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RESEARCH ARTICLE

Field investigation of intelligent compaction for hot mix asphalt resurfacing

Wei HU[a], Xiang SHU[a], Baoshan HUANG[a,*], Mark WOODS[b]

[a] *Department of Civil and Environmental Engineering, The University of Tennessee, Knoxville TN 37996, USA*
[b] *Division of Materials and Tests, Tennessee Department of Transportation, 6601 Centennial Blvd., Nashville TN 37243, USA*
[*] *Corresponding author. E-mail: bhuang@utk.edu*

ABSTRACT Intelligent compaction (IC) is a relatively new technology for asphalt paving industry. The present study evaluated the effectiveness and potential issues of the IC technology for flexible pavement resurfacing construction using two field projects. In the first project, a geostatistical semivariogram model was established and the parameters derived from it were compared with univariate statistical parameters for the Compaction Meter Value (CMV) data. Further analyses illustrated the effect of temperature on the CMV value and compaction uniformity. In the second project, a multivariate analysis was performed between in situ tests and IC data. The possibility of combining various IC data to predict the asphalt layer density and improve the current quality control and assurance system was discussed.

KEYWORDS intelligent compaction, compaction meter value (CMV), semivariogram, multivariate analysis

1 Introduction

Compaction is one of the key processes to acquire desired long-term pavement performance, especially for hot-mix asphalt (HMA) layers. Conventional compaction methods have worked reasonably to achieve the target compaction level of asphalt materials over the past decades. However, there are some long existing and nontrivial shortcomings. Typically, a conventional compaction method applies a standard vibratory roller for a certain number of passes to the material being compacted. A uniform roller pattern covering an entire lane is not an easy task to achieve because rollers are manually controlled by roller operators, and even a uniform fixed number of passes cannot guarantee a uniform compaction level since many other critical factors, such as changes in the underlying support, or non-uniform temperatures in HMA, also affect the degree of compaction. Unfortunately, these critical factors are invisible to roller operators sitting on a conventional roller compactor. Therefore, no timely adjustment can be made to avoid potential over-compaction or under-compaction.

Conventional methods for density quality control and assurance (QC/QA) of asphalt materials are also questionable [1,2]. Some spot tests, either core-drilling or nuclear gauge test (NG), are usually performed at selected spots and then the results are extended to determine whether the entire asphalt layer has achieved the required density level. As mentioned before, the changes in the critical factors affecting compaction may compromise the representativeness of these spot tests performed at limited locations. Also, merely using asphalt layer density as the acceptance criterion does not ensure the required stiffness and/or strength of the particular layer, or the quality of entire pavement structure to withstand traffic loading.

During the past decade, a new compaction technology – Intelligent Compaction (IC) – has gained an increasing attention in the asphalt paving industry. According to the Federal Highway Administration (FHWA), IC refers to "*an improved compaction process using rollers equipped with an integrated measurement system that consists of a highly accurate GPS, accelerometers, onboard computer reporting system, and infrared thermometers for HMA feedback control. By integrating measurement, documentation, and control systems, the use of IC rollers allows for real-time monitoring and corrections in the compaction process. IC rollers also maintain a continuous record of color-coded plots that indicate the number of roller passes, compaction*

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level, temperature measurements, and the precise location of the roller drum [3].” With the IC technique, some critical factors affecting compaction, such as roller passes and temperature, are made visible to roller operators in real time with color-coded displays. Therefore, it has the potential to improve the quality and uniformity of asphalt layers by timely adjusting the compaction pattern. The IC technology may also overcome the shortcomings of conventional QC/QA methods in two aspects: First, it can cover the compacted area with 100% coverage other than limited spots; second, the IC measurement value (ICMV) can served as an index to evaluate the stiffness or strength of pavement to a certain depth [4,5].

While applied successfully on soil compaction for many years [6–9], IC is still a relatively new technology for HMA compaction. Only few strong correlations between ICMV and in situ spot test results of HMA have been reported by former researches [2,10,11]. The effect of HMA temperature on the evaluation of compaction uniformity was rarely discussed in the existing literature. Therefore, further studies are needed to utilize ICMV as an index to evaluate the compaction effect under the current QC/QA system. Diverse ICMV definitions from different roller manufacturers also impede the standardization and implementation of IC technology on HMA compaction. The features of HMA resurfacing projects can further complicate the situation: mapping existing support materials using IC rollers prior to subsequent HMA paving can identify weak locations, but usually it is unfeasible for resurfacing projects when considering the potential damage both to the milled original surface and to the roller. For some resurfacing projects all rollers are in a vibration off mode, and no ICMV data can be displayed as an index for the roller operator.

