Automating WMA Construction Planning: A Physics-aware Framework

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Abstract –

The Dutch road construction industry is transitioning from hot mix asphalt (HMA) to more eco-friendly warm mix asphalt (WMA). While WMA offers clear environmental benefits, its distinct material properties, particularly the compactability, demand different construction practices. However, limited industry knowledge hinders WMA construction planning, driving the need for automated tools for more efficient WMA construction strategic planning. This research proposed a physics-aware surrogate modelling framework to improve strategy evaluation and optimization, and enable the automative exploration of optimal construction strategies. A preliminary feasibility study demonstrated the possibility of developing a surrogate model using Random Forest to efficiently capture the temperature-dependent compactability of a WMA mixture. The industrial adoption and potential advancement of this tool, including the integration with other sensing technologies and automatic construction, to ensure high-quality pavement construction were also discussed.

Keywords –

Asphalt construction; Warm mix asphalt; Physics-based simulation; Surrogate model

1 Introduction

In the Netherlands, in response to ever-growing environmental concerns about hot mix asphalt (HMA), the road construction industry is compelled to adopt more sustainable practices, e.g., exploring alternative materials. This created a strong ambition to transition from HMA to warm mix asphalt (WMA). For instance, the Dutch road construction industry is determined to complete this shift by January 2025. Compared to HMA, WMA is produced at lower temperatures (100–140 ℃) using synthetic or organic additives. It offers notable environmental benefits, including reduced emissions, lower fossil fuel consumption, and increased use of reclaimed asphalt pavement (RAP) without compromising mechanical performance [1]. Despite the change in the material, the contractors' primary goal remains the same, i.e., ensuring the asphalt construction process quality to achieve the desirable product quality, such as optimal density. Specifically, the asphalt must be compacted within an ideal temperature window since compaction at high temperatures can cause permanent deformation and compaction at low temperatures can hinder the densification process. However, asphalt construction is widely recognised as a dynamic environment where uncertainties abound. These uncertainties, coupled with the time-sensitive nature of road construction, make achieving optimal compaction efficiency highly challenging. This often results in significant variability during construction, leading to substandard road quality.

These challenges are not unique to HMA construction but are amplified in WMA due to the substantial difference in material characteristics (particularly the different compactability) and limited knowledge about its construction. This makes it more difficult to plan explicit operational strategies (e.g., required quantity of pavers and rollers, paving speed, compaction patterns and trajectories, etc. [2]). Addressing this issue is critical, as a key incentive for contractors to adopt WMA lies in building a solid knowledge base for a stable and sustainable construction process. This would help them meet quality requirements, avoid penalties under extended guarantee periods, and support the push for sustainable road construction. To stay competitive, contractors are motivated to adopt planning tools that can optimize WMA construction strategies by embedding a deeper understanding of WMA's material behaviour into automation techniques, to enable efficient and reliable assessment and adjustments in the decision-making process of WMA construction strategies.

On this premise, this paper presents a framework of a WMA construction planning tool that can provide contractors with an efficient and explicit assessment of pavement quality regarding different construction strategies, thus advancing automation in construction strategic planning. This study revolves around a central question of how a WMA construction planning tool can be developed with the embedment of WMA's unique material features and its structural responses towards different construction strategies. A framework that applies physical modelling and physics-aware surrogate modelling was then proposed. Unlike conventional models, it better captures WMA's compaction behaviour for more precise decision-making. The results of a preliminary feasibility analysis are presented in this paper.

The remainder of the paper is structured as follows. First, the research problem is investigated to derive the scope of this WMA construction planning tool. This is followed by a demonstration of the framework of developing such a planning tool, with a case study indicating the feasibility of the proposed framework. The paper ends with a conclusion.

2 Problem Investigation

Construction planning involves identifying explicit on-site activities and evaluating their implications [3]. Nonetheless, asphalt construction comprises a multitude of interconnected activities, resulting in considerable complexity for the effective planning of construction strategies.

Previous studies explored the development of asphalt construction planning tools, with particular attention to using simulation techniques, as simulations effectively capture construction processes and test scenarios, enabling more efficient and informed decision-making [4,5]. For instance, Dalence et al. proposed a framework integrating temporal (e.g., equipment, speed, roller passes) and spatial (e.g., trajectory, asphalt cooling rate) characteristics, where data on key factors influencing asphalt compaction is collected to generate decision variables [4]. These variables are fed into simulation models, which provide outputs such as equipment behaviours and operational feedback, facilitating strategy assessment and improvement.

