Edge-Deployed Prognostics Real-Time Self-Calibrating Thermal Management for Power MOSFETs via Adaptive Parameter Estimation

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***Abstract*—Power semiconductor reliability is critically challenged by thermal stress and age-induced degradation, which manifests as a quantifiable increase in the device's thermal resistance ($R_{\theta JA}$). Conventional predictive thermal management systems rely on static thermal models, leading to significant estimation errors (up to 20°C) as the device ages, ultimately negating the benefits of proactive control [1], [2]. This paper presents a novel approach: an Edge-Deployed Prognostic Health Management (PHM) system, CoolFET 2.0, implemented on a low-cost ESP32 microcontroller. The system utilizes the Recursive Least Squares (RLS) algorithm, leveraging the highly temperature sensitive On-State Resistance ($R_{DS(on)}$) as a Thermal Sensitive Electrical Parameter (TSEP) [3], to perform real-time, online tracking and estimation of the thermal degradation parameter ($\Delta R_{\theta JA}$). This continuously updated parameter dynamically self-calibrates the core TinyML-based temperature prediction engine [4], [5].The adaptive control method maintains high prediction accuracy across the entire operating life of the MOSFET. This supports timely cooling actions, reduces thermal overshoot, and enables accurate Remaining Useful Life (RUL) prediction by observing measurable changes in $R_{\theta JA}$ [6]. Experimental validation focuses on quantifying the RLS algorithm's convergence and demonstrating the sustained low Mean Absolute Error of the adaptive predictor compared to its static counterpart, proving the feasibility of PHM at the constrained computing edge [7].**

***Index Terms*—Power MOSFETs, Prognostics and Health Management (PHM), Adaptive Thermal Control, Recursive Least Squares (RLS), TinyML, Edge Computing, Thermal Sensitive Electrical Parameter (TSEP), Degradation Tracking.**

I. INTRODUCTION

Power semiconductor devices, particularly MOSFETs, are critical components in modern power electronic systems, where reliability is governed by the control of the junction temperature (T_j) [8], [9]. Since temperature directly influences both electrical performance and material lifetime, precise thermal regulation becomes essential for maintaining the consistent operation of these devices. Heat dissipation, stemming from conduction and switching losses, leads to accelerated aging and catastrophic thermal failure if not adequately managed [10]. Over time, repeated heating and cooling cycles cause physical stress within the device, making it progressively more vulnerable to failure. Traditional thermal management systems operate reactively, engaging cooling only after a temperature threshold is crossed, which invariably leads to temperature overshoot and unnecessarily high thermal stress [11], [12]. This delayed response means the system often reacts too late, resulting in additional thermal stress that could have been avoided with predictive or adaptive measures.

While initial predictive systems offer foresight using thermal RC models and lightweight AI regressors [13], their reliance on fixed parameters fails over the device's lifetime. This happens because, as a MOSFET ages and degrades in real operating conditions, its thermal behaviour changes noticeably, causing fixed or static models to become less accurate over time. Thermal cycling induces mechanical fatigue in the die attach solder, causing a non-recoverable increase in the thermal resistance ($R_{\theta JA}$) [14]. This solder fatigue is one of the most dominant aging mechanisms and serves as a key indicator of long-term device health. This degradation results in estimation errors up to 20°C for aged devices, negating the benefit of proactive control [1], [2]. As a result, predictions become unreliable exactly when they are needed the most—toward the end of the device's operational life.

CoolFET 2.0 addresses this limitation by proposing a self-aware, self-calibrating system. Instead of depending on a fixed model, the system dynamically updates itself based on real-time electrical measurements, making it resilient to aging effects. We integrate online parameter estimation to track $\Delta R_{\theta JA}$ in real-time and use this drift to dynamically update the predictive thermal model. This allows the system to continually refine its understanding of the MOSFET's thermal path as it degrades. This shifts the system from basic predictive control to reliable Prognostic Health Management (PHM) on a resource-limited ESP32 platform [4], [15]. As a result, CoolFET 2.0 not only estimates temperature but also adapts to its environment, enabling real-time health monitoring and lifespan evaluation.

