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Prediction of Thermal Cracks in Pavements Using Artificial Neural Network Modeling and Long-Term Pavement Performance Data

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Abstract

Improving riding quality, promoting sustainability and resiliency, and providing proper analysis procedures to maintain and predict the performance of existing structures have been profound goals of the transportation sector. Thermal cracks, also universally known as transverse cracks, are considered one of the most prevalent and critical forms of pavement distresses. Such cracks have been directly linked to various modes of pavement failure that not only adversely impact the performance and integrity of pavement structures and the riding quality experienced by typical road users. While recent studies have proven that the use of regression to explain thermal cracks is not an accurate representation to quantify distress, linear models are still commonly used in engineering practices. Using Long-term Pavement Performance (LTPP) data from 15 different sections located in the Midwest region of the US, an Artificial Neural Network (ANN) model was developed using MATLAB to predict the count of thermal cracks given the extracted input parameters: average annual temperature, annual average freeze index, 18 Kip ESAL, thermal conductivity, heat capacity, surface shortwave absorption, and coefficient of thermal contraction. The proposed ANN model divides the temperature and distress data: 70% training data, 15% testing data, and the remaining 15% validation data. The predicted and actual outputs were compared by calculating Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Comparably, the results for 7-9-9-1 ANN structure with TANSIG-LOGSIG transfer functions generated the closest thermal cracking estimate with RMSE of 0.089, MAPE of 0.10, and a regression coefficient (R) of 0.94, which confirmed that the model was adequate to predict thermal cracks in the pavement.

Introduction

Low thermal cracking is observed as permanent fracturing, resulting from tensile stresses that form in the asphalt concrete pavement when exposed to cold temperatures or rapid temperature fluctuations (Jung and Vinson, 1992). Air temperature is inversely related to the contraction behavior of asphalt concrete mixtures. Thus, as temperature decreases, the contraction increases. During the cooling stage of asphalt concrete, the pavement's propensity to contract and generate friction between the various pavement layers gradually induces thermal stresses (Zubeck et al., 1996). Low-temperature cracks will form at the surface if such thermal stresses are equivalent to the tensile strength of the asphalt mixture.

The main thermal contraction cracking develops in a pattern transverse to traffic direction with a typical crack spacing ranging from approximately 4 to 100 meters in length (Kanerva, 1993). The seepage of water and fines in and out of the pavement is facilitated by the proliferation of low-temperature cracks throughout the pavement structure (Zubeck et al., 1996). During winter, the localized thawing of the base and depression at the crack may result from the infiltration of deicing solutions into the base through the crack. Entering water freezes, yielding ice lenses that can cause vertical lipping at the margin. Pumping fine materials through the crack creates voids beneath the pavement structure, causing depression when loaded. The aforementioned factors lead to poor ride quality, shorter pavement service life, and high maintenance costs (Das, 2012). While low-temperature cracking is unavoidable in pavements constructed in cold climates, the asphalt industry has been moving towards performance-based methods to predict and evaluate the performance of existing and future pavement structures (Rahbar-Rastegar et al., 2018).

Objective and Scope of Work

This study intended to investigate the suitability of utilizing ANN to predict the number of thermal cracks of 15 pavement sections in the US Midwest region. The scope of the study entailed establishing a data collection methodology, developing a consistent ANN model, statistically analyzing the model's predicted results, and comparing the ANN predicted thermal crack count to the LTPP actual thermal crack count.

Long-Term Pavement Performance Data Overview

In order to build an efficient ANN model, a proper data collection procedure must be established. For this research, thermal cracking and related pavement data were not directly measured. An extensive research project, Long-Term Pavement Performance (LTPP), was implemented in 1987 to regularly collect and inspect existing pavement performance data for more than 2,500 sections across North America and Canada (FHWA, n.d.). This program was initially funded by the Strategic Highway Research Program (SHRP) for the first 5 years of its initiation. Then, the Federal Highway Administration (FHWA) preserved supporting and managing the program. LTPP classifies the collected data into two primary class studies, General Pavement Study (GPS) and Specific Pavement Studies (SPS). Within each study, pavement performance is presented in 7 modules categorized as follows: Inventory, Maintenance, Monitoring (Deflection, Distress, and Profile), Rehabilitation, Materials Testing, Traffic, and Climatic.