The objective of this paper is to evaluate the effectiveness and to identify the potential issues of IC technology on HMA resurfacing projects. The IC data and in situ tests of two HMA resurfacing projects in Tennessee were collected and analyzed for this purpose. This study identified the challenges of utilizing geostatistical model in characterizing the compaction uniformity, and analyzed the correlation between the IC data and in situ testing results. ArcGIS, Veda and JMP software packages were used as tools in the analysis process.

2 Methodology

For the IC technology, a number of different measurements are made during the compaction process, including GPS roller position, speed, number of roller passes, surface temperature and distribution of ICMV. Based on the collected data, the univariate statistics and geostatistics can be performed to evaluate the compaction uniformity. A brief introduction of ICMV and geostatistics is as follows.

2.1 IC Measurement Value (ICMV)

As mentioned above, different vendors use different types of ICMV with the same purpose of evaluating the level of compaction. Currently, at least six manufacturers adopted five different ICMVs on their machines [2]. IC roller basically records the machine–ground interaction data from an accelerometer that is mounted to the roller drum, and simultaneously calculates the ICMV value as an index related to the material stiffness [9,12]. Since all rollers in the two resurfacing projects used the vibratory-based Compaction Meter Value (CMV) as the ICMV, a brief description of CMV is provided here.

Developed by Geodynamik, CMV is a dimensionless compaction parameter that depends on roller dimensions (i.e., drum diameter and weight) and roller operation parameters (e.g., frequency, amplitude, and speed) and is determined using the dynamic roller response [13]. In the frequency domain, it is calculated as the ratio of vertical drum acceleration amplitudes at fundamental vibration frequency and its first harmonic. The fundamental vibration frequency is the operating frequency of roller.

$$CMV = C \times \frac{A_{2\Omega}}{A_{\Omega}}, \tag{1}$$

where C = constant; $A_{2\Omega}$ = acceleration amplitude of the first harmonic component of the vibration; A_{Ω} = acceleration amplitude of the fundamental component of the vibration. It was found that the force amplitude ‘F’ of the roller blows is proportional to $A_{2\Omega}$, and the displacement “s” during the blow can also be approximated by A_{Ω} [9]. As the ratio of the force and the corresponding displacement, the CMV can represent a “cylinder deformation module” Ec. Many studies have tried to correlate CMV to soil dry unit weight, strength, and stiffness [14,15].

2.2 Geostatistical model

Geostatistics is a branch of statistics focusing on spatial data sets, which is a much better method than the univariate model to characterize and quantify spatial variability. The semivariogram is a common tool used in geostatistical studies to describe spatial relationships. It is defined as one-half of the average squared differences between data values that are separated at a certain distance [16]. If this value is calculated repeatedly for as many different values of distance as the sample data support, a semivariogram plot can be obtained as shown in Fig. 1 [13]. The mathematical expression to achieve the experimental semivariogram $r(h)$ is as follows:

$$r(h) = \frac{1}{2n(h)} \sum\nolimits_{i=1}^{n(h)} [z(x_i + h) - z(x_i)]^2, \tag{2}$$

where h = lag distance; $z(x_i)$ = measurement taken at location xi; $n(h)$ = number of data pairs for lag distance h of a specific lag area [17].

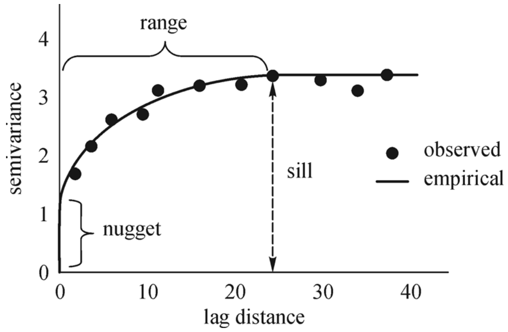


Fig. 1 Typical sample semivariogram

Three important parameters of a semivariogram plot are explained below:

1) Sill is defined as the plateau that the semivariogram reaches. A semivariogram generally has a sill that is approximately equal to the variance of the data.

