Krill herd algorithm-based neural network in structural seismic reliability evaluation

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ABSTRACT
In this research work, the relative displacement of the stories has been determined by means of a feedforward Artificial Neural Network (ANN) model, which employs one of the novel methods for the optimization of the artificial neural network weights, namely the krill herd algorithm. For the purpose of this work, the area, elasticity, and load parameters were the input parameters and the relative displacement of the stories was the output parameter. To assess the precision of the feedforward (FF) model optimized using the Krill Herd Optimization (FF-KH) algorithm, comparison of results has been performed relative to the results obtained by the linear regression model, the Genetic Algorithm (GA), and the back propagation neural network model. The comparison of results has been carried out in the training and test phases. It has been revealed that the artificial neural network optimized with the krill herd algorithm supersedes the afore-mentioned models in potential, flexibility, and precision.

1. Introduction
During the last three decades, nonconventional methods are becoming an important class of efficient tools providing solutions to complicated engineering problems. Among these methods, soft computing has to be mentioned as one of the most eminent approaches. Neural networks (NNs), fuzzy logic, and evolutionary algorithms are the most popular soft-computing techniques for the solution of structural engineering problems. Such an important significant issue in structural engineering with great interest for engineering of practice is the seismic vulnerability assessment of constructions. Detailed and in-depth state-of-the-art reports can be found in [1]–[9] and [10].

The protection of critical structures and infrastructure system has recently garnered attention with an emphasis on damage localization and quantification of such systems. With the abundance of new algorithms and data, researchers and engineers should be able to better inform preparedness and plan to avoid the unexpected failure of structural components. In this regard, many researchers have been developing and utilizing various algorithms to predict or detect structural damages ([11]–[13] and [14]).

The application of the optimization algorithms to the artificial neural networks (ANNs) has increased in the civil engineering domain and it includes the use of the genetic algorithm ([15], Khademi et al. [16]–[19]), the imperialist competitive algorithm [20], [21], and the social-based algorithm [22], [23].

This study aims to use the krill herd algorithm to optimize the weights of the artificial neural networks as a new optimization algorithm for the seismic reliability assessment of structures. Therefore, first the modeling and measurement methods were used to assess the seismic reliability of the structures and the results were recorded. Second, different parameters were assessed to identify the input parameters, and the krill herd algorithm was applied to the feedforward network for the optimization purposes. To validate the model, a comparison was made using the back propagation artificial neural network model [24] as well as linear and nonlinear regression models.

The remainder of this article is organized as follows. Section 2 is devoted to the introduction of the Krill Herd Algorithm. Sections 3 and 4 present, respectively, the case study and model we used for this study. Section 5 represents the final values of weights of the Neural Network. Finally, Section 6 presents our putative conclusions.

2. Introducing the krill herd algorithm (KH)
The Krill-herd algorithm (KH) is a swarm intelligence optimization algorithm, based on the behavior of a krill herd [25], and it used to improve the efficiency of artificial neural networks. In the KH algorithm, the krill population searches for the krill food sources in a multidimensional search space and then different decisions are proposed. However, the target is the distance between the krill individuals and the excess food associated with the costs. Accordingly, the time-dependent position of a krill individual is measured and (i) foraging movement and (ii) random physical diffusion [25]–[35]. The most
prominent advantages of KH algorithm are as follows; each agent plays a role in the process, the derivative information is not necessary, it takes advantage of crossover and mutation operators. On the other hand, it needs an optimal approach for determining the primary krill distribution and parameters and the basic motions in the KH algorithm should be more comprehensive. The flowchart of the krill herd algorithm is presented in Figure 1.