Extensive research has been conducted on determining parameters required for thermal crack prediction. The attributes of asphalt elements, mix design criteria, loading time, mode, temperature, stress state, and age are all potential factors that influence the cracking propensity of asphalt mixtures (Rahbar-Rastegar 2017). This report will primarily discuss the effects of stress and temperature-related parameters on the quantity of observed thermal cracks. While developing a model with a large number of input parameters may produce accurate model results, limiting the input variables to those that tend to generate the greatest impact on the targeted result and sustain a relatively accurate representation of the target is more efficient. The ANN model used in this paper analyzes approximately 90 samples of data consisting of the following 7 input parameters: average annual temperature, annual average freeze index, 18 Kip ESAL, thermal conductivity, heat capacity, surface shortwave absorption, and coefficient of thermal contraction. LTPP data limitation is a factor that must be taken into consideration while choosing model parameters. While LTPP is a great source for obtaining pavement performance data, it does not provide consistent data collection times. Therefore, finding all the required data for a specific date may not be possible.

Artificial Neural Network Modeling Overview

Once accurate data has been obtained, it can then be loaded into an ANN model. ANN modeling is widely used in the industry to predict various empirically correlated processes with a wide range of independent variables, which may or may not impose the presence of prominent non-linear relationships (Ammari, n.d.). While ANN can predict linearly correlated variables, it is more commonly applied to assess complex non-linear relationships. ANN is distinguished by its ability to imitate the cognitive effect of the human brain. It consists of numerous neurons arranged in one or more synaptically connected hidden layers, which tend to serve as the "nervous system" of the model. The hidden layers within the network can be connected linearly, logarithmically, exponentially, tangentially, etc. This can be considered by adding ANN transfer functions or manually transforming the data (Hossain et al., 2019). Figure 1. provides the ANN structure of the model used in this paper further to illustrate the concept of neurons and hidden layers. There are 7 parameters in the input layer, 2 hidden layers each consisting of 9 neurons, and a to be predicted one parameter in the output layer. The aforementioned ANN structure can also be represented as 7-9-9-1.

