NON-DESTRUCTIVE STRUCTURAL TEST USING WAVES AND SOFT COMPUTING. CASE STUDY: PILE INTEGRITY INSPECTION USING GENETICALLY OPTIMIZED NEURAL NETWORKS

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ABSTRACT

Non-destructive testing of structures using wave propagation and reflection and soft computing for the post-processing of the results is addressed in this contribution. As a case study, a neural network based scheme and its decision mechanism are utilized to classify defects in piles. Numerical simulation results are used, in combination to an island genetic algorithm, for the neural detector initialization, as well as, for performance validation.

1 INTRODUCTION

Complicated inverse and defect identification problems arise in various applications of civil, production, materials and mechanical engineering and in geophysics. Wave propagation and reflection carries enough information for the detection of subsurface defects, cracks and other damages. Accurate modelling is first required in order to design the experiments and check the feasibility of every proposed method. Furthermore, post-processing of measurements is by no means an easy task. In cases classical or genetic optimization for the solution of the arising parameter identification problem is not sufficient, soft computing tools like neural networks can be used. Previous work concentrated on the solution of crack and defect identification problems, as well as parameter identification problems [1], [2], [3], [4]. Pile integrity tests are considered in the present contribution.

Many civil structures, such as buildings, bridges, towers, dams and other massive structures need special foundation in the form of piles, built using precast and cast-in-situ techniques. Sometimes, precast piles may get damaged under the pile driving impact process, due to which long and deep cracks may appear. On the other hand, "necks" or "bulbs" may be created in the process of drilling. In both cases, these defects may affect considerably the bearing capacity of the piles. So the structural evaluation and monitoring of new and existing piles are becoming increasingly important.

Non-destructive testing (NDT) plays a key role in assuring the adequacy of manufactured components, and has been a core research area for many years [5], [6]. In NDT, the structure undergoes a dynamic input, such as the tap of a hammer or a controlled impulse. Key properties, such as displacement or acceleration at different points of the structure, are measured as the corresponding output. The test is based on wave propagation theory. The alternative name of the method, low strain dynamic test, stems from the fact that when a light impact is applied to a pile it produces a low strain. The impact produces a compression wave that travels down the pile at a constant wave speed. Changes in cross sectional area - such as a reduction in diameter - or material - such as a void in concrete - produce wave reflections.

In this paper, an innovative work for the NDT of piles is employed using a mixture of state of the art soft computing techniques and appropriate feature extraction and data generation procedures. The innovation of the current methodology is the fully automatic post processing techniques which show a high classification performance, easy implementation and noise tolerance using a limited training sample.

2 THE PROPOSED METHODOLOGY

Low strain integrity tests are conducted by either in time domain or in frequency domain, depending on the specific application [7]. In time domain reflectometry, the wave is generated by a hand held hammer blow impact and the response as a function of time is picked up by multiple accelerometers, placed on pile head and around it, on a circle base, close to the location of hammer blow. Monitoring and analysis of these reflections form the basis of integrity testing .

In this paper similar tests are modelled by employing an FEM/SBFEM approach [8], [9]. Numerical simulation is used for the data generation and neural detectors (genetically optimized) for the defect identification. Data generation involves the generated waveforms (time domain), while neural detectors provide results regarding the integrity testing, by exploiting the available information provided following a specific feature extraction. The input data for the identification algorithm is developed numerically by a coupled FEM/SBFEM simulation [10], [11].

The core of the detection model consists of the well know artificial neural networks which are topologically optimized using island genetic algorithms. Artificial neural networks are widely used in various cases because of their ability to deal effectively with complex, no stationary environments. Relating work on inverse analysis and defect identification problems solved by optimization and neural networks have been published in [12], [13].

The main purpose of this paper is to provide a solid basis for the development of a robust technique for defect recognition. Although, the initial evaluation sets are of simplified pile geometries, the applied techniques are also feasible for real life problems demanding only minor modifications. Experimental results also suggest so.
The rest of the paper is organized as follows: Section 3 describes the data set. Section 4 provides a brief description of the neural networks and the island genetic optimization scheme. Data extraction and experimental results are discussed in section 5 and 6, respectively. The conclusion is finally given in section 7.

