In-Time Density Monitoring of In-Place Asphalt Layer Construction via Intelligent Compaction Technology

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Abstract: Intelligent compaction (IC) has been successfully used for soil and base compaction of highways. However, the application of IC technology to monitor the construction quality of asphalt pavement faces complications with compaction processing. This study monitored the compaction process of asphalt layers using an IC-based method. The compaction data were first collected during the construction of a local road in Mardan, Pakistan, including IC data, in-place density, and temperature at the asphalt layer surface. The collected IC data were then used to compute the intelligent compaction measurement values (ICMVs). The support vector regression analysis was performed to predict the roller amplitude and in-place density using the ICMVs. To explore the correlations in compaction measuring/monitoring indicators, this study also explored the correlations between the ICMVs with core density, temperature, and amplitude. Experiment results indicated that the predicted roller amplitude values from the support vector regression model were close to the measured ones. There were high correlations between the roller amplitudes and temperatures with the compaction measurement values (CMVs). In contrast, the correlation between the in-place core densities and CMV values was low. Additionally, the CMVs of the backward pass were higher than the forward one in each compaction cycle because the pavement density increased and the air void decreased after each forward pass. **DOI: 10.1061/(ASCE)MT.1943-5533.0004558.** *© 2022 American Society of Civil Engineers.*

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Introduction

Conventional density quality control (QC) methods are still used for density checks during the compaction processes of asphalt layers, such as measuring the densities of drilled cores or using nuclear or nonnuclear gauges to obtain in-place densities. However, these methods have been limited by their disadvantages, such as low generality and time consumption (Mooney and Adam 2007; Mooney and Rinehart 2007). In addition, random sampling is not representative since they typically cover only 1% or even less of the entire construction area. Another problem is that QC density tests are generally performed after compaction, making the remedial measure expensive. The intelligent compaction (IC) method has been introduced in the past years as an alternative to the traditional QC techniques to improve the compaction quality during pavement construction.

The IC technology was initially used for soil compaction in the 1970s and is now adopted for the whole construction procedure of asphalt pavement (Scherocman et al. 2007; Mooney 2010; Xu and Chang 2013; Hu et al. 2019, 2021). The IC technology first collects the roller-ground interaction (vibration) data with an accelerometer and then computes the compaction indicators of investigated areas. Thus, the compaction quality is evaluated in real-time during the compaction procedure, making it possible to determine the areas with low compaction quality, which need extra compaction operations. All compaction indicators are synchronized with the other data using a global positioning system (GPS), such as the number of passes, frequency, speed of roller, and temperature of the asphalt layers. Thanks to these advantages, IC is accurate and timely for testing asphalt compaction density.

In the IC technique, there are three types of indicators to quantify compaction status: (1) acceleration signal-based indicators (Pettersson and Sandström 2004; Hu et al. 2017; Ma et al. 2021; Yuan et al. 2021; Ma et al. 2022), such as compaction measurement value (CMV), compaction control value (CCV), acceleration intelligent compaction value (AICV), and vibration compaction value (VCV); (2) stiffness-based indicators (White et al. 2007), such as compaction stiffness and vibration modulus; and (3) energy-based indicators (Mooney 2010), such as Omega value and machine drive power (MDP). Many studies have reported the possibility of using

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the IC technique to control and monitor the compaction quality of asphalt pavement by computing the relationships between the intelligent compaction measurement values (ICMVs) and the pavement in-place density (Beainy et al. 2010; Savan et al. 2015; Hu et al. 2017, 2019). It was found that ICMVs correlated well with nuclear gauge densities (Chang et al. 2014). ICMV is an acceleration signal-based indicator to quantify compaction status. In contrast, weak correlations between the CMV/CCV and core density were observed, contributing to the complex field construction processes. For instance, the field IC measurements are highly affected by the stiffness of the underlying support layers and vary from one location to another, even with the same roller compactor, materials, and paving pattern (Chang et al. 2011; Yuan et al. 2021; Zhang et al. 2021b). Recently, neural network–based models have been used to solve this problem, in which the densities of asphalt pavements were accurately predicted with the joint information of the measured vibration, mixture temperature, mixture type, and compaction pressure (Commuri et al. 2011; Zhang et al. 2021a).

This study aims to demonstrate the correlations between intelligent compaction values of asphalt pavement and in situ measured parameters, which has the potential to provide a method for real-time monitoring of compaction status. The nondestructive pavement probe (NDPP) software first collected compaction information, and core sampling was used to measure compaction density. Support vector regression analysis was then performed to predict the temperature, core density, and amplitude using the NDPP data. The predicted results from the support vector regression were compared with the in situ test results. Also, the correlation between the ICMVs and the measured data was discussed.

