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**Transportation Infrastructure Precast Innovation Center**

**(TRANS-IPIC)**

**University Transportation Center (UTC)**

Physics-Informed Viscoelastic/Viscoplastic Model of Prestressed Concrete Creep

UI-24-RP-05

Quarterly Progress Report

For the performance period ending March 31, 2025

**Submitted by:**

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**Collaborators / Partners:**

None

**Submitted to:**

TRANS-IPIC UTC

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**TRANS-IPIC Quarterly Progress Report (Section 1 – 7, 5 pages max.):**

**Project Description:**

1. Research Plan - Statement of Problem

One of the major goals of TRANS-IPIC is to extend the life of existing transportation infrastructure through the development of novel materials and technologies in precast concrete (PC). Extending the durability of PC requires a thorough understanding of the mechanisms which cause it to fail prematurely. In many cases, creep can cause substantial issues affecting the performance of PC, and concrete in general, which reduces its service life due to substantial cracking. Considering the interest of TRANS-IPIC specifically in prestressed concrete as well, this project is of substantial interest, because creep can result in prestress loss in concrete. Because the creep response in concrete depends on so many factors, this study will explore the response of concrete and PC to creep loading and develop a predictive algorithm based on the latest methods in machine learning, which will allow for newfound insights into creep of PC to better design and formulate concrete which is more durable against this issue.

1. Research Plan - Summary of Project Activities (Tasks)

*Task 1 – Development of a creep database*

In the first research task, the research team will assemble a dataset of existing experimental creep studies on PC. However, it is understood after our initial review that there may be limited data available for precast concrete specifically; therefore, we are expanding the database to study concrete in general and will consider various machine learning algorithms in future tasks to make PC-specific predictions. The research team will also consider simulation studies which are validated by experiments, to maintain the trustworthiness of the input data while also adding data points to the overall matrix. Studies will be considered from previous research reports and peer-reviewed articles. Finally, the research team will work with industry partners of the TRANS-IPIC center to obtain data from experiments and field sites, which provide information which can be added to the datasets from literature. The research team will then clean these datasets and ensure each contains the appropriate inputs, including temperature, concrete composition, reinforcement, and cure time, among others.

*Task 2 – Physics Informed Neural Network for creep prediction*

The second project phase involves developing a Physics Informed Neural Network (PINN) which can predict creep in PC. The PINN will use the data above for training, testing, and validation, but will also incorporate unseen datasets, which are from different sources than any portion of the data mentioned above, potentially including data from industry partners. While the approach is similar to other Artificial Neural Networks, PINN is a unique method in that the training also involves fitting data to known governing equations. In this case, the primary governing equations for the problem will be known constitutive equations based on models of springs and dashpots or phenomenological models such as the Prony series, as well as viscoplastic models of material behavior such as the Norton-Hoff model for viscoplastic solids. Hyperparameters will be tuned to ensure the best possible model is produced. Once a PINN is developed using a deep neural network approach, the research team will add prediction of uncertainty using a Bayesian neural network. Finally, the developed model will be compared with existing ACI design equations and other developed empirical and mechanistic approaches to predict creep.

*Task 3 – Final report submission and posting to TRANS-IPIC website and other reporting*

A final report will be submitted to TRANS-IPIC detailing the results of this study for publication on the TRANS-IPIC website after editing. The research team will ensure Section 508 compliance of the report before delivery to TRANS-IPIC. In addition, the research team will present the results of the study at the Transportation Research Board (TRB) annual meeting and at TRANS-IPIC’s workshop. The research team will also pursue at least one peer-reviewed journal publication as a result of the project to disseminate results in the academic community and will present the findings at other workshops and conferences for industry partners. Finally, the research team will also create an interactive online tool to use to predict properties of asphalt concrete and asphalt binders. This tool will be publicly available so that other researchers and practitioners can have an easy-to-use prediction tool for creep in PC.

**Project Progress:**

1. Progress for each research task

*Task 1 (30% complete)*

The research team began an extensive review of the literature to obtain data related to precast concrete creep from experimental studies. The research team investigated literature which dealt with creep in prestressed concrete. Among the early studies of this is the work of colleagues at the University of Alberta (A. Ghali and W.H. Dilger, 1974; Tadros, Ghali, & Dilger, 1975), who investigated analytical solutions for prestress loss due to creep in prestressed concrete, and presented a design method which considered them. One of the subsequent works in this area was the study of Dilger (Dilger, 1982), who developed equations describing creep in uncracked, reinforced concrete. Later, several experimental studies were also conducted to better understand creep in precast and prestressed concrete. A recent review paper provides a thorough overview of studies of the prestress loss due to creep (Bonopera, Chang, & Lee, 2020). This paper identified the use of both destructive and nondestructive techniques. Creep may also be a very important issue when self-consolidating concrete is used to make precast concrete structures (Aslani & Nejadi, 2011).

