

**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 June 30, 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:**

*Task 1 (50% complete)*

The research continued our literature review and data acquisition from the literature. The research team reviewed extensively the previous work by Prof. Bazant’s group at Northwestern University (Bazant & Panula, 1978; Bazant & Li, 2008; Hubler et al., 2015; Wendner et al., 2015). It is worth noting that the recent advances in this database and the associated model were motivated by observations of excessive creep resulting in reduced service life in existing bridges (Bazant et al., 2011). The use of this database to form better predictive creep models therefore may result in enhanced resistance to creep-related damage in precast/prestressed concrete structures.

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 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 as stated before.

*Task 2 (25% complete)*

As mentioned in the previous quarterly report, a new approach to machine learning for development of closed-form functions is the use of Kolmogorov-Arnold Networks (KANs) (Liu et al., 2024). 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.

The KAN model can be supplemented by Physics Informed Neural Networks (PINN) to better incorporate mechanics into the prediction of creep and shrinkage. 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.

As a start to this task, the research team explored the mathematical formulation of KAN to ensure it can be used herein. The universal theorem underlying the development of MLPs posits that a feed-forward network with a single hidden layer, comprising a finite set of neurons, has the capability to approximate continuous functions within compact subsets of Rn. KAN, on the other hand, is based on the Kolmogorov-Arnold representation theorem [Ref], which states that any multivariate continuous function can be decomposed into univariate functions and additions. The theorem states that any continuous multivariate function: f[0, 1]n → R can be articulated as:

$$f\left(x\right)= \sum\_{q=1}^{2n+1}Φ\_{q}\left(\sum\_{p=1}^{n}φ\_{q,p}\left(x\_{p}\right)\right)$$

where $φ\_{q,p}$ and $Φ\_{q}$ are are univariate functions mapping each input variable xp, such that $φ\_{q,p}$: [0,1] → R, and $Φ\_{q}$. KAN is composed of multiple hierarchical layers, as demonstrated in 1, which depicts a KAN architecture with two such layers. KAN structures each layer as a matrix of these learnable 1D functions as:

$$Φ=\left\{φ\_{q,p}\right\}, p=1,2,…,n\_{in}, q=1,2,…,n\_{out}$$



Figure 1. KAN Architecture.

Each function $φ\_{q,p}$ can be expressed as a B-spline, a piecewise-defined polynomial function consisting of a linear combination of basis functions, improving the capacity of the network to learn complex data representations. In this context, nin signifies the number of input features for a given layer, whereas nout indicates the number of output features generated by that layer, illustrating the dimensionality changes throughout the network layers. The activation functions $φ\_{l,j,i}$ in this matrix are these parameterizable spline functions, represented as:

$$spline\left(x\right)= \sum\_{i}^{}C\_{i}B\_{i,k}\left(x\right)$$

where Ci represents the control points and Bi,k(t) denotes the basis splines. Here, Bi,k(t), with i as the index of the basis spline and k as the order, is recursively defined over a non-decreasing sequence of knots t0, t1, tn+k+1 as:



This formulation enables each $φ\_{l,j,i}$ to adjust its shape according to the data, providing exceptional flexibility in modeling the interactions between inputs within the network. By combining the above three equations to define each layer of the network, the overall architecture of a KAN resembles stacking layers in MLPs, but it improves upon this by employing complex functional mappings instead of simple linear transformations and nonlinear activations:



Where $Φ\_{L}$ is the function matrix for the lth layer of the KAN or a set of pre-activations. If neuron i in the lth layer is referred to as the ith, and neuron j in the (l+1)th layer is referred to as the jth, then the activation function $φ\_{l,j,i}$ connects neuron (l,i) to neuron (l + 1, j):



The transformation ($Φ\_{l}$) of each layer processes the input xl to generate the input xl+1 for the subsequent layer. As illustrated in Figure 1, the activation functions are located on the edges rather than the nodes, differing from MLPs. Hence, the pre-activation of $ϕ\_{l,i,j}$ is xl,i, and the post-activation is $\tilde{x}\_{l,i,j}$. Subsequently, the values $\tilde{x}\_{l,i,j}$ are summed to compute xl+1,I, representing the activation value at the (l + 1, j)-node:

$$x\_{l+1,j}=\sum\_{i=1}^{n\_{l}}\tilde{x}\_{l,i,j}=\sum\_{i=1}^{n\_{l}}ϕ\_{l,i,j}(x\_{l,i})$$

Thus, the transformation matrix $Φ\_{l}$ can be expressed as an nl+1 x nl matrix of activations:



*Task 3 (0% complete)*

Task 3 has not started yet.

1. Percent of research project completed: 25%

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 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. The team will also draft and submit a paper for the Transportation Research Board Annual Meeting.

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:

Presented a poster at the TRANS-IPIC Annual Workshop in Rosemont, IL in April 2025:

Asadi, B. & Hajj, R. (2025). **Interpretable and Physics-Informed Machine Learning for Modeling and Discovering Concrete Creep.** In *TRANS-IPIC 2025 Workshop.*

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 = 3 (as of May 2025 before dissolving of all TRB committees)
	+ 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 = 1 (Babak Asadi, Graduate Research Assistant)
* No. of full-time positions = 0

**References:**

Bazant, Z. P., Hubler, M. H., & Yu, Q. (2011). Pervasiveness of excessive segmental bridge deflections: Wake-up call for creep. *ACI Structural Journal*, *108*(6), 766.

Bazant, Z. P. and Li, G.-H. (2008). “Comprehensive database on concrete creep and shrinkage.”, ACI Materials Journal, 106(6, Nov.-Dec.), pp. 635–638.

Bazant, Z. P. and Panula, L. (1978-79). “Practical prediction of time-dependent deformations of concrete.”, Materials and Structures, RILEM, Paris (11) Part I, “Shrinkage”, pp. 307–316. Part II, “Basic creep”, pp. 317–328. Part III, “Drying creep”, pp. 415–424. Part IV, “Temperature effect on basic creep”, pp. 425–434.

Hubler, M.H., Wendner, R., and Bazant, Z.P. “Comprehensive database for concrete and shrinkage: Analysis and recommendations for testing and recording.” ACI Materials Journal 112 (4), 547–558.

Hubler, M.H., Wendner, R., and Bazant, Z.P. (2015). “Statistical justification of model B4 for drying and autogenous shrinkage of concrete and comparisons to other models.” Materials and Structures 48 (4), 797–814.

Liu, Z., Wang, Y., Vaidya, S., Ruehle, F., Halverson, J., Soljačić, M., … Tegmark, M. (2024). *KAN: Kolmogorov-Arnold Networks*. 1–50. Retrieved from http://arxiv.org/abs/2404.19756

Wendner, R., Hubler, M.H., and Baˇzant, Z.P. (2015). “Statistical justification of model B4 for multi-decade concrete creep using laboratory and bridge databases and comparisons to other models”. Materials and Structures 48 (4), 815–833.