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A Neural Network Surrogate Model for Structural Health Monitoring of Miter Gates in Navigation Locks

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ABSTRACT

Structural health monitoring (SHM) of miter gates of navigation locks is crucial for facilitating cargo ship navigation. Closure of these inland waterway structures causes considerable economical loss to the marine cargo and associated industries. In practice, strain gauges are often mounted in many of these miter gates for data collection, and various inverse finite element techniques are used to convert the strain gauges data to damage-sensitive features. Arguably, these models are computationally expensive and sometimes they are not suitable for real-time health monitoring or for monitoring confounding environmental effects. In this work, a Muti-Layer Artificial Neural Network (MANN) is designed to serve as a "run time" surrogate model that links data (from the strain gages) to damage classification (gaps in the miter gate contact). Three cases of complexity, combining hydrostatic and thermal loading scenarios with varying gap scenarios, are considered to design the MANN. A confusion matrix is used to evaluate the performance of the networks and derive probabilities. Results show the potential of MANNs as a reliable surrogate model for computationally expensive inverse finite element modeling in damage classification for this application.

Keywords: Miter Gates, Artificial Neural Networks, Surrogate Model, Finite Element, Inverse Model.

INTRODUCTION

In the United States, the U.S. Army Corps of Engineers (USACE) owns and operates 236 locks at 191 sites [1]. According to a report published by USACE in 2017, more than half of these assets are older than their economic design life, 50 years, and need a prudent structural health monitoring solution to ensure their safe and reliable operation [2].

Damage to the locks may lead to closures of the lock chamber, which impose economic losses on the commercial shippers. Two types of closures (i.e. scheduled and unscheduled) apply to miter locks. Scheduled lock closures allow commercial shippers to adjust their activities to be coordinated to optimize their benefit. However, unexpected events such as accidents, weather, or emergency maintenance needs can result to unscheduled closures, which can negatively impact commercial activities [3]. Therefore, there is a need to identify the current state of lock gates to see how reliable they are when unforeseen events are present. Knowing the condition of a lock gate and its components can allow to take preventive measures to avoid or minimize the loss in unscheduled closures. Miter gates are the most common type in the United States with other types of lock gates being sector, tainter and vertical lift [4].

For miter gates, some experienced engineers and lock operators from USACE [2] agree that one of the primary concerns for inspection, maintenance and repair are the condition of the quoin and gaps between the lock wall and the quoin block. A "gap" is referred to as the loss of bearing contact between the quoin attached to the gate and the lock wall. A "gap" in the quoin block changes the load path in the miter gate, leading to higher stresses on some places in the lock gate (e.g., the pintle) and leading to operational and/or structural failure. Therefore, monitoring the condition of the "gap" can be used to extend the life of the gate and/or suggest repairs and maintenance in a timely manner. Some other concerns related to miter gates are corrosion and fatigue deterioration [5].

Most of the miter gates owned by USACE are strategically instrumented with strain gauges for data acquisition [6]. The strain topography in the structure changes as the boundary conditions change, in other words, as the size of a gap changes for a gate. Therefore, finite element (FE) models could be used to map the strain gauges data to a specific "gap" in an inverse analysis. However, these models are computationally expensive and sometimes they are not feasible for real-time health monitoring or for monitoring fluctuating environmental effects. Consequently, a surrogate model with fast predictions of the target damage (e.g., the "gap") can be used.

Artificial neural network (ANN) modeling, which are lately used extensively in many areas of science and engineering, could be a powerful way to predict the contact "gap" at the quoin block. Some researchers have used ANNs as surrogate models, using validated FE models to generate data to train the network [5-6].

In this paper, a Multi-Layer Artificial Neural Network (MANN) is designed to serve as a computational inexpensive surrogate model that links the strain gages data to the "gap" in the quoin block. An ABAQUS FE model of a miter gate is used to obtain synthetic strain data to design such MANN.

The paper first explains the finite element model and then describes the architecture of the MANN. In the result section, the efficiency of MANN is examined by considering three cases of different complexity. A confusion matrix is used to evaluate the performance of the networks under these realistic cases. Results show the potential of MANNs as an inexpensive reliable alternative for computationally expensive inverse finite element modeling in the classification of the "gap" size in miter gates. Other analysis would have to be performed to see which "gap" size is critical in redistributing the load in such a way that some failure in the gate or in one of its component may happen rapidly.