2) Range is defined as the distance at which the semivariogram reaches the sill. Longer range values suggest greater spatial continuity or spatial coherence.

3) Nugget effect is defined as the vertical height of the discontinuity at the origin which mostly represents sampling error or short scale variations.

From a semivariogram model, a lower “sill” and longer “range” indicates an improved uniformity and spatial continuity, while the opposite represents an increasingly non-uniform condition. An empirical semivariogram model is used to fit to the observed semivariogram as shown in Fig. 1. The major purpose of it is to quantify the geospatial variability using the model parameters. Many models can be used here to fit an observed semivariogram, such as linear, spherical, exponential, and Gaussian models [16]. The exponential model is used in the Veda software, which is developed by the Transtec Group for viewing and analyzing geospatial IC data.

3 Project I

3.1 Information

The first resurfacing project using the IC technology was performed in Crockett County, Tennessee in October 2013. The project was 8.704 miles in length on a four lane portion of State Route 20, which consisted of a 1.25 inches (3.2 cm) thick overlay on an existing asphalt pavement surface in accordance with the Tennessee Department of Transportation (TDOT) specification. The HMA job mix formulas are presented in Table 1. This type of HMA has been successfully applied on resurfacing program by TDOT for many years.

Table 1 Job Mix Formula

aggregate gradation	sieve Size	percent passing (%)	
		project I	project II
	5/8 in.	100	100
	1/2 in.	97	98
	3/8 in.	88	88
	No.4	68	65
	No.8	52	44
	No.30	29	25
	No.50	17	13
	No.100	9.4	7.7
	No.200	6.2	5.4
mix properties	AC content, %	6.2	5.9
	AC binder type	PG70-22	PG64-22
	theoretical maximum density (g/cm^3)	2.301	2.420

A high frequency double drum vibratory roller, HAMM HD120, was equipped with IC system as shown in Fig. 2. The roller was operated at a nominal frequency of 38 Hz and at an amplitude of 0.8 mm during breakdown rolling. One accelerometer was mounted in the front drum and the ICMV data were collected in both forward and reverse directions. An offset has been validated between GPS antenna and center of front drum before the compaction. Two temperature sensors were mounted to collect the temperature data in both directions. The number of breakdown roller passes for this project was set at two. Another same model roller, also equipped with IC but in static mode, was used for intermediate rolling. The roller parameters such as speed and frequency were selected by the paving crew based on their experience. All IC data for both rollers during construction, including roller passes, temperature, CMV, etc., were recorded and stored during compaction for further analysis.

3.2 Compaction curve

Many prior studies have demonstrated the advantages of IC on improving the roller pattern and identifying the optimum roller pass, or applying the geostatistical model to evaluate the compaction uniformity [18,19]. However, unlike the soil and base materials, these benefits may require a more comprehensive consideration due to the effects of temperature and the viscoelastic nature of HMA. Before the IC data from Project I can be used for further analysis, it is necessary to filter some invalid data since the roller left the compacting area occasionally. A criterion as surface temperature > 50°C should perform this duty well. The reason of choosing a 50°C to filter some data out is because that the roller left the compacting area occasionally. When the roller is on the old cold pavement and the

(a) (b)

