimations, the concrete contribution V_c has been included and, furthermore, a strut-and-tie mechanism with struts inclined to 45° has been adopted. On the

Table 2
Comparison between experimental results and predictions.

V_{test}/V_{pred}	Theoretical		GAs		Theoretical	GAs	Theoretical	GAs	Neural networks
	EHE+FIB14	EC2+FIB14	EHE+FIB14	EC2+FIB14	EC2+CNR	EC2+CNR	ACI+ACI	ACI+ACI	
V2-U90-S530-L	1.16	1.16	1.15	0.91	1.37	1.04	1.14	1.09	0.72
V2-U90-S530-C	1.02	1.02	0.91	0.74	1.21	0.86	1.01	0.87	0.64
V3-U90-C530-L	0.97	0.93	1.01	0.82	1.23	0.87	0.93	0.91	0.76
V3-U90-C530-C	0.92	0.88	0.88	0.72	1.16	0.77	0.88	0.72	0.71
V5-U90-C530-L	1.15	1.09	1.19	0.97	0.87	0.81	0.77	0.71	0.98
V5-U90-C530-C	1.23	1.17	1.12	0.93	0.93	0.78	0.82	0.63	1.05
V8-U90-S300-L	1.16	1.09	1.23	0.97	1.26	1.08	1.21	1.21	1.27
V8-U90-S300-C	1.29	1.20	1.16	0.94	1.40	1.08	1.35	1.20	1.41
V9-U90-S300-L	0.96	0.90	1.00	0.78	1.05	0.89	0.99	0.99	0.96
V9-U90-S300-C	1.47	1.38	1.16	0.96	1.61	1.21	1.51	1.38	1.47
V11-U90-S530-L	1.27	1.23	1.30	1.01	1.10	0.93	0.94	0.89	0.90
V11-U90-S530-C	1.43	1.39	1.18	0.96	1.23	0.94	1.06	0.96	1.01
V13-U90-C300-L	1.02	1.00	1.05	0.83	1.07	0.87	0.96	0.93	0.83
V13-U90-C300-C	1.24	1.21	1.02	0.84	1.30	0.94	1.17	1.01	1.01
V14-U90-C300-L	0.98	0.96	1.01	0.80	1.03	0.86	0.93	0.91	0.80
V14-U90-C300-C	1.17	1.14	1.00	0.82	1.23	0.94	1.10	0.96	0.95
μ	1.15	1.11	1.08	0.88	1.19	0.93	1.05	0.96	0.97
σ	0.17	0.16	0.12	0.09	0.18	0.12	0.19	0.19	0.23
COV	14.43	14.02	11.01	10.47	15.52	13.01	18.54	20.15	24.18

contrary, since in the 'theoretical' predictions with Eurocode 2 concrete contribution is not included, a limiting value of cotθ = 2.5 has been considered for the inclination of the struts. However, in spite of the fact that Eurocode 2 does not consider the concrete contribution in the 'theoretical' estimation of the shear capacity of a shear reinforced beam, in the model predictions performed here this term has been added by considering that its cumulative capacity is essential to the correct interpretation of the shear resistance mechanism of the RC beam.

All the comparisons are also shown graphically in Fig. 4. The predictions lie above or below the target line, i.e., the line where the predicted value is equal to the experimental value. The nearer the points gather around the diagonal line, the better the predicted values.

From the tables and figures above, it is clear that, in general terms, the predictions with the two proposed approaches improve the 'theoretical' predictions. Statistical parameters in Table 2 show that predictions carried out with the proposed optimization procedure are better than those obtained using the equations of the design guidelines since the shear mechanism has been considered in a more realistic way. On the other hand, predictions obtained with the NN approach show the best mean value of all the predictions carried out. However its standard deviation value is the highest one. This demonstrates that the proposed method appears to be very promising although by using more beam tests to train the neural network the predictions might improve considerably. The more the amount of experimental data used to train the NN, the fitter the predicted values since the neural network model will improve.