Nevertheless, existing simulation-based asphalt construction planning tools predominantly rely on indirect assessment of the process quality (e.g., paver and roller output, compaction efficiency, and process consistency), where the actual structural response of asphalt mixture (which will be reflected in the pavement product quality, such as density) during the construction process are not explicitly considered. Although, intuitively, good construction process quality leads to good pavement product quality, not being able to precisely quantify the exact impact of construction strategies on the resultant structural responses of the pavement during the simulation can considerably affect the accuracy/reliability of simulation-based assessment of different construction strategies.

Therefore, understanding the interplay between mechanical and thermal characteristics during asphalt compaction is vital for precise construction planning and decision-making. However, the current body of knowledge lacks a clear understanding of the quantifiable correlation between construction quality and pavement properties. In essence, this would make the planning of WMA construction performance-based, where the most suitable on-site operations will be selected based on the resultant pavement quality and performance in other indicators (e.g., cost and productivity). In other fields, the similarity can be found in strategic planning of earth moving activities. Traditional earthwork planning focused on minimizing material transport, relying heavily on workers' experience. However, construction automation has enhanced efficiency and productivity by reducing these constraints, by optimizing operations, particularly coordinating excavators and dump trucks to maximize efficiency [6,7].

To address this limitation, advanced physical modelling is needed to capture the structural and thermal behaviour of WMA during its interaction with equipment and the environment. Two widely applied approaches are Finite Element Method (FEM) [8] and Discrete Element Method (DEM) [9]. FEM can accurately model asphalt's structural response under dynamic loads but lacks granular-level accuracy. In contrast, DEM effectively simulates contacts within granular systems and micro-mechanics. Nevertheless, DEM greatly increases the computational time. To address this, Komaragiri et al. [10], developed a simulation model using a physics engine (i.e., Bullet Physics [11]), which significantly improves computational efficiency without compromising performance. However, existing physics-based simulation models calibrated for HMA are unsuitable for WMA due to differences in material characteristics. Thus, developing physics-based models tailored to WMA is crucial for capturing its unique behaviour during compaction. Additionally, the high computational cost of physics-based models limits their use in process simulation, where analysis of multiple simulation scenarios for optimised processes is always required. One potential solution is to use data-driven techniques, such as machine learning (ML), to quantify the correlation between asphalt construction process indicators and resultant product quality indicators. In the research of Shen [12], on-site data was collected, including real-time machinery movement and asphalt cooling patterns, to capture key asphalt construction process characteristics. The data was then paired with density measurements from pavement samples to develop a dataset for machine learning model training. However, this study also highlighted critical issues, such as limited and inconsistent data availability, ineffective data management practices, and variability in data collection methods, which greatly influenced the accuracy and generalizability of data-driven approaches.

To tackle these difficulties, surrogate modelling offers a solution by approximating physics-based models with data-driven techniques, such as machine learning (ML), allowing for faster predictions without sacrificing accuracy [13]. By generating datasets from physics-based simulations under varying input conditions, ML-based surrogate models can be developed to predict WMA's structural responses efficiently, enabling the exploration of optimal construction strategies without excessive computational expense.

3 Framework for Physics-aware WMA Construction Planning Tool

3.1 The Scope of the WMA Construction Planning Tool

To identify the scope of the WMA construction planning tool for this research context, a workshop was held with Dutch public clients and contractors in the asphalt construction sector. The workshop explored: (1) the impact of material transitions on WMA compaction, (2) factors influencing strategy formulation, and (3) the structure of the tool. The workshop identified the tool's primary functional requirement: to assess construction strategies accurately and to offer intuitive feedback on compaction quality (primarily density consistency) considering specific project characteristics.

Specifically, the proposed planning tool should begin by extracting pre-construction information, such as design data, ambient conditions, and project constraints, to define the scope of construction strategy exploration. It must evaluate strategies by assessing the resultant pavement quality. This calls for the development and integration of physics-aware models to comprehensively explore the complex system's behaviour, characteristics, and dynamics in WMA construction. The tool's output will focus on two aspects: resource allocation (e.g., equipment, materials, staffing, budgeting) and operational strategies (e.g., trajectory planning, sequencing, and equipment coordination), ensuring timely and cost-effective project execution.

Therefore, the framework of the physics-aware WMA construction planning tool can be determined, as shown in Figure 1. The rest of this chapter will provide a detailed description of each component.