Methodology

This study first adopted the NDPP data acquisition software on the Android platform, which collected the operational status of the roller compactor in real-time, including vibration data, speed, GPS coordinates, amplitude, etc. At the same time, the information on field temperature and core density was obtained through the field measurement from the Mardan project. The collected vibration data were then used to extract the fundamental operating frequency and subharmonics at different frequencies using the fast Fourier transformation (FFT) analysis (Rader and Brenner 1976; Beainy et al. 2010). The fundamental operating frequency and subharmonics were then adopted to compute two signal-based indicators of compaction status, CMV and CCV. Finally, a support vector regression (SVR) was implemented to predict the correlations between the parameters of the roller compactor (e.g., amplitude, pavement temperature) and core density.

NDPP Mobile Application

The NDPP signal acquisition framework is software that can be downloaded and installed on both the Android and Apple platforms. It outputs latitude and longitude through a GPS for positioning. The data were then converted into a local working coordinate system based on the construction site. It can also use built-in sensors to collect the velocity values and vibration acceleration in three directions of XYZ with a required acquisition frequency (1–1,000 Hz). Each sensor in the framework measures a physical quantity and changes it into a signal that an electronic instrument can deliver. It has the characteristics of high accuracy, vital convenience, and diversified measurements. In this study, the NDPP signal monitoring software collected the compaction information, including the roller's vibration acceleration, coordinates, speed, time, and sampling interval. During compaction, the cell phone was attached to the steady-state of the vibration wheel, and the NDPP software then collected the compaction data with the input sampling interval and display interval. The NDPP user interface is shown in Fig. 1.

The data were collected using the NDPP software on February 2, 2021, on the eastern and western bypass near Mardan, Pakistan. The project was executed on a local road with a one-way direction, and the width of the road was 6.3 m. The length of the section was 30 m, and the weight of the roller was 12,000 kg. The cross-sectional of the road consisted of a 38 mm asphalt wearing course, 70 mm base course, and 70 mm subbase course. Dynapac roller CC10 was used for asphalt mat compaction operation with an operational speed of 3.6 km/h. The mobile phone was attached to the roller drum vibration wheel to collect the vibration data with the stable position of the vibration wheel, as shown in Fig. 2. The cross-sectional profile of the road is shown in Fig. 3. It was divided into three lanes, and each lane had five grids. The roller moved forward and backward, so the pairwise forward and backward passes were considered a single pass in which vibration was performed. After the compaction operation, core samples were collected to test the in-place density of the asphalt layers.

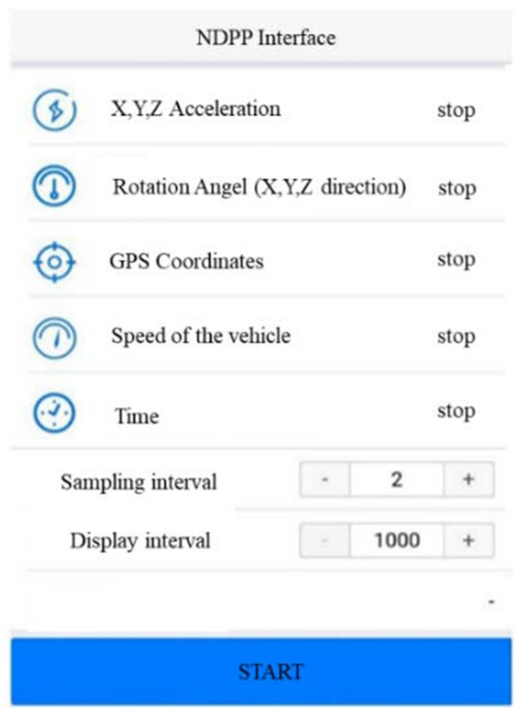

Fig. 1. NDPP mobile application interface.

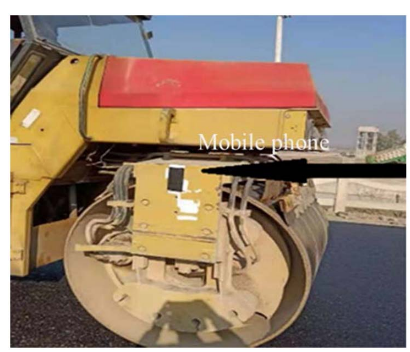

Fig. 2. Mobile phone attached to the vibratory roller drum.

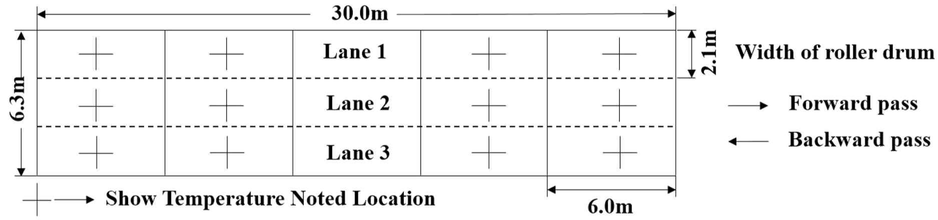

Fig. 3. Grid layout of the test section.