FINITE ELEMENT MODELING

Instrumentation on miter gates have started recently. Additionally, tracking the "gap" size has not been monitored constantly. Therefore, due to the lack of actual experimental data, FE simulations are needed to understand the effect of different "gap" size on the strain gage readings and the redistribution of loads along the miter gate. The FE model has been previously validated with the available strain gage readings from the Greenup miter gate. The Greenup gate is a brand-new gate where a very small or nonexistent "gap" can be assumed for validation purposes.

Consequently, simulated data was used for training and testing, which are generated by integrating ABAQUS and Python. In this paper, a single gap scenario is used as shown in Figure 1 to generate the training and testing data.

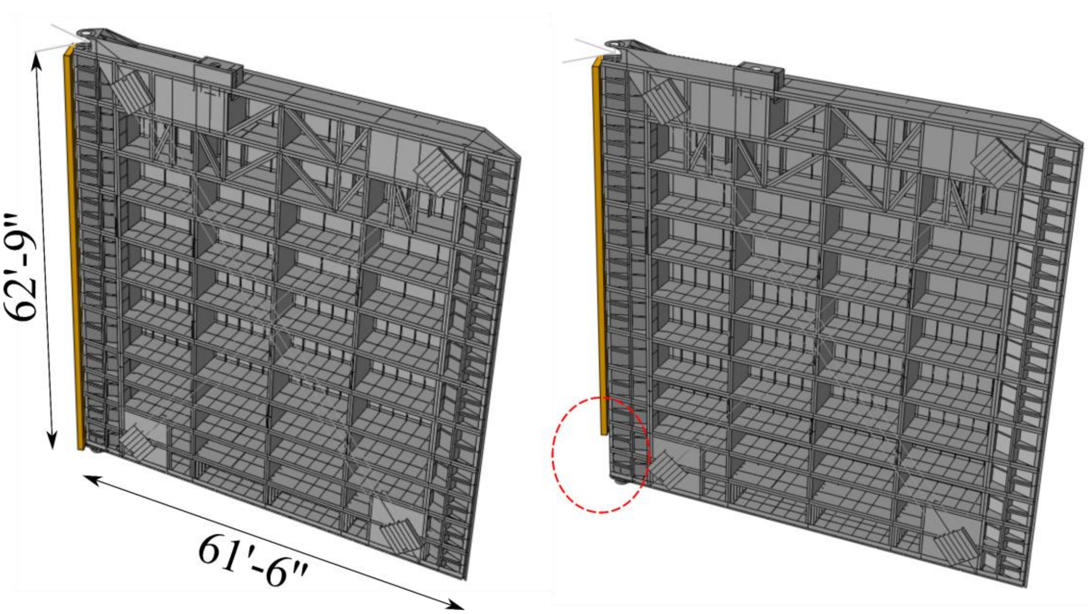

Figure 1: Gap modeling (Left: No gap, Right: Schematic gap)

Gap length is a random number between zero and 180 in. under random loading scenarios defined by two normal distributions for upstream and downstream hydrostatic pressure [9]. For simplification purposes, the gate and the quoin block attached to the gate are modeled as a single part (denoted in gray). All the elements in the domain are 3D linear shells elements to reduce the computational cost of such a large model.

A hard-contact condition is used between the lock wall (denoted in yellow) and the gate (denoted in gray), making this a nonlinear problem. The opposite side of the lock wall uses fixed boundary conditions. Symmetry boundary conditions are used at the right end (i.e., miter) of the gate to simulate the right leaf. The miter gate is subjected to upstream and downstream hydrostatic loading as shown in Figure 2.

