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Neural Network-based Intelligent Compaction Analyzer for Estimating Compaction Quality of Hot Asphalt Mixes

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Abstract: The development and validation of a tool that can estimate the level of compaction of a Hot Mix Asphalt (HMA) pavement during its construction is addressed in this paper. Densification of asphalt pavements during their construction is usually accomplished through the use of vibratory compactors. During compaction, the compactor and the asphalt mat form a coupled system whose dynamics are influenced by the changing stiffness of the mat. In this paper, it is shown that the measured vibrations of the compactor along with the process parameters such as lift thickness, mix type, mix temperature, and compaction pressure can be used to predict the density of the asphalt mat.

Contrary to existing techniques in the literature where a model is developed to fit the experimental data and to predict the density of the mat, a novel neural network based approach is adopted that is model-free and uses pattern-recognition techniques to estimate the density. During compaction of a HMA mat, the neural network then classifies the observed vibrations as those corresponding to a known level of compaction. The results also show that the analyzer can estimate the density continuously, and in real-time with accuracy levels adequate for quality control in the field. Using this tool, for the first time, the overall quality of construction of a HMA pavement can be verified thereby creating the potential to improve the quality of the roads.

1. INTRODUCTION

The construction of an asphalt pavement starts by combining heated aggregates with liquid asphalt cement at temperatures in the range of 250 to 300 degrees Fahrenheit. At the site, the asphalt concrete is deposited directly into a paver or placed in a windrow to be picked up and moved through a paver. The paver spreads the material across the pavement in a thickness ranging from 2.54 to 10.16 centimeters (1 to 4 inches), and provides a modest amount of initial compaction. As the material cools, compaction is provided by a series of vibratory rollers until the desired density is achieved (Tunnicliff, et al., 1974).

Vibratory rollers are commonly used in the field to compact asphalt mats. The steel drum of the roller is mounted on an axle to which eccentric weights are attached. These weights are rotated by means of the vibration motors. The rotation of these eccentric weights within the drum causes an impact force at the contact between the drum and the asphalt mat. The amplitude of these impacts is a function of the displacements of the eccentric weights. The spacing between subsequent impacts on the mat is a function of the speed of rotation of the eccentric weights and the forward speed of the roller.

1.1 Specification of Compaction Quality

The objective of compaction is to increase the density of the asphalt mix so that the desired load bearing and mechanical properties of the asphalt mat are achieved. Generally, the target density is set on the basis of either relative or absolute measure of compaction. A relative measurement of target density may use a percentage of a laboratory standard test. For example, a specification may require a minimum of 95% of the maximum density obtained from a Marshall test (White, 1985). Another type of specification commonly used is an absolute measure of a void-less mix or a percentage of the maximum theoretical density as determined by the AASHTO Test Method T-209.

The quality assessment in the field is usually performed by taking point-wise readings using a nuclear density gauge. The process is slow and typically 3-5 readings are taken per lane mile of the constructed pavement. Extraction of roadway cores and the measurement of the density in the laboratory provide accurate indication of the quality but the process is destructive in nature. The coring process is also a primary cause of potholes and results in other signs of early deterioration of the pavement. Moreover, the density levels are usually not available at the time of compaction. Therefore, compaction issues are not identified before the asphalt mix cools down to an extent where additional compaction is not possible. Inadequate compaction is one of the leading causes for the onset of rutting, cracks, potholes and other signs of degradation in the pavements. Thus, there is a need for the development of a density measuring device that can monitor the level of compaction in real-time, continuously over the length of the pavement during its construction.

In this paper, the vibrations of the compactor during the construction of the pavement are analyzed and pattern recognition techniques are used to determine the level of compaction. The procedure is based on the hypothesis that the compactor and the asphalt mat form a coupled system whose vibration characteristics are influenced by the stiffness (density) of the pavement (Commuri and Zaman, 2006). The hypothesis was validated to a limited extent in the laboratory (Commuri and Zaman, 2007). In this paper, the hypothesis is validated during the construction of a HMA overlay on a test site under controlled test conditions.

The rest of the paper is organized as follows. In Section 2, early attempts to develop Intelligent Compaction tools are discussed. Section 3 details the test setup and the experimental procedure. The field compaction results and the validation of the IACA are presented in Section 4 and the conclusions and future work are presented in Section 5.