This study used the Nyquist sampling theorem to determine the sampling frequency. A signal can be reconstructed from its samples if the waveform is sampled twice as fast as its highest frequency component (Shannon 1949), such that

$$F_s > 2^* f_{\max} \tag{1}$$

where $f_{\max}$ = operational frequency of a roller; and F_s = sampling frequency. The operational frequency of the compaction roller in this study was 44 Hz, so the sampling frequency should be higher than 88 Hz. In this study, the sampling frequency was 90 Hz.

Fast Fourier Transformation-Based Signal Processing

In this study, the collected vibration signals in the time domain were converted to the ones in the frequency domain using the FFT analysis, which output the fundamental operating frequency and subharmonics at different frequencies. Fig. 4(a) shows an instance of the original vibration signal in the time domain collected from NDPP software. Fig. 4(b) shows the signal waveform after the FFT analysis. The signal in Fig. 4(a) includes some complex noise and interference, which should be removed for data analysis. Figs. 4(c and d) show the time-domain signal filtered by the finite impulse response algorithm and its FFT result. As shown

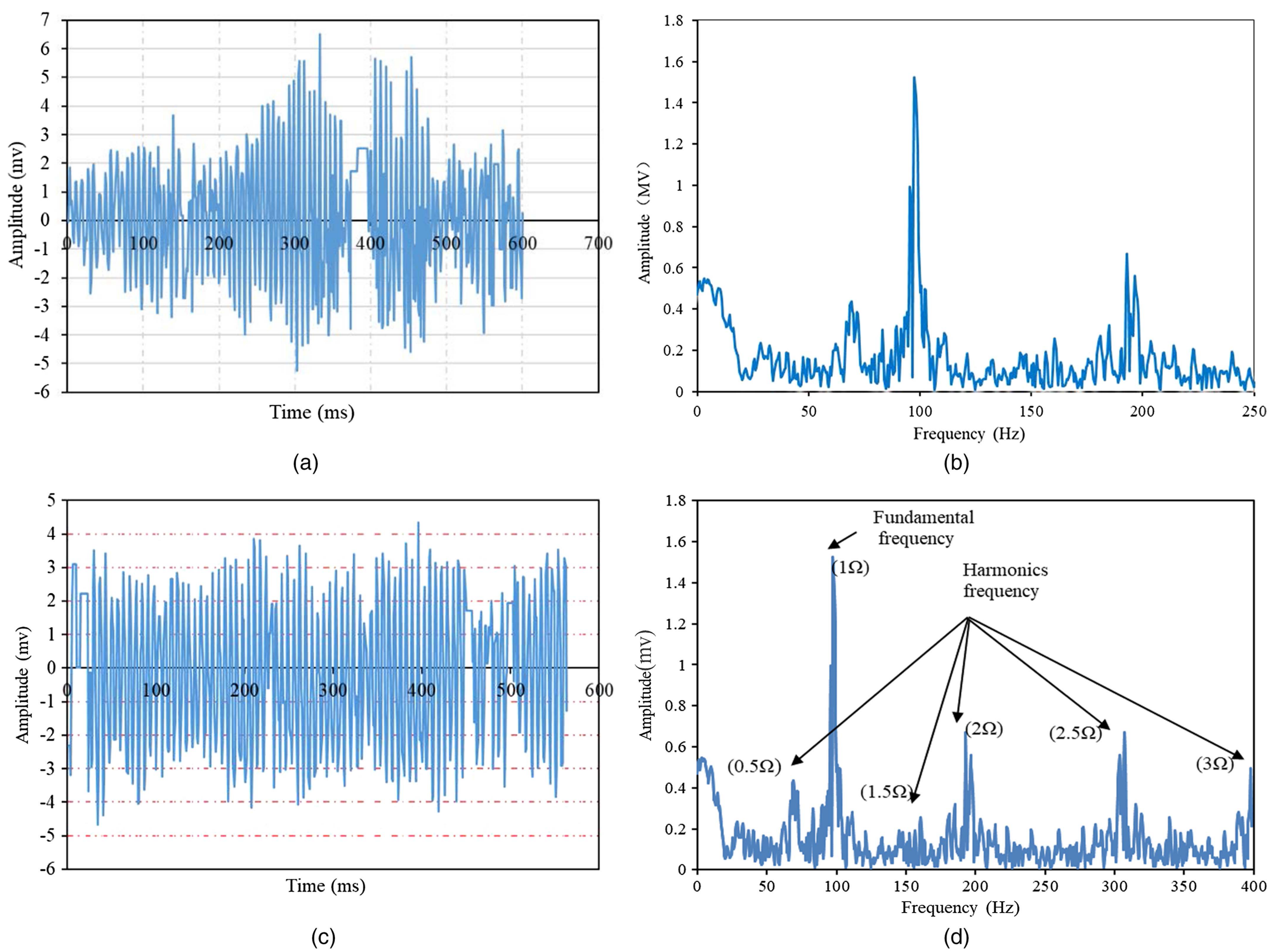

Fig. 4. Processing of vibration signal: (a) the original signal waveforms; (b) the original signals of frequency waveforms; (c) filtered signal waveforms; and (d) filtered signal of a frequency waveform.