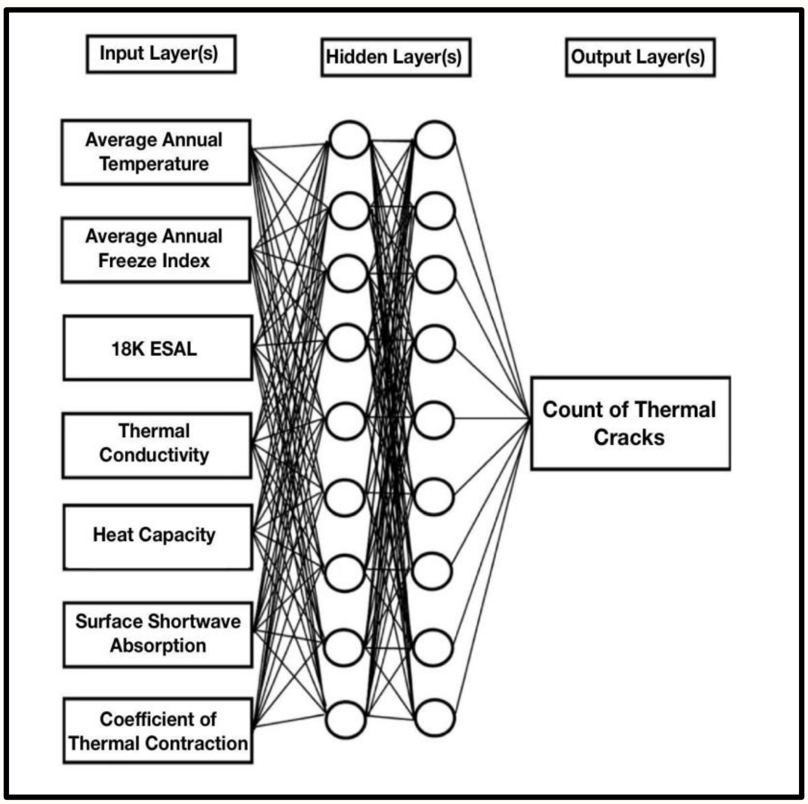

Figure 1. ANN Thermal Crack 7-9-9-1 Structure

ANN Model Development

ANN modeling is considered to be an iterative process that is purely based on a trial-and-error mechanism. A research working paper written by Aymen Ammari, titled "MATLAB Code of Artificial Neural Networks Estimation," provided an ANN code that can be modified for various educational applications, which was used as a base and was tailored to meet the purpose of building an effective thermal cracking prediction model.

The customized ANN Matlab script used to produce the presented thermal cracking results is attached to the Appendix of this report.

Before developing an ANN code, a thorough understanding of the presented data and how it is statistically identified will provide a better insight into how the data should be embedded in the code. Figure 2. displays individual histogram graphs for each input and their relative impacts on the output. As can be inferred, the data is not normally distributed. The non-constant parameters are mostly right-skewed, which means that measures of central tendency (ex., mean, median, standard deviation, etc.) are being overestimated (Zack, 2021). Therefore, normalization of the data through "log transposition" will reduce the skewness seen in the probability distributions.