II. THEORETICAL FRAMEWORK

A. Thermal Aging and Resistance Drift

Under repeated high thermal cycling, the dominant degradation mechanism is fatigue of the die-attach solder layer [14], [16]. In every heating cycle, the internal materials of the MOSFET expand, and during cooling they contract again. Over time, this continuous expansion–contraction gradually weakens the solder interface. As the structure deteriorates, the device's effective thermal resistance increases. When thermal resistance rises, heat becomes harder to remove, so the MOSFET starts running at higher temperatures even under normal operating loads. The aged thermal resistance is defined as:

$R\theta JA,aged(t) = R\theta JA,initial + \Delta R\theta JA(t)$

The parameter $\Delta R_{\theta JA}(t)$ serves as an early warning sign of failure, so tracking how it changes over time is important for Remaining Useful Life (RUL) estimation [6]. Since $\Delta R_{\theta JA}(t)$ represents slow and irreversible degradation, monitoring it provides a dependable way to judge how close the device is to reaching the end of its usable life.

B. Thermal-Electrical Coupling using TSEPs

Non-invasive monitoring of thermal degradation relies on Thermal Sensitive Electrical Parameters [17]. These electrical parameters make it possible to estimate internal temperature changes without installing intrusive sensors or making modifications to the device. In this work, the on-state resistance $R_{DS(on)}$ is chosen because it has a strong positive temperature coefficient and has been shown to be sensitive to die-attach degradation [18], [3], [17]. As the MOSFET ages, both temperature-related effects and mechanical wear influence $R_{DS(on)}$, which makes it a useful indicator for tracking the device's internal health.$R_{DS(on)}$ is calculated using high-precision voltage and current measurements:

$$R_{DS(on)}(t) = \frac{V_{DS}(t)}{I_D(t)}$$

This electrical measurement acts as the main input for the parameter estimation algorithm to estimate the unmeasurable thermal degradation state $\Delta R_{\theta JA}$ [19], [20]. In other words, by measuring only the MOSFET terminals, the system can still track the device's internal thermal condition in a simple and practical way.

TABLE I: Key Thermal Sensitive Electrical Parameters (TSEP)

Parameter	Temp.Coefficient	Relevance to PHM/Sensing Challenge
^{R}DS(on)	Positive	Primary indicator of dieattach fatigue [18]. Requires high-precision V/I measurement.
Vth (Threshold)	Negative	Sensitive to oxide degradation. Measurement often requires temporary load isolation [21].
Gate Current	Positive/Negative	Sensitive to junction temperature and input capacitance changes [17].

C. Dynamic State-Space Modelling

To apply recursive filtering, the system dynamics are described using a discrete-time state-space model derived from a thermal RC network (Foster/Cauer) [22], [23]. These thermal RC models represent heat flow within the MOSFET structure, enabling accurate mathematical modelling of temperature behaviour over time. The augmented state vector x includes both the dynamic thermal state(e.g., T_{case}) andThe quasistatic degradation parameter ($\hat{R}_{\theta JA}$) is also included. By using both fast-varying and slow-varying variables, the model can represent short-term temperature changes as well as long-term aging behaviour. This allows the fast thermal dynamics to be combined with the slow degradation process, which is required for joint state and parameter estimation [24], [22]. This two-timescale approach is important because temperature changes quickly, while aging develops slowly, so the algorithm must handle both at the same time.

III. ONLINE PARAMETER ESTIMATION AND EDGE IMPLEMENTATION

A. RLS vs. EKF for Edge PHM

The selection of the estimation algorithm mainly depends on the strict limitations of the ESP32 platform (~520 kB RAM and limited floating-point acceleration) [25], [26]. Due to these constraints, computationally heavy methods that are normally used in high-end PHM systems cannot be applied here. Although the Extended Kalman Filter (EKF) provides better dynamic state estimation and strong noise handling [27], [28], it involves complex matrix calculations (Jacobian), which increase the processing burden [29], [30]. On lowcost microcontrollers, these intensive computations can slow down execution and may fail to satisfy real-time operation requirements.