Table 1. Metaparameters of the SVR models

Parameter	Cost function k	Epsilon $\in$	Tolerance	Kernel	Gamma	Preprocessing
Temperature	1	0.1	0.001	RBF kernel	0.5	Standardization
Amplitude	1	0.1	0.001	RBF kernel	0.5	Standardization
Core-density	1	0.1	0.001	RBF kernel	0.5	Standardization

in Fig. 4(d), the fundamental frequency (1 Ω) with the highest peak is the operational frequency of the roller. Subharmonics at different frequencies are the frequency caused by the inherently non-uniform property of asphalt mixture, such as 0.5 Ω, 1.5 Ω, 2 Ω, 2.5 Ω, and 3 Ω.

The filtered signal with different frequencies was used to compute the CMV, a metric to characterize the compaction degree of asphalt pavement. The CMV, first introduced by Geodynamik (Forssblad 1980; Thurner 1980), is a function of drum weight and diameter, roller frequency, speed, and roller amplitude, which is resolved to analyze the response of the dynamic roller. The vibratory roller's drum periodically impacts the road surface during construction. Some studies reported that the degree of compaction had a significant relationship with the ratio of the amplitude of the harmonic frequency to the one of the fundamental frequency (Forssblad 1980; Sandström 1994). The CMV, as a dimensionless compaction parameter value, is defined as

$$CMV = C \times \frac{A_{2\,\Omega}}{A_{\Omega}} \tag{2}$$

where C = constant used to fit the laboratory and field values (C was 100 in this study); and A_{Ω} and $A_{2\,\Omega}$ = acceleration amplitude of the fundamental component and the first harmonic component of the vibration, respectively. The value of $A_{2\,\Omega}/A_{\Omega}$ measures the nonlinearity of a system. In a linear drum-asphalt concrete system, a drum with 30 Hz produces a drum acceleration response of 30 Hz, where $A_{2\,\Omega}/A_{\Omega}$ is equal to 0. In practice, asphalt concrete is a nonlinear material, and some contact loss occurs between asphalt and drum. The contact surface changes nonlinearly during each loading cycle, which leads the drum acceleration response to be distorted rather than pure sinusoidal. Fourier analysis can be adopted to reproduce distorted waveforms by summing multiples of the excitation frequency. Therefore, the value of $A_{2\,\Omega}/A_{\Omega}$ can evaluate the degree of distortion or nonlinearity.

The CCV is similar to CMV, except for the additional subharmonic frequencies (the first subharmonic $A_{0.5\,\Omega}$ and higher-order harmonics $A_{1.5\,\Omega}$, $A_{2\,\Omega}$, $A_{2.5\,\Omega}$, and $A_{3\,\Omega}$) to consider the higher-order motions of a roller, such as chaotic and double jump (Sandström 1994; Scherocman et al. 2007). CCV value is calculated as

$$CCV = \frac{A_{0.5\,\Omega} + A_{1.5\,\Omega} + A_{2\,\Omega} + A_{2.5\,\Omega} + A_{3\,\Omega}}{A_{0.5\,\Omega} + A_{\Omega}} \times 100 \tag{3}$$

where $A_{0.5\,\Omega}$, $A_{1.5\,\Omega}$, $A_{2\,\Omega}$, $A_{2.5\,\Omega}$, and $A_{3\,\Omega}$ = acceleration at the different subharmonic frequencies, and A_{Ω} denotes the acceleration at the fundamental harmonic frequency.

Support Vector Regression

Machine learning, especially SVR, has been widely used in the prediction and analysis of pavement structural conditions and traffic information, such as resilient modulus (Maalouf et al. 2008), pavement roughness (Ziari et al. 2016), and pavement deformation (Cheng et al. 2019). SVR has achieved many successful applications in recent years, including the correlation prediction between core density and IC parameters (Asif Imran et al. 2018; Zhang et al. 2021b) and pavement response monitor (Seraj et al. 2015; Hadjidemetriou et al. 2018). Such achievements demonstrate the accuracy and stability of SVR on pavement performance prediction once given enough information on pavement conditions. Therefore, this study designed three SVR models to predict the surface temperatures, the amplitude of the used roller, and pavement densities using the CMV results.

