Proceedings of the 9th World Congress on Civil, Structural, and Environmental Engineering (CSEE 2024)
London, United Kingdom – April 14-16, 2024
Paper No. ICGRE 157
DOI: 10.11159/icgre24.157

Thermal Digital Twins of Asphalt Pavements using Physics-informed Neural Networks

Deepthi Mary Dilip
BITS Pilani Dubai Campus
Academic City, Dubai, UAE
deepthimary@dubai.bits-pilani.ac.in

Abstract - To address the adverse effects of climate change on road surfaces, the creation of a thermal digital twin for asphalt pavements is proposed in this paper. The global increase in temperatures, coupled with heavy traffic loads, has resulted in the premature deterioration of asphalt roads. In response to these early failures, recent efforts have focused on enhancing pavement structural integrity by incorporating asphalt modifiers and cool pavement strategies. Regardless of the chosen approach, continuous monitoring of pavement characteristics using embedded sensors plays a crucial role in enabling timely maintenance and rehabilitation (M&R) decisions. One of the ways to achieve this is through the estimation of the thermal diffusivity of the pavement layers which can be directly related to structural condition. To estimate the diffusivity, an inverse-Physics-informed Neural Network model is proposed, which facilitates the integration of sensor data and the heat transfer mechanisms within the pavement. A finite-difference numerical model is adopted to serve as the groundtruth model, to provide the temperature data within the pavement layer, given the boundary conditions. Using the weather data of Dubai, this study has shown the feasibility of adopting Physics-informed Neural Networks (PINNs) to predict the temperature within the pavement layer, despite the complex mixed boundary conditions. Moreover, the i-PINN can be used to estimate the thermal diffusivity with an error of around 0.0001 m^2/h, using temperature data taken from five depths of the asphalt layer. The contribution of this study, is therefore, a novel condition monitoring of asphalt pavements that can significantly improve existing road maintenance programs.

***Keywords*:** Asphalt Pavement, Condition Monitoring, Physics-informed Neural Networks, Thermal Diffusivity

1. Introduction

Climate resilience in the context of pavement refers to the pavement's capacity to endure and maintain its intended performance despite the challenges posed by a changing climate. [1]. The long-term pavement performance is highly influenced by the ambient temperature and moisture [2]. In the desert climatic conditions of the United Arab Emirates, temperature may play a bigger role on the rate of deterioration. According to the 2022 IPCC report (2022) [3], a hotter climate is inevitable in the coming decades. This is consistent with the total observed increase in global surface temperature observed historically, and the UAE conditions where the air temperature has risen by around 1°C in the past few decades [4].

The expected increase in temperature can significantly affect the structural performance of asphalt pavements [5], as the stresses and strains induced is heavily dependent on the temperature profile within the layers [6,7]. The temperature in the surface layers is influenced by the ambient temperature through radiation and convection, while the heat is transferred through the underlying layers via conduction [8]. In the summer, these high temperatures can soften the asphalt layers, leading to bleeding or rutting [9], and temperature fluctuations can cause thermal fatigue damage [10,11]. As asphalt concrete pavements continue to deteriorate with time because of asphalt layer aging, cumulative traffic loads, environmental conditions, and/or inadequate maintenance [12], condition monitoring to assess the pavement health is crucial.

With the development in the Internet of Things (IOT) technology, embedded sensors have begun to play a major role in the condition (or health) monitoring of civil engineering structures. In the case of pavement structures, the condition monitoring of an asphalt pavement in Ireland was carried out by developing a thermal Digital Twin Model (DTM), to describe the thermo-mechanical behavior of structure [13]. The thermal state of the structure is based on the one-dimensional heat equation, with thermal diffusivity as a characteristic parameter to be updated, as it reflects the structural health of the pavement. In their work, the DTM is solved numerically by means of an implicit finite-difference scheme, and the thermal diffusivity is updated with the periodic execution of Nelder-Mead simplex (NMS) multidimensional optimization algorithm [14]. In this study, a machine-learning approach is proposed to develop the DTM of the asphalt model, specifically the physics-informed neural network model (PINN). While this study builds on the work of [13], in the present work, both the solution of the digital twin and the parameter updating are carried out simultaneously through the inverse-PINN model.