Fig. 2 Rollers with IC equipment. (a) Project I; (b) project II

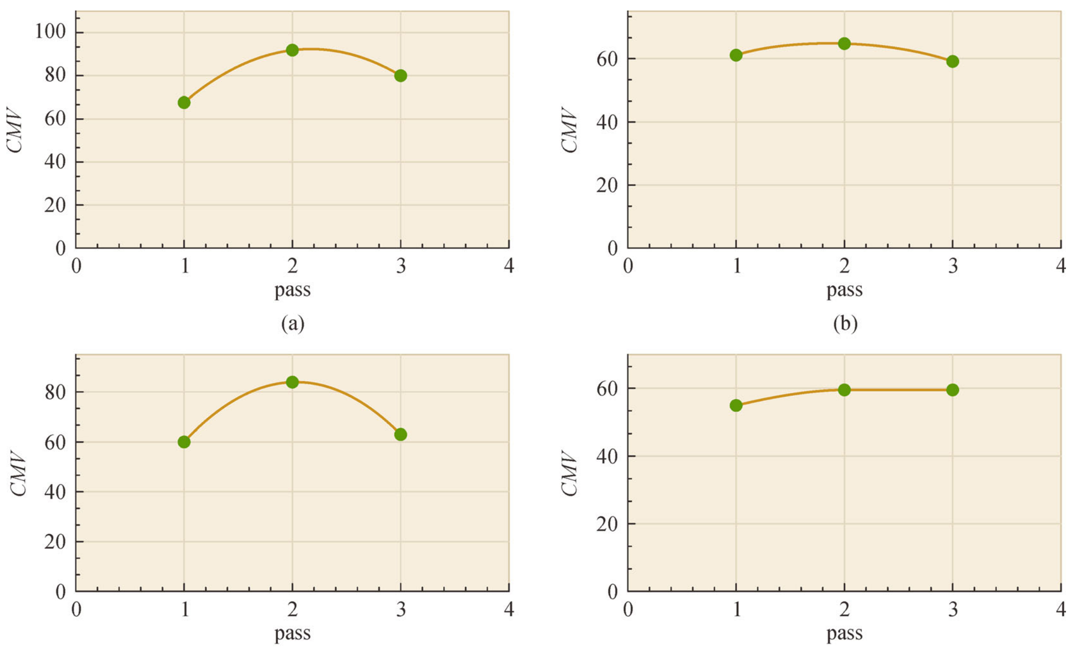
vibration mode is still on, it will give a higher and useless CMV data and impair the result of analyses. Using this filter can remove the data from the old pavement.

One major benefit of the IC technology is the capability of tracking and evaluating the compaction pattern: The mean CMV of a compacted area for each roller pass is computed with the Veda (compaction curve function), then the optimum roller pass number can be identified based on the changes of mean CMV. Figure 3 shows the compaction curves for the breakdown roller for four working days. As mentioned above, the CMV value can be used as an index relating to the material stiffness with certain depth for the same location. Since the property of the underlying material keeps constant for the same location, the decrease of CMV value will largely reflect the change in the stiffness of the surface HMA material. It is found in Fig. 3 that generally the mean CMV increases in the second pass and then decreases in the third pass of the roller. Therefore, the optimum roller pass number according to compaction curves coincided with the target number set by experience. The compaction curve also demonstrates that excess vibrating passes on compacted asphalt material does not help the compaction of HMA.

With the help of IC record, the compaction quality can be evaluated more accurately. According to the optimum pass number from compaction curves, the IC data of this project revealed that over 85% paving areas had reached two passes compaction of the breakdown roller. This project also successfully demonstrated the capability of the IC roller to track the surface temperature of HMA, therefore the compaction job could be accomplished during the appropriate temperature range.

3.3 Compaction uniformity

Using geostatistical semivariogram model, many research-



(a) (b) (c) (d)

Fig. 3 Compaction curves. (a) October 14; (b) October 15; (c) October 17; (d) October 18 ers, such as Pavana K. R. Vennapusa et al., have successfully quantified the nonuniformity of compacted earth materials [13]. Utilizing Veda, a summary of spatial and univariate statistics results of CMV for the breakdown roller for each construction day are presented in Table 2 and Fig. 4, which usually had a sample size over 10,000 and a compaction length over 1 mile. The exponential model is used here and the nugget value equals zero. The daily surface temperature records are also presented here as a reference. In general, the results of spatial statistics showed a trend similar to that from the univariate statistics. When the mean μ and standard deviation σ of univariate model had a significantly rise, the range and sill of semivariogram model usually also became large on that day. In particular, the sill and the standard deviation shared an identical trend, which agrees with the statement that a semivariogram generally has a sill that is approximately equal to the variance of the data. On other hand, the mean of surface temperature showed an opposite trend comparing to the mean of CMV. From Table 2, the semivariogram model generally shared similar results with the univariate model using daily record. However, this conclusion no longer holds for relatively small sections. When the daily IC data on 24 October were divided into sections around 300 ft in length, some sections had various values for semivariogram model when the univariate model results kept very alike.

