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

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Continuous real-time estimation of the quality of compaction during the construction of a Hot Mix Asphalt (HMA) pavement is addressed in this paper. Densification of asphalt pavements during 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. The neural network is first trained using several vibration patterns corresponding to different density levels. During compaction of a HMA mat, the neural network then classifies the observed vibrations as those corresponding to a known level of compaction. Compaction studies of HMA mixes on a stiff subgrade indicate that the changes in the vibration characteristics of the roller are due to increased compaction of the HMA base. 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.

Keywords: Intelligent Compaction, Asphalt Pavements, Neural Networks, Compaction Analyzer

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

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1. Introduction

Compaction of Hot Mix Asphalt (HMA) using vibratory rollers is a commonly accepted practice for increasing the density and the stiffness of an asphalt pavement. The rolling pattern adopted during construction depends on the desired 'lift' thickness, the type of roller used, and the properties of the HMA mix. During field compaction, the density achieved is usually verified by taking point-wise measurements with a nuclear density gauge. Such readings are time consuming and rarely reflect the overall quality of the constructed pavement. The viscosity of the asphalt binder in the mix changes with temperature making it harder to compact a HMA layer after it cools down below the cessation temperature (typically 132 $^{\circ}C$). This makes it imperative to quickly determine the achieved density before the mix cools down to an extent where it cannot be compacted any further.

The importance of good construction practices and quality assurance in the field for achieving the desired levels of compaction is well understood (HAPI, 2003). Improper compaction of asphalt pavements is one of the leading contributors to the early degradation of pavements. The practice of extracting roadway cores to measure the density also leads to early onset of potholes and moisture induced damage in pavements (Scherocman, 1984). The ability to estimate the quality of compaction of a Hot Mix Asphalt (HMA) pavement under construction has been pursued by many researchers. For example, Yoo and Selig (1979) studied the dynamic characteristics of vibratory compactors and developed an analytical model to predict the amount of energy transferred to the asphalt mat during compaction. Machine parameters (frequency, speed) are then altered to maximize the energy transferred, thereby increasing the level of compaction. However, this method does not directly yield the compacted density. Researchers have also tried to study the performance of a compactor by observing its vibratory response (Mooney, 2002, 2005). Sandstrom (1998) utilized frequency and amplitude of vibration of the roller as it passes over the ground to compute the shear modulus and a "plastic" parameter pertaining to subgrade soil. These values were then used to adjust the speed of the compactor and its frequency and amplitude. Minchin (1999, 2001, 2003) estimated the 'degree of compaction' by comparing the amplitude of the fundamental frequency of vibration with the amplitudes of its harmonics. By relating the ratio of second harmonic of the vibratory signal to amplitude of third harmonic, it was possible to predict the compacted density, with 80% accuracy in some cases. To estimate density, Swanson (2000) attempted to account for some of the variations seen in the vibratory responses of compactors by considering properties of HMA and site characteristics, in addition to the vibratory response of the compactor. The use of microwave signals in determining the density of the pavement was investigated by Jaselskis (1998). In recent years, some of these techniques have been used to develop commercial prototypes by equipment manufacturers. Compactometer (GEODYNAMIK, 2004), Bomag VarioControl (BVC) (BOMAG, 2005), AMMANN Compaction Expert (ACE) (AMMANN, 2005) are some of the Intelligent Compaction tools that are being validated by the asphalt community.

While Intelligent Compaction techniques are gradually being accepted by the construction industry, the existing techniques are not yet commercially available largely due to their inability to account for factors in the field such as the characteristics of the compactor, subgrade characteristics, and mix properties that cause inaccuracies in the estimated density. These unaccounted parameters make the practical application of the techniques difficult. 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) developed in that study was shown to be capable of estimating the density of compaction using an Asphalt Vibratory Compactor in a laboratory setting. 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.

In this paper, the validation of the IACA during compaction under controlled field conditions is presented. The IACA is based on the hypothesis that a vibratory compactor and the Hot Mix Asphalt (HMA) form a coupled system with characteristic vibrations during compaction. In order to minimize the effect of the subgrade on the vibrations of the compactor, a test strip with a rigid subgrade is first constructed and the functioning of the IACA is studied. Calibration procedures are developed using the vibration data and density measured from the roadway cores. The performance of the IACA is then verified against density measured using a Transtech non-nuclear density gauge, PQI 301, and the densities measures from the extracted cores from the compacted pavement.