2. Background

An asphalt pavement structure is a multi-layer system constantly interacting with its environment, with each layer having its own thermo-mechanical properties. The temperature in the surface layers is influenced by the ambient temperature through radiation and convection, while the heat is transferred through the underlying layers via conduction [8]. Since the pavement thickness is smaller than the other dimensions of the road, the one-dimensional thermal conduction phenomenon is generally adopted [8,15]. The continuous changes in the environment (such as the surrounding air temperature, solar radiation and wind speed) significantly affects the material properties and the performance of asphalt, making the heat flow process unsteady and varying in time and space [16,17], and the transient (unsteady) one-dimensional Fourier heat conduction equation is given by

$$\frac{\partial T}{\partial t} = \propto \frac{\partial^2 T}{\partial x^2}$$

Where T is the temperature in °C, x denotes space in m, t denotes time in hr and $\propto$ is the thermal diffusivity in m^2/hr.The overall rate of heat flow to and from the surface of the pavement layers can be expressed as

$$q_{net} = q_c \pm q_r \pm q_k$$

where q_c and q_r are the heat flux due to convection and radiation respectively, q_k is the conduction heat flux in W/m^2. The heat convection equation, from Newton's law of cooling, is given as

$$q_c = h_c [T_{surf} - T_{air}]$$

where h_c is the heat convection coefficient in $J/(m^2.°C)$, and T_{surf} and T_{air} are the surface and air temperatures respectively.

The heat transfer by radiation, q_r includes the solar radiation absorbed, q_s and the energy emitted by the pavement surface as long-wave radiation. At the pavement surface the total heat flux, q_{surf} can be expressed as

$$q_{surf} = q_r \pm q_c = q_s + h [T_{air} - T_{surf}]$$

where h is the comprehensive heat transfer coefficient that accounts for convection and radiation i.e $h = h_c + h_r$ where h_r is the long-wave radiation. The surface flux may be reconstructed as

$$q_{surf} = h * [T_{eff} - T_{surf}]$$

where T_{eff} is a synthetic temperature that considers the effect of atmospheric temperature and solar radiation, and is given by [17]

$$T_{eff} = T_{air} + \frac{q_s}{h}$$

As the effect of changes in the heat transfer coefficient due to radiation is very small in most cases, and the influence of the wind speed on h_c is dominant, h may be computed as [17]

$$h = c_1 * v + c_2$$

where v is the wind speed in m/s and c_1 and c_2 are empirical coefficients. The solar energy absorbed by the pavement is proportional to its absorptivity, a as

$$q_s = a\, q_{\text{solar}}$$

where q_{solar} is the solar radiation intensity at the surface in W and $a = 1 - \hat{a}$ where $\hat{a}$ is the albedo.

2.1. Numerical Solution for Pavement Temperature Distribution

The approaches for predicting the temperature of the asphalt pavement layer may be divided into three primary categories. The analytical [18] and numerical approaches are based on the heat transfer theories and thermal properties of of asphalt pavement, while the empirical method, uses regression modelling techniques to learn the relationship between measured pavement temperatures and climatic data [5]. Numerical models, such as the finite difference method or the finite finite element method, can capture complex boundary conditions more accurately than the analytical approaches and empirical models [8]. In this study, the Finite-Difference (FD) method is adopted to serves ground truth as the groundtruth model. In other words, since this is a preliminary study, and the data from sensors physically embedded in the pavement layer is not available, the data from the FD model is adopted instead to train and validate the Machine Learning (ML) models.

2.2. Physics-informed Neural Networks

Due to the complexity of variabilities in boundary conditions, material properties and weather conditions, advanced data analytical techniques and neural network models have been adopted to predict the temperature patterns in pavement layers, to complement the mechanistic models [19]. In the case of Physics-informed Neural Networks (PINNs), prior knowledge is incorporated with the neural network models through governing differential equations that enable these algorithms to 'understand' the problem being tackled [20]. Through automatic differentiation, the heat transfer differential equation in Equation 1 is embedded into the neural network's loss function by the PINN. Since the PINN model, NN is used to approximate the pavement temperature as

$$NN(x,t) \approx T(x,t)$$

the function f is defined as

$$f(x,t) = \left(\frac{\partial NN}{\partial t} - \propto \frac{\partial^2 NN}{\partial x^2}\right)$$

This enables the integration of both measurement data and the underlying physics of the problem. Further details on solving the PINN using Google Colab can be found in [21].

3. Methodology

As stated earlier, the goal of this study is to estimate the thermal diffusivity of the asphalt layer using the inverse-PINN model. The first step is to develop a PINN model to accurately predict the pavement layer temperature over time and space (in the thickness direction), to establish the feasibility of adopting PINNs for flexible pavement modelling. To validate this, the finite-difference numerical model is first developed using solar radiation and ambient air temperature data. The description of the data, model parameters as well as the models adopted have been detailed in the following sub-sections.