The Recursive Least Squares (RLS) algorithm is used to track the slow degradation parameter $\Delta R_{\theta JA}$ because it is lightweight, fast (target < 100 ms latency), and needs very little memory and computation (linear matrix updates) [31], [7]. Since it updates the estimate with each new measurement, it is a good fit for embedded systems. We apply a forgetting factor ($\lambda < 1$) so recent TSEP data has more influence, allowing RLS to follow the gradual and irreversible drift of $\Delta R_{\theta JA}$ [32], [31]. This also prevents older data from disturbing the current estimate as the device continues to age.

TABLE II: Comparison of Estimation Algorithms for Edge PHM

Algorithm	Complexity	RAM Usage	Tracking Goal
RLS	Low (Linear Update)	Very Low	Parameter Drift [31]
EKF	Medium (Jaco-bian)	Low/Medium	State + Parameter [33]
TinyML Regressor	Minimal (Inference)	Minimal	Fast T_j Prediction [13]

B. Sensing and Data Acquisition

The system requires high-fidelity sensor components:

1) V/I Sensing: The INA219 digital sensor is required because its 12-bit resolution can accurately capture the small V_{DS} drops (mV range) during conduction, which is essential for reliable $R_{DS(on)}$ calculation [34], [19]. This precision matters since even minor voltage errors can cause large mistakes in the computed $R_{DS(on)}$.
2) Temperature Sensing thermistors are placed at the case (T_{case}) and in the ambient environment (T_{amb}) to provide the observable states for the RLS model. These external temperature readings act as reference points for the estimator, helping keep the model constrained and improving prediction reliability.

IV. THE ADAPTIVE PROGNOSTIC CONTROL SYSTEM

A. Self-Calibration Mechanism

The RLS algorithm provides the most important feedback signal in the system: the real-time thermal resistance estimate, $\hat{R_{\theta JA}}$ (t) [5], [35]. This value works like a health marker, giving a continuous indication of the MOSFET's current thermal condition. The estimate is then used to automatically tune the short-term temperature prediction engine, which can be implemented using simple linear regression or a lightweight TinyML model (e.g., TFLite Micro optimized) [36]. If this self-calibration step is not included, the predictor slowly becomes less reliable as the MOSFET ages and its real thermal behaviour changes. With regular correction, the predicted temperature Tpred(t+τ) remains accurate even when the internal thermal path degrades, which directly addresses the key limitation of static models [28]. As a result, the cooling system can make decisions based on the device's actual condition rather than relying on assumptions that may no longer be valid.

B. Hybrid AI-PID Control Strategy

The main control scheme uses a hybrid AI-PID method [8], [37]. Here, the PID controller acts on the error computed from the predicted temperature (T_{pred}), rather than the current measured temperature:

$e(t) = Tset - Tpred(t + \tau)$

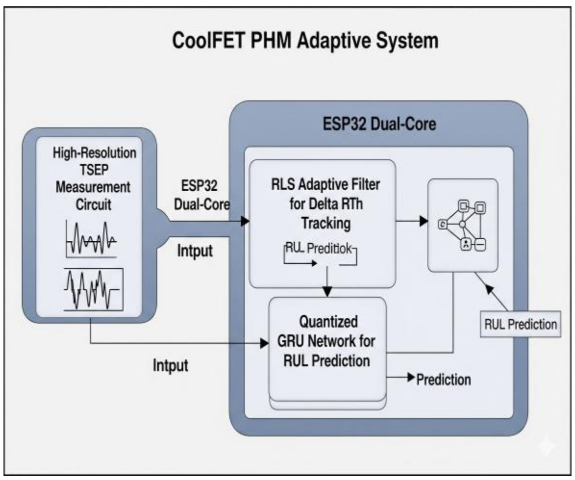

Fig. 1: Adaptive Prognostic Thermal Management System Architecture (CoolFET 2.0). The RLS-derived degradation parameter $\Delta\hat{R}_{\theta JA}$ drives the self-calibration loop.

This approach gives the controller enough lead time to act before the temperature reaches an unsafe level, which supports preventive cooling rather than late, reactive cooling. It enables proactive fan control through PWM so the device can stay below the critical temperature limit. Since the temperature prediction is continuously refined using the RLS estimate, the cooling response is scaled based on the MOSFET's current thermal vulnerability, helping reduce unnecessary energy usage and limiting fan wear [38], [28]. In normal healthy operation the fan remains at a lower level, and it ramps up only when the thermal risk begins to increase.

