

Physics-Informed LSTM-Based Heat Pipe Temperature Estimation for Microreactor

Ik Jae Jin and In Cheol Bang*

Department of Nuclear Engineering., Ulsan National Institute of Science and Technology (UNIST).,
50 UNIST-gil., Ulsu-gun., Ulsan., Republic of Korea

*Corresponding author: icbang@unist.ac.kr

***Keywords** : heat pipe, microreactor, physics-informed LSTM, temperature estimation

1. Introduction

Heat pipe microreactors have recently attracted considerable attention because of the passive heat removal capability, compact configuration, and inherent safety characteristics [1]. Since heat pipes constitute the primary heat transfer pathway between the fuel and the heat dissipation system, continuous monitoring of the thermal condition is essential for ensuring effective heat removal and reactor safety. However, microreactor designs employ hundreds to thousands of heat pipes, preventing comprehensive temperature monitoring of individual heat pipes. Consequently, methodologies capable of estimating heat pipe temperatures from a limited number of accessible measurements are desirable

Recent advances in artificial intelligence have enabled data-driven prediction of heat transfer characteristics, thermal performance, and transient thermal behavior in various energy systems [2-3]. Nevertheless, most previous studies assume the availability of direct heat pipe temperature measurements, and their prediction capability is primarily based on statistical relationships learned from training datasets. As a result, prediction accuracy could deteriorate under operating conditions that differ from those represented during training.

Physics-informed neural networks (PINNs), which incorporate governing physical relationships into the learning process, have recently been investigated for nuclear reactor applications [4]. Although previous studies demonstrated improved physical consistency and computational efficiency, applications to inaccessible heat pipe temperatures under unseen operating conditions remain limited.

In this study, a PINN-based heat pipe temperature estimation method is proposed using accessible temperature measurements obtained from a heat pipe experimental facility. The proposed approach is evaluated under extrapolation conditions by training the model using start-up, steady-state, and shutdown data, while performance evaluation was performed on a loss of cooling scenario that is excluded from the training dataset. The developed method provides physically consistent estimation of unmeasured heat pipe temperatures while reducing instrumentation requirements for sensor-limited heat pipe microreactor monitoring.

2. Method and Methodology

Experimental data in previous studies on sodium heat pipe based thermal systems were utilized as training data in this study [5]. The dataset was obtained based on a phenomena identification ranking table, focusing on operating, transient, and accident conditions relevant to heat removal system behavior. The considered conditions included startup, steady-state operation, shutdown, loss of cooling, and inclination angle change scenarios at both horizontal and vertical orientations, considering the various designs of heat pipe cooled microreactors. The configuration of the data utilized for the heat pipe temperature estimation is summarized in Table 1 at each scenario.

Table I: Configuration of dataset

Scenario	Dataset	Objective
Start up [0°]	4,531	Training/ Validation/ Test [Interpolation]
Steady state [0°]	3,931	
Shutdown [0°]	3,953	
Start up [90°]	3,931	
Steady state [90°]	3,931	
Shutdown [90°]	3,915	
Total	24,192	
Loss of cooling [0°]	426	Test only [Extrapolation]
Loss of cooling [90°]	506	
Total	932	

The configuration of the data was categorized according to startup, steady state, accident scenarios, and shutdown conditions. The proportions of training, validation, and test datasets were 80%, 10%, and 10% for separate experimental data, respectively. Locations for the thermocouples to obtain temperature datasets are represented in Figure 1. A total of ten thermocouples were utilized to measure the surface temperature of the cartridge heaters. Five thermocouples were attached between the heaters (HT_HT) to measure the temperature distribution, while another five thermocouples were installed between the heaters and the heat pipe (HT_HP). In addition, fourteen K-type thermocouples were installed along the outer wall of the heat pipe. Five TCs were positioned in the evaporator section (Evap), five in the adiabatic section (Adia), and four in the condenser section (Cond).