To further investigate the effect of temperature on semivariogram and CMV, a section around 1500 ft in length at the beginning part of 24 October was chosen, and only the data of the first pass of the breakdown roller were used to eliminate the possible effect of different HMA density on the CMV value. The exponential model in ArcGIS was used to fit the observed semivariograms with different surface temperature filters as shown in Table 3 and Fig. 5. It can be seen that filtering the data of relatively low surface temperature decreased the sill value. According to that a lower “sill” and longer “range” indicates an improved uniformity and spatial continuity, this operation improves the results of semivariogram model.

As an index related to the material stiffness, the CMV value measured from the roller drum is actually an integral value influenced by deeper layer. The literature shows inconclusive results about the measurement depth of a vibration roller (from 50 to 100 cm), which is much larger than the thickness of resurfacing layer [13,20]. For both soil and HMA compaction, a desired uniform density is the goal of current QC/QA system, which is also the semivariogram model attempting to quantify. If the underlying support is stable, for the soil compaction, semivariogram model may reveal the uniformity of soil density. However, the situation is more complicated for the HMA compaction, since the stiffness of HMA relies not only on the density of HMA, but also on the temperature of asphalt. The original Witczak model, which relates the dynamic modulus of HMA to parameters such as temperature, asphalt content, and air voids content, was utilized here to further demonstrate the effect of temperature [21]. Using the job mix formula and roller parameters of this project, the dynamic modulus of HMA was calculated under the scope of air voids and temperatures during compaction. As shown in Fig. 6, if the same air voids is assumed as 10% for the first pass, the dynamic modulus of HMA will still vary from 53 ksi in 88°C to 14 ksi in 143°C during the same roller pass.

The temperature has a significant effect on the CMV value, therefore one should be careful when using CMV to evaluate the compaction level of asphalt. For example, a

Table 2 Comparison of spatial and univariate statistics of CMV

date	univariate model of CMV		semivariogram model of CMV		temperature (°C)	
	μ	σ	range (ft)	sill	μ	σ
15/10	61.68	18.80	7.87	320.31	109.6	18.25
17/10	60.84	20.10	9.19	387.01	114.2	15.87
18/10	55.76	18.30	9.19	308.86	118.2	16.26
21/10	63.32	19.80	7.87	335.14	108.6	18.58
22/10	76.14	26.80	11.81	438.67	98.6	21.32
23/10	85.30	27.46	15.75	495.73	99.1	19.50
24/10	70.53	19.57	11.81	309.52	106.4	17.62

Table 3 Results of statistics of CMV with different temperatures range

temperature (°C)	univariate model of CMV		semivariogram model of CMV		sample size
	μ	σ	range (ft)	sill	
all data	78.08	22.76	13.07	297.35	4,169
>80	71.84	17.96	11.30	251.94	3,462
>105	71.67	17.61	11.77	239.23	3,164

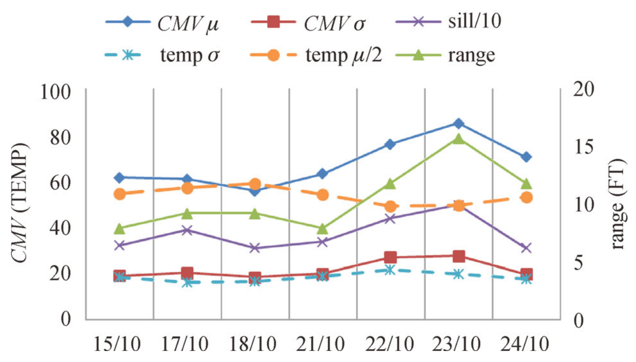


Fig. 4 Comparison of spatial and univariate statistics of CMV

higher CMV may be accompanied with low temperature. However, the viscoelastic properties of asphalt and other factors such as underlying support may complicate the correlation between temperature and CMV. It is clear that the variability of temperature will cause changes in HMA modulus, resulting in variations in CMV and semivariogram value eventually. Back to Fig. 4, when comparing the statistical results of CMV on daily basis, the underlying layer support and the average density of asphalt layer can be assumed constant on daily basis with relatively large data set, therefore the means of temperature and that of CMV had a direct opposite relationship. For the purpose of evaluating the compaction uniformity, the authors suggest that the statistical results of CMV should be corrected to a same reference temperature in the future research. When considering the correlation between CMVs and in situ spot test results, both the effects of temperature and underlying layer support are significant, so it is not surprising that the relationship between them is hard to define [2,17]. Thirty cores were randomly selected after the whole compaction and the laboratory densities (Gmm%) were measured. Due to the variability of temperature and underlying pavement structure, there is no direct correlation between CMVs and core densities for this project using Veda as shown in Fig. 7.