2. BACKGROUND ON INTELLIGENT COMPACTION

The behavior of the HMA under load conditions is dependent of the properties of the individual components and of the volumetric composition of the mix. In mechanistic-empirical modeling of HMA pavements, the stress-strain relationship under a continuous sinusoidal loading is defined by the complex dynamic modulus. The complex modulus is defined as the ratio of the amplitude of the sinusoidal stresses and the amplitude of the sinusoidal strain. The “dynamic modulus” is defined as the absolute value of the complex modulus. This modulus is useful in predicting the response of the pavement to compactive loading e.g., deflections, stresses, and strains within the pavement structure (including HMA layers).

The “Witczak” model (Ayers et al., 1998; Commuri and Zaman, 2007) is a common empirical relationship used to predict the dynamic modulus based on the individual components of the HMA. In this model, the dynamic modulus at a given loading time and temperature depends on a number of design factors like the viscosity of the asphalt binder, the effective asphalt content (% by volume), the loading frequency (in Hz), the air void content (% by volume), the effective bitumen content (% by volume), and the properties of the aggregates in the mix.

The ability to estimate the quality of compaction of a Hot Mix Asphalt (HMA) pavement under construction has been pursued by many researchers (Jaselskis, 1998; Minchin et. al, 2003; Mooney, 2005; Sandstorm, 1998; Swanson, 2000; Yoo and Selig, 1979). Many of the earlier attempts tried to develop a relationship between the frequency components of the observed vibrations and the achieved level of compaction. However, the effect of the various parameters that can affect the vibrations, for instance, the thickness of the asphalt mat, the design of the HMA mix, the type of subgrade, the compaction equipment used, etc., were ignored to a large extent. This made it difficult to achieve the level of accuracy needed for quality assessment in the field. Typically, the contracting agency requires compaction of the pavement to 94% of the theoretical maximum density as determined by the AASHTO T-209 method. Density below 92% compaction, corresponding to 8% air void content in the pavement, is the cut off below which the contractor is penalized. Thus, it is necessary for the compaction analyzer to have accuracy within 2% of the true measurement.

In research conducted at the University of Oklahoma (Commuri and Zaman, 2007), the authors implemented a neural network based strategy to estimate the level of compaction. The Intelligent Asphalt Compaction Analyzer (IACA) that was developed was shown to be capable of estimating the density of compaction using laboratory Asphalt Vibratory Compactor. The neural network was shown to have the ability to classify the features extracted from the vibration signals as those corresponding to the densities of the asphalt specimen. Further, the generalization capabilities of the neural network enabled it to provide reasonable density estimations when presented with data different from the set used to train the network.

3. TEST SETUP AND EXPERIMENTAL PROCEDURE

The experimental setup used to examine the changes in the frequency content of vibrations during the compaction process is shown in Figure 1. This experimental set up comprises of an Ingersoll-Rand DD138HF dual drum vibratory compactor instrumented with accelerometers, and a real-time data acquisition system to analyze the vibration characteristics and predict density. Vibrations of the roller during compaction are translated into voltages using a tri-axial accelerometer capable of measuring accelerations along three orthogonal axes. A CXL10HF3 accelerometer from Crossbow (Crossbow, 2005), capable of measuring 10g acceleration up to 10 kHz, was mounted on the axle of the drum of the roller to measure the vibrations of the drum during compaction tests. The signal produced by this accelerometer is then read by the data acquisition system. The data acquisition system used in this case, the xPC target (The MathWorks, 2005), is a rapid prototyping tool that can convert graphical models of the data acquisition circuitry into software that can be executed in real-time. The xPC target is an Intel Pentium processor-based embedded computer and is configured using Simulink (The MathWorks, 2005).

The development of the compaction analyzer is based on the hypothesis that the features extracted from the vibration signal of a compactor are sufficient and reliable to determine the level of densification achieved during the compaction process (Commuri and Zaman, 2007). The following steps are used to achieve this goal:

Read the signals from the instrumented compactor and filter the signals to eliminate noise and other undesirable quantities.