The SVR performance is affected by the kernel function, kernel parameters, cost function k, and insensitive tube radius $\in$. This study used a radial basis function (RBF) as the kernel function of each SVR model (Schölkopf et al. 2002). The cost function k was used to control the function smoothness and flatness in each SVR. A high value of C corresponds to an increased penalty of errors. The insensitive tube radius $\in$ was used to control the precision of the approximation method. The optimal parameters of SVR models for predicting the surface temperatures, the amplitude of the used roller, and pavement densities are summarized in Table 1.

Result and Discussion

Effect of Passes on CMV and CCV

The entire test pavement section was divided into grids (6 m × 2.1 m), which is the same as the width of the Dynapac CC10 roller. After collecting vibration data from the roller as described in the above sections, the FFT analysis introduced in Section 2.3 was performed to compute the ICMVs (CMVs and CCVs) for each forward–backward pass by MATLAB software. Fig. 5 presents the CMVs and CCVs results on different lines. Fig. 5(a) indicated that CMVs in the lines varied from the forward pass to the backward one. The CMV of each backward pass exceeded the corresponding forward one for each line. The same behaviors of average CCV were also found in Fig. 5(b). The reason was that the pavement density increased, and the air void decreased after each forward pass. Lane 2 generally achieved the highest CMV, while Lane 3 had the lowest. In addition, the CCV and CMV results had high standard deviations. This is because the first compaction step used a breakdown roller to compact the loose material. Such roller required variable force, which also provided variable reaction force.

The asphalt pavement compaction is achieved by vibrating crushing rollers, intermediate rollers, and pneumatic tire rollers (PTRs) in sequence and compaction at elevated temperatures. A pair of forwarding and backward passes is considered a single pass in the compaction processes. After the compaction operation of each pairwise pass, the in-place density of the asphalt layer was tested by core sampling. Fig. 6 presents the core density and temperature curves versus the number of passes. Density is the ratio of mass to volume, while compaction is the process to improve the density of an object. The core density was approximately proportional to the number of compaction passes at passes 1–6. This was because the asphalt concrete was loose in the early

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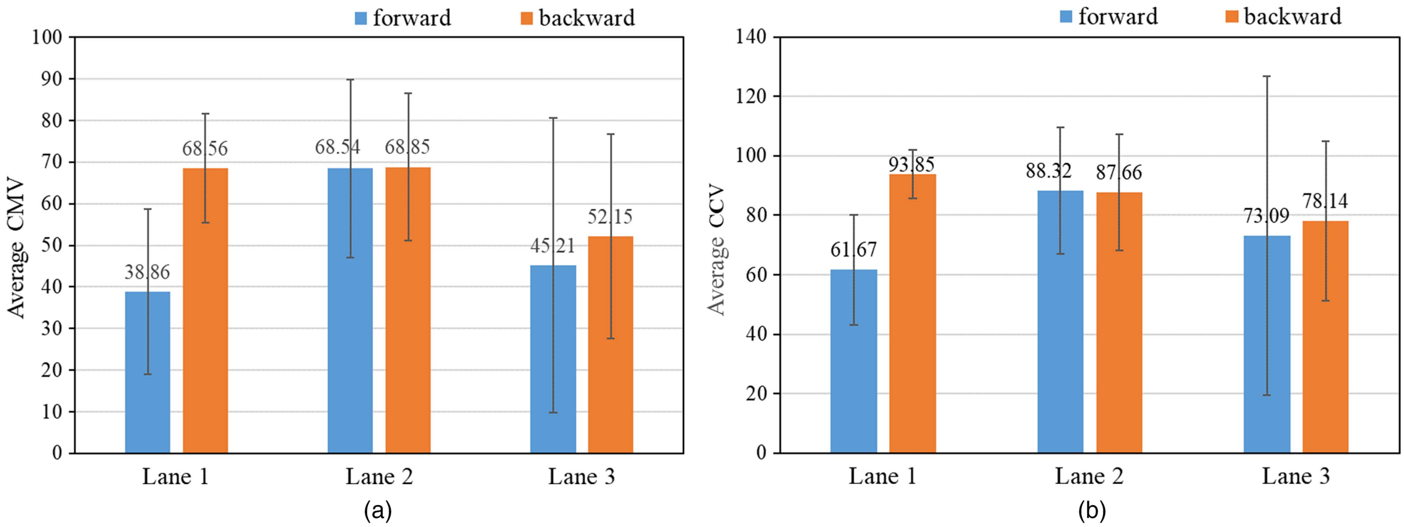

Fig. 5. Forward and backward pass comparison of different lanes: (a) CMV; and (b) CCV.