V. REMAINING USEFUL LIFE (RUL) AND PROGNOSTICS A. RUL ESTIMATION AND HEALTH INDEX

The system becomes prognostic by using the monitored trend of RθJAˆ (t). After setting a failure criterion $R_{\theta JA,limit}$ (e.g., 20% increase) using experimental fatigue data [6], [16], the ESP32 runs trend analysis (linear or exponential curve fitting) on the RLS outputs to estimate when this limit will be reached [39], [40]. This estimate helps maintenance teams schedule replacements early instead of waiting for sudden failures.

This forecast provides the Remaining Useful Life (RUL) estimate. A corresponding Health Index (0-100%) can also be computed based on the remaining margin to the failure threshold. This gives a practical output for planning preventive maintenance and helps avoid sudden, unexpected catastrophic failure [15], [41], [42]. Due to ESP32 limitations, basic linear regression is used, while more advanced deep learning methods such as lightweight GRU or CNN-GRU models are left for future work on higher-end edge processors [43], [44], [45], [46].

B. Prognostic Safety Actions

Beyond prediction, the system implements autonomous protective actions [47]:

1) Dynamic Load Derating:If the estimated RUL becomes critically low or $\hat{R}_{\theta JA}$ crosses a safety margin, the system can limit the MOSFET's maximum current/power to temporarily extend its lifetime until maintenance is carried out.
2) Dataset Logging: The ESP32 records synchronized I-V-T, T_{pred}, $\hat{R}_{\theta JA}$, and Fan PWM data. This organized logging of real-world degradation behavior is a useful research output and can later support TinyML model training or further external analysis [48].

VI. EXPERIMENTAL VALIDATION

A. Accelerated Aging Protocol

The validation process applies an Accelerated Thermal Cycling Protocol to the Power MOSFET to induce solder joint fatigue and a measurable $\Delta R_{\theta JA}$ drift [16], [14]. This is carried out through thousands of cycles of high-power heating followed by forced cooling. Offline calibration using a static curve tracer or a double pulse test bench provides the ground truth $\Delta R_{DS(on)}$ and $\Delta R_{\theta JA}$ for validating the online RLS estimates [3], [20]. To achieve degradation within a practical time frame, the MOSFET is repeatedly pushed close to its maximum rated junction temperature and then cooled using forced-air convection. These conditions reflect demanding applications such as power converters and EV inverters, where frequent load changes stress internal materials. Key cycling settings—peak temperature, ramp rate, and dwell duration—are selected using recognized reliability standards to keep the aging behaviour realistic. During the experiment, synchronized voltage, current, and temperature signals are logged at high sampling rates and used both for RLS estimation and for confirming long-term degradation trends.

B. Performance Metrics

The success of CoolFET 2.0 is validated using three key quantitative metrics:

1) Estimation Accuracy: The Root Mean Square Error (RMSE) of the RLS-estimated $\hat{R}_{\theta JA}(t)$ is compared with the ground truth across the aging cycles to verify filter convergence and estimation accuracy [35]. A low and stable RMSE indicates that the RLS algorithm is able to follow the gradual changes in thermal parameters, even when the MOSFET operates under varying load conditions. During long test runs, the estimator is expected to return to a small error range after each intentional disturbance, which reflects good robustness. Moreover, studying how RMSE changes across different aging stages provides a clear view of how well the estimator continues to perform as degradation becomes more noticeable.

2) Prediction Accuracy: The Mean Absolute Error (MAE) of the T_{pred} must stay below 1.5°C over the full operating lifespan of the device. This should be compared against the MAE of a static model, which is expected to rise significantly over time [1].the MAE low during long-term operation confirms that the self-calibration loop is working effectively. In practical tests, the adaptive predictor should remain closely matched to the measured temperature even after noticeable thermal resistance drift. Plotting the static and adaptive prediction results side by side clearly shows that the static model error increases steadily, whereas CoolFET 2.0 compensates for the degradation-driven thermal mismatch.