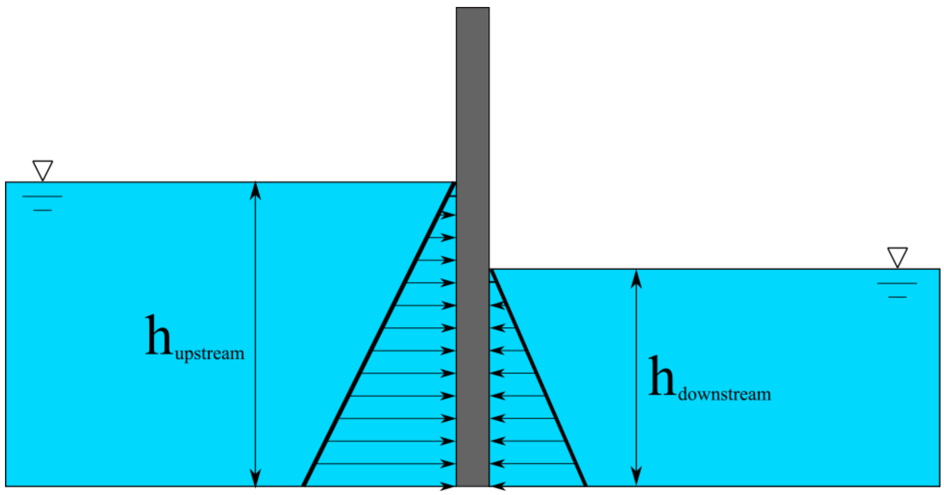

Figure 2: Hydrostatic Loading on miter gates

The ABAQUS Greenup model was run with python to obtain 3000 realizations, 2000 for training and 1000 for testing data. Generating this data took almost one week using a 4-cpu desktop.

MULTI-LAYER ARTIFICIAL NEURAL NETWORK

Preliminary Design

The MANN was designed using the open-source platform TensorFlow, which has been used for several real-world applications [10-11]. In the first demonstration, only three damage levels were defined (i.e., low, moderate, and high) based on the gap length (i.e. 0-60 in., 60-120 in. and 120-180 in.). In this MANN, shown in Figure 3, a 99% accuracy was reached. 2000 data sets are used to create 300000 mini-batches, which are small random sets of the original data sets. Then, Mini-batch Gradient Descent algorithm uses the mini-batches sets used for training and validation to minimize the loss function by changing the weights and biases. After, the MANN finishes its training and validation stage, 1000 new data sets not seen in training are used for testing the MANN.

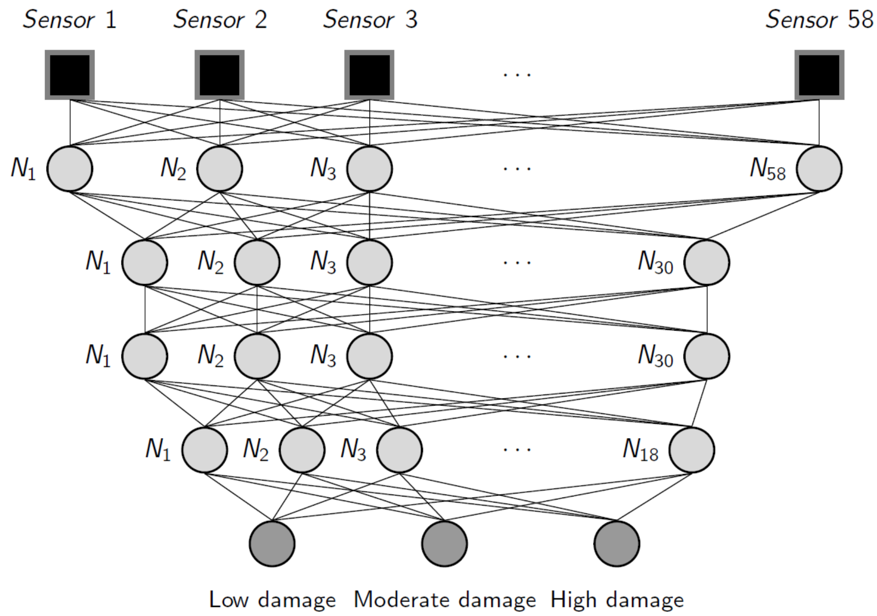

Figure 3: MANN to classify 3 different gap length ranges (levels)

Extended Design

Subsequent to the first demonstration, the MANN was extended to consider 18 cases based on the gap length (i.e. increments of 10 in. within a range of 0-180 in.). The new MANN was designed with 6 hidden layers (228 neurons) with a decreasing learning rate to improve the final accuracy. The Softmax function is used for the last layer as an activation function to reach a value between zero and one for each class, allowing indication of the damage case. Three cases of complexity, combining hydrostatic and thermal loading scenarios with varying gap scenarios, are considered to design the MANN.