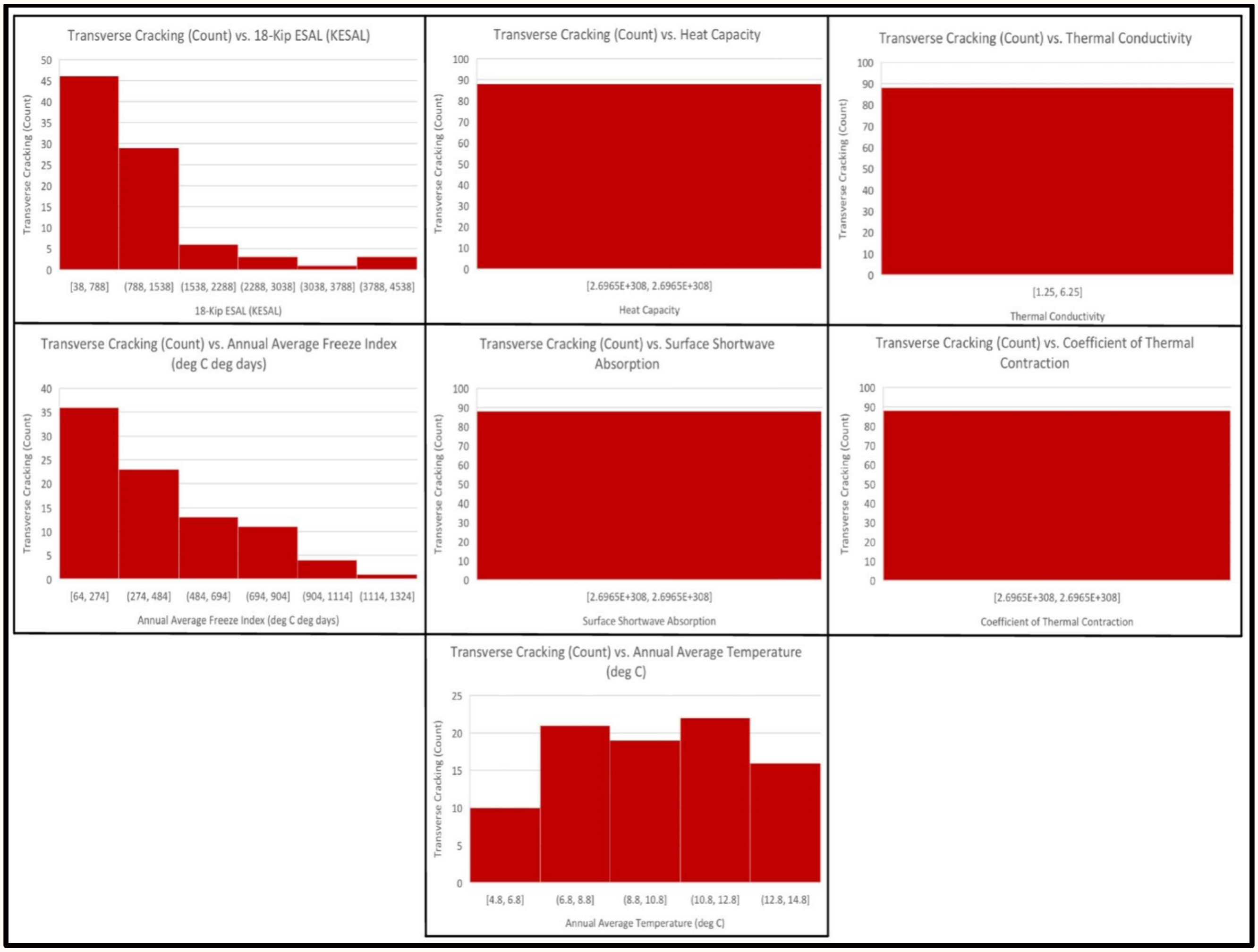

Figure 2. Histogram of each input parameter as compared to the output

It is essential to consider certain aspects of ANN model development to generate an adequately functioning ANN code. First and foremost is having a proper dataset. A model with incorrect data will not produce expectable results. When introducing the data, input and output variables must be identified to ensure that Matlab interprets the data correctly. As part of the data interpretation process, the data should be divided into three sets: training, testing, and validation data. The most common form of data division, which is also used in this report, is the 70% training, 15% validation, and 15% testing configuration (Hossain et al., 2020). As the network randomly assigns the ratios every time the code is run, introducing a "for loop" with stated minimum and maximum iterations will produce more consistent results and dramatically reduce the fluctuation seen in many ANN models. Increasing the number of maximum iterations will reduce the resulting MAPE. This, however, may not be ideal as it takes more time to run more iterations. Therefore, a reasonable number of maximum iterations is considered efficient enough to produce good results without compromising the computation time needed to run the model.

As previously mentioned, the determination of the number of neurons and hidden layer(s) is primarily based on trial and error, and the result proposing the least amount of error is selected. The line graph in Figure 3. represents the mean squared error (MSE) value associated with each number of neurons (nn) in the hidden layer(s). Note that the code developed for this research paper generates the same number of neurons in all hidden layers. The minimum MSE value found on the graph is at 9 neurons. This indicates that when the number of neurons in the hidden layers is set to 9, the model will produce a predicted thermal cracking count with the least error compared to the actual count of thermal cracks.

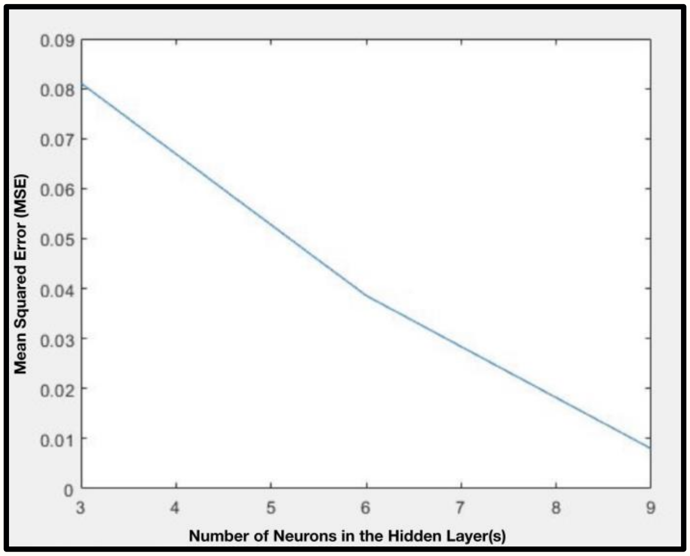

Figure 3. Mean squared error (MSE) associated with different numbers of neurons in the hidden layer(s)

