Development of Hybrid Virtual Thermal Sensor for High-Voltage Relays via Multivariate Time-Series Temperature Prediction

Sewoong Gim[1], Jaephil Park[1], and Sanghoon Lee[*]

[1,*] *Reliability R&D Division, Korea Automotive Technology Institute, Cheonan-Si, 31214, South Korea*

kimsw@katech.re.kr
jppark@katech.re.kr
shlee2@katech.re.kr

ABSTRACT

High-voltage (HV) relays are essential in electric vehicle (xEV) power systems, but they are subject to thermal stress that accelerates contact degradation and can cause severe failures such as power outages or fires. Monitoring internal terminal temperature is critical for early detection of such degradation, yet direct sensor installation is restricted by packaging, cost, and sealing constraints. To overcome this limitation, we propose a hybrid Virtual Thermal Sensor (VTS) that estimates internal relay temperatures using only external signals, including ambient temperature, busbar temperature, coil voltage, and load current. The framework integrates a physics-based RC thermal circuit State-Space Model (RC-SSM) with a residual Temporal Convolutional Network (TCN), where the RC-SSM provides baseline thermal behavior and the residual TCN compensates for modeling inaccuracies through multivariate time-series learning. Experimental evaluation was conducted using accelerated life test data collected under controlled environments and high-current conditions, with a total of six multivariate variables, including load current and busbar temperature. For ground truth, thermocouples were inserted inside terminals via special machining to measure internal temperatures. Compared to existing related studies, our hybrid VTS demonstrated superior performance in both prediction sensitivity and steady-state stability. The proposed technology is applicable to HV relays and other components where internal temperature measurement is not feasible, providing a robust foundation for state estimation and fault prognosis.

1. INTRODUCTION

HV relays are essential components of xEV power conversion systems, serving to maintain or interrupt the flow of current between the HV battery and the inverter. The operational reliability of HV relays has a direct impact on vehicle performance and safety, making the early diagnosis and management of potential failures critically important. Among various environmental stresses, thermal stress exerts a dominant influence on the performance degradation of HV relays. At the electrical contact interface, contact resistance is formed, and when high current is applied, resistive heating occurs, leading to a rise in temperature. This, in turn, accelerates the thermal degradation of surrounding polymer materials and can cause deformation of internal structures, resulting in abnormal opening or short-circuiting. Such failures can lead to serious safety issues at the vehicle level, including system power shutdowns or component damage.

Monitoring the temperature of internal electrical contact surfaces is essential for the early detection of thermal degradation. However, installing sensors directly inside a sealed relay housing is often impractical due to packaging constraints, sealing requirements, insulation design considerations, and cost limitations. External temperatures such as those measured at the busbar or housing surface can be obtained relatively easily, but they do not accurately reflect the actual thermal state at the internal contact interface. Consequently, reliably estimating internal terminal temperature under sensor placement constraints is becoming increasingly important for effective relay condition monitoring. To address this challenge, VTS (Shin, Ko, & So, 2022) (Ahn, Oh, Kim, Park, & Kim, 2022) have been investigated as a non-intrusive temperature estimation technology that infers internal thermal states from measurable external signals. Traditional physics-based models such as RC thermal circuits (Silva, 2022) offer physically interpretable results and stable long-term trends, but they struggle to capture nonlinear effects, material degradation, and transient dynamics under diverse operating conditions. In contrast, data-driven models(e.g., RNN/LSTM/TCN) can directly learn complex patterns from data but risk overfitting and lack physical consistency.

Sewoong Gim et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

This study proposes a hybrid VTS framework that integrates an RC-SSM with a residual TCN (van den Oord et al., 2016) (Bai, Kolter, & Koltun, 2018) to estimate the internal contact temperature of relays, which is difficult to measure directly, using measurable parameters. To address the degradation in prediction accuracy caused by outliers in time-series forecasting, a preprocessing method based on temperature fluctuation characteristics is applied. The RC-SSM generates baseline temperature estimates grounded in physical heat transfer dynamics, ensuring stability under steady-state conditions, while the residual TCN learns to compensate for dynamics that are difficult to model and nonlinear effects, improving sensitivity during dynamic transitions. This hybrid approach is designed to overcome the limitations of single-model methods and provides a robust and accurate solution for real-time thermal estimation and health monitoring of HV relays in practical operating environments. The main contributions of this study are as follow:

- A novel VTS model combining RC-SSM and residual TCN was developed to reliably estimate the internal temperature of a relay.
- Accurate estimation of internal temperature from only measurable parameters eliminates the additional processing and cost constraints of direct sensing.
- The proposed model is designed to be expandable beyond hardware relays to other sealed applications where internal temperature measurement is not possible, demonstrating high versatility and scalability.