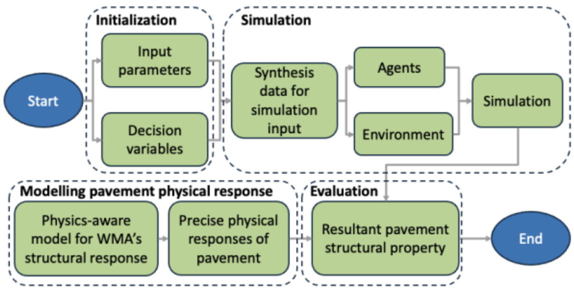

Figure 1. The overview of the WMA construction planning tool

3.2 Initialization

The initialization of the planning tool gathers input parameters and decision variables. Input parameters, which reflect fixed project characteristics, include design and engineering details (e.g., road geometry, and asphalt mixture properties) and project-specific constraints (e.g., equipment configurations), as listed in Table 1.

Identified decision variables, adjustable by decision-makers, focus on resource allocation and operational strategies, with particular emphasis on the compaction strategy in asphalt construction planning, due to its vital role in meeting asphalt pavement's functional requirements. These decision variables allow the exploration of various WMA construction strategies, as demonstrated in Table 2. The compaction strategy involves defining each roller's trajectory, determined by the length and width of the compaction section, and the number of and distance between compaction lanes (Figure 2). Additionally, the mobility of rollers is also affected by the compaction patterns, which regulate the number of compaction corridors and other rules that each roller needs to follow during compaction, especially when multiple rollers are compacting simultaneously. These compaction patterns will be pre-defined by the decision-makers as the input to the planning tool.

Table 1. Identified input parameters of the WMA construction planning tool framework

Data category	Data	Unit
Road geometry	Road width	m
Asphalt	Mixture design	-
	Production temperature	°C
	Initial density	kg/m^3
	Cooling rate	°C/min
Paver	Screed width	m
Truck	Truck capacity	m^3
	Dumping rate	m^3/min
Roller	Drum width	m
	Wheel length	m
	Compaction force	kN

Table 2. Identified decision variables of the WMA construction planning tool framework

Data category	Data	Unit
Resource allocation	Paver quantity	#
	Roller quantity	#
	Truck quantity	#
Operational strategies	Paver speed	m/min
	Roller speed	m/min
	Length of compaction section	m
	Width of compaction section	m
	Number of compaction lanes	#
	Hauling duration	hours
	Returning duration	hours
	Compaction pattern	-

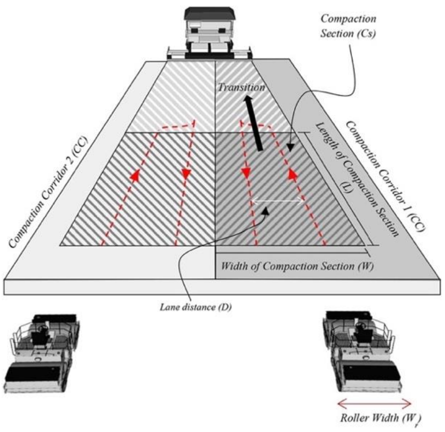

Figure 1. Asphalt compaction strategy [2]

3.3 Simulation

The collected data from the previous layer will then be fed into a simulation model to assess the corresponding impact on the product quality. Specifically, the simulation model will be informed by the previous work of Dalence et al. [4], where an agent-based simulation (ABS) model was proposed to create a context-realistic simulation of the HMA construction process. It is worth noting that despite differences in material properties, WMA and HMA share similar construction logic and workflow, making the ABS simulation model's scope a valuable reference for the WMA. This simulation model aligns closely with the functional requirements of the planning tool and operates within the same contextual framework. Given its demonstrated applicability and relevance, re-developing a new simulation model is deemed unnecessary.

The simulation, using inputs from Tables 1 and 2, defines agents, interactions, and conditions. Figure 3 shows key agents: trucks deliver asphalt, coordinating with the paver for continuous transfer. The paver operates at a set speed, signaling trucks as needed, while rollers compact within the optimal temperature window. Predefined compaction strategies are used to maintain continuity and efficiency. Furthermore, Asphalt cell agents will model asphalt's structural and thermal behavior by dividing the asphalt layer into a grid (Figure 4). Each cell cools at a set rate, while environmental conditions and contractor-provided road geometry (Table 1) define the simulation space and agent interactions.