To account for the non-linear relationship between the input and output parameters, transfer functions are introduced to create a relationship between the various neurons and assess their anticipated impacts on the output (Hossain et al., 2019). The most common ANN transfer functions that are used interchangeably to normalize the inputted data are hyperbolic tangent sigmoid (TANSIG), logarithmic sigmoid (LOGSIG), and pure linear (PURELIN). They are also numerically represented as:

$$TANSIG(x) = \frac{2}{1+e^{-2x}} - 1 \quad (1)$$

$$LOGSIG(x) = \frac{1}{1+e^{-x}} \quad (2)$$

$$PURELIN(x) = x \quad (3)$$

The number of hidden layers and transfer functions was determined by following a procedure similar to that used to determine the number of neurons in a hidden layer. Increasing the number of hidden layers will not make the model more accurate. One hidden layer is typically used for linear/semi-linear relationships, while 2 - 3 hidden layers are commonly used for more complex non-linear models. Table 1. provides a summary of the calculated MAPE values associated with various transfer function combinations and numbers of hidden layers with 9 neurons in each layer. Initially calculated, MAPE values were computed based on a maximum iteration of 20.

Table 1. RMSE and MAPE of 1,2, and 3-layered network with various transfer function combinations

Number of Hidden Layers	Transfer Function Combination	MAPE
1	-	0.25
	TANSIG	0.28
	LOGSIG	0.25
	PURELIN	0.36
2	-	0.29
	TANSIG-TANSIG	0.26
	TANSIG-LOGSIG	**0.15**
	TANSIG-PURELIN	0.29
	LOGSIG-TANSIG	0.29
	LOGSIG-LOGSIG	0.28
	LOGSIG-PURELIN	0.30
	PURELIN-TANSIG	0.28
	PURELIN-LOGSIG	0.31
	PURELIN-PURELIN	0.35
	TANSIG-TANSIG-TANSIG	0.26
	TANSIG-TANSIG-LOGSIG	0.22
	TANSIG-TANSIG-PURELIN	0.24
	TANSIG-LOGSIG-TANSIG	0.27
	TANSIG-LOGSIG-LOGSIG	0.28
	TANSIG-LOGSIG-PURELIN	0.23
	TANSIG-PURELIN-TANSIG	0.26
	TANSIG-PURELIN-LOGSIG	0.30
	TANSIG-PURELIN-PURELIN	0.27

	LOGSIG-TANSIG-TANSIG	0.28
	LOGSIG-TANSIG-LOGSIG	0.28
	LOGSIG-TANSIG-PURELIN	0.31
	LOGSIG-LOGSIG-TANSIG	0.31
	LOGSIG-LOGSIG-LOGSIG	0.25
	LOGSIG-LOGSIG-PURELIN	0.28
	LOGSIG-PURELIN-TANSIG	0.27
	LOGSIG-PURELIN-LOGSIG	0.25
	LOGSIG-PURELIN-PURELIN	0.28
	PURELIN-TANSIG-TANSIG	0.27
	PURELIN-TANSIG-LOGSIG	0.23
	PURELIN-TANSIG-PURELIN	0.29
	PURELIN-LOGSIG-TANSIG	0.30
	PURELIN-LOGSIG-LOGSIG	0.33
	PURELIN-LOGSIG-PURELIN	0.28
	PURELIN-PURELIN-TANSIG	0.29
	PURELIN-PURELIN-LOGSIG	0.33
	PURELIN-PURELIN-PURELIN	0.36

ANN Model Results and Analysis

Based on Table 1. analysis, it was determined that a two-layered network consisting of 9 neurons in each layer with a transfer function combination of TANSIG-LOGSIG produced the lowest MAPE value of 0.15. To achieve a more accurate model, the maximum number of iterations was raised to 500, and the same network was run. Increasing the number of iterations lowered the MAPE value to 0.10. Furthermore, a calculated RMSE value is equal to 0.089. The equations for MAPE and RMSE are shown below:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{A-P}{A}\right| \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (A-P)^2}{n}} \tag{5}$$

Where n = the number of data points, A = actual thermal crack count, and P = predicted thermal crack count.