2.1. The process inducing motion

The speed of a krill individual is influenced by the movements of other krill individuals in the multidimensional search space, where speed drastically and dynamically varies by the local impact, the target herd, and the repulsive impact. The movements of a krill individual are expressed using the following Eqs. (1)–(6) [26]:

\[
\theta_i^{\text{new}} = \theta_i^{\text{old}} + \mu_n \theta_i^{\text{max}} \\
\varepsilon_i = \varepsilon_i^{\text{local}} + \varepsilon_i^{\text{target}} \\
\varepsilon_i^{\text{local}} = \sum_{j=0}^{N_p-1} f_{ij} x_{ij} \\
f_{ij} = \frac{x_i - x_j}{|f_w - f_b| \text{rand}(0.1)} \\
\varepsilon_i^{\text{target}} = 2 \left( \text{rand}(0.1) + \frac{i}{t_{\max}} \right) f_i^{\text{best}} x_i^{\text{best}}
\]

In the above equations, \(\theta_i^{\text{max}}\) represents the maximum induced motion, and \(\theta_i^{\text{old}}\) denotes the induced motion. In addition, \(\mu_n\) is the algebra size of the induced motion, whereas the target impacts are shown by \(\varepsilon_i^{\text{local}}\) and \(\varepsilon_i^{\text{target}}\). Besides \(f_w\) and \(f_b\) denote the worst and best population positions, respectively. \(f_i\) and \(f_j\) are the fitness values of the \(i\)th and \(j\)th krill individuals, respectively. Finally, \(t_{\max}\) shows the current and maximum quantities [26]. The sensing distance parameter was used to identify the neighbors of each krill individual (Figure 2). Note that if the distance between two krill individuals is shorter than the sensing distance, that given krill individual is considered the neighbor of the other krill individual. Eq. (7) shows the formula for calculating the sensing distance [26].

\[
SD_i = \frac{1}{5n_p} \sum_{j=0}^{n_p-1} |x_i - x_j|
\]

As shown in Eq. (7), \(n_p\) stands for the number of the krill individuals in the population, while \(x_i\) and \(x_j\) denote the positions of the \(i\)th and \(j\)th krill individuals, respectively [26].

2.2. Foraging motion

The foraging motion of each krill individual is formulated as Eqs. (8) and (9) under the conditions of the existing position of the food and the previous knowledge of the food position [26]:

\[
F_m = \frac{1}{\mu_f} a_i + \mu_f F_i^{\text{old}} \\
a_i = a_i^{\text{food}} + a_i^{\text{best}}
\]

In the above equations, \(F_m\) is the initial motion, \(V_f\) is the foraging speed, and \(\mu_f\) is the algebraic size of foraging in the [0, 1] range. In addition, \(F_i^{\text{old}}\) denotes the previous foraging motion, \(a_i^{\text{food}}\) is food absorption, and \(a_i^{\text{best}}\) shows the best fitness of each krill individual [26].
3. Materials and methods

3.1. Model description

The present work has applied the model in the case of a 3-story steel frame building (Figure 3) modeled by OpenSees [36]. The building parameters used for the development of the model are listed in Table 1. In total, 1000 different cases were analyzed in order to investigate the influence of several parameters on the maximum story relative horizontal displacements of the 3-story steel frame building. Five random variables are presented to consider different sources of uncertainties in load and structural modeling. The random variables are columns’ area of the first (A₁), second (A₂), and third floor (A₃), elasticity modulus (E), and gravity loads (G). The distribution of each random variable is selected based on Haldar & Mahadevan (Haldar & Mahadeva, 2000) [40]. 1000 samples random numbers provided 1000 structural models. The nonlinear time history analysis of the 1978 Tabas earthquake [37] has been performed for each model by OpenSees. The random variables are used as the input parameters and the maximum relative horizontal displacement of the first (δ₁), second (δ₂), and third (δ₃) story are considered as the output parameters. Their mean values together with the minimum and maximum values are listed in Table 2.