The rest of this paper is organized as follows. Section 2 presents the methodology of this study, including data preprocessing, the design of the RC-SSM, the design of the TCN model, and the integration of these into the hybrid model. Section 3 describes the experimental study, and finally Section 4 concludes the paper.

2. METHODOLOGY

The following section presents the overall methodology for developing the proposed VTS framework, which combines a physics-based RC-SSM with a residual TCN for multivariate time-series prediction. The workflow consists of four main stages:

1. Raw data acquisition and preprocessing (sequence structuring, outlier removal)
2. RC thermal model estimation using steady-state padding and N4SID-based RC-SSM
3. TCN modeling with dilated causal convolutions for sequence-to-sequence prediction
4. Hybrid integration of RC-SSM with Residual TCN with performance evaluation

Figure 1 summarizes the pipeline.

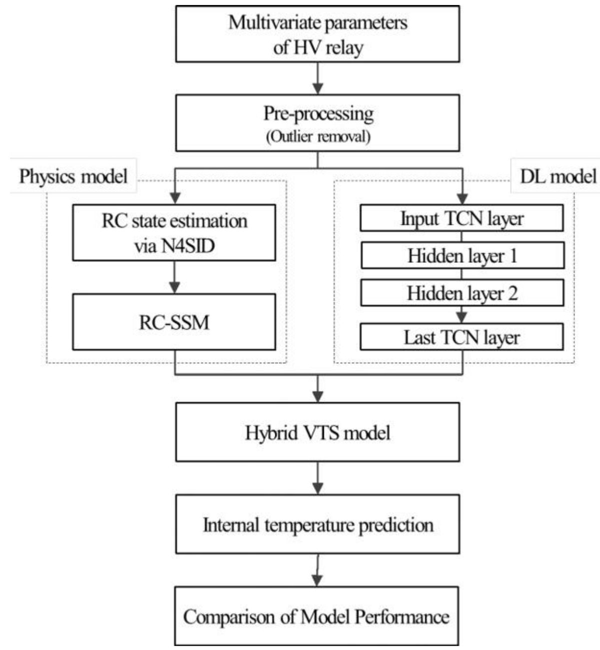

Figure 1. Overall workflow.

2.1. Data Preprocessing

Measured data can be contaminated by outliers due to environmental factors, sensing errors, and electrical noise. Such an outlier can degrade the model accuracy during training. Therefore, by removing outliers from the input dataset, the model learns only the data that are meaningful and relevant to the target prediction. In this study, outlier detection is performed based on the fluctuation pattern of "temperature" (Liu, Yang, Zhang, Gao, & Li, 2023). The temperature gradient between consecutive samples is calculated and any value exceeding a predefined threshold is considered abnormal and removed from the dataset. The dataset is segmented into multiple sequences, where each sequence contains time-continuous operational data without any interruptions or missing segments. This ensures that the temporal dependencies required for multivariate time-series learning are preserved, enabling the model to accurately capture both short-term and long-term dynamics for precise internal temperature estimation.

2.2. RC-SSM (RC Thermal Circuit State-Space Model)

To establish a physically interpretable baseline for internal temperature prediction, we model the relay's internal contact node using a lumped RC thermal circuit (Fig. 2) (Liu et al. 2023). With ambient temperature T_1, internal temperature T_2, thermal resistance R_{th}, and thermal capacitance C_{th}, the governing equation is expressed by Eq. (1):

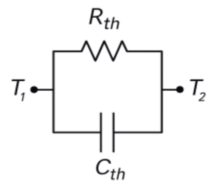

Figure 2. Equivalent RC thermal circuit.

$$C_{th}\,\frac{d(T_2-T_1)}{dt} = P_{contact}(t) + P_{coil}(t) - \frac{T_2-T_1}{R_{th}} \quad (1)$$

The coil power is directly measurable, $P_{\mathrm{coil}}(t) = V_{\mathrm{coil}}(t)\, I_{\mathrm{coil}}(t)$. When the contact resistance is unavailable, the contact heating is approximated as $P_{\mathrm{contact}}(t) \approx k\, I_{\mathrm{load}}^2(t)$, which is consistent with Joule heating and is practical for sealed relays.