The regression analysis plot in Figure 4 compares the ANN predicted output to the LTPP measured the number of thermal cracks for each of the three datasets (training, testing, and validation) and all the data combined. Additionally, as seen in the figure, on average, a regression coefficient (R) of 0.93 is calculated, which suggests a strong correlation between the predicted and actual target. Although the results have shown a good correlation, an absolute correlation of R = 1 is not possible as other variables impact thermal cracking, not only temperature-related parameters.

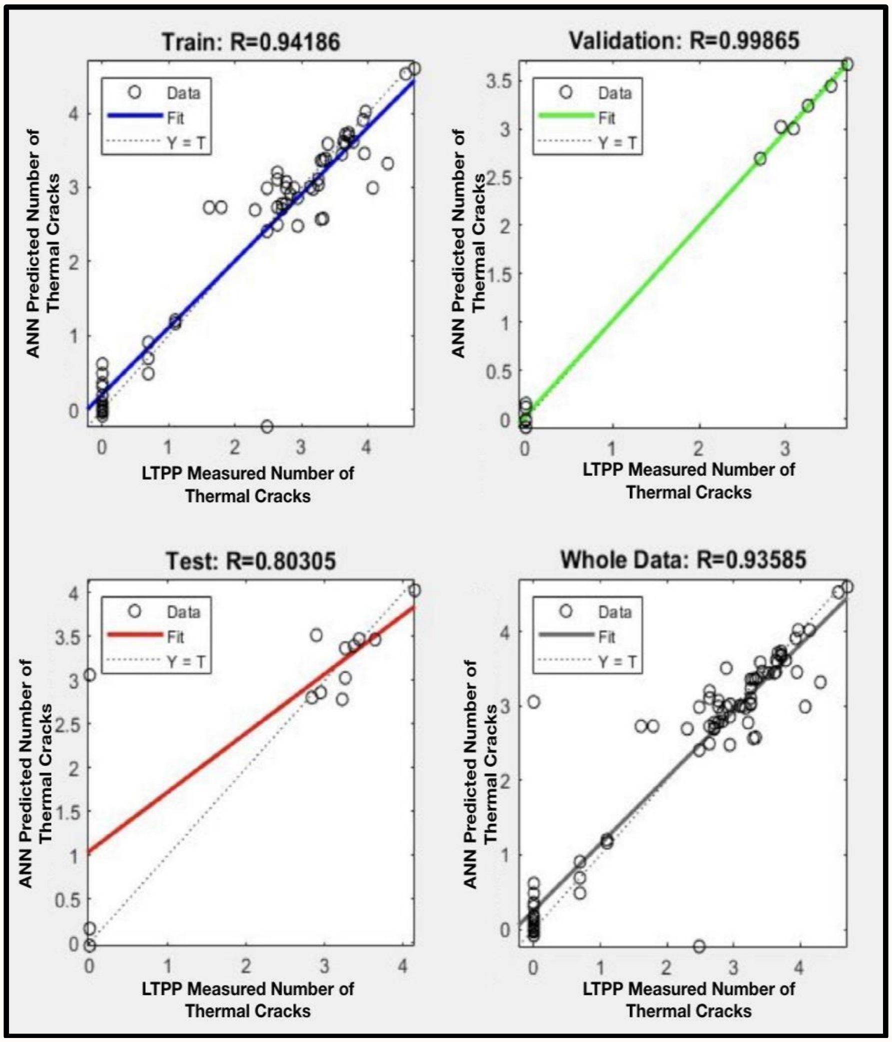

Figure 4. Predicted vs. actual count of thermal cracks for training, testing, validation, and all data