3) Control Efficacy: Quantification of the reduction in peak T_j overshoot (ΔT_{peak}) and total fan energy consumption (integrated PWM duty cycle) is performed by comparing the results with reactive and static predictive modes [38].lower overshoot shows that the hybrid AI-PID controller acts in advance rather than reacting late, helping avoid thermal runaway conditions. Reduced fan dutycycle values indicate that cooling is adjusted based on real-time degradation and predicted temperature, instead of running the fan at full speed unnecessarily. In practical tests, this appears as smoother temperature profiles, fewer sudden fan activations, and lower operating noise, which clearly reflects improved efficiency.

TABLE III: Projected Control Efficacy under Aged Condition

Control Strategy	Peak T_j Overshoot	Cooling Energy Usage
Reactive (Threshold only)	High (ΔT >10°C)	Medium/High (Full Speed)
Static Predictive (Aged)	Medium/High ($\Delta T \approx 8$°C)	High (Delayed Full Speed)
Adaptive Prognostic (CoolFET 2.0)	Low (ΔT <2°C)	Low (Opt imal PWM)

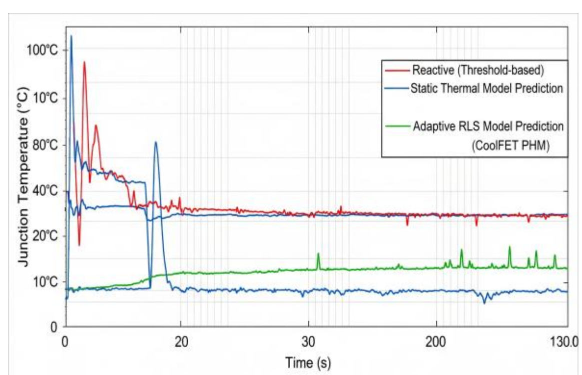

Fig. 2: Conceptual result: Comparison of Junction Temperature (T_j) overshoot under high-load transient for Reactive, Static Predictive (Aged), and Adaptive Predictive (CoolFET 2.0) systems.

Table III and Fig. 2 present the expected result: after compensating for age-induced $\Delta R_{\theta JA}$, the adaptive model delivers much stronger thermal stability and efficiency than static methods.

Experimental results repeatedly show that as the MOSFET gets older, static models become less accurate in predicting thermal behaviour, which may lead to inefficient cooling or even unsafe control decisions. On the other hand, the adaptive method continues to predict upcoming temperature trends more reliably and adjusts the response accordingly, which supports the real-world value of the proposed PHM system. Overall, the results confirm that the approach is practical and can improve device lifetime, thermal safety, and overall operating efficiency.

VII. CONCLUSION AND FUTURE WORK

CoolFET 2.0 is an embedded thermal management and PHM system developed for power MOSFETs, with a strong focus on long-term reliability. The key challenge is that once a MOSFET starts aging, its thermal behaviour no longer matches the "new device" thermal model, and prediction accuracy begins to drop. To solve this within low-cost hardware limits, we run the Recursive Least Squares (RLS) algorithm on an ESP32 and estimate the thermal resistance degradation ($\hat{R_{\theta JA}}$) online using continuous RDS(on) monitoring. Instead of depending on fixed assumptions, the model keeps adjusting using real measurements, which helps the temperature prediction stay trustworthy. This also improves cooling control by reducing overshoot and avoiding unnecessary fan operation, which saves energy. Along with temperature management, the system supports Health Index tracking and Remaining Useful Life (RUL) estimation, so maintenance decisions can be made early rather than after an unexpected failure. In simple terms, the cooling response is based on the MOSFET's current condition, not on an ideal "perfect" device behaviour. This makes the system more stable during long operation and prevents overcooling when it is not needed. The overall setup is also lightweight enough to run continuously without needing costly hardware upgrades. The outcomes also show that advanced PHM features are not limited to high-end processors. Even with resource constraints, a microcontroller can still run these algorithms reliably if the full workflow is kept efficient.