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameters</th>
<th>Units</th>
<th>Parameter type</th>
<th>Max</th>
<th>Min</th>
<th>Average</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cross-section area of the columns of the 1st story (A₁)</td>
<td>cm²</td>
<td>Input</td>
<td>0.067633389</td>
<td>0.032249158</td>
<td>0.050059696</td>
<td>0.004904</td>
</tr>
<tr>
<td>2</td>
<td>Cross-section area of the columns of the 2nd story (A₂)</td>
<td>cm²</td>
<td>Input</td>
<td>0.065831266</td>
<td>0.03128909</td>
<td>0.050216893</td>
<td>0.00507</td>
</tr>
<tr>
<td>3</td>
<td>Cross-section area of the columns of the 3rd story (A₃)</td>
<td>cm²</td>
<td>Input</td>
<td>0.066330994</td>
<td>0.034635057</td>
<td>0.049945525</td>
<td>0.00493</td>
</tr>
<tr>
<td>4</td>
<td>Elasticity Modulus (E)</td>
<td>kN/m²</td>
<td>Input</td>
<td>2.0714E+11</td>
<td>1.93856E+11</td>
<td>1.99972E+11</td>
<td>2.03E+09</td>
</tr>
<tr>
<td>5</td>
<td>Gravity Load (G)</td>
<td>kN</td>
<td>Input</td>
<td>534.0753237</td>
<td>471.3860024</td>
<td>500.551526</td>
<td>9.888367</td>
</tr>
<tr>
<td>6</td>
<td>Maximum relative horizontal displacement of the 1st story (δ₁)</td>
<td>cm</td>
<td>Output</td>
<td>0.030775</td>
<td>0.002225</td>
<td>0.010617467</td>
<td>0.003839</td>
</tr>
<tr>
<td>7</td>
<td>Maximum relative horizontal displacement of the 2nd story (δ₂)</td>
<td>cm</td>
<td>Output</td>
<td>0.036258</td>
<td>0.005412</td>
<td>0.0180434</td>
<td>0.004475</td>
</tr>
<tr>
<td>8</td>
<td>Maximum relative horizontal displacement of the 3rd story (δ₃)</td>
<td>cm</td>
<td>Output</td>
<td>0.037876</td>
<td>0.007873</td>
<td>0.022580832</td>
<td>0.004636</td>
</tr>
</tbody>
</table>

Figure 3. Cross-section details and the maximum relative horizontal displacements of the three-story steel frame.
RMSE, and mean square error (MSE) statistical parameters, and the convergence coefficient ($R^2$) are used in Table 5. According to these results, the FF-KH yielded the best results with the 5-5-4-3 structure. The hyperbolic tangent sigmoid (tansig) activation function has been used in the final model.

Figure 5 depicts the comparison of the “exact” computational values with the predicted values of the optimum FF-KH model with topology 5-5-4-3 for the three maximum relative horizontal displacements. These results clearly show that the three maximum relative horizontal displacements predicted from the Krill Herd Algorithm-Based multilayer feed-forward neural network are very close to “exact” computational results.

4. Model validation

The statistical models used in this research were the multiple linear regression and the nonlinear regression models. In the multiple linear regression, two or several independent variables substantially influence the dependent variable as shown in the following equation [38].

\[ y = f(x_1, x_2, \ldots) \rightarrow y = a_0 + \sum_{i=1}^{n} a_i x_i \]  

In the above equation, $y$ is the dependent variable, $x_i$ are the independent variables, and $a_i$ are the regression coefficients [38]. In this research, different linear regression models were studied in MINITAB 14.0 [41] for the input and output variables. The best multiple linear regression model that mostly complied with the maximum relative horizontal displacements of the stories is expressed by

\[
\begin{align*}
y_1 &= -0.733^*x_1 + 0.100^*x_2 + 0.050^*x_3 + 0^*x_4 + 0^*x_5 + 0.048 \\
y_2 &= -0.620^*x_1 - 0.475^*x_2 + 0.078^*x_3 + 0^*x_4 + 0^*x_5 + 0.085 \\
y_3 &= -0.566^*x_1 - 0.438^*x_2 - 0.323^*x_3 + 0^*x_4 + 0^*x_5 + 0.104
\end{align*}
\]  

where $y_1$, $y_2$, and $y_3$ denote the maximum relative horizontal displacements of the first, second, and third story, respectively. Moreover, $x_1, x_2, x_3, x_4$, and $x_5$ stand for $A_1, A_2, A_3, E$, and $G$, respectively (see Tables 1 and 2).