Perform a Fast Fourier Transform (FFT) on the data from the accelerometer and determine the power (in decibels) of the signal at different frequencies. Extract the key features of the signals, i.e. frequencies and the corresponding power.

Compare the extracted features with the features corresponding to a set of known densities.

Calculate the predicted density based on the results from the previous step and the knowledge of the process parameters, i.e. mix type, mat temperature, type of compactor, etc.

The sensor module consists of accelerometers for measuring the vibrations of the compactor during operation, infrared temperature sensors for measuring the temperature of the mix, means for selecting the amplitude and frequency of the vibration motors, and means for recording the mix type and lift thickness. The vibration signals were sampled at 1000 samples/second using a Mathworks xPC real-time computer running on an Intel Pentium 4 processor and with IO301 embedded data acquisition system. The sampled input is presented to the feature extractor (FE) module. The FE module implements a Fast Fourier Transform (FFT) of the input signal to extract the features corresponding to vibrations at different salient frequencies. Pre-processing the data to extract the features reduces the amount of data to be considered in the classification process, and therefore the algorithmic complexity of the classifier is reduced. The Neural Network Classifier is a multi-layer Neural Network (NN) that is trained to classify the extracted features into different classes. The Compaction Analyzer then post-processes the output of the NN and predicts the degree of compaction in real time.

In the experimental setup described in this paper, a window of 256 contiguous samples was used to compute the FFT at each instant in time. The window had an overlap of 128 past values. The size of the window and the overlap were fixed to provide equal resolution to the time and frequency content of the signal. The output of the FFT is a vector with 256 elements, where each element corresponds to the signal power at the corresponding frequencies. In this case, since the signal is sampled at 1 kHz, the frequency spectrum is uniformly distributed from 0 to Nyquist frequency, i.e. 500 Hz. In order to classify these vibrations, the 200 elements corresponding to the response above the excitation frequency of the compactor are used as input to the classifier.

The NN classifier implemented is a three layer NN with 200 inputs, 10 nodes in the input layer, 4 nodes in the hidden layer, and 1 node in the output layer. The inputs of the NN correspond to the outputs of the feature extraction module, i.e. in this case 200 features in the frequency spectrum were considered. The output corresponds to a signal indicative of the level of compaction reached. The method to extract the training data, and validate the performance of the Compaction Analyzer is discussed in the next section.

4. EXPERIMENTAL RESULTS

In order to minimize the effect of the subgrade on the vibrations of the compactor, a test pad consisting of a continuously reinforced concrete pavement (CRCP) is designed so as to provide a stiff uniform subgrade over which HMA overlays can be performed. It is anticipated that the properties of such a subgrade would not alter during the course of the compaction. Thus, any changes observed in the vibration spectrum of the compactor during construction would be a result of changing properties of the asphalt mat.

The test site selected was a stretch of unused road on Mendel Plaza near Max Westheimer Airport in Norman. The center line of the street was located and a section 7.62 meters (25 feet) wide by 106.7 meters (350 feet) long and soil characterization tests were performed. The results of the tests were then used to stabilize the subgrade, and design and build a reinforced concrete slab 4.27 meters (14 feet) wide and 106.7 meters (350 feet) long and 15.24 centimeters (6 inches) thick for use in the project.

The performance of the IACA prototype was analyzed during the compaction of asphalt mixes on the controlled test strip described above. Initially, several overlays were constructed using the S3 (PG64-22OK) mix and the vibrations of the machine were collected and the corresponding spectrograms were computed. Several readings were also taken during each roller pass using a PQI 301 non-nuclear density gauge. On completion of the overlay, several cores were extracted from the compacted pavement and their density was measured in the laboratory in accordance with the AASHTO T 166 and OHD L-45 specifications.

The vibration data from the spectrogram was correlated with the density measurements in order to extract the data for training the neural network. Locations on the mat with densities of 90%, 92%, 94% were identified and the FFT output corresponding to these locations were identified using the GPS measurements. Eight columns of FFT data, corresponding to a linear travel of 1 foot, were selected at each of these locations to constitute the training data for the neural network. The training error for each epoch of the training is shown in Figure 5. The training is stopped once the required precision (10^{-6}, corresponding to 1 prediction error in 10^{-6} trials using the training data) is obtained.