3 DATA SET DESCRIPTION

In order to simulate of the wave propagation through the piles a coupled finite element method (FEM) and scaled boundary finite element method (SBFEM) approach is used. This approach satisfies Sommerfeld's radiation condition and allows simulating an infinite half-space. This ensures that the applied impulse will not be reflected at the artificial boundary which is introduced by the boundary of the numerical discretisation. The coupled approach proposed here requires only the discretisation of a small domain compared to a purely FEM based approach. FEM and SBFEM are used to model the near- field and far-field, respectively.

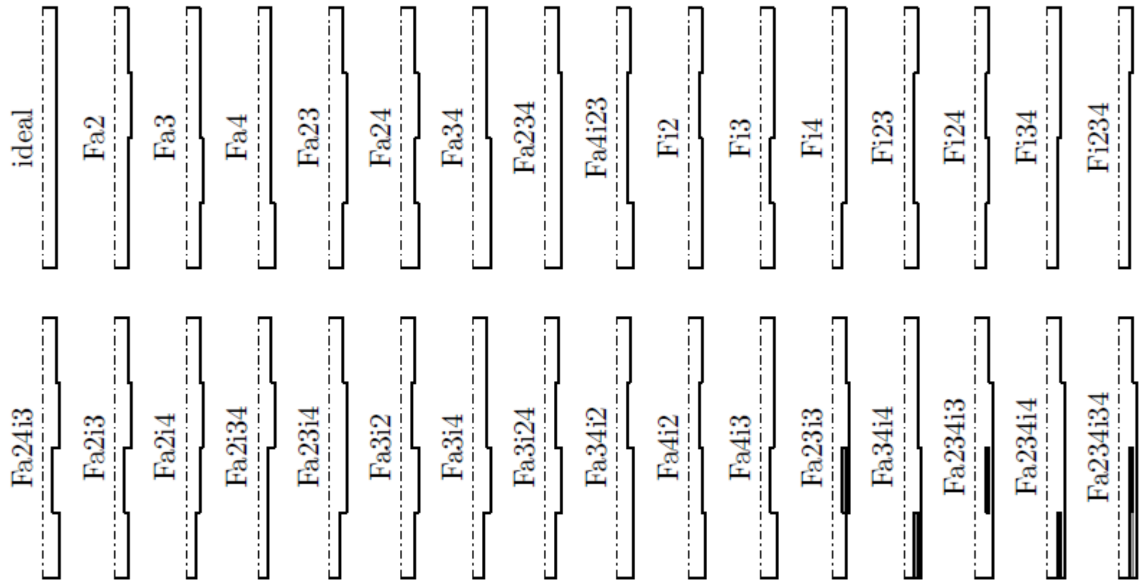

Figure 1. Illustration of various pile examples used during the evaluation of the model.

Different three-dimensional pile configurations are analysed using linear finite and scaled boundary finite elements. One clean pile without defects (ideal), is discretised. Length l_0 and radius r_0 are chosen as 2.1 *m* and 0.1 *m*, respectively. The surface of the ground is defined at 0.0 *m*, the pile's head is located +0.1 *m* over the surface, while the pile's toe is at -2.0 *m* in the ground. Additional piles with defects are discretised as well, the geometry of these modified piles are shown in Figure 1.

4 NEURAL NETWORKS AND GENETIC OPTIMIZATION

Neural networks and genetic algorithms demonstrate powerful problem solving ability. They are based on quite simple principles, but take advantage of their mathematical nature: non-linear iteration. Neural networks with back-propagation learning showed results by searching for various kinds of functions. However, the choice of the basic parameter (network topology, learning rate, initial weights) often determines the success of the training process. The selection of these parameter follow in practical use rules of thumb, but their value is at most arguable. Genetic algorithms are global search methods, which are based on principles like selection, crossover and mutation. A good deal of biological neural architecture is determined genetically. It is therefore not surprising that as some neural network researchers explored how neural systems are organized that the idea of evolving neural architectures should arise [14]. In this paper, the topology of neural network is determined using island genetic algorithms.