From cooling segments ($I_{\mathrm{load}} \approx 0$), we fit exponential decays to estimate a representative time constant τ. From steady-state heating, the temperature rise ΔT_{ss} is obtained by Eq. (2):

$$\Delta T_{ss} \approx a\, I_{\mathrm{load}}^2 + b\, P_{\mathrm{coil}} \quad (2)$$

which decouples $R_{\mathrm{th}} = b$ and $k = a/b$. Finally, $C_{\mathrm{th}} = \tau / R_{\mathrm{th}}$. Applying this procedure yields the parameters in Table 1. These values are physically plausible for a terminal and busbar assembly, indicating that the simplified RC model captures the effective thermal behavior.

Table 1. Estimated RC thermal parameters.

Parameter	Value	Unit
R_{th}	5.6072	°C/W
C_{th}	100.9	°C
$\tau = R_{\mathrm{th}} C_{\mathrm{th}}$	566.0	s

To incorporate multivariate excitations and higher-order dynamics, we further identify a discrete-time state-space model using the N4SID (Numerical Algorithms for Subspace State Space System Identification) method (Fig. 3) ((van Overschee & de Moor, 1993):

$$x_{t+1} = Ax_t + Bu_t \quad (3a)$$

$$y_t = Cx_t + Du_t \quad (3b)$$

Where:

x_t : State vector at time step t

u_t : Input vector at time step t

y_t : Output scalar at time step t

$A \in \mathbb{R}^{3\times3}$: State-transition matrix

$B \in \mathbb{R}^{3\times6}$: Input matrix

$C \in \mathbb{R}^{1\times3}$: Output matrix

$D \in \mathbb{R}^{1\times6}$: Direct-feedthrough matrix

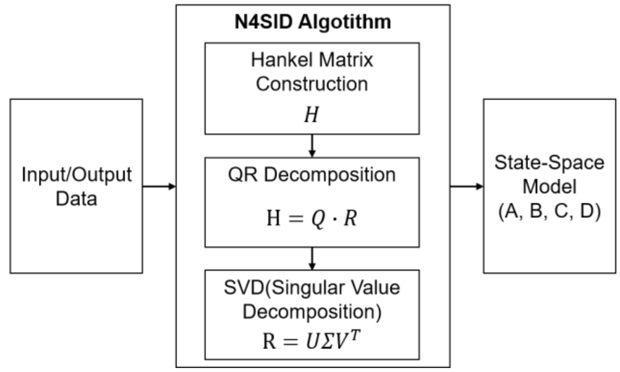

Figure 3. Structure of the N4SID Algorithm.

Before identification, each sequence is prepended with a constant-temperature segment. This "steady-state padding" allows the observer state x_0 to converge to a realistic condition before dynamic variations occur, improving stability and accuracy.

In summary, the RC-SSM combines effective single-lump parameters $(R_{\mathrm{th}}, C_{\mathrm{th}}, \tau)$ with an N4SID-based multivariate realization (A, B, C, D). The former provides physical interpretability, while the latter captures data-driven dynamics. This stable baseline will be extended with a residual TCN in Section 2.4 to enhance dynamic sensitivity.

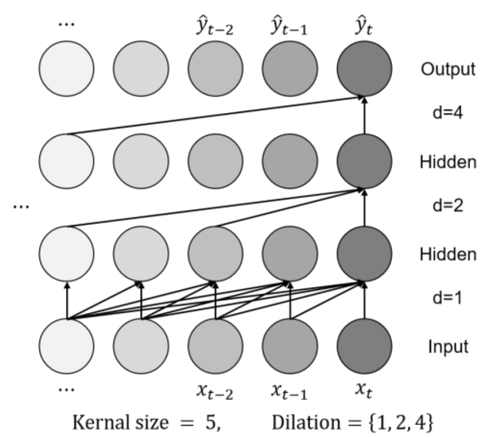

Figure 4. Structure of TCN (Kernal size = 5, Dilation={1, 2, 4})