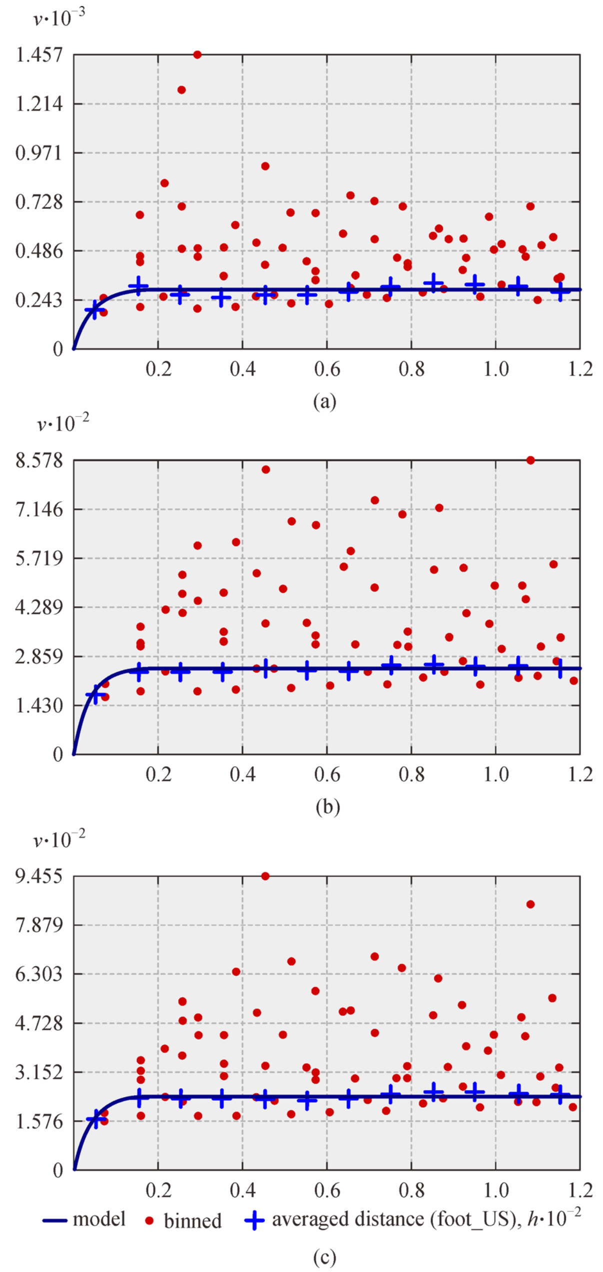


Fig. 5 Semivariograms with different temperature filters. (a) All data included; (b) temperature > 80°C; (c) temperature > 105°C

4 Project II

4.1 Information

The second resurfacing project using the IC technology was conducted in Lincoln County, Tennessee in October 2013. The project was 6.386 miles in length on a four lane portion of State Route 15, which also consisted of a 1.25 inches thick overlay on an existing asphalt pavement surface in accordance with the TDOT specification. The job mix formula is shown in Table 1. A HAMM HD120 was used as the breakdown roller as shown in Fig. 2, and the number of breakdown roller passes for this project was also set at two. An Ingersoll Rand DD110 was used as the intermediate roller. It should be noted that both the breakdown and intermediate roller were in static mode for the entire project.

4.2 Analyzing IC data from project II

According to the result of the first project, using CMV solely to predict the point density of HMA is hard to achieve under the existing ICMV model. Apparently, combining more IC parameters, such as the number of roller passes, locations and temperature measurements, is necessary to improve the current density QC/QA system besides the function of real-time monitoring.