2. Theoretical background for intelligent compaction

The behavior of an HMA pavement under traffic and environmental 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 (E^*) . The complex modulus is defined as the ratio of the amplitude of the sinusoidal stresses (σ) and the amplitude of the sinusoidal strain (ε) . Thus, the complex dynamic modulus is mathematically expressed by the following equation (Cline, 2003):

$$E^* = \frac{\sigma}{\varepsilon} = \frac{\sigma_0 \sin(\alpha t)}{\varepsilon_0 \sin(\alpha t - \phi)},\tag{1}$$

where $\sigma_0 = Peak \ (maximum) \ stress,$ $\varepsilon_0 = Peak \ (maximum) \ strain,$ $\phi = Phase \ angle \ (radians),$ $\alpha = angular \ velocity \ (radians/second), \ and$ $t = time \ (seconds).$

The "dynamic modulus" is defined as the absolute value of the complex modulus, i.e. $|E^*| = \frac{\sigma_0}{\varepsilon_0}$, and is usually denoted as E^* . 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 material model for the asphalt cement (AC) layer relates the dynamic modulus of the AC to parameters such as temperature, asphalt content and air voids content. 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 is assumed to be the elastic modulus and depends on a number of design factors like the viscosity of the asphalt (η), the effective asphalt content (% by volume – Vb_{eff}), etc., and the construction parameters like the percentage air void. The dynamic modulus, E^* (in 10^5 psi), can be expressed using the Witczak equation as follows (Ayers et al., 1998):

$$\log E^{*} = -1.249937 + 0.02923\rho_{200} - 0.001767(\rho_{200})^{2} - 0.002841\rho_{4} - 0.005809V_{a} - 0.82208\frac{Vb_{eff}}{Vb_{eff} + V_{a}} + \frac{3.871977 - 0.0021\rho_{4} + 0.003958\rho_{38} - 0.000017(\rho_{38})^{2} + 0.00547\rho_{34}}{1 + e^{(-0.603313 - 0.313351\log(f) - 0.393532\log(\eta))}}$$
(2)

where 'f' is the loading frequency (in Hz), ' η ' is the binder viscosity at the temperature of interest (in 10⁶ poise), ' V_a ' is the air void content (% by volume), ' V_{beff} ' is the effective asphalt content (% by volume), ' ρ_{34} ' is the cumulative % retained on the 19 mm sieve (% by mass), ' ρ_{38} ' is the cumulative % retained on the 9.5 mm sieve (% by mass), ' ρ_4 ' is the cumulative % retained on the 4.76 mm sieve (% by mass), and ' ρ_{200} ' is the cumulative % retained on the 0.075 mm sieve (% by mass).

It can be seen from Equation (2) that even when the design parameters are fixed, the dynamic modulus is influenced by the amount of air voids in the HMA specimen being compacted. Since the vibration of the asphalt compactor during the construction of the pavement is a function of the dynamic modulus of the pavement, these vibrations can be monitored to estimate the amount of air voids in the compacted HMA. However, such estimations of the density assume that the underlying subgrade does not have any influence on the nature of the vibrations of the compactor. If this is not the case, then

changing subgrade properties cause variations in the vibrations of the roller and such variations cannot be correctly accounted for during the construction.

In the research presented in this paper, a test site was constructed with a rigid subgrade. This rigid subgrade does not cause any appreciable change in the vibrations of the roller during the compaction. Thus, any variations in the vibrations of the roller would be the result of the densification of the underlying HMA layer. The design and construction of the reinforced concrete slab that functions as a rigid subgrade for the validation of the IACA hypothesis is presented in the following section. Compaction of HMA mixes is then carried out in a controlled manner on the top of this concrete pad.

3. Design and construction of a test site for the controlled field testing

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 constructed. 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 it was divided into five stations. A total of 24 boreholes were selected to give a better soil properties distribution throughout the project. Dynamic cone penetration (DCP) tests were performed at each hole to a depth of approximately 0.76 meters (30 inches). Bulk samples were then collected at every 15 centimeters (6 inches), down to 91.4 centimeters (36 inches) and the moisture content was analyzed. Standard proctor tests were performed on the collected bulk samples according to the AASHTO-T99 test method. The maximum dry density (MDD) was found to be approximately 1675 $\frac{kg}{m^3}$ (104.4 $\frac{lb}{ft^3}$) and the optimum moisture content (OMC) was approximately 19%. This information was utilized in the design of the concrete slab for the test site.

The existing subgrade was stabilized using cement kiln dust and compacted to $1675 \frac{kg}{m^3}$ (104.4 $\frac{lb}{ft^3}$). The subgrade moisture content was also determined to be within two percent of the optimum moisture content (19%). A concrete slab 4.27 meters (14 feet) wide and 106.7 meters (350 feet) long and 15.25 centimeters (6 inches) thick was then constructed on top of the compacted subgrade. The completed test strip is shown in Figure 1.