2.3. TCN(Temporal Convolutional Network) Model

The TCN is a convolution-based architecture widely applied in time-series forecasting due to its ability to efficiently capture both short- and long-term temporal dependencies. Unlike recurrent neural networks, TCN processes all time steps in parallel, which enables faster training and inference while avoiding issues such as vanishing or exploding

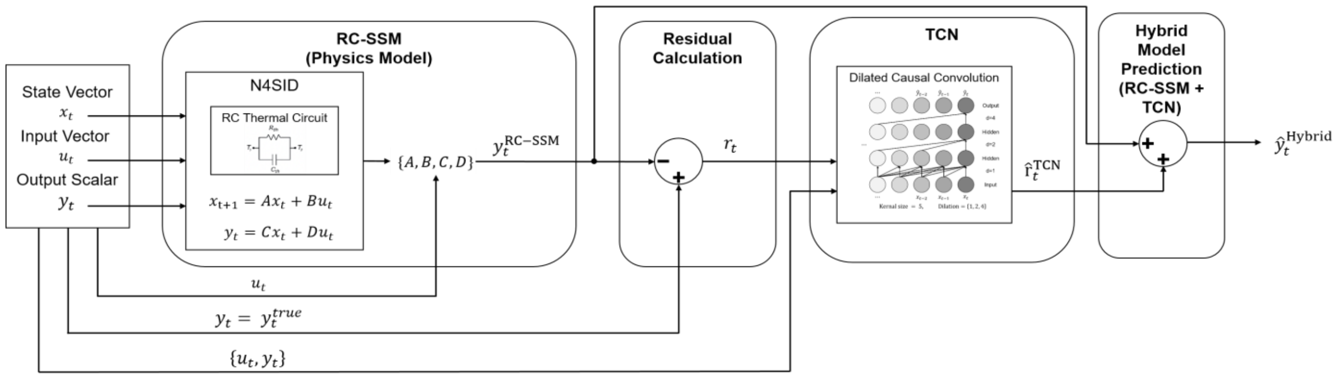

Figure 5. Structure of hybrid VTS model (RC + Residual TCN).

gradients. A central characteristic of TCN is the use of causal convolutions, which ensure that the output at time step t depends only on the current and past inputs, thereby preserving the chronological order of the data. This can be expressed as Eq. (4) (Bai et al. 2018):

$$y_t = \sum_{i=0}^{k-1} w_i \cdot x_{t-i} \tag{4}$$

Where:

x_t : Output feature at time step t

k : Kernel size (number of taps

w_i : Convolution weight at lag i

x_{t-i} : Input at lag i (from time $t - i$)

To expand the receptive field without excessively increasing model depth, TCN employs dilated convolutions. The dilated causal convolution at time step t with dilation factor d is defined as Eq. (5) (Yu and Koltun, 2016):

$$y_t = \sum_{i=0}^{k-1} w_i \cdot x_{t-di} \tag{5}$$

Where:

d : dilation factor

In this study, the TCN architecture consists of three sequential 1D convolutional layers with a kernel size of $\boldsymbol{k} =$ 5 and dilation factors $\boldsymbol{d} \in \{1,2,4\}$, each followed by a ReLU activation. As illustrated in Figure 4, padding is applied to preserve sequence length across layers, and a final $\mathbf{1} \times \mathbf{1}$ convolution layer maps the hidden representation to the predicted temperature output.

This architecture provides several benefits. By leveraging multiple dilation factors, the network can effectively capture temporal dependencies at both short and long time horizons. The parallel processing of all time steps enhances computational efficiency, while the absence of recurrent feedback loops contributes to stable gradient propagation during training. Furthermore, the structure can be applied to sequences of varying lengths without requiring architectural modifications, making it highly flexible for different datasets and application scenarios.

2.4. Hybrid Model

While the RC-SSM provides physically interpretable and stable long-term predictions, its assumption of constant parameters and linear dynamics limits its ability to capture nonlinear effects, rapid transients, and degradation-induced changes. Conversely, the TCN excels at learning complex temporal dependencies directly from data but lacks physical constraints, which may lead to unrealistic extrapolation under unseen operating conditions. To leverage the complementary strengths of both approaches, a hybrid modeling framework is proposed in which the RC-SSM captures the dominant thermal dynamics, and a data-driven residual model corrects for its systematic errors. The overall structure of the hybrid VTS is shown in Figure 5. Let the residual at time step t be defined as Eq. (6):

$$r_t = y_t^{\text{true}} - y_t^{\text{RC-SSM}} \tag{6}$$

Where:

r_t : Temperature residual

y_t^{true}: Measured terminal temperature

$y_t^{\text{RC-SSM}}$: Temperature predicted by the RC-SSM

The residual $\mathbf{r_t}$ therefore represents the temperature component unexplained by the RC-based thermal circuit, including nonlinear heating, unmodeled thermal paths, and environmental perturbations.