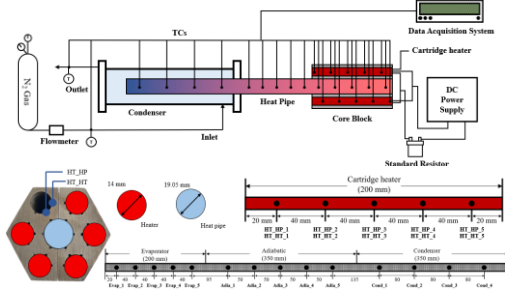


Fig. 1. Schematic of experimental facility for database [5]

An LSTM-based model was employed to estimate the temperature distribution of the heat pipes. The input variables consisted of the temperature distribution of the surrogate core block over the preceding 60 s and the inlet and outlet temperatures of the heat exchanger. The architecture adopted in this study is represented in Fig. 1, and the model was designed to predict the temperature distribution of the heat pipes. For the data-driven model, the loss function was defined solely based on the reference temperature data. For the physics-informed model, the transient heat conduction equation was applied by utilizing the finite difference method and incorporated into the loss function as a physics constraint. The most physical parameters in the loss function are derived from the input and output temperature variables. The effective thermal conductivity in the physics loss was evaluated based on the transferred heat load and the temperature difference between the evaporator and condenser sections. The mean squared error (MSE) was adopted as the loss function, and the model was optimized using the Adam optimizer with a learning rate of 0.001. The model was trained for 200 epochs.

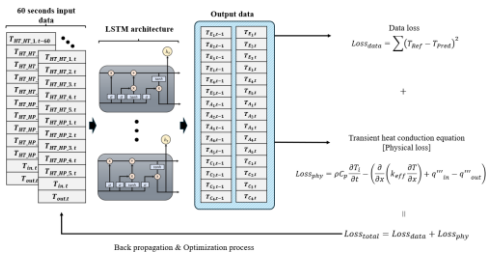


Fig. 2. Configuration of PI-LSTM architecture

3. Results and Discussions

Performance was evaluated using the MAE, RMSE, MAPE, and coefficient of determination (R^2). The estimation results of the conventional LSTM and the proposed PI-LSTM models are summarized in Tables 2 and 3. Under the interpolation condition, both models achieved high prediction accuracy, whereas the PI-LSTM exhibited consistently lower prediction errors and a higher R^2 value. Under the extrapolation condition, where the model was evaluated using the unseen loss of cooling scenario, the PI-LSTM maintained higher estimation performance compared with the conventional LSTM. The improved

performance can be attributed to the incorporation of the transient heat conduction equation into the training process, which constrained the predicted temperature distribution to satisfy the underlying heat transfer physics. Consequently, the proposed PI-LSTM demonstrated improved generalization capability and produced more physically consistent temperature predictions under operating conditions that were not included in the training dataset. The proposed method enables physically consistent estimation of unmeasured heat pipe temperatures under both interpolation and extrapolation conditions.

Table II: Performance evaluation of LSTM architecture

	MAE	RMSE	MAPE	R^2
Interpolation	1.30	2.27	0.21%	0.9998
Extrapolation	27.54	39.73	3.22%	0.6732

Table III: Performance evaluation of PI-LSTM architecture

	MAE	RMSE	MAPE	R^2
Interpolation	0.87	1.57	0.14%	0.9999
Extrapolation	19.04	33.95	2.26%	0.7613

4. Conclusions

In this study, a physics-informed LSTM (PI-LSTM) architecture was proposed to estimate unmeasured heat pipe temperatures in microreactors using limited accessible measurements. By incorporating the transient heat conduction equation as a physical loss constraint into the training process, the model effectively reflected the underlying thermal dynamics. Evaluation under an unseen loss of cooling scenario demonstrated that the PI-LSTM significantly outperformed the conventional LSTM in extrapolation conditions, achieving R^2 of 0.7613 compared to 0.6732. Consequently, the developed methodology provides physically consistent temperature estimation while reducing instrumentation requirements, offering a reliable approach for thermal monitoring in heat pipe microreactors.

REFERENCES

- [1] R. Testoni, A. Bersano, and S. Segantin, "Review of nuclear microreactors: Status, potentialities and challenges," Progress in Nuclear Energy, Vol. 138, 103822, 2021.
- [2] L. Lin, J. Oncken, and V. Agarwal, "Autonomous control for heat-pipe microreactor using data-driven model predictive control," Annals of Nuclear Energy, Vol. 200, 110399, 2024.
- [3] I. J. Jin and I. C. Bang, "Fuel surrogate temperature prediction for microreactor using heat pipe under transient conditions," Applied Thermal Engineering, 132596, 2026.
- [4] D. Jiang, Z. Wang, L. Yuan, J. Gou, and J. Shan, "Physics-informed neural network for rapid prediction of the temperature fields in fuel-heat pipe assemblies," Energy, Vol. 332, 137268, 2025.
- [5] I. J. Jin and I. C. Bang, "Experimental investigation of transient behavior in sodium heat pipe system for microreactor," Applied Thermal Engineering, 131048, 2026.