4. Experimental setup for use in simulated field tests

The IACA functions on the hypothesis that the vibratory roller and the underlying HMA pavement form a coupled system whose response is determined by the excitation frequency and the natural vibration modes of the coupled system. In order to analyze the vibrations of the roller, tri-axial accelerometers are fixed on the frame of the roller and the vibrations of the roller are captured using a data acquisition system. The following discussion relates to the extraction of the frequency content of the vibration signal and the analysis performed by the IACA.

<u>a. Fast Fourier Transform (FFT) (Ingle, 2007).</u> The frequency content of a continuous time signal x(t) can be analyzed using the well known Fourier Transform. In the case of sampled signals, the Discrete Time Fourier Transform (DTFT) operates on aperiodic,

discrete signal and relates it with a periodic, continuous frequency spectrum. If x[n], n = 0....N-1, be a collection of 'N' samples of x(t) obtained by sampling x(t) at a rate of f_s Hz, then the DTFT $X(e^{j\omega})$ decomposes the sequence x[n] into sine and cosine waves, with frequencies equally spaced between zero and one-half of the sampling rate. The frequency spectrum of x[n] is represented by $Re X(\omega)$ and $Im X(\omega)$, with $0 \le \omega \le \pi$, where

$$Re X(\omega) = \sum_{n=-\infty}^{+\infty} x[n] \cos(\omega n)$$

$$Im X(\omega) = -\sum_{n=-\infty}^{+\infty} x[n] \sin(\omega n),$$
(3)

such that

$$X(e^{j\omega}) = \operatorname{Re} X(\omega) + j \operatorname{Im} X(\omega) = \sum_{n=-\infty}^{n=+\infty} x[n]e^{-j\omega n}.$$
(4)

The Discrete Fourier Transform (DFT) of the sequence x[n], n = 0....N-1, is a finite length sequence

$$X[k] = X(e^{j\omega})\Big|_{\omega=2\pi k/N} = \sum_{n=0}^{N-1} x[n]e^{-j2\pi kn/N}, 0 \le k \le N-1.$$
(5)

The Fast Fourier Transformation (FFT) is a practical approach to the numerical computation of the DTFT of a finite length sequence and provided the power contained at each frequency in the spectrum of the signal.

<u>b. Experimental Setup.</u> The experimental setup used to examine the changes in the frequency content of vibrations during the compaction process is shown in Figure 2. 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 Simulink software is widely used for graphical programming and has capabilities that allow designing and testing systems using real data. Furthermore, models created in Simulink can be compiled to run in real time on different hardware platforms.

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.

- 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 were 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 frequency. Since the original signal is sampled at 1 kHz, the frequency spectrum is uniformly distributed from 0 and 500 Hz. The upper frequency limit, 500Hz in this case, is called the Nyquist frequency and is equal to half of the sampling rate. This frequency indicates the highest frequency content in the input signal that can be reconstructed back using the sampled signal.

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.

5. Experimental Results

<u>a. Verification of IACA hypothesis in the field.</u> In order to verify the suitability for application in real-life conditions, vibration data from several construction sites across Oklahoma was collected and studied to determine the effect of the process parameters (lift thickness, mix type, subgrade, etc.) on the vibrations of the compactor during the

compaction of the asphalt pavement. The spectrograms for some typical parameters are shown in Figure 3. It can be seen that the vibration characteristics are impacted by the process parameters. The study indicated that the spectrograms, while showing differences between different projects, remain consistent over the course of a single construction for a given set of construction parameters (lift, lift thickness, compactor vibration settings, etc.). Further, the intensity of the colors in the spectrogram indicates the power density associated with the vibrations. Regions with the maximum power intensity, shown in red in the spectrograms were visually located and their locations correlated with the GPS measurements. Figure 4 shows the power spectral density of the measured vibrations and the density of the roadway (in the center of the roller path) measured using a Troxler Nuclear density gauge. It can be seen that the observed spectral densities correspond with the measured densities.

<u>b. Testing of IACA under controlled Field Conditions.</u> The performance of the IACA prototype was analyzed during the compaction of asphalt mixes on the controlled test strip described in Section 3. The pavement was 91.44 m (300 feet) long, 3.6576 m (12 feet) wide, 7.63 cm (3 inch) thick, and was constructed using a S3 (PG64-22OK) mix (see Table 1). Initially, several overlays were constructed using the S3 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 measured core densities

were used to calibrate the PQI 301 density gauge. The calibration data was used to adjust the raw density readings of the PQI 301 gauge.

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 $(10^{-6}, \text{ corresponding to 1 prediction error in } 10^{6} \text{ trials using the training data})$ 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 using the PQI 301 gauge (Table 2). The densities measured after each pass are shown in Figure 6. It can be seen from this figure that the density increases after each pass. However, "roll over" occurs after the third pass and subsequent roller passes cause a reduction in the density of the compacted pavement. The spectrogram of the vibrations of the compactor over the first two passes is shown in Figure 7, where the effect of increased density on the vibration of the compactor can be easily observed.