A TCN is then trained to model the mapping from the original input features to $\mathbf{r_t}$. The TCN input can optionally include $\mathbf{y_t^{\text{RC-SSM}}}$ itself, enabling the network to learn correction patterns relative to the physics-based baseline. During inference, the final hybrid prediction is obtained as Eq. (7):

$$\hat{y}_t^{\text{Hybrid}} = y_t^{\text{RC-SSM}} + \hat{r}_t^{\text{TCN}} \tag{6}$$

Where:

$\hat{y}_t^{\text{Hybrid}}$: Predicted temperature by the hybrid model

$\hat{r}_t^{\text{TCN}}$: Temperature residual predicted by the TCN

Training process:

1. RC-SSM identification using N4SID with steady-state padding, producing stable baseline predictions.
2. Residual computation from measured data and RC-SSM outputs.
3. Residual TCN training to minimize the mean squared error between predicted and measured residuals.

By combining the physical consistency of RC-SSM with the flexibility of TCN, the hybrid model maintains robust long-term trends while significantly improving prediction accuracy in nonlinear and dynamic operating regions. This architecture is particularly advantageous for real-world deployment, where operating conditions may deviate from those observed during model training.

3. EXPERIMENT & RESULTS

Table 2. Categories and parameters of the test data.

Index	Category	Parameter	Unit
1	Input	Coil voltage	V
2		Load current	A
3		Coil current	A
4		Busbar temperature	°C
5		Ambient temperature 1	°C
6		Ambient temperature 2	°C
7	Target	Internal terminal temperature	°C

Table 3. Dataset summary.

Item	Value	Description
Number of sequences	994	Distinct time-series segments in the dataset
Total time steps	4,252,144	Sum over all sequences

3.1. Data Sets

In this study, an HV relay used in a power relay assembly (PRA) was employed. Relay state and environmental data obtained from accelerated high-temperature operation life tests of the HV relay were used for model training. Figure 6a, Figure 6b show the target point of the VTS and the test setup.

When a high current is applied to the relay, the circuit temperature increases due to the Joule heating principle. In this study, the relay was placed in a high-temperature environment of 60 °C and subjected to a load current of 200 A for testing. During the test, the coil voltage and current for relay operation control, the load current applied to the

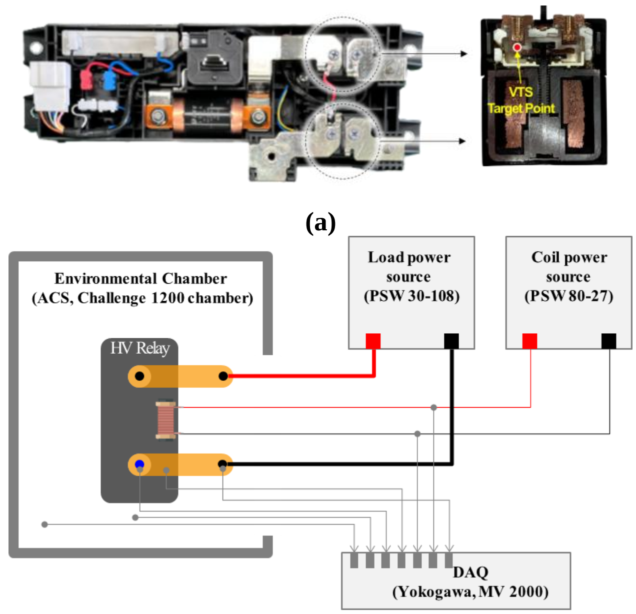

Figure 6. (a) VTS target point inside the HV relay, (b) Test setup

contacts, the chamber ambient temperature, and the temperature of the busbar connected to the terminal were measured. The target point of the VTS is the internal electrical contact temperature of the relay. To provide ground truth for the accuracy analysis of the developed prediction model, the temperature inside the terminal connected to the contact was also measured. All parameters were acquired at 1 Hz using a data logger. The categories and parameters of the test data are listed in Table 2.