In the proposed techniques, sometimes, the predictions of the shear capacity are unconservative which is logical in both cases. In the first case, neural networks are directly trained with the experimental results and, therefore, predictions will be sometimes higher than experimental values and other times lower. In the second case, GAs are an stochastic optimization technique and in the optimization procedure the design equations have been applied considering unit strength reduction factors; therefore, GAs predictions can result sometimes unconservative.

6. Proposal for a new shear design equation

Basing on the observed behaviour from the analyses carried out with the neural networks and genetic algorithms, some modifications might be proposed for the equations defining the shear capacity of concrete beams strengthened in shear with FRP external reinforcement. As an example to illustrate the procedure ACI design equations and GAs predictions have been be taken as a reference.

In the ACI proposal [17] the shear contribution of the FRP shear reinforcement in Eq. (1) is given by:

$$V_f = \frac{2nt_f w_f E_f \varepsilon_{fd,e}(\cos\beta + \mathrm{sen}\beta)d_f}{s_f} \quad (5)$$

where n = number of plies of FRP reinforcement, $\varepsilon_{fd,e}$ = design value of effective FRP strain, d_f = depth of FRP shear, t_f = thickness of the FRP transversal reinforcement, s_f = spacing of the FRP transversal reinforcement, w_f = breadth of the FRP transversal reinforcement. The other symbols were defined previously.

To illustrate the influence of some of the parameters which affect Eq. (5) a parametric study was carried out initially by using the proposed genetic algorithm. The most important conclusions are presented next.

6.1. Influence of the FRP reinforcement ratio (ρ_f)

The FRP reinforcement ratio ρ_f is calculated like $2t_f\mathrm{sen}\alpha/b_w$ for continuously bonded shear reinforcement and $2(t_f/b_w)(w_f/s_f)$ for strips or sheets of width b_f at a spacing s_f; α is the angle of diagonal crack with respect to the member axis. This ratio has a very important influence on the failure shear strength. Fig. 5 shows the influence of this parameter on the predictions calculated using the proposed GA model and the ACI design guideline for a ratio a/d equal to 2.5. Both curves follow a similar tendency although, observing the slope of the curves, the model gives a slightly higher relative importance to this parameter than the ACI guideline.

6.2. Influence of the elastic modulus of the FRP reinforcement (E_f)

Fig. 6 shows the influence of the FRP elastic modulus. As with the previous parameter, the GA model and the ACI design guidelines follow a similar tendency. However, unlike the previous case, the model does not give a higher relative importance to this parameter when compared to the ACI predictions.

6.3. Influence of the inclination of the FRP fibres (β)

In the study of the influence of the inclination of the FRP fibres, angles between 30° and 90° have been considered. Results are