4.2 Island genetic algorithm

The usefulness of the genetic algorithms (GAs) is generally accepted [15]. The island GA uses a population of alternative individuals in each of the islands. Every individual is a feed forward neural network (FFNN). While eras pass networks’ parameters are combined in various ways in order to achieve a suitable topology. A pair of FFNNs (parents) is combined in order to create two new FFNNs (children). Children inherit randomly their topology characteristics from both their parents. Under specific circumstances, every one of these characteristics may change (mutation). The quartet, parents and children, are then evaluated and the two best will remain, updating that way the island’s population. An era has passed when all the population members participate in the above procedure. In order to bate the genetic drift, population exchange among the islands, every four eras. The algorithm terminates when all eras have passed. Initially, the parameters’ range is described in Table 1 and the main steps of the genetic algorithm are the same as in [16]. The island algorithm is used to parameterize the topology of the non-linear classifier.

Table 1. Island genetic algorithm parameters' range.

Parameter	Min value	Max value
Training epochs	100	400
Number of layers	1	3
Number of neurons (per layer)	4	10
Number of islands	3	3
Number of eras	10	10
Population (per island)	16	16

5 FEATURE EXTRACTION

The behaviour of specific nodes on the pile's surface is examined using a FFNN. In total, 25 piles with various defections were used for the training and the evaluation phase of the model. Each one of the piles is described by the behaviour of 23 nodes, in terms of displacement, velocity and acceleration, during a pre-defined time period. Each node's behaviour was used for the features extraction. In every case, vectors of constant size had to be created, due to neural networks' formulation scheme, as input and output vectors.

Once the load is applied, at the top of the pile, every node oscillates (an illustration of nodal oscillation is shown in Figure 2); the overall behaviour of the pile is described by signal $\boldsymbol{S}_{pile}$, defined as:

$$S_{pile} = \begin{pmatrix} S_{1,t_1} & \cdots & S_{23,t_1} \\ \vdots & \ddots & \vdots \\ S_{1,T} & \cdots & S_{23,T} \end{pmatrix} \quad (1)$$

where T denotes the oscillating time period for every of the 23 nodes. The signal, for a specific time instance, at the node n, can be presented as a matrix:

$$\boldsymbol{S}_{n,t} = \begin{bmatrix} x_{d,t} & y_{d,t} & z_{d,t} \\ x_{v,t} & y_{v,t} & z_{v,t} \\ x_{a,t} & y_{a,t} & z_{a,t} \end{bmatrix} \quad (2)$$

where d, v, a stand for displacement, velocity and acceleration respectively, and $n=\{1,\ldots5,10,\ldots27\}$ denotes the corresponding node, see Fig. 3. That signal is then transformed to a vector, using an appropriate feature extraction process in order to be evaluated using a FFNN to detect possible defects on the pile.

At first, the signal, produced by the load impact on the pile, is recorded. Then, a new signal is created by subtracting the investigated pile's signal from an ideal pile's signal, S_{ideal}. The data fed to the FFNN originates from the newly created signal, in a process described in Table 2. It is important to note that signal is one-dimensional of size 40×1. Although the signal duration is 2000 time steps (or 0.012 seconds), only the first 400 time steps of the transient period were utilized.

Table 2. FFNN detector input creation.

Define node n , axis $k \in \{\mathrm{x,y,z}\}$ turbulence period duration, $\mathrm{T_{tur}}$, and which descriptor to use, and number of nodes for training.
Allocate memory for every node $i = 1,\ldots,n$ for vector of size 1×40.
For $j = 1,\ldots,40$ depending the descriptor calculate:
- Mean square error for consecutively time intervals
- Mean absolute square error for consecutively time intervals
- Plain value every 10 time steps

Do $vector(j) := calculated\ value$

The creation of the output vectors involves the pile separation in four divisions. The first division is located above the ground. There, we apply the load and observe the nodal behaviour; all the nodes are located on the surface. The rest divisions are located underground. An assumption is made that on every division one defect is allowed. That defection can either be a radius above or below normal.