Conclusion

This study uses ANN modeling to use readily available LTPP distress and climate data to predict the count of thermal cracks for 15 sections in the Midwest region of the US. The data comprises average annual temperature, annual freeze index, 18K ESAL, thermal conductivity, heat capacity, surface shortwave absorption, and coefficient of thermal contraction. The limitations introduced by LTPP data resulted in a limited available dataset to be used for modeling, randomly divided into 70% training, 15% validation, and 15% testing to obtain an adequate model structure of 7-9-9-1 with a transfer function combination of TANSIG-LOGSIG. This model presents an RMSE of 0.089, MAPE of 0.10, and a regression coefficient (R) of 0.94. Based on the MSE graph, it was determined that the minimum MSE value exists when 9 neurons are used in both hidden layers. As a result of the ANN model, the analysis comparing the ANN-predicted number of thermal cracks and the measured LTPP number of thermal cracks suggested that the model is representative and can be used to predict thermal cracking.

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Appendix

```
%% ANN Thermal Cracking Prediction Code

% Reema Sweidan, 2022;

*********************************************************************************
*

%% Data Input and Preparation

clc;clear;close all;

in=xlsread('Input(1).xlsx');  % Input File

out=xlsread('Input(1).xlsx');    % Output File

data=[in out];

input=[1 2 3 4 5 6 7]; % Input Layer

p=data(:,input);

output=[8]; % Output Layer

t=data(:,output);
```

```
p=p'; t=t';

% Normalizing/Transposing the Imported Dataset

t=log(t+1);

% Defining Training, Validation, and Testing Datasets

trainRatio1=0.7;

valRatio1=0.15;

testRatio1=0.15;

% Network Definition

trainFcn = 'trainlm';  % Levenberg-Marquardt backpropagation.

nnn1=3;  % First Number of Neurons in the Hidden Layers

nnnj=3;  % Jump in Number of Neurons in the Hidden Layers

nnnf=9; % Last Number of Neurons in the Hidden Layers

net1.trainparam.lr=0.1;

net1.trainParam.epochs=500;

% Training Network

it=20;      % Maximum Number of Iterations

ii=0; % Initial Number of Iterations

netopt{:}=1:nnnf;

for nnn=nnn1:nnnj:nnnf

   ii=ii+1; nnn;

   net1=newff(p,t,[nnn nnn]);  % For more functions see: 'Function Reference' in
'Neural Network Toolbox' of Matlab help

   evalopt(ii)=100;

   for i=1:it

       [net1,tr,y,et]=train(net1,p,t);

       net1.layers{1}.transferFcn = 'tansig';

       net1.layers{2}.transferFcn = 'logsig';

       net1.divideParam.trainRatio=trainRatio1;
```

```
        net1.divideParam.valRatio=valRatio1;
        net1.divideParam.testRatio=testRatio1;
        estval=sim(net1,p(:,tr.valInd));
        eval=mse(estval-t(:,tr.valInd));
        if eval<evalopt(ii)
           netopt{(ii)}=net1;
           tropt(ii)=tr; evalopt(ii)=eval;
        end
    end
End
*********************************************************************************
*
%% MSE Plot
plot(nnn1:nnnj:nnnf,evalopt)
*********************************************************************************
*
%% Output
nn=3;
ptrain=p(:,tropt(nn).trainInd);
ttrain=t(:,tropt(nn).trainInd);
esttrain=sim(netopt{nn},ptrain);
ptest=p(:,tropt(nn).testInd);
ttest=t(:,tropt(nn).testInd);
esttest=sim(netopt{nn},ptest);
pval=p(:,tropt(nn).valInd);
tval=t(:,tropt(nn).valInd);
estval=sim(netopt{nn},pval);
estwhole=sim(netopt{nn},p);
```

```
*********************************************************************************
*

%% Calculation of MAPE

pre_MAPE = abs((y-t)./t);

MAPE = mean(pre_MAPE(isfinite(pre_MAPE)))*100

*********************************************************************************
*

%% Visuals

view(net1)

figure;plot(ttrain,esttrain,'.b');

figure;plot(tval,estval,'.g');

figure;plot(ttest,esttest,'.r');

figure;plot(t,estwhole,'.k')

Figure;plotregression(ttrain,esttrain,'Train',tval,estval,'Validation',ttest,esttes
t,'Test',t,estwhole,'Whole Data');
```