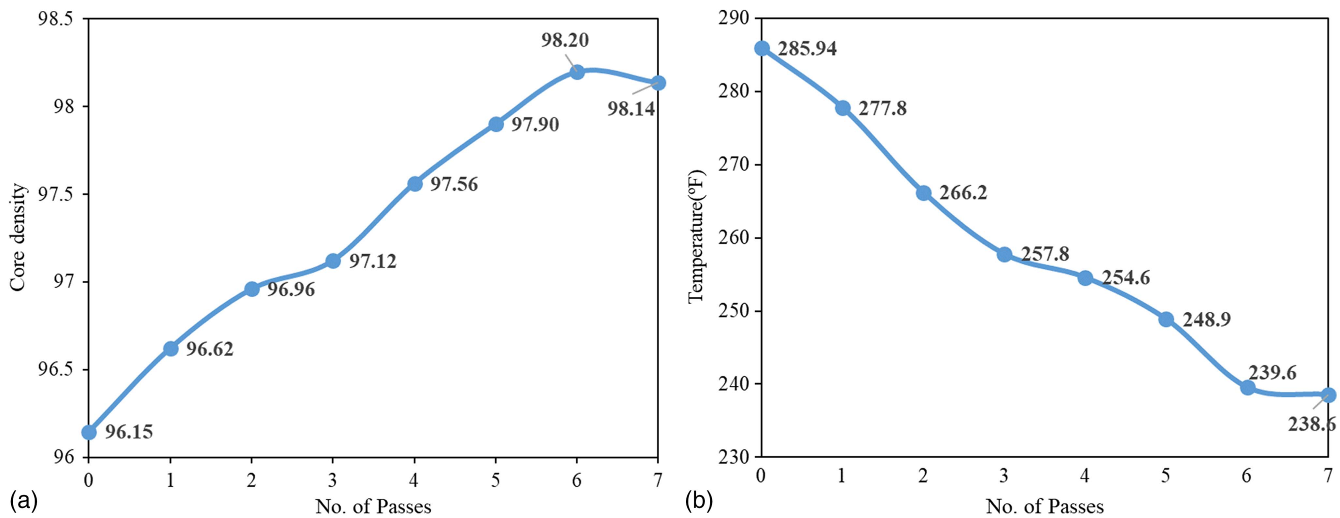

Fig. 6. Curves of density during the compaction: (a) compaction; and (b) temperature.

compaction stage. With the increase in the number of passes, the volume sum of pores in the inner structure of asphalt concrete decreased, while no extra mass was introduced in the processes. However, at passes 6 and 7, the density did not increase due to no pores in the inner structure of asphalt concrete. In addition, during the stage of the PTR compaction, the number of passes 6 and 7, the core density decreased because of the decrease in the asphalt temperature.

Fig. 6 indicated a high correlation of the pavement densities and roller passes, as well as surface temperatures of asphalt pavement. However, in practice, pavement densities were tested by core sampling, which was destructive and led to negative effects on pavement performance. Besides, surface temperatures of asphalt pavement are not easy to be tested in time. Therefore, this study tried to predict pavement densities and surface temperatures based on the information from roller passes. A metric CMV was computed using the vibration information of roller passes, as introduced in Section 2.3. SVR-based models were then designed to predict the pavement densities and surface temperatures using the CMV results, as presented in Section 2.4.

Correlation between CMV and Temperature

To predict the temperature from the integrated roller values, an SVR model was used, as introduced in Section 2.4. Fig. 7(a) presents the test results of the model. Generally, the predicted temperatures were close to the real ones. Therefore, the SVR model could predict the temperatures of pavement layers. Fig. 7(b) presents the correlation between CMV and temperature. The correlation analysis indicated a mean square error (MSE) of 0.405 and an R-squared value (R^2) of 0.7473. This demonstrated that the CMV had a high correlation with the surface temperature of the asphalt mixture. Therefore, the surface temperature had a significant effect on the compaction results.

Correlation between CMV and Amplitude

An SVR model was designed to predict the amplitude of IC rollers. Fig. 8(a) presents the testing results of the SVR model. The predicted amplitudes were close to the real ones. Therefore, the SVR model could predict the amplitude of IC rollers using ICMVs.