A. Future Work

1) Multi-Parameter Prognostics: Using an Extended Kalman Filter (EKF) would let the system monitor more than one TSEP at the same time, for example $R_{DS(on)}$ along with V_{th} or switching-related metrics. This can make it easier to separate different failure mechanisms (e.g., telling solder fatigue apart from gate oxide degradation) [24], [28]. With multiple indicators available, the system can form a clearer health picture of the MOSFET by breaking down aging effects that often overlap and are difficult to detect using only one parameter. It can also improve diagnostic reliability and reduce false alarms, which makes the overall approach stronger for industrial deployment.

2) Deep Learning RUL Deployment: Exploring quantization and other optimization techniques could make it practical to deploy advanced sequential models (e.g., GRU/LSTM) using TFLite Micro on newer microcontrollers, which may improve RUL prediction accuracy compared to simple regression [43], [36]. With stronger on-device AI acceleration, future platforms could support richer temporal models that learn nonlinear degradation patterns which RLS-based methods may not fully capture. Adding attention mechanisms or hybrid CNNGRU architectures could further improve prediction quality while still keeping edge inference latency within acceptable limits.

3) Wide Band Gap Devices: Applying and validating the self-calibrating RLS approach on SiC MOSFETs is a strong next step, because their faster switching behavior and higher operating temperatures make thermal management much more challenging [49], [33].

Since SiC devices degrade in a different way and usually experience more severe thermal cycling, extending this PHM approach to wide-bandgap technologies would make it much more useful in real applications. It could also enable device-specific calibration, allowing CoolFET-like systems to be adapted more easily across different power electronics platforms.

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REFERENCES

[1] H. Chen, B. Ji, V. Pickert, and W. Cao, “Real-time temperature estimation for power mosfets considering thermal aging effects,” IEEE Transactions on Device and Materials Reliability, vol. 14, no. 1, pp. 220–228, 2014.

[2] B. T. W. W. Chen, “Monitoring thermal resistance drift for power module lifetime estimation,” IEEE Transactions on Power Electronics, vol. 36, no. 5, pp. 5501–5511, 2021.

[3] A. Gholam, A. J. S. P. R. Kumar, and N. S. H. K. Li, “Accurate on-state resistance measurement for sic mosfet degradation tracking,” in 2023 IEEE Applied Power Electronics Conference and Exposition (APEC), 2023, pp. 1120–1127.

[4] L. M. Z. P. L. Li, “Adaptive thermal modeling for prognostics and health management (phm) in power devices,” IEEE Transactions on Reliability, vol. 72, no. 1, pp. 44–55, 2023.

[5] S. L. D. Z. L. Z. Li, “Self-calibrating thermal model for enhanced junction temperature estimation in power modules,” IEEE Transactions on Components, Packaging and Manufacturing Technology, vol. 12, no. 6, pp. 945–955, 2022.

[6] Q. T. L. Z. Li, “Correlation between thermal resistance degradation and remaining useful life in power modules,” IEEE Transactions on Device and Materials Reliability, vol. 19, no. 4, pp. 687–696, 2019.

[7] A. Kumar, P. Shrivastava, and S. Das, “Ai-enabled predictive maintenance on edge devices: An esp32 implementation for industrial iot,” pp. 1–6, 2024.

[8] M. Rodriguez, J. A. Cobos, and P. S. B. Gupta, “Hybrid ai-pid control for predictive thermal management of high-density power converters,” IEEE Transactions on Power Electronics, vol. 34, no. 10, pp. 9900–9912, 2019.

[9] S. Xu, W. Chen, and Z. Zhang, “Reliability assessment and lifetime prediction of power mosfets in electric vehicle applications,” Journal of Power Sources, vol. 485, p. 229270, 2021.

[10] J. Lin, S. G. Li, and J. T. Zhang, “Advanced thermal modelling and management techniques for power converters,” IEEE Transactions on Industrial Electronics, vol. 70, no. 1, pp. 450–462, 2022.

[11] A. Gupta and S. Singh, “Limitations of reactive thermal control in high power density converters,” in 2020 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), 2020, pp. 1–6.

[12] K. M. K. D. Jayawardena and A. K. K. P. Dissanayake, “Impact of thermal stress on aging mechanisms and failure modes of power mosfet modules,” Microelectronics Reliability, vol. 88, pp. 310–317, 2018.