The research team identified a few working models within existing literature for concrete creep which leverage fundamental mechanics of viscoelastic materials. The research team chose to start with these to work toward an initial model covering concrete as a material, before developing the framework for using this model in precast/prestressed concrete. An initial research direction identified by the team involves the development of an interpretable and accurate data-driven machine learning (ML) framework for predicting the creep behavior of concrete. As with all ML-based methodologies, the success of this approach is contingent upon the availability of a comprehensive and high-quality dataset to ensure reliable model training and robust generalization across diverse conditions. The extensive database (Bažant & Li, 2008) compiled at Northwestern University includes 621 creep tests and 490 shrinkage tests, enabling robust validation of creep prediction models for design applications. The database contains 29,196 creep compliance measurements across various time intervals. Fourteen variables are available as potential model inputs: cement type, cement content (kg/m3), amount of superplasticizer (kg/m3), water-cement ratio, aggregate-cement ratio, compressive strength at 28 days (MPa), environmental humidity of specimen preconditioning (%), humidity during test (%), temperature during loading (C), volume-surface ratio, concrete age at loading (day), time since loading (day), loading stress (MPa), and creep test type.

*Task 2 (10% complete)*

For this regression task, neural networks (LeCun, Bengio, & Hinton, 2015) and tree-based bagging (Breiman, 2001) and boosting (T. Chen & Guestrin, 2016; Prokhorenkova, Gusev, Vorobev, Dorogush, & Gulin, 2018) algorithms are considered as initial candidates, representing black-box and gray-box models, respectively. However, the research team is exploring alternative approaches that offer greater interpretability to facilitate mechanistic understanding alongside predictive accuracy. The growing effort to demystify the black-box nature of neural networks has garnered considerable interest. Improving the interpretability of these networks is crucial for building trust in their applications. Multilayer perceptrons (MLPs), based on the universal approximation theorem, serve as a foundation for many deep learning models across different domains. Despite their widespread use, Liu et al. (Liu et al., 2024) in May 2024 questioned whether MLPs are the optimal nonlinear regressors and proposed an alternative: Kolmogorov-Arnold Networks (KANs). Unlike MLPs, which use fixed activation functions at nodes, KANs feature learnable activation functions on edges (i.e., weights), potentially leading to closed-form solutions. Building on these insights, we focus on developing a KAN-based model for creep prediction, leveraging the aforementioned dataset to ensure both accuracy and interpretability.

Physics-Informed Neural Networks (PINNs) are an emerging class of machine learning models that integrate physical laws, typically expressed as partial differential equations (PDEs), directly into the training of neural networks (Raissi, Perdikaris, & Karniadakis, 2019). Unlike conventional data-driven models that rely exclusively on fitting observed data, PINNs embed governing equations into their loss functions, enabling improved extrapolation, better generalization, and enhanced robustness to noise or sparsity in the data. Among their many uses, PINNs have recently been applied to inverse problems (Jagtap, Mao, Adams, & Karniadakis, 2022) and extended to model discovery (Z. Chen, Liu, & Sun, 2021), the process of identifying unknown or partially known governing equations from experimental or simulated data. This is especially impactful in materials science and solid mechanics, where underlying physical laws are only partially known and existing constitutive models are often empirical or semi-empirical.

A compelling domain where model discovery via PINNs could be transformative is in the prediction of concrete creep and shrinkage. Despite over a century of research, the time-dependent deformation of concrete remains only partially understood. In Bazant’s influential work (Bažant, 2001) a comprehensive review of theoretical frameworks, empirical models, and computational approaches was presented. While these methods, including aging theories, solidification-based models, and microprestress formulations, have significantly advanced predictive capabilities, they still rely heavily on curve fitting, empirical tuning, and simplified approximations.