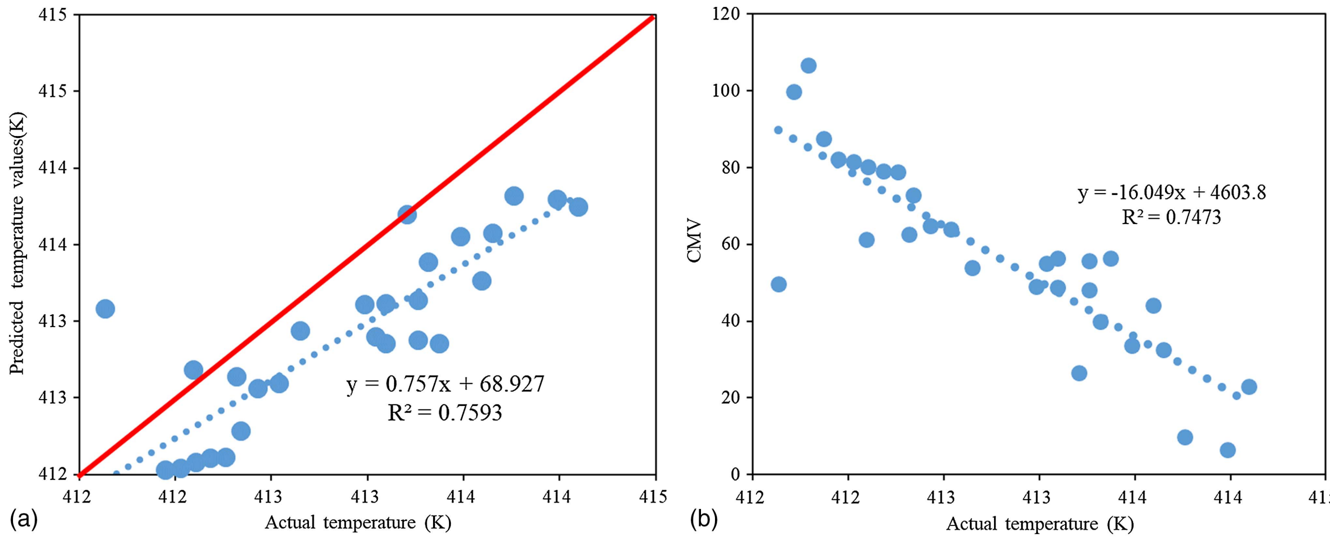

Fig. 7. Experiment results of the correlation between CMV and temperature: (a) SVR model between CMV and temperature; and (b) correlation between CMV and temperature.

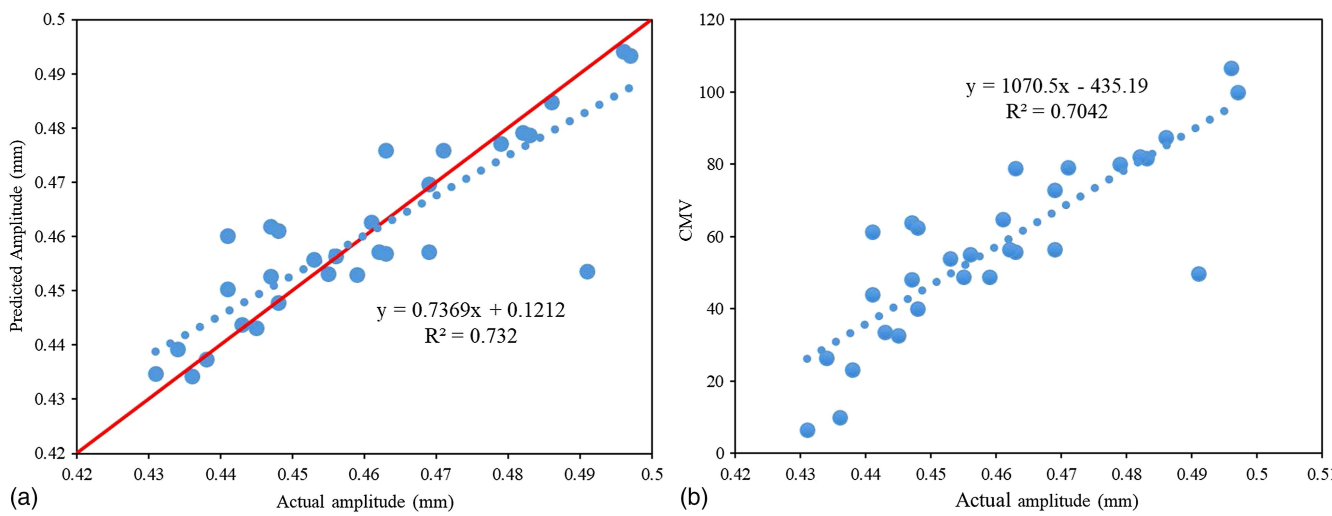

Fig. 8. Experiment results of the correlation between CMV and amplitude: (a) SVR model between CMV and amplitude; and (b) correlation between CMV and amplitude.

Fig. 8(b) displays the correlation between CMV and amplitude, indicating a high R^2. This demonstrated that the amplitude of IC rollers had effects on the compaction results. This was because an increased amplitude of the IC roller led to a high reaction force between the roller and the ground, which improved the pavement density and CMV.

Correlation between CMV and Core Density

As a destructive method, core sampling has been used to measure pavement construction quality, such as density and compaction degree. However, such an operation negatively affects pavement performance, leading to pavement distress. In addition, the results of core sampling were not representative and time-consuming. Therefore, this study used an SVR model instead of destructive measurements to predict the pavement after compaction. Fig. 9(a) presents the testing results of the SVR model. There is a gap between the predicted and actual density, indicating that CMV cannot be used to predict the density.