3.1. Model Parameters and Data Description

The solar radiation, ambient air temperature as well as the wind velocity was taken from the HOBO Weather station installed in the BITS Pilani Dubai Campus in Dubai, United Arab Emirates for a day in the month of January. The thickness of the pavement was assumed as 2 m at which the temperature was assumed to be 20°C. The other model parameters adopted for the heat transfer model are given in Table 1.

Table 1: Model Parameters for Heat Transfer Model.

c,J/(kg°C)	ρ, kg/m^3	k,W/(m °C)	T^0_{surf}	$a = 1 - \hat{a}$
980	2350	1.28	27	0.87

The thermal diffusivity, $\propto$ is computed as

$$\propto = \frac{\mathrm{k}}{\rho c}$$

for the PINN model, $\propto$ and is the parameter to be computed in the i-PINN model. Here k is the thermal conductivity, ρ is the density of the solid material, c is the specific heat capacity and T^{0}_{surf} is the pavement surface temperature at time k =0.

3.2. Numerical Model Description

In order to compute the temperature in the asphalt pavement in space and time, the pavement thickness direction is divided into N layers (or grid elements) and K time intervals. The N^{th} layer represents the bottom of the asphalt layer in this study and the time starts at $t = 0$; thus t_n^k represents the temperature of grid n at time k. The bottom temperature is assumed as a constant temperature boundary, and a mixed boundary is assumed at the top surface, to account for the various external factors. The finite difference model is adopted from [17] as follows:

Internal Element :
$$\left(1 + {}^{2\lambda\Delta t}/_{\rho c\Delta x^2}\right) T_n^{k+1} = {}^{\lambda\Delta t}/_{\rho c\Delta x^2} \left(T_{n-1}^{k+1} - T_{n+1}^{k+1}\right) + T_n^k \tag{1}$$

Mixed Boundary Condition:
$$\begin{aligned} 1 + 2\left({}^{\lambda\Delta t}/_{\rho c\Delta x^2}\right)\left({}^{h\Delta x}/_{\lambda}\right) + 2\left({}^{\lambda\Delta t}/_{\rho c\Delta x^2}\right)\left(T_1^{k+1}\right) \\ = 2\left({}^{\lambda\Delta t}/_{\rho c\Delta x^2}\right)\left(T_2^{k+1} + \left({}^{h\Delta x}/_{\lambda}\right) T_e^{k+1}\right) + T_1^k \end{aligned} \tag{2}$$

$$T_N^k = T_0 \tag{3}$$
Constant Boundary Condition :

4. Results and Discussion

The temperature predicted using the PINN model is compared the finite-difference (groundtruth) model in Figure 1. The PINN is trained using only the boundary conditions (initial, surface and bottom boundary conditions). The total loss function minimizes the error at these locations as well as the loss function f. As can be seen, the PINN can predict the temperature in space (upto pavement thickness of 2m) and time with sufficient accuracy.