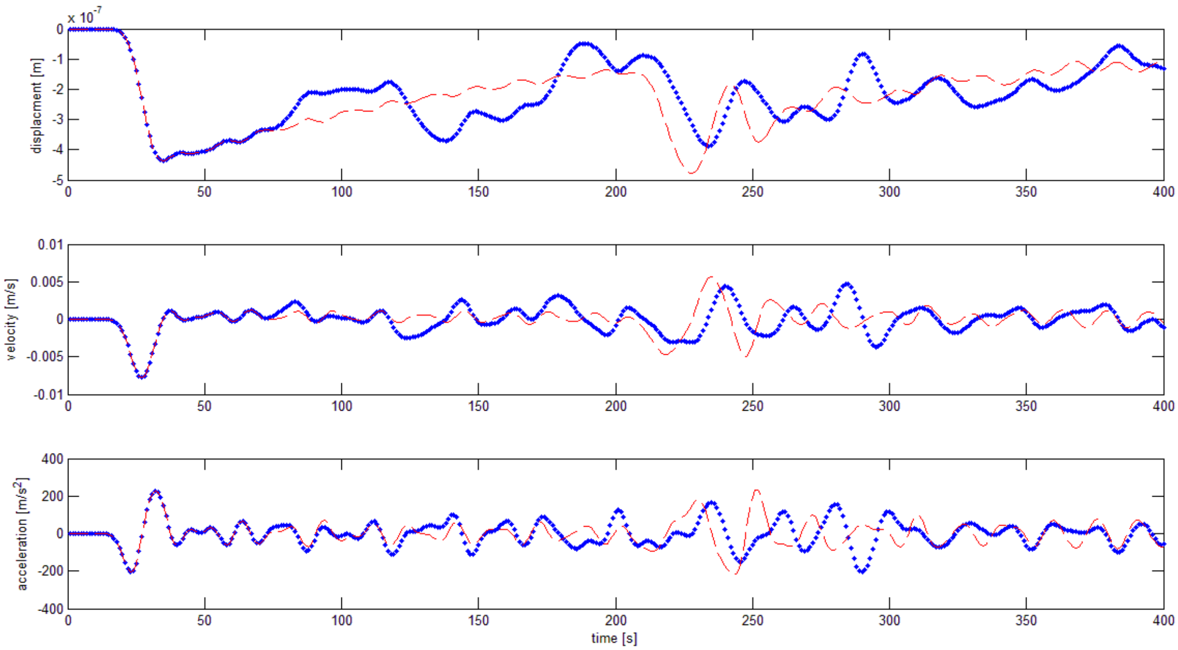

Figure 2. Nodal behavior during the transient period. Comparison between ideal pile (dots) and pile Fa24i3 (dashes). Displacement appear to have the most distinctive results.

6 EXPERIMENTAL VALIDATION

The entire defect recognition scheme is based on neural detectors (topologically optimized FFNN). The detection system produces a numerical output for all the pile's parts; pile's defects are identified using only a short-length vector as an input (see section 5). The system produces a corresponding output vector of size $n \times 1$, where n denotes the number of pillar parts that are investigated. For every part a specific number, p_i, is produced; the value of each number maps to a specific defect type, d_f, according to the following equation:

$$d_f = \begin{cases} -1, & p_i \in (-\infty, 0.5) \\ 0, & p_i \in [-0.5, 0.5] \\ 1, & p_i \in (0.5, \infty) \end{cases} \qquad (3)$$

There are nine possible descriptors to use in order create the input vectors (displacement, velocity, and acceleration at x, y and z-axis). Only few nodes were used for the detector initialization (i.e. nodes 1, 16, 27).