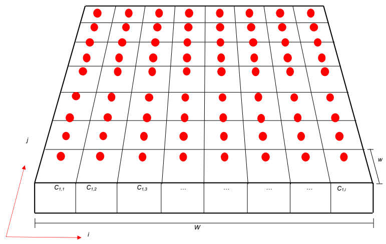

Figure 4. The asphalt pavement cell grid [2]

3.4 Modelling Physical Responses of WMA

Next, the precise physical responses of WMA during the construction process will be obtained, following the workflow shown in Figure 5.

Firstly, a generic physics-based model to accurately simulate the interaction between WMA and the compaction process will be developed. The quality of asphalt pavement is highly dependent on its bulk mechanical properties, which are determined by the contact state of the individual aggregates and the resulting skeleton structure formed between these particles [14]. During the construction process, the compaction force rearranges asphalt mixture aggregates, leading to the development of a denser skeleton structure. Meanwhile, due to the viscoelastic attributes of the asphalt binder, the mechanical properties of asphalt mixtures are also subject to change over different asphalt

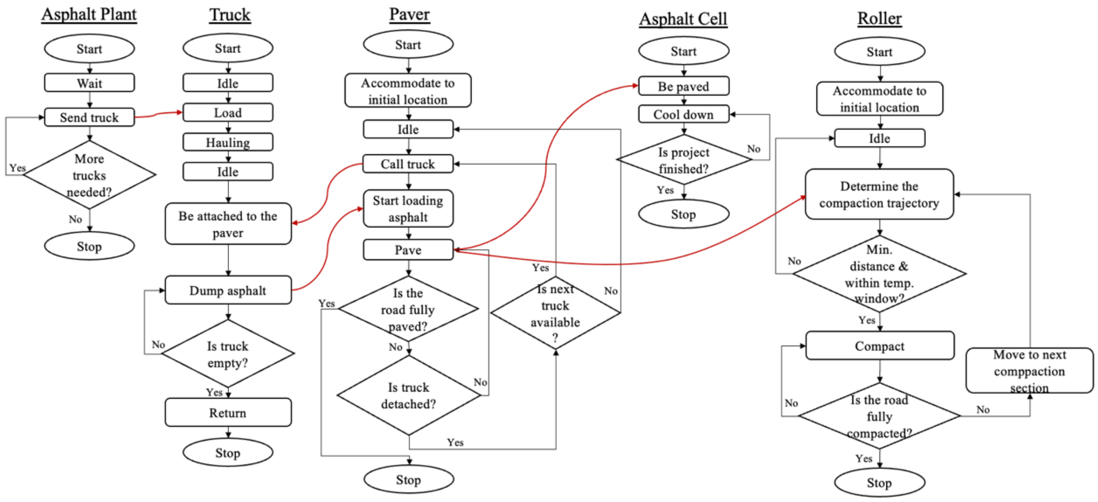

Figure 3. An overview of agents and their states [4]

temperatures. Therefore, this compaction model is expected to be able to capture the WMA's behaviour at the microscopic scale with its granular structure and can be eventually upscaled to derive the macroscopic response of the entire road pavement during compaction.

Overall, the modelling process scales from micro to macro levels. It begins with selecting a contact model to define microscopic interactions, followed by creating mesoscopic models based on WMA mixture designs, calibrated with lab tests at various temperatures. Finally, these models are upscaled to represent WMA pavement, with accuracy tested during field compaction.

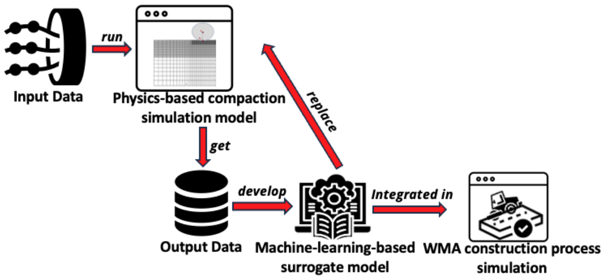

Figure 5. The overview of the WMA construction planning tool development framework

3.5 Surrogate Modelling

The physics-based compaction model will be replaced by a surrogate model to reduce computational costs in analyzing asphalt-compaction interactions. To predict structural responses based on input data, including mixture design, temperature, thickness, density, and applied compaction force.