The entire dataset consists of 994 sequences, where the number of time steps in each sequence varies and the operating conditions differ. Among these sequences, 25 were carefully selected to capture representative characteristics and used exclusively for testing. The remaining sequences were then divided into 80% for model training and 20% for model validation in this study. Table 3 shows the composition and size of the dataset.

3.2. Evaluation Results

To qualitatively assess the prediction performance of the three models (RC-SSM, TCN, and the proposed Hybrid model), four representative validation sequences with distinct thermal behaviors were selected. Figure 7(a)-(d) show the comparison between the measured internal terminal temperature (Ground-truth) and the predicted values from each model.

- Sequence 1:

  This case corresponds to a scenario where the relay is energized, causing a temperature rise due to Joule

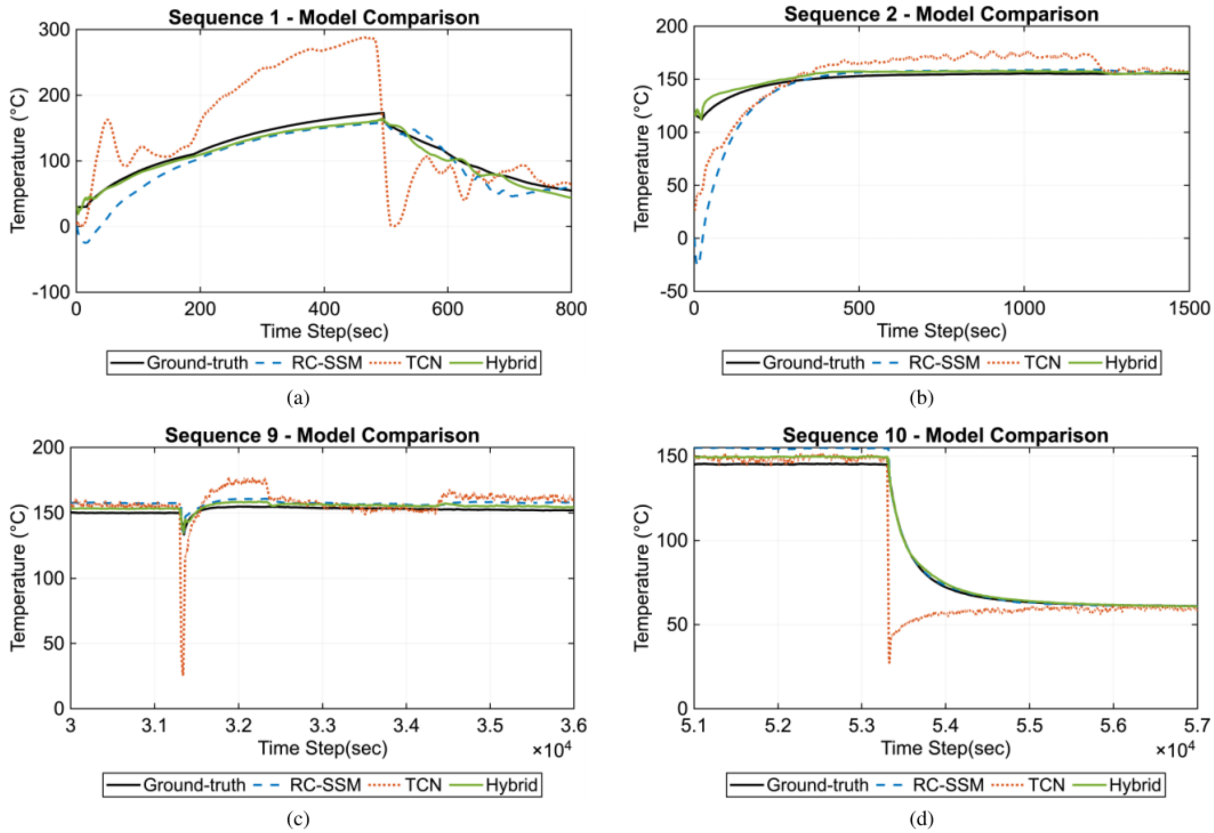

Figure 7. Comparison between ground truth and model predictions for representative sequences: (a) Temperature rise and subsequent decay after current application; (b) Initial heating after current application; (c) Relay off–on switching after thermal saturation; (d) Cooling to ambient temperature after thermal saturation.

heating, followed by a cooling phase after the load current is removed. The RC-SSM captures the general long-term trend but underestimates the initial heating rate. The TCN-only model responds quickly to changes but exhibits significant oscillations in the cooling phase. The Hybrid model closely follows both the heating and cooling transitions, achieving high fidelity in both steady-state and transient periods.