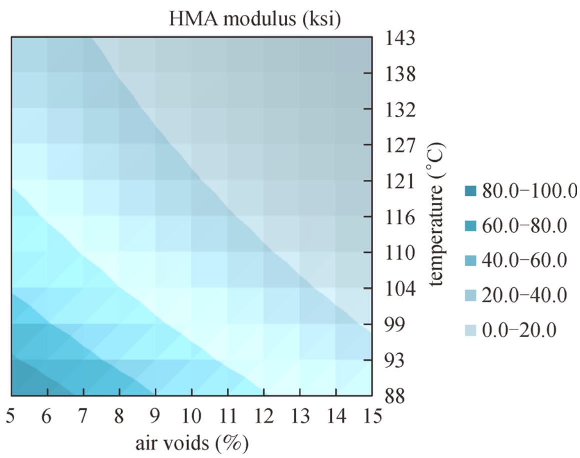


Fig. 6 Distribution of HMA modulus

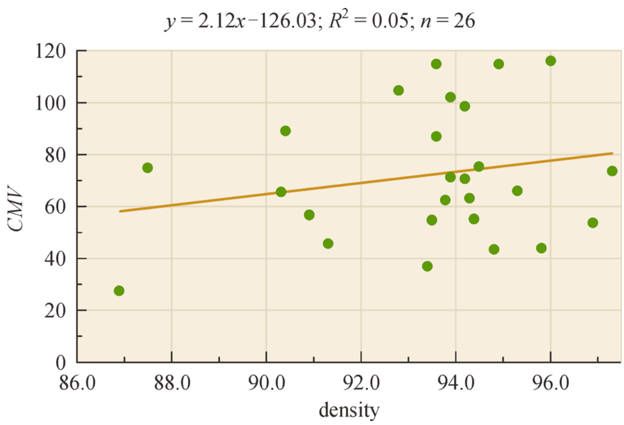


Fig. 7 Relationship between CMV and core densities

Since all rollers were in the static mode, no CMV data were available to evaluate the stiffness or strength of pavement. For the second project, the possibility of combining other IC data to predict the HMA density and improve the current QC/QA system was evaluated. Generally, many variables can affect the ability of the roller to properly densify an HMA layer, such as aggregate gradation, type and amount of asphalt binder, type and condition of underlying pavement layers, thickness of the HMA layer, as well as environmental factors. Though not all factors can be monitored by IC roller, some important factors, the number of passes and the surface temperature, can be obtained through daily compaction.

The NG tests were calibrated with asphalt cores on the first day of the project. Later, it was performed randomly during the whole construction period and approximately 60 NG measurements with GPS location were obtained. The multivariate analysis was utilized to test the correlation between the IC data and NG densities. After considering any possible factors in a preliminary analysis, five factors were included for the correlation analysis: the number of passes for the breakdown roller (roller 1) and the intermediate roller (roller 2) respectively, the start temperature for roller 1 and 2 respectively, the total interval from the first pass of roller 1 to the last pass of roller 2, since the temperature may be inappropriate for the latter compaction if the total interval is too long. Only the closest IC data were connected to the NG data because the measurements for the neighboring IC data are same or quite similar (passes, temperature, time, etc.). The distributions of five factors and the degree of compaction of HMA are shown in Fig. 8, and the statistical results are summarized in Table 4.

Figure 8 and Table 4 show that the number of passes of the breakdown roller and the total interval had a statistically significant effect on the HMA density: More passes of the breakdown roller in shorter interval helped to increase HMA density in vibration off mode. The large p value in Table 4 of the start temperature may suggest it did not affect the result of compaction beyond some certain range. However, the role of temperature should not be under-estimated. In fact, the significance of total intervals indicates that compaction should be finished before the temperature is too low. These findings, when consistent with the former experience, are necessary to quantify and integrate the IC data into the density QC/QA system for a particular HMA and area.

To further validate the accuracy of the IC data, using the IC recorded locations, three groups of cores for same day were taken based on the number of passes and temperatures of IC records. The core densities and the corresponding IC data are presented in Table 5. It can be seen that the weak compaction areas could be located using the records of IC data, and unsurprisingly, most of core samples in group 1 were located on the edge of the pavement. Among the total 17,492 proofing data on that day, the breakdown roller had 278 samples with only one total pass and surface temperature under 100°C. Apparently, comprehensive use of IC data could potentially provide a more reliable QC/QA method than the current point-testing QC/QA approach.