The surrogate model development will be initiated with the data synthesis to generate a dataset, by performing simulations using the physics-based WMA compaction model under different compaction scenarios (considering different compaction forces from the roller drum and roller speed). In this step, a parametric model will be developed to streamline the data synthesis, and to rapidly construct different compaction scenarios covering the input. Next, based on the established dataset, ML models will be trained and tested, which will be used as the surrogate model to replace the original physics-based compaction model once the former is validated.

3.6 Integrating Surrogate Model into WMA Construction Process Simulation

Lastly, the developed surrogate models for WMA-roller and WMA-environment interactions will be integrated into the WMA construction process simulation model described in Chapter 3.3, to enable a more accurate evaluation of the resultant pavement product quality according to adopted construction strategies. The pavement's mechanical properties can be updated after each roller pass, based on the information including the asphalt temperature and mechanical properties (e.g., density) before compaction, and received compaction energy from the roller.

With the surrogate model, WMA construction simulation can enable automated planning using optimization algorithms like Particle Swarm Optimization (PSO) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to generate, assess, and refine strategies for optimal density, productivity, and cost efficiency.

A field test with contractors will validate the planning tool using pre-determined engineering details and weather conditions (Table 1). Optimal construction strategies will be generated where experts from contractors will decide the strategy they will adopt on-site. Two test sections will be prepared: one following the selected optimal strategy and the other using conventional simulation-based planning tools that rely on indirect process quality assessment as a benchmark for quality and efficiency comparison.

4 Preliminary Feasibility Analysis

In this section, a preliminary feasibility study of developing such a planning tool for WMA construction following the framework proposed in Chapter 3 is conducted through a case study. It focuses on demonstrating the feasibility of developing a surrogate model, using the data generated from a physics-based simulation model (which simulates the WMA compaction process on the laboratory scale), to efficiently and accurately capture the temperature-dependent compactability of the target WMA mixture, which is key to precisely map the impact of on-site construction strategies into the resultant pavement quality in the planning tool. Therefore, this preliminary feasibility study concentrates on validating the foundational aspects of the framework and setting stages for future development.

Specifically, five gyratory compaction tests were performed on one type of WMA mixture at five different testing temperatures. Using the gyratory compaction process, the study evaluates the ability of the physics-based model to replicate key structural and thermal responses during compaction. Additionally, it demonstrates the feasibility of calibrating the model using experimental data, ensuring its relevance for future applications. This controlled environment allows for precise analysis and eliminates external complexities, making it an ideal setting for validating the proposed framework's foundational components.

4.1 Gyratory Compaction Test Scheme

Gyratory compaction, a common lab method, simulates field compaction to produce asphalt specimens for mechanical testing. The stabilized mixture in a cylindrical mold undergoes constant vertical pressure while rotating at a set speed and angle to apply shear forces. Table 3 details the test setup, where compaction stops after 60 gyrations.

Table 3. Gyratory compaction test configurations

Configuration	Value
The internal diameter of the mould	100 mm
Minimum height of the compacted mixture	77 mm
Compaction pressure	600 kPa
Gyration angle	0.82°
Gyration frequency	1/30 Hz
Target number of gyrations	60

The WMA mixture used in the tests was prepared using the design indicated in Table 4. Specifically, this WMA mixture uses a DAT-7 additive, a surface tension reducer, to decrease its production temperature. A total of 5 samples were made. Each sample had a different temperature for performing the compaction test, ranging from 120°C to 40°C with an interval of 20°C (120°C, 100°C, 80°C, 60°C, 40°C).

The testing output is the void ratio of the specimens. The output data was collected after each gyration, to represent the densification process.

Table 4. Gradation of the WMA mixture

Sieving size (mm)	Mass percentage (%)
16 - 11	23.09
11 - 8	3.99
8 - 4	27.33
>2	34.04
Filler	7.14
Asphalt (PEN 40/60)	4.2
Additive (DAT-7)	0.21

4.2 Physics-based Gyratory Compaction Simulation

Following the methodology of Komarairi et al. [10], the gyratory compaction process was simulated using Bullet Physics engine [11]. The engine can effectively detects collisions, calculates contact forces, and updates particle positions [10,11]. Unlike DEM, which simplifies aggregates as spheres, Bullet Physics models real aggregate shapes, improving accuracy while remaining computationally efficient.