The performance of the trained IACA was verified during the construction of an asphalt pavement on the test strip. The output of the accelerometer and the GPS measurements of the location of the compactor were collected and the spectrogram was plotted against the distance traveled by the compactor for each roller pass. After each roller pass, the density was measured at specific points on the asphalt mat. The spectrogram of the vibrations of the compactor over the first two passes is shown in Figure 2, where the effect of increased density on the vibration of the compactor can be easily seen.

The data obtained was used to train the IACA to extract the relevant features from the vibration signal and estimate the level of compaction. The estimated density and the training data are shown in Figure 3. It can be seen that the predicted density correlates very well with the densities used in the training set. The IACA was used during the compaction of an overlay on top of the test strip. Figure 4 shows the final compacted density of the entire test strip as predicted by the IACA. Comparison with the densities measured from the cores extracted from the completed pavement show a very good correlation between the measured and predicted densities (Figure 5).

5. CONCLUSIONS

In this paper, the design of a neural network based Intelligent Asphalt Compaction Analyzer (IACA) was presented. A procedure to calibrate the IACA using field compaction data was presented and the performance of the IACA was validated during construction in controlled field settings. The experimental results show that the IACA can be trained to classify the observed vibrations as those corresponding to density levels in the training set. Thus, variations from site to site can be easily accommodated by the generation of appropriate training sets for the IACA. The estimated density correlates well with the density measured from compacted cores and the measurement error is comparable to the errors observed using tools that measure the density at discrete points. Furthermore, the IACA output is continuously available to the operator in real time and can serve as a useful guide during the compaction process.

Planned future work includes the testing of IACA in real life conditions and in extending the process for determining the modulus of elasticity during compaction of soils.

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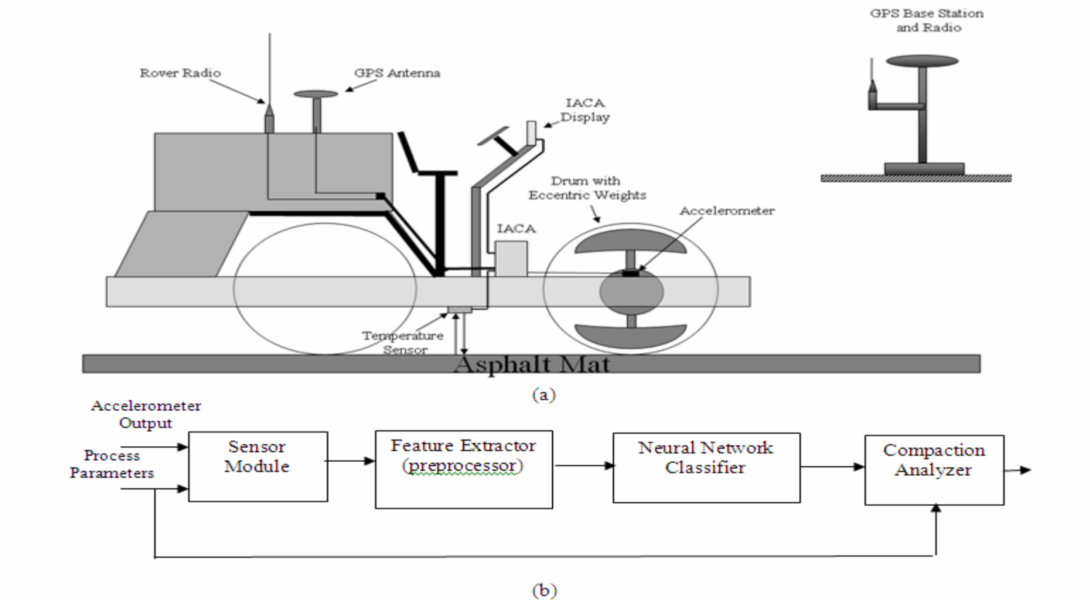

Fig. 1 Experimental setup: (a) Instrumentation of the compactor; (b) Functional schematic of the analyzer