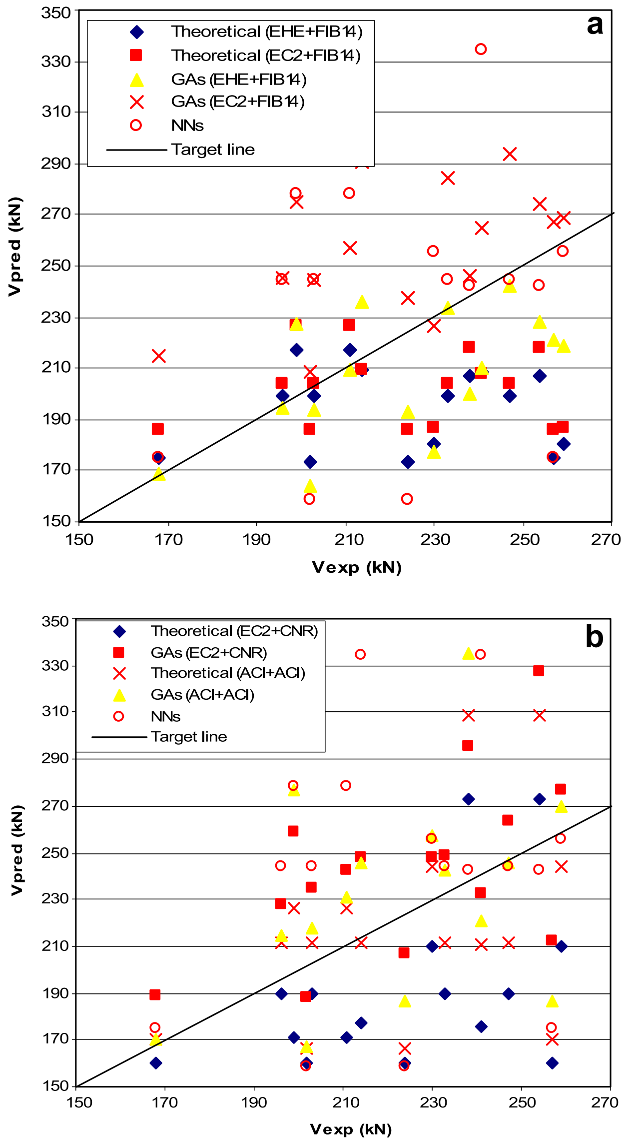

Fig. 4. (a) Comparison of shear strength predictions with experimental results. (b) Comparison of shear strength predictions with experimental results.

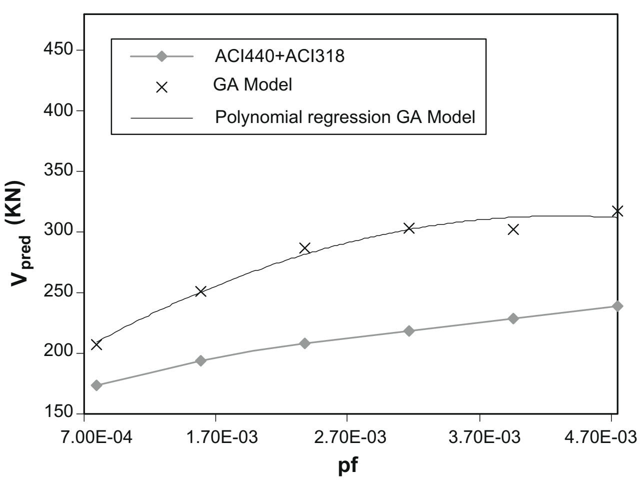

Fig. 5. Influence of the ratio ρ_f in the predicted failure shear force.

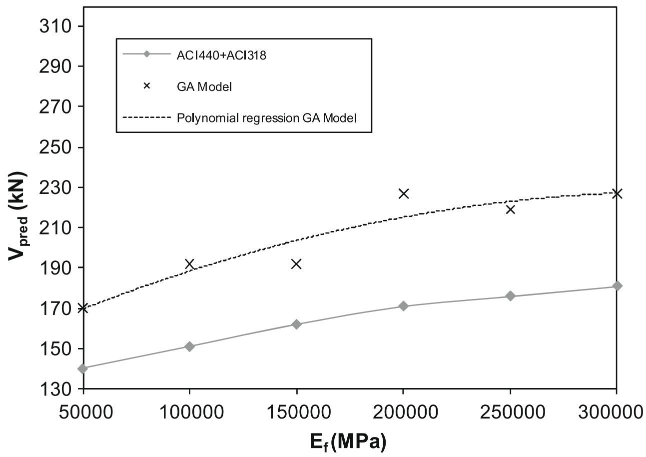

Fig. 6. Influence of E_f in the predicted failure shear force.

shown in Fig. 7. Both, GA model and ACI follow a similar tendency reaching the maximum value when $\beta = 45°$.

6.4. Proposed shear design equation

After considering the conclusions of the parametric study, the original form of the shear equation in Eq. (5) has been modified with the purpose of representing more suitably the dependence on the ratio ρ_f. For it, Eq. (5) has been rewritten as follows

$$V_f = c_1 \rho_f^{c_2} n E_f \varepsilon_{fd,e} (\cos\beta + \mathrm{sen}\beta) d_f b_w \tag{6}$$

where c_1 and c_2 are unknown coefficients to be determined.

Of course, this study should be only considered as a first illustrative attempt of improving the original shear design equation and not like a wide and detailed study.