Based on the gradation in Table 4, a digital representation of the tested asphalt mixture was created using 10 3D aggregate models obtained via laser scanning (Figure 6). The number of aggregate particles was determined from the asphalt sample mass (1.4 kg) and aggregate density (2686 kg/m³). All particles were scaled to a unit size of 1 mm and adjusted according to gradation to closely match the actual specimen. For computational efficiency, fine aggregates (<2 mm), fillers, and binders were modelled as a mortar layer covering the coarse aggregates, whose thickness is calculated using Equation (1):

$$t = \frac{V_{motar}}{\sum_{i=1}^{n}(SA)_i} \tag{1}$$

where t stands for the thickness of the mortar layer, V_{mortar} refers to the total volume of the mortar, n refers to the total number of coarse aggregates, and $(SA)_i$ refers to the surface area of each coarse aggregate.

These mortar layers also provide viscoelastic contact forces, which are cohesive force in the normal direction between two contacted particles and viscous damping in the tangential direction. Equation (2) specifies the cohesive force:

$$F_c = c\gamma\sqrt{A} \tag{2}$$

where F_c is the cohesive force, c is a proportionality constant, γ is the surface tension of the mortar layer, and A is the contact area between two colliding particles. Together, $c\gamma$ represents the linear stiffness between the two colliding aggregate particles, thus can be replaced by a new parameter k, referring to the contact stiffness.

The viscous force will be simulated using linear and angular velocities [10], as specified in Equation (3) and (4) below:

$$v = v_0\eta_{linear} \tag{3}$$
$$w = w_0\eta_{angular} \tag{4}$$

where v and w stand for the linear and angular velocities of the particle after contact, v_0 and w_0 are the linear and angular velocities of the particle before the contact, and η_{linear} and $\eta_{angular}$ are linear and angular damping factors respectively.

Figure 6. An example of the aggregates

4.3 Calibration and Validation

To test the capability of the physics-based gyratory compaction model in correctly simulating the temperature-dependant compactibility of the target WMA mixture, the compaction model was calibrated using laboratory testing data described in Chapter 4.1. The primary objective is to calibrate the models to determine the corresponding values of k, η_{linear}, and $\eta_{angular}$ at various temperatures. Furthermore, this study assumes that these calibrated parameters will form three temperature-dependent functions for the target WMA mixture through curve fitting. These functions provide a continuous representation of the temperature dependency of each parameter, enabling the derivation of parameter values at any given temperature without the need for additional laboratory tests. Specifically, to validate this assumption, tests conducted at 120°C, 100°C, 60°C, and 40°C were used to calibrate the models to derive corresponding values of k, η_{linear}, and $\eta_{angular}$ and to form the temperature-dependency functions for these parameters. These functions were then used to predict values at 80°C, where simulation outputs (i.e., the densification curve) were validated against laboratory data.

Conventional calibration of physics-based simulations requires iterative parameter adjustments and repetitive fine-tunings, making it highly time-consuming and computationally expensive. To streamline calibration, the surrogate modelling technique was also applied, where an ML model was developed to replace the physics-based gyratory compaction model. A dataset of 96 instances with varying contact parameters was generated using a full factorial design (Table 5) and simulated to pair input parameters with densification curve outputs. The densification curves were transformed into logarithmic slopes and intercepts, forming inputs for two Random Forest (RF) models: RF-A for slopes and RF-B for intercepts. After training on 80% of the data and testing on the remaining 20%, RF-A achieved an R^2 of 0.9667 and RF-B an R^2 of 0.9871. As for the computational time, using ML-based surrogate models to obtain the densification curve costs 0.003228 seconds, while running each physics-based simulation costs around 7 hours (25200 seconds).

Table 5. Levels of parameters in data generation

Parameter	Levels
Stiffness	1, 100, 1000, 10000, 100000, 1000000
Linear damping factor	0.01, 0.1, 0.5, 0.99
Angular damping factor	0.01, 0.1, 0.5, 0.99

These models facilitated calibration by solving an optimization problem to maximize the R^2 between reconstructed and actual densification curves, as defined by Equation (5):

$$maximize\ R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (5)$$

where y_i is the ith element from the actual curve, $\hat{y}_i$ is the ith element from the reconstructed curve, and $\bar{y}$ is the mean of the actual curve.