5 Conclusions and summary

In this study, the effectiveness of IC technology was evaluated through two HMA resurfacing projects in Tennessee. In the first project, the challenges of utilizing geostatistical model in characterizing the compaction uniformity of HMA layer were identified. The geostatistical semivariogram model of the CMV data was compared with the univariate model, and the effect of temperature on statistical results and CMV was illustrated. In the second project, the IC data and in situ measured HMA density results were correlated when all rollers were in the vibration-off mode. The possibility of combining various IC data to predict the HMA density and to improve the

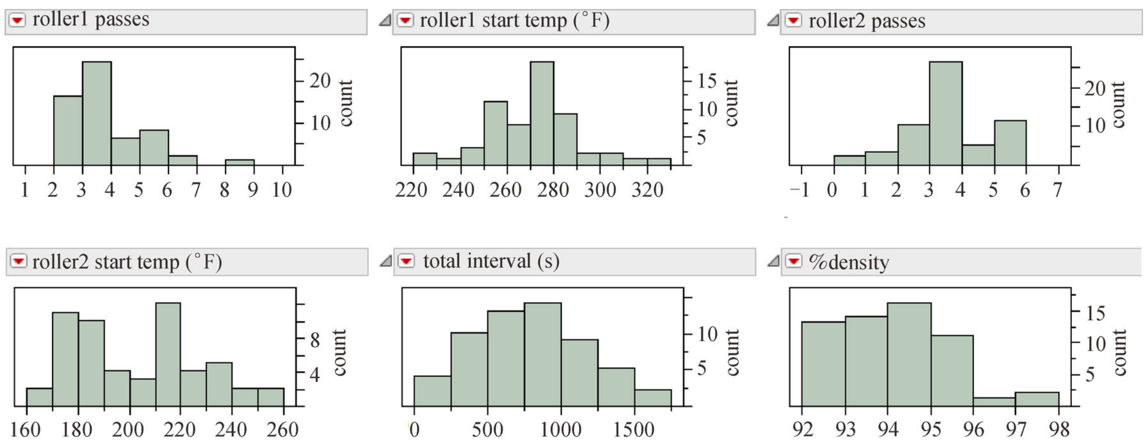


Fig. 8 Distributions of factors and % density

Table 4 Results from multivariate correlation

term	estimate	Std error	*t* ratio	*p* value
intercept	93.9701	2.4119	38.96	< 0.0001
roller1 passes	0.3587	0.1347	2.66	0.0105
roller1 start temp	0.0053	0.0096	0.55	0.5824
roller1 passes	0.1709	0.1481	1.15	0.2543
roller1 start temp	–0.0090	0.0073	–1.22	0.2272
total interval	–0.0014	0.0004	–3.18	0.0026

Table 5 Core densities and IC records

group	core number	%density		range of IC records			
				roller 1		roller 2	
		mean	range	number of passes	start temp (°C)	number of passes	start temp (°C)
1	3	87.5	86.3-89.8	1	82-86	0-1	0-58
2	5	94.1	92.7-95.9	2-4	129-143	2-4	90-136
3	5	96.1	95.9-96.3	4-8	126-143	7-9	98-123

current QC/QA system was discussed. The conclusions and recommendations are summarized as follows:

1) The compaction curves during construction period for the first project showed a consistent pattern, which could be used to prevent over or under compaction.

2) The spatial and univariate statistical results of CMV on daily basis showed very similar tendency. However, this similarity may vary if the IC data were divided into small sections.

3) Filtering the data of relatively low surface temperature improved the results of semivariogram. It was suggested that the semivariogram of CMV should be corrected to a same reference temperature to better quantify the compaction uniformity.

4) The results of the multivariate analysis and the results of core samples showed that the IC technology was able to accurately locate poor compaction areas even without the CMV data.

5) Although more researches are still needed, comprehensive use of IC data could potentially provide a more reliable QC/QA method than the current density-only QC/QA approach.

To improve the understanding of IC for the asphalt compaction application, more future studies are needed and the compaction uniformity should be evaluated by considering the effect of underlying support, the drum behavior and the HMA temperature on the ICMV value. It is also recommended that the IC data be incorporated into a pavement management system (PMS) so that long-term benefits of IC technology may be realized in the future.

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