The mean absolute error (MAE), mean error (ME), age absolute error (AAE), root mean square error (RMSE), and mean square error (MSE) statistical parameters, and the convergence coefficient ($R^2$) are used in Table 6.

Figure 6 depicts the comparison of the “exact” computational values with the predicted values of the linear regression model for the three maximum relative horizontal displacements.

In addition, in the nonlinear regression model, two or several independent variables substantially influence the dependent variable as shown in Eq. (15) [39].

\[ y = e^{(a_1 x_1 + b_1 x_2 + c_1 x_3 + d_1 x_4 + e_1 x_5 + f_1 x_6 + g_1 x_7 + h_1)} \]  

Table 3. The characteristics of the feedforward artificial neural network combined with the krill herd algorithm.

<table>
<thead>
<tr>
<th>Features neural network</th>
<th>Model Number of Krills</th>
<th>number of output</th>
<th>Neural Network</th>
<th>Hidden Layers</th>
<th>Nodes</th>
<th>Transfer Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>FF_KH</td>
<td>5</td>
<td>3</td>
<td>newff</td>
<td>2</td>
<td>5,4</td>
<td>Tansig</td>
</tr>
</tbody>
</table>

Table 4. The characteristics of the krill herd algorithm used in the feedforward network.

<table>
<thead>
<tr>
<th>Features Krill Herd Algorithm</th>
<th>Model Number of Krills</th>
<th>minimum number of Krill Herd</th>
<th>maximum number of Krill Herd</th>
<th>Maximum Iteration</th>
<th>number of clusters</th>
<th>maximum induced speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>FF_KH</td>
<td>5</td>
<td>2</td>
<td>10</td>
<td>200</td>
<td>1</td>
<td>0.01</td>
</tr>
</tbody>
</table>
where $y$ is the dependent variable, $x_i$ are the independent variables, and $a, b, c, \ldots$ are the nonlinear regression coefficients. In this research, different nonlinear regression models were examined in Datafit 9.0 for the input and output variables. In addition, the best nonlinear regression model, which complied the most with the data on the maximum relative horizontal displacements of the stories, is defined by

\begin{align*}
y_3 &= e^{-66.689x_1+13.4677x_2+5.112x_3+0.001x_4+0.001x_5-2.480} \quad (16) \\
y_4 &= e^{-30.292x_1-23.845x_2+4.655x_3+0.0x_4+0.0x_5-0.942} \quad (17) \\
y_5 &= e^{-22.037x_1-17.431x_2-13.460x_3+0.0x_4+0.0x_5-0.683} \quad (18)
\end{align*}

Table 6. The statistical results of linear regression model in determining the maximum relative horizontal displacement of each story.

<table>
<thead>
<tr>
<th>Data</th>
<th>Story number</th>
<th>ME</th>
<th>MSE</th>
<th>RMSE</th>
<th>MAE</th>
<th>AAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Data</td>
<td>1</td>
<td>0.0087</td>
<td>0.0001</td>
<td>0.0088</td>
<td>0.0087</td>
<td>100.3175</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.0160</td>
<td>0.0003</td>
<td>0.0161</td>
<td>0.0160</td>
<td>97.1304</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.0150</td>
<td>0.0002</td>
<td>0.0151</td>
<td>0.0150</td>
<td>71.4632</td>
</tr>
<tr>
<td>Train</td>
<td>1</td>
<td>0.0087</td>
<td>0.0001</td>
<td>0.0088</td>
<td>0.0087</td>
<td>100.0480</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.0160</td>
<td>0.0003</td>
<td>0.0161</td>
<td>0.0160</td>
<td>97.4718</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.0150</td>
<td>0.0002</td>
<td>0.0152</td>
<td>0.0150</td>
<td>71.7464</td>
</tr>
<tr>
<td>Test</td>
<td>1</td>
<td>0.0086</td>
<td>0.0001</td>
<td>0.0087</td>
<td>0.0086</td>
<td>100.9463</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.0158</td>
<td>0.0003</td>
<td>0.0160</td>
<td>0.0158</td>
<td>96.3338</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.0149</td>
<td>0.0002</td>
<td>0.0150</td>
<td>0.0149</td>
<td>70.7975</td>
</tr>
</tbody>
</table>

Figure 5. Comparison of the computational ('Exact') with predicted values of the maximum relative-story displacement using KHA-ANN model (All data).