The optimum values of c_1 and c_2 are obtained by solving a minimization problem of the objective function defined from the difference between the measured shear strength of RC beams externally shear strengthened with FRP and that calculated using the Eqs. (1) and (6). Genetic algorithms have been used to solve the optimization problem. The final form of the optimized equations is:

$$V_f = 4.44 \rho_f^{1.11} n E_f \varepsilon_{fd,e} (\cos\beta + \mathrm{sen}\beta) d_f b_w \tag{7}$$

With the modifications proposed, new predictions have been carried out for the beams tested in the Eduardo Torroja Institute for Construction Science (Spain). The comparison with experimen-

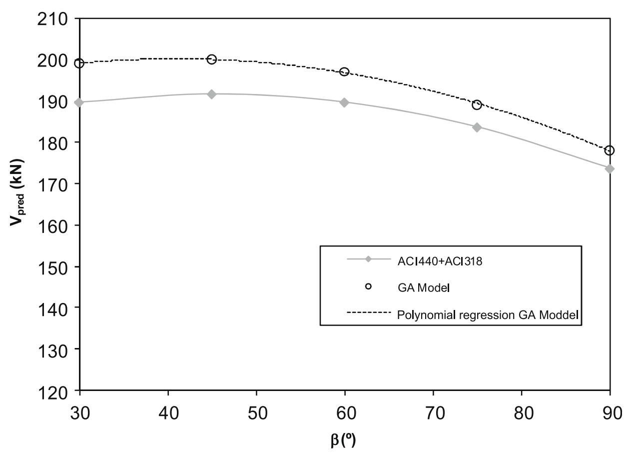

Fig. 7. Influence of β in the predicted failure shear force.

Table 3
Comparison between experimental results and modified ACI predictions.

V_{test}/V_{pred}	Standard ACI+ACI	Proposal ACI+ACI
V2-U90-S530-L	1.14	0.99
V2-U90-S530-C	1.01	0.88
V3-U90-C530-L	0.93	0.87
V3-U90-C530-C	0.88	0.84
V5-U90-C530-L	0.77	0.94
V5-U90-C530-C	0.82	1.01
V8-U90-S300-L	1.21	1.22
V8-U90-S300-C	1.35	1.36
V9-U90-S300-L	0.99	0.98
V9-U90-S300-C	1.51	1.5
V11-U90-S530-L	0.94	1
V11-U90-S530-C	1.06	1.15
V13-U90-C300-L	0.96	0.85
V13-U90-C300-C	1.17	1.03
V14-U90-C300-L	0.93	0.82
V14-U90-C300-C	1.10	0.97
μ	1.05	1.02
σ	0.19	0.18
COV	18.54	18.20

tal values is shown in Table 3. As may be observed, the agreement of the predictions with the experimental tests is satisfactory and for almost all the specimens the estimations have improved when compared to the standard ACI predictions in Table 2.

7. Conclusions

Two artificial intelligence techniques have been applied for the first time to the problem of estimating the capacity of FRP shear-strengthened RC beams which remains as an open question nowadays. The AI-based simulation techniques offer an alternative approach to conventional techniques and, from them, some advantages can be obtained. Conventional models are based on the assumption of predefined empirical equations dependent on unknown parameters. However, in problems for which the modelling rules are either not known or extremely difficult to discover, like our problem, the conventional methods do not work well. By using artificial neural networks these difficulties are overcome since they are based on the learning and generalization from experimental data; furthermore, they are able to adapt solutions over time to consider the added experience.

On the other hand, by using genetic algorithms the basic characteristics of the strut-and-tie models, taken as a basis to estimate the shear capacity of RC beams strengthened with FRP, have been revised with the purpose of representing models more consistent with the physical reality of the shear mechanism.

Based on the work presented here and the obtained predictions it is believed the two proposed approaches offer a potential alternative method to predict the shear strength of externally strengthened beams, which should not be underestimated for the future.

Finally, taking as a basis the proposed GA model and the ACI design guidelines, a design formula has been developed with successful results although more exhaustive studies should be carried out about this approach.

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