Case 1: Consider "gap" length to be a random number between zero and 180 in. with a constant (known) hydrostatic loading, and neglect thermal environmental load effects.

Figure 4 shows a confusion matrix, sometimes called matching matrix, for the testing data, which reveals the MANN performance on classifying the gap length when only raw strain gauge data are used as an input. The obtained confusion matrix for the MANN is a heavily-banded matrix with a few gap lengths misclassified to an adjacent class. This happens because sometimes a gap length, which in fact is a continuous parameter, lays in the boundary of two discretely-divided classes. Overall, the confusion matrix shows an accuracy of 98.8%.

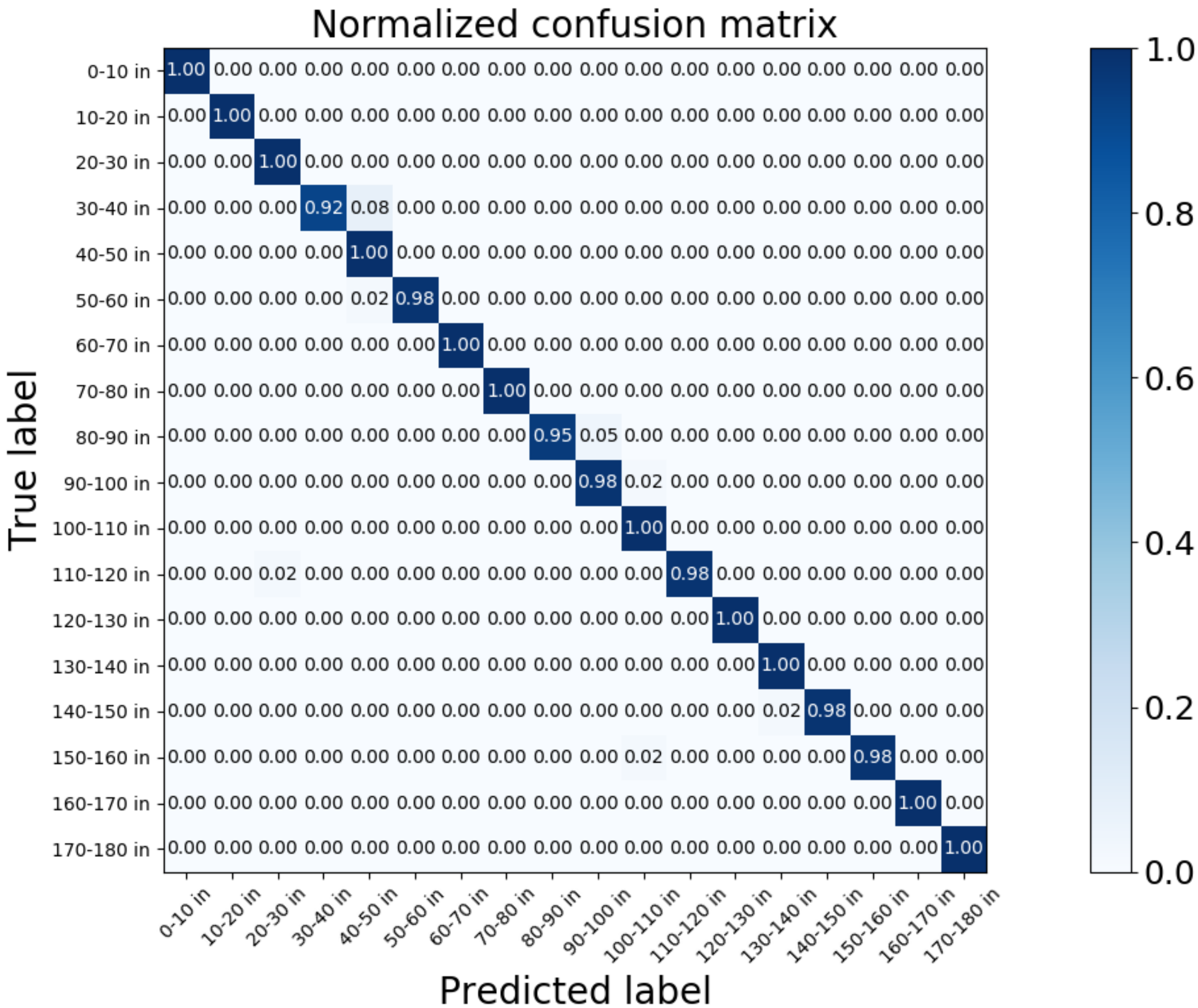

Figure 4: Confusion (Matching) Matrix using NN to classify 18 scenarios (Case 1)

Case 2: Consider "gap" length to be a random number between zero and 180 in. with a random loading scenario defined by two normal distributions for upstream and downstream hydrostatic pressure, and neglecting thermal environmental load effects.

Case 3: The same as Case 2 except that the environmental temperature, which will add thermal strain effects, is defined as a random number based on the lowest and highest temperature value recorded by thermometers in the actual Greenup gate data.

Table 1: Testing accuracy of MANN designs

Case	Testing accuracy
1	0.988
2	0.961
3	0.958

Again, the ABAQUS Greenup model was run with Python to obtain 3000 realizations, 2000 for training and 1000 for testing data for every case.

Table 1 summarizes the accuracy obtained for Cases 1 through 3. Interestingly, a very high accuracy is reached for all cases. It is important to note that the number of layers and neurons were manually modified to allow Case 1 reach a very high accuracy. Alternatively, a higher accuracy may be reached by optimizing the number of layers along with a dropout function to prevent overfitting. For Cases 2 and 3, the same numbers of layers and neurons as Case 1 were used. Therefore, an individual optimization of the number of layers cab also be performed to improve the case by case testing accuracy.

Cross Verification