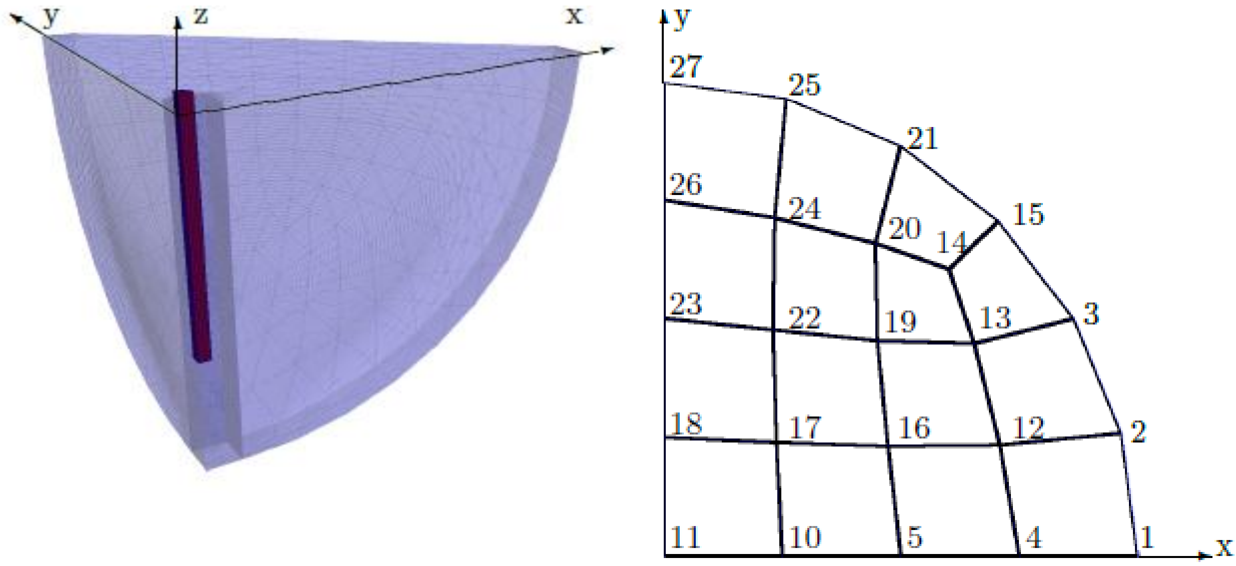

Figure 3. Near field discretization with mesh of the pile and surrounding soil, using finite elements; Right: Top view with finite element discretization of pile surface and corresponding node numbers.

The overall classification percentages, as well as, the confusion matrices are presented for the various quality metrics and descriptors. The following results are the average values from 268 simulations. In every simulation the following steps took place:

1. Data creation. In total, there were 23 nodes available. From these few were utilized for the neural detectors training and the rest for its evaluation. Due to modelling assumptions, for specific nodes oscillation patterns had to be excluded from the training data generation. These oscillations refer to x and y-axes, but not to z-axis. To be precise, oscillation patterns on x-axis for nodes {11, 18, 23, 26, 27} and patterns on y-axis for nodes {1, 4, 5, 10, 11} where excluded from the training sets.
2. Descriptor selection. There are three possible descriptor that we use in this paper. MSE, MAE, and plain differences in specific moments. All of them were based in subtraction of ideal pile's oscillations from investigating pile's oscillations.
3. Detector's topology optimization. The island genetic algorithm defined the ideal topology for the FFNN given the corresponding training sample.
4. Performance evaluation using various metrics. Given the results we need to say that oscillations in z-axis provide by far better and robust results. In addition feature vectors based on plain difference in oscillations performs better that features based on MSE or MAE. This can be partially explained by the averaging factors of the latter.

6.1 Results

It is becoming clear that pile's defects significantly affect the oscillation patterns in z-axis. Thus, displacement at z axis is the best descriptor (see Table 3) leading to higher than 90% correct classification rate. It is intriguing that the part closer to the surface (middle up) provide lower detection rates than the lowest part when *z*-axis observations are used. Despite the low training data, performance is more than satisfactory.