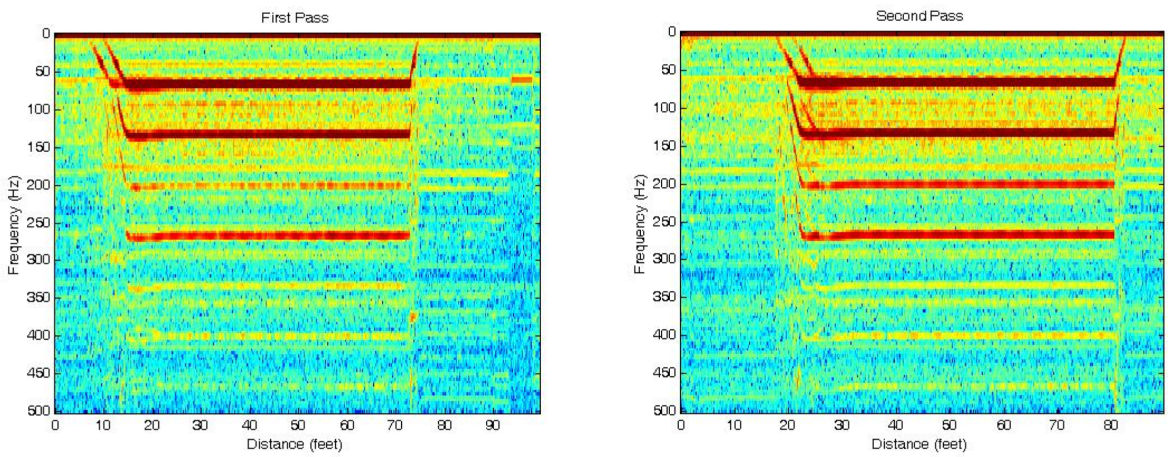

Fig. 2. Spectrogram showing the effect of changes in density between the first pass and the second pass

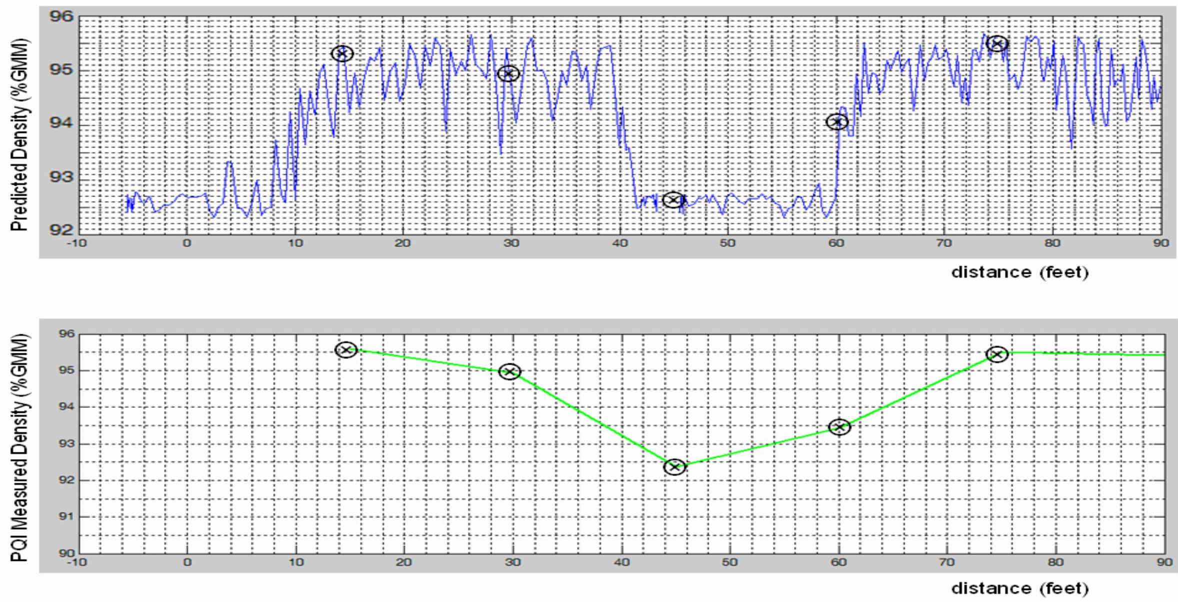

Fig.3 Comparison of IACA estimated density and the density corresponding to the training set