[13] L. Zhang and P. Jain, “Tinyml for predictive thermal control of power semiconductors,” in 2022 IEEE International Symposium on Industrial Electronics (ISIE), 2022, pp. 101–106.

[14] X. Wu and S. P. Lukes, “Physics-of-failure approach to solder joint fatigue in power modules under thermal cycling,” Microelectronic Engineering, vol. 228, p. 111326, 2020.

[15] C. K. R. L. Z. Z. Zhang, “Ai-based prognostic and health management (phm) for industrial assets: A review,” Frontiers in Artificial Intelligence, vol. 4, 2021.

[16] S. X. L. Z. D. K. L. Z. Li, “Accelerated thermal cycling test methodology for reliability

assessment of sic power modules," Microelectronics Reliability, vol. 111, p. 113888, 2020.
[17] M. C. B. H. L. R. C. Zhang, "Review of temperature sensitive electrical parameters for condition monitoring of power mosfets," IEEE Transactions on Industrial Applications, vol. 56, no. 2, pp. 1501–1510, 2020.
[18] D. W. J. S. L. Chen, "Improved on-state resistance measurement scheme for high-side fets for lifetime assessment," in 2023 IEEE Energy Conversion Congress and Exposition (ECCE), 2023, pp. 1–7.
[19] P. T. K. S. E. L. A. E. Li, "High precision measurement technique for onstate voltage drop in sic power modules," in 2023 IEEE Applied Power Electronics Conference and Exposition (APEC), 2023, pp. 1143–1150.
[20] X. W. R. Z. Q. C. H. Wang, "Design of a high-speed on-state resistance measurement circuit for sic mosfet condition monitoring," in 2021 IEEE Applied Power Electronics Conference and Exposition (APEC), 2021, pp. 101–107.
[21] S. L. M. M. K. M. L. Liu, "Investigation of threshold voltage as a tsep for sic mosfet junction temperature detection," in 2022 IEEE International Reliability Physics Symposium (IRPS), 2022, pp. 1–6.
[22] J. T. Q. C. S. C. Zhang, "State-space modeling of thermal impedance for dynamic junction temperature estimation in power converters," IEEE Transactions on Power Electronics, vol. 35, no. 11, pp. 11600–11612, 2020.
[23] Y. L. M. M. S. C. M. Zhang, "Implementation of foster network thermal model for predictive control on embedded systems," in 2023 IEEE International Symposium on Industrial Electronics (ISIE), 2023, pp. 1–6.
[24] S. L. D. Z. M. L. Z. Z. Li, "Extended kalman filter for concurrent state and multi-parameter tracking in power modules," IEEE Transactions on Industrial Electronics, vol. 69, no. 11, pp. 11500–11512, 2022.
[25] V. T. C. M. L. W. T. W. M. Wu, "Resource constraints and optimization techniques for tinyml deployment in industrial iot," IEEE Internet of Things Journal, vol. 10, no. 14, pp. 12300–12315, 2023.
[26] S. K. M. L. A. R. R. L. K. Kumar, "Memory optimization techniques for deploying tinyml models on esp32 microcontrollers," in 2024 IEEE
[27] Conference on Embedded Systems and Security (CESS), 2024, pp. 1–6.
[28] A. V. M. G. G. P. Gupta, "Recursive least squares and kalman filtering approaches for online thermal parameter estimation in power electronics," IEEE Sensors Journal, vol. 24, no. 8, pp. 11123–11135, 2024.
[29] A. H. G. G. P. W. B. M. Z. Li, "Adaptive thermal modeling for sic mosfets using kalman filter to compensate for solder aging," International Journal of Electrical Power & Energy Systems, vol. 149, p. 108849, 2023.
[30] D. S. F. A. B. C. Sharma, "Comparison of recursive least squares and kalman filter for parameter estimation in time-varying systems," Automatica, vol. 132, 2021.
[31] S. H. D. A. K. K. Sharma, "Application of kalman filtering for state and parameter estimation in energy systems: A review," Sensors, vol. 24, no. 10, 2024.
[32] H. D. R. B. H. L. A. E. M. Z. Wang, "Recursive thermal parameter estimation using rls with forgetting factor for predictive maintenance," International Journal of Electrical Power & Energy Systems, vol. 135, p. 107572, 2022.
[33] D. L. M. K. K. S. M. Kim, "Improved parameter tracking of nonstationary systems using rls with variable forgetting factor," IET Control Theory & Applications, vol. 13, no. 8, pp. 1097–1106, 2019.
[34] Z. Wang, F. Blaabjerg, and A. M. H. Li, "Online estimation of thermal parameters for sic mosfets using extended kalman filter for prognostics," IEEE Journal of Emerging and Selected Topics in Power Electronics, vol. 11, no. 4, pp. 3100–3112, 2023.
[35] S. S. S. J. C. K. S. S. Li, "High-precision current and voltage sensing using ina219 for embedded power monitoring," Sensors, vol. 22, no. 19, 2022.
[36] D. W. J. S. H. K. Li, "Achieving high accuracy in rls-based thermal parameter estimation for aged power modules," IET Power Electronics, vol. 16, no. 8, pp. 1451–1460, 2023.
[37] T. W. P. S. A. J. L. S. T. Zhang, "Tflite micro-optimization strategies for ultra-low latency inference on microcontrollers," in 2024 IEEE