In general, it could be expected that the MANN trained for Case 3 be used to predict Case 1 and 2, since Case 3 includes all Case 1 and Case 2 effects. Conversely, the MANN trained for Case 1 should have very poor results when predicting Case 2 and 3. Therefore, to verify the results shown in Table 1, the following was observed using different data of each case for training and testing of the MANN:

Table 2: MANN Verification (Testing accuracy)

Cross verification	Test Case 1	Test Case 2	Test Case 3
Train Case 1	0.988	0.459	0.097
Train Case 2	0.887	0.961	0.213
Train Case 3	0.798	0.911	0.958

As expected, the MANN trained with the data of Case 3 achieves a good testing accuracy when using data of Case 1, 2 and 3 as shown in Table 2. Similarly, the MANN trained with the data of Case 2 performs god for Cases 1 and 2. On the other hand, a very poor accuracy is obtained when a MANN is trained with Case 1 but tested with Case 2 or 3 and when is trained with Case 2 but tested with Case 3. Based on the table above, it can be concluded that variability in the loading and temperature are both very critical to consider in the training because inevitable the data in a real SHM setup would be affected by such effects. Again, note that 2000 data points were used for training and 1000 were used for testing for every value shown in Table 2.

CONCLUSION AND FURTHER WORK

A MANN can successfully predict the condition of a “gap” in the quoin blocks when enough data is available. For this paper, the FE model was used as a source of generating synthetic training and testing data. Cross Verification can be useful to identify what effects are important to consider in the training phase of a MANN. Finally, a MANN with three sources of variability was designed that can accurately predict a “gap” between 79.8% to 95.8% of the times. And when not, it can predict the value to a very close class (i.e. a banded confusion matrix). In the real world, testing data should be obtained directly from physical strain gages. As demonstrated, a MANN can have a very high testing accuracy up to 95.8% if trained with all the sources of variability that a real strain gauge is subjected. Contrarily, a MANN can have a very poor testing accuracy as low as 9.7% if trained with data obtained from an oversimplified FEM model. Additionally, strain gauges are installed in specific places and record the strain in a specific direction. Any additional information can be used to build a more sophisticated network.

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