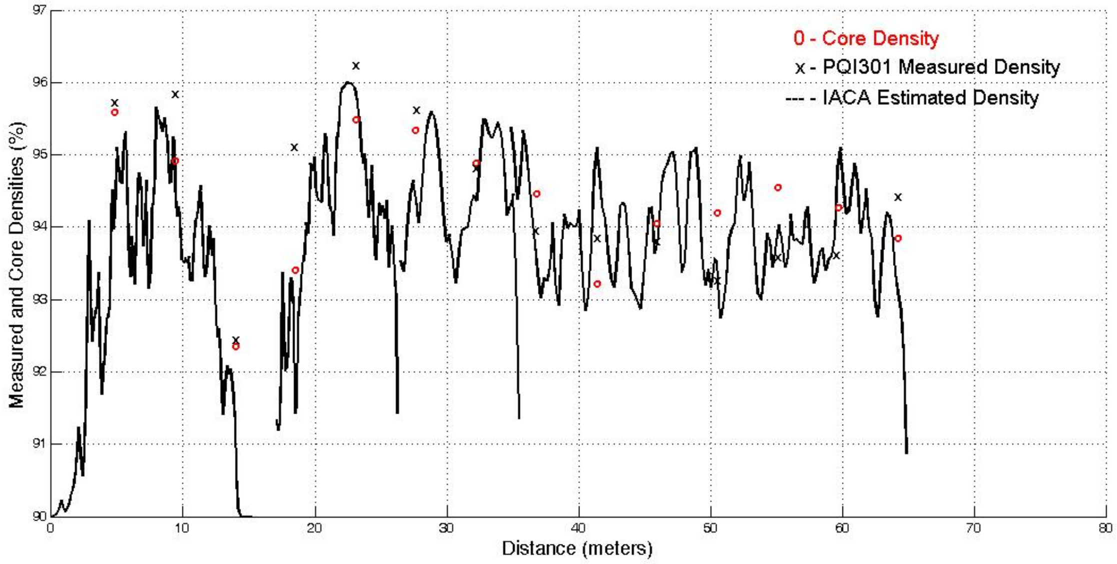

Fig.4. As-built density of the test pavement estimated by the IACA

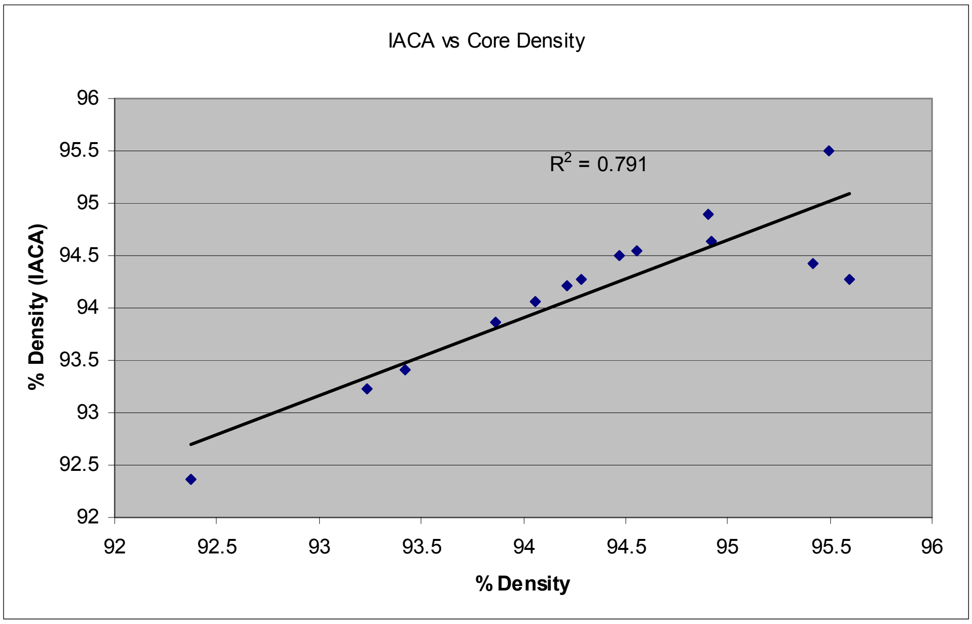

Fig. 5 Correlation between estimated density (IACA) and density of the extracted core