Table 3. Confusion matrix using training data from 3 nodes (that is < 40 % of the available data). The outcome is based on the plain difference metric.

descriptor	upper part				middle up				middle low				lower part			
x_d	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1
	-1	0	0	0	-1	0.670	0.318	0.011	-1	0.663	0.338	0.000	-1	0.719	0.125	0.156
	0	0	1	0	0	0.031	0.969	0.000	0	0.333	0.638	0.029	0	0.531	0.188	0.281
	1	0	0	0	1	0.000	0.331	0.669	1	0.088	0.675	0.238	1	0.417	0.188	0.396
x_v	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1
	-1	0	0	0	-1	0.653	0.324	0.023	-1	0.575	0.425	0.000	-1	0.813	0.125	0.063
	0	0	1	0	0	0.156	0.844	0.000	0	0.583	0.379	0.038	0	0.594	0.336	0.070
	1	0	0	0	1	0.000	0.319	0.681	1	0.350	0.325	0.325	1	0.340	0.264	0.396
x_a	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1
	-1	0	0	0	-1	0.665	0.330	0.006	-1	0.588	0.125	0.288	-1	0.648	0.109	0.242
	0	0	1	0	0	0.109	0.734	0.156	0	0.121	0.329	0.550	0	0.438	0.148	0.414
	1	0	0	0	1	0.038	0.344	0.619	1	0.038	0.150	0.813	1	0.396	0.146	0.458
y_d	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1
	-1	0	0	0	-1	0.744	0.250	0.006	-1	0.713	0.288	0.000	-1	0.328	0.398	0.273
	0	0	1	0	0	0.141	0.313	0.547	0	0.183	0.613	0.204	0	0.297	0.391	0.313
	1	0	0	0	1	0.000	0.188	0.813	1	0.100	0.350	0.550	1	0.278	0.278	0.444
y_v	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1
	-1	0	0	0	-1	0.710	0.227	0.063	-1	0.263	0.325	0.413	-1	0.547	0.336	0.117
	0	0	1	0	0	0.391	0.219	0.391	0	0.254	0.433	0.313	0	0.508	0.258	0.234
	1	0	0	0	1	0.000	0.238	0.763	1	0.188	0.350	0.463	1	0.417	0.257	0.326
y_a	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1
	-1	0	0	0	-1	0.205	0.619	0.176	-1	0.675	0.263	0.063	-1	0.258	0.273	0.469
	0	0	1	0	0	0.141	0.688	0.172	0	0.313	0.383	0.304	0	0.078	0.242	0.680
	1	0	0	0	1	0.000	0.238	0.763	1	0.138	0.438	0.425	1	0.049	0.250	0.701
z_d	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1
	-1	0	0	0	-1	1.000	0.000	0.000	-1	0.970	0.030	0.000	-1	1.000	0.000	0.000
	0	0	1	0	0	0.000	1.000	0.000	0	0.000	1.000	0.000	0	0.000	1.000	0.000
	1	0	0	0	1	0.000	0.005	0.995	1	0.000	0.000	1.000	1	0.000	0.000	1.000
z_v	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1
	-1	0	0	0	-1	1.000	0.000	0.000	-1	1.000	0.000	0.000	-1	0.981	0.019	0.000
	0	0	1	0	0	0.000	1.000	0.000	0	0.013	0.987	0.000	0	0.025	0.963	0.013
	1	0	0	0	1	0.000	0.010	0.990	1	0.000	0.000	1.000	1	0.000	0.000	1.000
z_a	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1	A\C	-1	0	1
	-1	0	0	0	-1	1.000	0.000	0.000	-1	0.970	0.030	0.000	-1	0.994	0.006	0.000
	0	0	1	0	0	0.000	0.850	0.150	0	0.023	0.927	0.050	0	0.069	0.763	0.169
	1	0	0	0	1	0.000	0.060	0.940	1	0.000	0.000	1.000	1	0.000	0.006	0.994

7 DISCUSSION AND CONCLUDING REMARKS

A genetically optimized neural detector was used for the identification of structural flaws in underground piles. Experimental results provide very promising results. The defect recognition rate was up to 100%. Although the defects have a rather plain form (i.e. easily identifiable), the formulation of the detector allow us to expect similar results in more complex cases. Piles with more complex structure (e.g. Fa23i3) will be evaluated in future work. Another advantage of the proposed methodology is the significantly small amount of the training data required for the initialization (training phase). Surprisingly, the phrase “deeper the defect harder to be located” does not appear to be valid. More details related to the present work can be found in [17]. A parallel investigation using ant colony classification tools has been reported in [18].

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