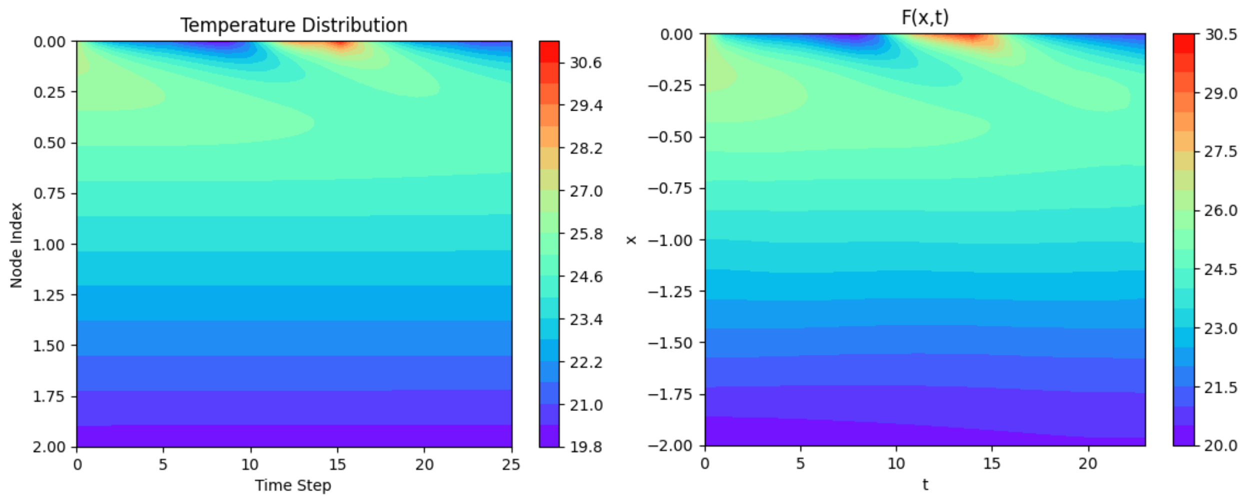

Fig. 1: Comparison of heat distribution of (a) Ground-truth model and (b) Prediction from PINN model

Given that the PINN can replicate the results of the finite-difference model, the i-PINN model was implemented to to estimate the thermal diffusivity. For this, the assumption was made that the data at 4 different depth, $x = 0.005, 0.02, 0.1, 0.2$ have also been made available. This is done to replicate the conditions when the temperature data will be available from physical embedded sensors that can measure the temperature every hour. The results are shown in Figure 2, where the depth of the asphalt layer was assumed to be 0.3m. This was based on the previous study results [13] on the thermal digital twin, where only the data for the top 30 cm was utilized for estimating the thermal diffusivity. Moreover, in the PINN model results the temperature pattern after 0.3m did not show much variation. The thermal diffusivity estimated from the i-PINN model was $\lambda_{est} = 0.0022$ m^2/h as compared to $\lambda_{real} = 0.0021$ m2/h .

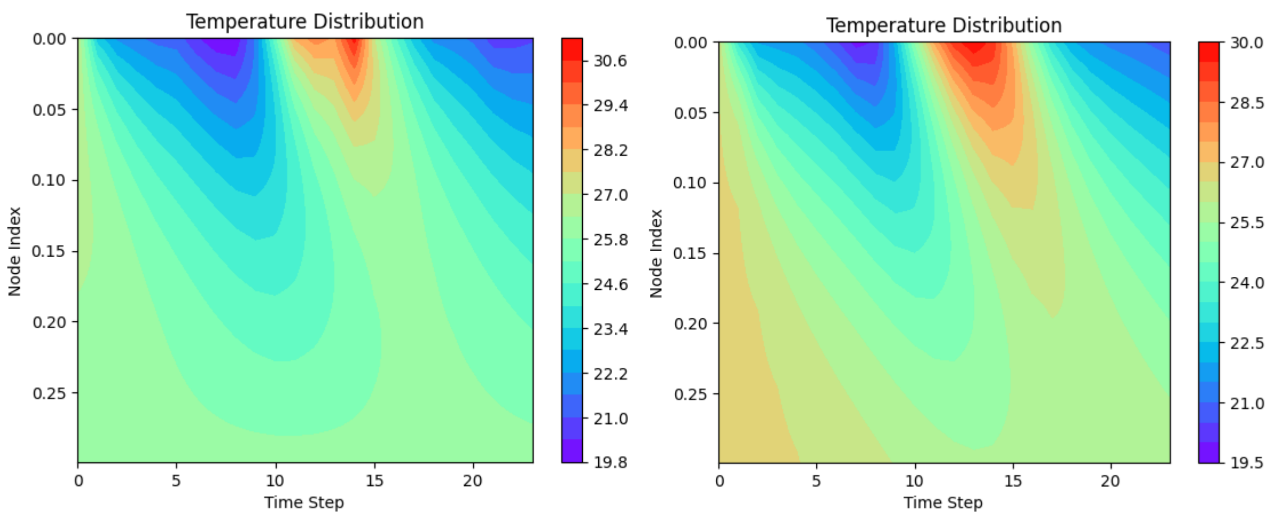

Fig. 2: Comparison of heat distribution of (a) Ground-truth model and (b) Prediction from i-PINN model

4. Conclusion

In this study, a thermal DT was developed for a typical pavement section based the one-dimensional heat equation using PINNs. The objective was to demonstrate how the thermal diffusivity values, which reflect the pavement condition [13], can be updated to achieve thermal twinness using i-PINNs. For this study, the bottom boundary condition for the i-PINN model corresponds to a depth of 30 cm, ignoring the edge effects. The model can be extended to the estimation of the thermal diffusivity of all the pavement layers, which has been left for a further study. Moreover, a continuous condition monitoring system can be established by periodically updating the i-PINN model with real-time data.