- Sequence 2:

  When the relay is turned on, the temperature rises sharply before stabilizing. RC-SSM predictions lag during the early heating phase, while the TCN-only model captures the fast rise but produces minor overshoots. The Hybrid model successfully reproduces the rapid initial temperature increase and the subsequent steady-state plateau with minimal deviation.

- Sequence 9:

  In this case, the relay is operated under continuous load until thermal saturation, then briefly turned off and on again. RC-SSM predictions track the overall trend well but exhibit slight residual errors, particularly during the transient phases, resulting in continuous small discrepancies between predicted and actual temperatures. The TCN-only model reacts quickly but overshoots during the transient. The Hybrid model effectively tracks the abrupt temperature dip and recovery while maintaining accuracy in the saturated state.

- Sequence 10:

  After the relay reaches thermal equilibrium under load, the load current is removed, and the temperature decreases toward the chamber's ambient temperature. RC-SSM accurately follows the cooling trend but exhibits small residual errors that persist during the saturation state. The TCN model captures the initial temperature drop but produces a pronounced undershoot during the cooling phase, leading to unrealistic predictions of low temperatures before settling. The Hybrid model maintains close agreement with the ground truth throughout the entire cooling process.

Across all four representative sequences, the Hybrid model consistently outperforms the individual RC-SSM and TCN-only models. By leveraging the RC-SSM's stability in steady-state conditions and the TCN's adaptability in dynamic transitions, the Hybrid approach achieves superior tracking performance in both transient and equilibrium regimes.

Table 4. Dataset summary.

Model	Type	RMSE	MAE	R^2
RC-SSM	Physics-only	8.081	5.601	0.918
TCN	Deep learning	10.725	7.158	0.856
RC + TCN (Optimized)	Hybrid	4.710	2.946	0.970

3.3. Performance Comparison (RMSE, MAE, R^2)

To quantitatively evaluate the three models (RC-SSM, TCN, and the Hybrid model), we compute the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) on the validation dataset, and the results are summarized in Table 4.

The RC-SSM exhibits stable long-term prediction capability, but shows relatively higher errors due to its inability to capture nonlinear dynamics and rapid transients. The TCN-only model exhibits a higher overall error than RC-SSM in this dataset, despite its high responsiveness in dynamic regions, and it is more sensitive to unseen operating conditions, sometimes producing overshoots or undershoots. The hybrid model achieves the lowest RMSE and MAE while obtaining the highest R^2 value, indicating superior predictive accuracy under both steady-state and dynamic operating conditions. This confirms that combining the physical interpretability of RC-SSM with the adaptive learning capacity of TCN results in a more robust and accurate prediction framework.

4. CONCLUSION

This study proposed a Hybrid VTS framework that integrates a physics-based RC-SSM with a data-driven TCN to estimate the internal terminal temperature of an HV relay under limited sensor availability. The RC-SSM provides physically interpretable and stable long-term predictions, while the TCN compensates for nonlinear behaviors, rapid transients, and environmental effects not captured by the physics model. Using data from accelerated high temperature operation life tests, the proposed model was shown to outperform RC-SSM and TCN-only approaches in both steady-state and dynamic regimes, achieving the lowest RMSE and MAE and the highest R^2 among the compared methods. Although the proposed framework demonstrated high prediction accuracy, it was trained and validated only on a single relay, and therefore its performance has not been verified for relays with different specifications, load profiles, or environmental conditions. Furthermore, the RC-SSM parameters were treated as constant, which may limit its ability to reflect degradation-induced changes over extended operation. Future work will address these limitations by incorporating adaptive parameter identification into the RC-SSM, applying transfer learning to adapt the TCN across different relay types, and employing domain adaptation techniques for deployment in real-world field environments. The results of this study suggest that hybrid VTS can be effectively integrated into EV battery management systems (BMS) and PRA to enable real-time internal temperature estimation without direct sensing. Beyond HV relays, the framework has potential applications in predictive maintenance and health monitoring of HV switching devices, contactors, and power electronic modules where accurate internal thermal state estimation is essential to ensure safety, reliability, and extended service life.