Cores were extracted at various locations of the pavement to measure water content, density, and void ratio. Fig. 9(b) showed the correlation between actual density values and CMV. The R^2 of 0.04 indicated a slight correlation between CMV and core density. A possible reason for the weak correlation was that the factors on in situ core density were complex, such as the size of the roller, vibration amplitude and frequency, roller speed, asphalt type, and the stratum under the compacted asphalt layer. These factors should all be analyzed to correlate well between CMV and in situ core density. Compared to the core density, the variability of the other two parameters, temperature and amplitude, was small because they were directly set or measured during compaction. Therefore, the correlation between CMV and temperature, as well as roller amplitude, was better than the one between CMV and core density.

Conclusion

This paper presents an application of IC technology to monitor the compaction processes of asphalt layers. The data were collected

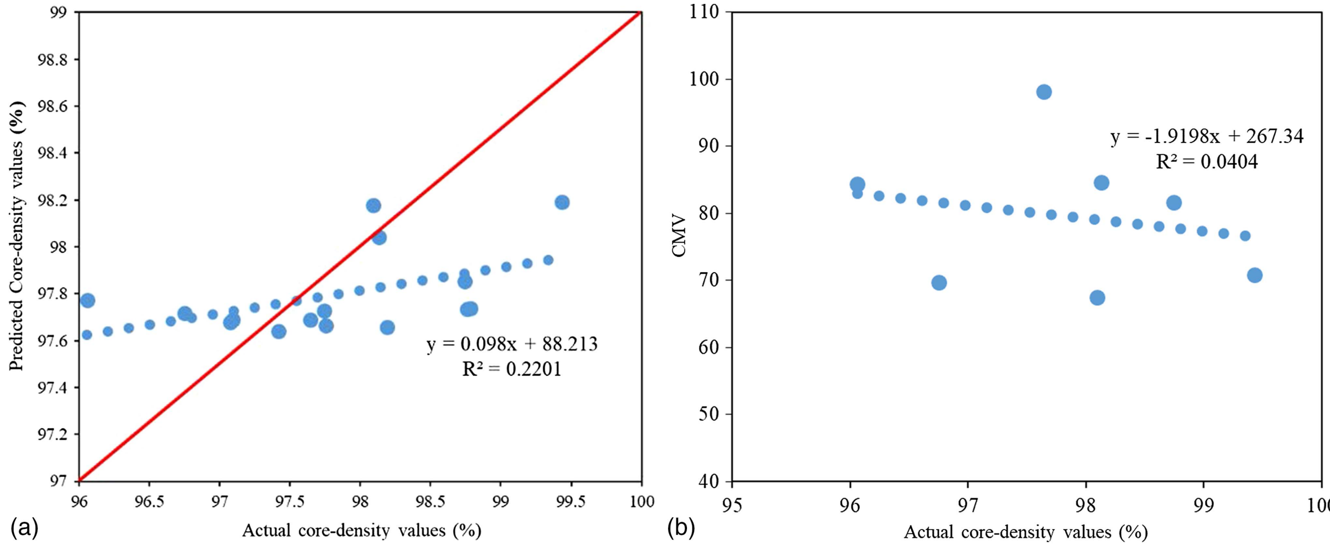

Fig. 9. Experiment results of the correlation between CMV and core density: (a) SVR model between CMV and core density; and (b) correlation between CMV and core density.

during the construction of a local road in Mardan, Pakistan, including IC data, in-place density, and temperature at the surface of the asphalt layer. The SVR analysis was conducted to predict the roller amplitude and in-place density. The following conclusions are summarized.

- The predicted surface temperatures and roller amplitudes using the SVR models were close to the measured ones. It is practical to obtain the surface temperatures and other related parameters through CMVs. However, the core densities obtained by the SVR model were significantly different from the actual ones.
- Both roller amplitudes and temperatures at the surface of the asphalt layer correlated well with CMVs. However, there was a poor correlation between the in-place core density and the CMV. The complex factors influenced the in-place core densities, including roller size, roller speed, vibration amplitude, vibration frequency, and asphalt type.
- In most cases, the ICMV of a backward pass is higher than the one of the corresponding forward pass, considering both the low and high amplitude values. Such difference was because the pavement density increased and the volume of air voids decreased after the first forward pass.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Notation

The following symbols are used in this paper:

$A_{0.5\,\Omega}$, $A_{1\,\Omega}$, $A_{1.5\,\Omega}$, $A_{2\,\Omega}$, $A_{2.5\,\Omega}$, and $A_{3\,\Omega}$ are the = amplitudes at the different subharmonic frequencies;
A_{Ω} = fundamental harmonic;
C = constant used to fit the laboratory and field values;
F_s = is sampling frequency;
$f_{\max}$ = is the operational frequency of the roller;
k = cost function; and
$\in$ = insensitive tube radius.

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