Acknowledgements

The author gratefully acknowledges Dr Meghana Charde who provided the weather data for BITS Pilani Dubai Campus.

References

[1] S. A. Blaauw, J. W. Maina, G. A. Mturi, & A. T. Visser (2022), "Flexible pavement performance and life cycle assessment incorporating climate change impacts," *Transportation Research Part D: Transport and Environment, 2022* 104, pp. 103203.

[2] Y. Qiao, A. R. Dawson, T. Parry, G. Flintsch, & W. Wang, "Flexible pavements and climate change: A comprehensive review and implications," *Sustainability*, 2020, *12*(3), 1057.

[3] I. C. Change, " Mitigation of climate change," in *Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change*, 2014, *1454*, 147.

[4] https://climateknowledgeportal.worldbank.org/country/united-arab-emirates.
[5] Y. Li, L. Liu and L. Sun, "Temperature predictions for asphalt pavement with thick asphalt layer," *Construction and Building Materials*, 2018, *160*, pp. 802-809.
[6] J. Chen, H. Wang, M. Li, and L. Li, "Evaluation of pavement responses and performance with thermal modified asphalt mixture," *Materials & Design,* 2016, *111*, 88-97.
[7] H. Wang and I. L. Al-Qadi. "Importance of nonlinear anisotropic modeling of granular base for predicting maximum viscoelastic pavement responses under moving vehicular loading," *Journal of engineering mechanics*, 2013, *139*(1), 29-38
[8] U. B. Ayasrah, L. Tashman, A. AlOmari and I. Asi, "Development of a temperature prediction model for flexible pavement structures," *Case Studies in Construction Materials*, 2023, *18*, e01697.
[9] C. Zhang, Y. Tan, Y. Gao, Y. Fu, J. Li, S. Li and X. Zhou. "Resilience assessment of asphalt pavement rutting under climate change," *Transportation Research Part D: Transport and Environment*, 2022, *109*, 103395.
[10] Z. H. Khan, M. U. Ahmed and R. A. Tarefder, *Properties of asphalt pavement layers through field instrumentation at I-40*, 2017, No. 17-06543.
[11] Z. H. Khan, M. R. Islam, and R. A. Tarefder, " Determining asphalt surface temperature using weather parameters. *Journal of Traffic and Transportation Engineering, 2019, 6*(6), 577-588.
[12] W. Xue, L. Wang, D. Wang and C. Druta, "Pavement health monitoring system based on an embedded sensing network," *Journal of Materials in Civil Engineering*," 2014, *26*(10), 04014072.
[13] L. Barisic, E. Levenberg, A. Skar, A. Boyd and P. Zoulis, "A thermal digital twin for condition monitoring of asphalt roads," In *Green and Intelligent Technologies for Sustainable and Smart Asphalt Pavements,* CRC Press, *2021,* pp. 709-713.
[14] J. A. Nelder and R. Mead, "A simplex method for function minimization," *The computer journal*, 1865, *7*(4), 308-313.
[15] M. R. Hall, P. K. Dehdezi, A. R. Dawson, J. Grenfell and R. Isola, "Influence of the thermophysical properties of pavement materials on the evolution of temperature depth profiles in different climatic regions," *Journal of materials in civil engineering*, 2012, *24*(1), 32-47.
[16] Y. Sun, R. Guo, L. Gao, J. Wang, X. Wang and X. Yuan, "Study on dynamic response characteristics of saturated asphalt pavement under multi-field coupling," *Materials*, 2019, *12*(6), 959.
[17] N. Zhang, G. Wu, B. Chen and C. Cao, "Numerical model for calculating the unstable state temperature in asphalt pavement structure," *Coatings*, 2019, *9*(4), 271.
[18] D. Wang (2012). "Analytical approach to predict temperature profile in a multilayered pavement system based on measured surface temperature data," *Journal of Transportation Engineering*, 2012, *138*(5), 674-679.
[19] V. Shankar and S. Senadheera, "Improved empirical convection heat transfer coefficient model to predict flexible pavement layer temperatures," *Construction and Building Materials*, 2024, *411*, 134206.
[20] M. Usama, R. Ma, J. Hart and M. Wojcik. Physics-Informed Neural Networks (PINNs)-Based Traffic State Estimation: An Application to Traffic Network. *Algorithms*, 2022, *15*(12), 447.
[21] https://github.com/jdtoscano94/Learning-Python-Physics-Informed-Machine-Learning-PINNs-DeepONets