The data from Table 2 was used to train the IACA to extract the relevant features from the vibration signal and estimate the level of compaction. The estimated density during the final pass of the first stretch is shown in Figure 8. It can be seen that the predicted density correlates very well with the densities measured using the PQI 301 gauge. Figure 9 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 10).

6. 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 extract the features from the vibrations of the compactor and use these features to estimate the level of compaction. The calibration procedure is straightforward to implement and can easily take into account the different parameters, like base/intermediate/surface course, lift thickness, mix type, construction equipment, etc., encountered at each site. 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. The validation of IACA at different construction sites is currently underway and the results will be communicated in a forthcoming paper.

Acknowledgements

The authors gratefully acknowledge the financial assistance of the Oklahoma Center for the Advancement of Science and Technology (OCAST) through grant # AR032-011. Assistance of Haskell Lemon Construction Company, Broce Construction Inc., Oklahoma Department of Transportation, and the Oklahoma Department of Environmental Quality is also gratefully acknowledged.

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Table 1. Gradation for mix S3 (PG64-22OK)

Sieve No.	Job Formula (% passing sieve)				
25.4 mm (1 in)	100				
19 mm (0.75 in)	98				
12.7 mm (0.5 in)	88				
9.52 mm (0.375 in)	72				
No. 4; 4.75 mm (0.187 in)	40				
No. 8; 2.36 mm (0.0929 in)	30				
No. 16; 1.18 mm (0.0464 in)	21				
No. 30; 0.6 mm (0.0236 in)	16				
No. 50; 0.3 mm (0.0118 in)	11				
No. 100; 0.15 mm (0.0059 in)	8				
No. 200; 0.075 mm (0.0029 in)	4.2				

	Point	Left			Center			Right		
Pass				Relative			Relative			Relative
1 435		Moisture	Density	Density		Density	Density		Density	Density
		(%)	(pcf)	(%)	H20	(pcf)	(%)	H20	(pcf)	(%)
1	1	4.6	143.2	92.2				4	142.8	91.9
	2	5	144.1	92.8				4.6	143.6	92.5
	3	4.9	144	92.7						91.9
	4	4	142.5	91.8						
	5									
2	1	4.4	143.8	93.1				4.8	147.5	93.1
	2	4.9	144.8	93.4	4.8	144.4	93	4.7	144.9	93.4
	3	5	144.7	93.2	5	144.2	92.9	4.8	144.7	93.3
	4	4.8	144.3	93.3	5.4	145.3	93.6	4.8	145.1	93.5
	5	5.1	145.3	93.6	5.3	143.5	92.5	6.7	147	94.1
3	1	4.3	144.8	93.3	4.3	144.2	92.9			
	2	4.9	145.1	93.5	4.1	143.9	92.7			
	3	5	145.4	93.7	4.7	144.3	92.8			
	4	4.9	145.3	93.4	5.1	145.2	93.6			
	5	5.4	146.6	94.4	5.4	143.4	92.4			
4	1	3.9	143.6	92.5	3.5	142.9	92.1	4.2	145.8	93.5
	2	4.9	144.8	93.2	4.1	143.8	92.7	4.4	144.9	93.4
	3	4.7	145	93.1	4.6	145.4	93.4	4.2	144.5	93.1
	4	4.3	144.7	93.2	6.3	146.4	93.3	4.6	145.5	93.5
	5	4.9	144.5	93.1	5.3	144.1	93.8	7.7	145.6	94.1
5	1	4.4	144.6	92.9	3.4	143.1	92.1			
	2	5.1	145.7	92.8	4.1	144.1	92.9			
	3	4.6	142.8	93.1	4.9	146.3	94.2			
	4	4.4	144.8	93.3	4.5	145.3	93.1			
	5	5	145.8	92.1	5.6		93			

Table 2. Pass by pass density reading using PQI 301



Figure 1. Completed test strip with CRCP subgrade



(b) Figure 2. Experimental setup: (a) Instrumentation of the compactor; (b) Functional schematic of the analyzer



Figure 3. Spectrograms of the vibrations of the compaction for different process parameters





Figure 4. Output of the compaction analyzer along with actual density measurements from a nuclear density gauge



Figure 5. Output prediction error of the neural network after each training cycle



Figure 6. Changes in the density of the asphalt mat over successive roller passes



Figure 7. Spectrogram showing the effect of changes in density between the first pass and the second pass



Fig. 8. Comparison of predicted and measured density (a) Density predicted by the IACA; (b) Density measured by PQI 301



Figure 9. As-built density of the test pavement estimated by the IACA



(a) (b) Figure 10. Comparison between measured density and density of the extracted core: (a) PQI301; (b) IACA