Figure 6. Comparison of the computational ('Exact') with predicted values of the maximum relative-story displacement using LR model (All data).
where \(y_3, y_4, \) and \(y_5\) denote the relative displacements of the first, second, and third stories, respectively. Moreover, \(x_1, x_2, x_3, x_4, \) and \(x_5\) stand for \(A_1, A_2, A_3,\) area, Elasticity Modulus \(E_s,\) and Gravity Loads \(G,\) respectively. The results obtained by means of the multiple linear regression model are listed in Table 7. Figure 7 depicts the comparison of the ‘exact’ computational values with the predicted values of the nonlinear regression model for the three maximum relative horizontal displacements.

The analytic and statistical criteria listed in Tables 6 and 7 were used to assess the linear and nonlinear regression models. The analysis results indicated that the LR model shown in Eqs. (12)–(14) yielded the best results in determining the relative displacements of the stories. In other words, the linear regression model even led to more suitable results than the nonlinear regression model.

To assess the precision of the FF model with the krill herd optimization algorithm, the back propagation neural network model was used along with the linear and nonlinear regression models (as two statistical models) [24]. In addition, the RMSE statistical criterion was used to assess all models against a single criterion, which was also used by [24]. The results of all of the model comparisons are shown in Table 8. For the final assessment of the models, the best state of each model was selected, and eventually four models, namely the KH-ANN, back propagation neural network [24], nonLR, and LR models, were selected as the best models. The results of determining the relative displacement of the stories are also shown in Table 8. Considering the observed and calculated RMSE values of each model and the related results it is concluded that the artificial neural network optimized using the krill herd algorithm determines the relative displacement of each story with more precision than the other models.

5. Final values of weights of the NN model

It is common practice, in the majority of the published articles on NNs Models, for authors to present the architecture of the optimum NN model without any information about the final values of NN weights. Any architecture without the values of final values of NN model weights has very little value for others researchers and practicing engineers. In order to be useful, a proposed NN architecture should be accompanied by the (quantitative) values of weights. In such a case, the NN model can

![Figure 7. Comparison of the computational ('Exact') with predicted values of the maximum relative-story displacement using NonLR model (All data).](image)
be readily implemented in an MS-Excel file, available to anyone interested in the problem of modeling.

To this end, in Table 9 the final weights for both hidden layers and bias are presented. By using the weights and bias values between different layers of ANN the value of the maximum displacements for each one story can be estimated (predicted).

6. Conclusions

■ The results of testing the proposed method on the structure of the artificial neural network revealed the notable success of the krill herd algorithm in finding the optimum point of the functions.

■ The optimization potential of the krill herd algorithm can be used as a powerful tool for the optimization of the weights of the artificial neural networks. The comparison between the training and testing results of the different ANN models optimized with the KH algorithm indicated that the artificial neural network with the 4-5-4-3 structure, 10 krill individuals, 2 minimum krill herds, 5 maximum krill herds, and 50 maximum iterations offered the best results as compared to the other models under study.

■ The precision of the maximum relative story horizontal displacement determined by the KH-optimized artificial neural network model was higher than the other models of this type. In addition, the MSE, ME, MAE, and RMSE statistical coefficients were smaller in this model; this reflected the lower error rate of this model.

■ To assess the artificial neural network model optimized using the krill herd algorithm, the model was compared to the multiple linear and nonlinear regression models and the back propagation neural network model. The comparison results indicated that the KH optimized artificial neural network determined the relative displacement of each story with more precision and flexibility than the other models.

Conflict of interest

The authors confirm that this article content has no conflict of interest.

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