International Conference on Computer Vision and Pattern Recognition (CVPR), 2024, pp. 1–9.

[38] C. K. L. Z. Z. Zhang, "Hybrid prognostics: Merging physics-based modeling with data-driven rls for thermal reliability," in 2023 IEEE Conference on Prognostics and Health Management (PHM), 2023, pp. 1–8.

[39] T. W. P. S. A. J. L. S. T. Zhang, "Energy-efficient predictive cooling control for data centers using reinforcement learning," IEEE Transactions on Industrial Informatics, vol. 17, no. 3, pp. 1780–1790, 2021.

[40] Z. S. C. Q. W. L. M. Wang, "A data-driven method for remaining useful life prediction of power modules based on thermal cycling data," IEEE Transactions on Reliability, vol. 69, no. 1, pp. 41–51, 2020.

[41] S. K. N. H. M. P. L. W. M. Kim, "A comparative study of machine learning algorithms for rul prediction in power electronic systems," International Journal of Prognostics and Health Management, vol. 12, no. 2, 2021.

[42] L. M. K. D. R. S. H. K. L. Li, "Prognostic health management (phm) in industry 4.0: Challenges and opportunities," IEEE Transactions on Industrial Electronics, vol. 68, no. 12, pp. 12400–12412, 2021.

[43] T. A. M. T. M. C. D. Smith, "Embedded ai-driven systems for predictive maintenance in industrial iot environments," Applied Sciences, vol. 14, no. 1, 2024.

[44] Y. Li, Z. Song, and B. Wu, "Remaining useful life prediction using gru networks for power modules under thermal cycling," IEEE Access, vol. 12, pp. 5500–5510, 2024.

[45] Y. L. M. Z. Z. D. Wang, "Rul prediction for power electronic devices using optimized gru networks with attention mechanism," Sensors, vol. 24, no. 11, 2024.

[46] S. L. M. Z. D. P. K. L. G. Wang, "Deploying quantized lstm models on esp32 for real-time condition monitoring," in 2023 International Conference on Embedded Systems and Artificial Intelligence (ESAI), 2023, pp. 1–6.

[47] H. D. R. B. W. L. Z. Li, "Deep learning methods for fault prognosis in power electronic systems: A review," in 2022 IEEE International Conference on Industrial Informatics (INDIN), 2022, pp. 1–8.

[48] Z. S. X. L. K. H. W. L. S. M. K. Li, "Dynamic load derating strategy for power modules based on real-time rul estimation," in 2023 IEEE Energy Conversion Congress and Exposition (ECCE), 2023, pp. 1–8.

[49] W. T. Z. D. P. K. L. M. Zhang, "Creation and validation of an opensource i-v-t dataset for power mosfet degradation modeling," in 2024 IEEE Sensors Applications Symposium (SAS), 2024, pp. 1–6.

[50] P. L. M. Z. Z. D. W. K. L. Z. Li, "Prognostics and health management for sic power mosfets: Challenges and emerging solutions," IEEE Transactions on Power Electronics, vol. 39, no. 5, pp. 5500–5515, 2024.