RF-A and RF-B were used to predict the values of slope and intercept to reconstruct the (logarithmic) densification curve $\hat{y}$, as shown in Equation (6).

$$\hat{y} = a + b\ln(x) \quad (6)$$

where:

$a = f_{RF-A}(k, \eta_{linear}, \eta_{angular})$

$b = f_{RF-B}(k, \eta_{linear}, \eta_{angular})$

$k \leq 1000000$

$\eta_{linear} \leq 1$

$\eta_{angular} \leq 1$

$k, \eta_{linear}, \eta_{angular} \in Z^+$

Specifically, a and b are the predictions from RF-A and RF-B respectively based on the set of input parameters $k, \eta_{linear}, \eta_{angular}$, and the three input parameters are all positive integers, whose ranges are pre-defined.

This optimization problem was solved by the Genetic Algorithm (GA), to automatically generate, evaluate, evolve, and select optimal sets of input parameters that can fit the actual densifications the best. Each iteration will start with 100 population, where the offsprings will be created with a crossover rate of 0.8 and a mutation rate of 0.2. The GA process will stop after 100 iterations.

Based on the input parameters determined through calibration, three exponential decay functions were determined accordingly, as shown in Figure 7.

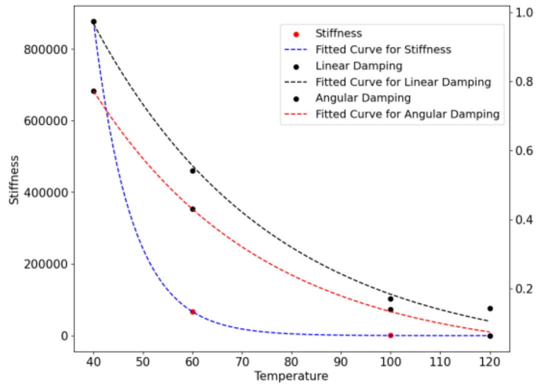

Figure 7. Temperature-dependant decay functions through curve fitting

Values of parameters at 80°C were then determined, resulting in a promising accuracy, with an R^2 score of 0.88 by comparing the obtained densification curve using RF models with the actual laboratory data at this temperature, as shown in Table 6 and Figure 8.

Table 6. Results of the validation

Temperature (°C)	Stiffness (N/mm)	Linear Damping	Angular Damping	R^2
80	5077.99	0.32	0.24	0.88

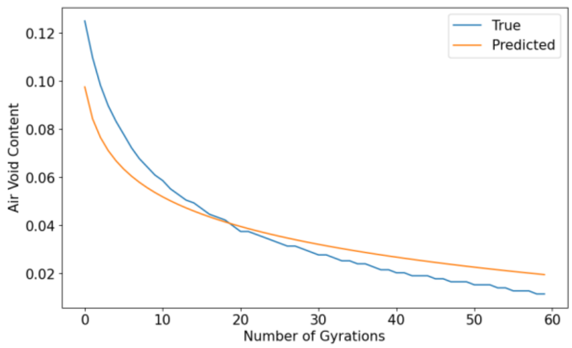

Figure 8. Plots of the validation at 80°C

5 Conclusion

This study proposed a framework for WMA construction planning that incorporates precise physical responses of asphalt, integrating project-specific data with physics-aware models and simulations. Furthermore, a case study demonstrated the feasibility of developing and calibrating a physics-based simulation model for WMA compaction at the laboratory scale. The model effectively replicated key structural and thermal responses during compaction, capturing granular interactions and material behaviour of the WMA mixture. Calibration using experimental data enabled the derivation of decay functions for contact parameters, which were used to interpolate values across different temperatures. This approach not only ensured a focused validation of the framework but also revealed the model's capability to capture the nuanced relationships between temperature, contact parameters, and compaction dynamics. These findings affirm the foundational premise of the framework, providing a strong basis for extending its application to larger-scale scenarios. However, to validate the surrogate model demonstrated in Chapter 4, only very limited laboratory data was used for the calibration and validation, where it will be more beneficial to include more data and more mixture types to enhance its generalizability.

Additionally, while the integration of a surrogate model is part of the broader research plan, its validation is beyond the scope of this preliminary study and will be pursued in future work. Although real-world adoption of the tool remains challenging due to construction uncertainties and contractor risk aversion, the planning tool can still provide contractors with valuable early-stage planning insights, where the on-site uncertainty can be further overcome by integrating the planning tool with real-time construction data (e.g., pavement temperature, weather conditions, machinery location, etc.), enabling automated adjustments to compaction strategies based on sensor feedback. Ultimately, this would support full automation in WMA construction, enhancing efficiency, consistency, and sustainability in road projects.

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