ACKNOWLEDGEMENT

This study was supported by the Hyundai Motor Group (HMG) (Grant No. TM00047501) and the Korea Institute for Advancement of Technology (KIAT) (Grant No. RS-2025-25397256)

REFERENCES

Chen, W., (1991). *Nonlinear Analysis of Electronic Prognostics.* Doctoral dissertation. The Technical University of Napoli, Napoli, Italy.

Ahn, C.-U., S. Oh, H.-S. Kim, D. I. Park, and J.-G. Kim. 2022. "Virtual Thermal Sensor for Real-Time Monitoring of Electronic Packages in a Totally Enclosed System." *IEEE Access* 10: 50589–600. https://doi.org/10.1109/ACCESS.2022.3174287.

Bai, S., J. Z. Kolter, and V. Koltun. 2018. "An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling." *arXiv Preprint arXiv:1803.01271*. https://arxiv.org/abs/1803.01271.

Liu, J., D. Yang, K. Zhang, H. Gao, and J. Li. 2023. "Anomaly and Change Point Detection for Time Series with Concept Drift." *World Wide Web* 26: 3229–52. https://doi.org/10.1007/s11280-023-01181-z.

Shin, S., B. Ko, and H. So. 2022. "Noncontact Thermal Mapping Method Based on Local Temperature Data Using Deep Neural Network Regression." *International Journal of Heat and Mass Transfer* 183: 122236. https://doi.org/10.1016/j.ijheatmasstransfer.2021.122236.

Silva, D. 2022. "Modeling the Transient Response of Thermal Circuits." *Applied Sciences* 12 (24): 12555. https://doi.org/10.3390/app122412555.

van den Oord, A., S. Dieleman, H. Zen, et al. 2016. "WaveNet: A Generative Model for Raw Audio." *arXiv Preprint arXiv:1609.03499*. https://arxiv.org/abs/1609.03499.

van Overschee, P., and B. de Moor. 1993. "N4SID: Numerical Algorithms for State Space Subspace System Identification." IFAC Proceedings Volumes 26 (2, Part 5): 55–58. https://doi.org/10.1016/S1474-6670(17)48221-8

Yu, F., and V. Koltun. 2016. "Multi-Scale Context Aggregation by Dilated Convolutions." arXiv Preprint arXiv:1511.07122. https://arxiv.org/abs/1511.07122.

BIOGRAPHIES

Sewoong Gim received his B.S. degree in Mechanical Engineering from Jeonbuk National University, Jeonju, South Korea, in 2023. Since 2023, he has worked at the Reliability R&D Division of the Korea Automotive Technology Institute (KATECH), Cheonan, South Korea, where he is currently a researcher. He is currently pursuing an M.S. degree in Automotive Engineering from Hanyang University, Seoul, South Korea. His research interests include failure-based lifetime prediction, prognostics and health management (PHM), deep learning–based data augmentation, and transfer learning.

Jaephil Park received his B.S., M.S., and Ph.D. degrees in Mechanical Engineering from Pusan National University, Busan, South Korea, in 2015, 2018 and 2022, respectively. Since 2023, he has worked at the Reliability and Certification Research Laboratory of the Korea Automotive Technology Institute (KATECH), Cheonan, South Korea, where he is currently a senior researcher. His research interests include modeling of degradation phenomena with both physics and measured data.

Sanghoon Lee received his B.S. and M.S. degrees in Automotive Engineering from Kookmin University, Seoul, South Korea, in 2008 and 2009, respectively. From 2009 to 2011, he worked as a research engineer at the Korea Institute of Science and Technology (KIST), Seoul, South Korea. Since 2011, he has worked at the Reliability and Certification Research Laboratory of the Korea Automotive Technology Institute (KATECH), Cheonan, South Korea, where he is currently a principal researcher. He is currently pursuing a Ph.D. degree in mechanical engineering from Yonsei University, Seoul, South Korea. His research interests include failure-based lifetime prediction and the health management of automotive systems.