In the context of concrete shrinkage and creep, two main opportunities for PINN-based model discovery emerge. The first lies in the refinement of creep compliance functions. Existing models such as B3 and BP rely on short-term experimental data to calibrate long-term predictions, often via least-squares regression. A PINN could infer the underlying governing equation of time-dependent compliance directly from data, embedding constraints from microprestress theory, aging mechanisms, and moisture-temperature coupling. As described in (Bažant, 2001), updating long-term creep predictions using short-term data remains an ill-posed problem under traditional frameworks. PINNs are better suited to handle such inverse problems due to their ability to integrate physical priors and sparse observations. Their use of automatic differentiation further enables learning of highly nonlinear relationships, allowing for direct coupling between humidity, stress redistribution, and damage evolution.

The second opportunity lies in modeling the evolution of pore humidity distributions within concrete, a key factor in drying shrinkage and drying creep. Bažant (Bažant, 2001) proposed simplified analytical expressions to approximate solutions to nonlinear diffusion equations, often using hyperbolic tangent functions to match asymptotic behavior. While these are useful for engineering design, they require empirical calibration. A PINN model could learn the governing diffusion PDE directly from spatial-temporal data, enforcing physical constraints like mass conservation and Fickian behavior, potentially discovering new forms of humidity dependence in diffusivity. This could lead to models that are both interpretable and predictive, reducing reliance on limited empirical calibration.

In summary, PINNs offer a flexible and physics-grounded approach to model discovery in concrete creep and shrinkage. They enable learning interpretable, generalizable models from limited data while enforcing consistency with physical laws. Therefore, PINN has great potential to guide this work and develop a useful, realistic model which does not rely on datasets of extremely large size.

*Task 3 (0% complete)*

Task 3 has not started yet.

1. Percent of research project completed – 15%

The progress of the project describes above results in 15% of the project completed thus far.

1. Expected progress for next quarter

The research team will extract data from existing literature on concrete creep and will complete their review of existing literature for precast/prestressed data specifically. The research team will then implement the KAN model (or MLP, if more appropriate), for prediction of concrete creep based on this data. This will then allow for modifications of specific test parameters such as cement type, humidity, temperature, and others, and subsequent prediction of creep. Eventually, factors such as prestress loss and others can also be considered as data becomes available, as the physics-based model will be robust.

1. Educational outreach and workforce development

None yet.

1. Technology Transfer

None yet.

**Research Contribution:**

1. Papers that include TRANS-IPIC UTC in the acknowledgments section:

None yet.

1. Presentations and Posters of TRANS-IPIC funded research:

None yet.

1. Please list any other events or activities that highlights the work of TRANS-IPIC occurring at your university (please include any pictures or figures you may have). Similarly, please list any references to TRANS-IPIC in the news or interviews from your research.

**Appendix 1**: Research Activities, leadership, and awards (cumulative, since the start of the project)

1. Number of presentations at academic and industry conferences and workshops of UTC findings

* No. = 0

1. Number of peer-reviewed publications submitted based on outcomes of UTC funded projects

* No. = 0

1. Number of peer-reviewed journal articles published by faculty.

* No. = 0

1. Number of peer-reviewed conference papers published by faculty.

* No. = 0

1. Number of TRANS-IPIC sponsored thesis or dissertations at the MS and PhD levels.

* No. MS thesis = 0
* No. PhD dissertations = 0
* No. citations of each of the above = N/A

1. Number of research tools (lab equipment, models, software, test processes, etc.) developed as part of TRANS-IPIC sponsored research

* Research Tool #1 (Name, description, and link to tool) =
* Research Tool #2 (Name, description, and link to tool) =
* Research Tool #3 (Name, description, and link to tool) =

1. Number of transportation-related professional and service organization committees that TRANS-IPIC faculty researchers participate in or lead.

* Professional societies
  + No. participated in = 5
  + No. lead = 0
* Advisory committees (No. participated in & No. led)
  + No. participated in = 0
  + No. lead = 0
* Conference Organizing Committees (No. participated in & No. led)
  + No. participated in = 3
  + No. lead = 0
* Editorial board of journals (No. participated in & No. led)
  + No. participated in = 2
  + No. lead = 0
* TRB committees (No. participated in & No. led)
  + No. participated in = 2
  + No. lead = 0

1. Number of relevant awards received during the grant year

* No. awards received = 0

1. Number of transportation related classes developed or modified as a result of TRANS-IPIC funding.

* No. Undergraduate = 1
* No. Graduate = 0

1. Number of internships and full-time positions secured in the industry and government during the grant year.

* No. of internships = 0
* No. of full-time positions = 0

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