

Random Forest-Based Early Fault Detection and Classification in DC-DC Converters Using Multi-Sensor Electrical and Thermal Features

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ABSTRACT- Intelligent condition monitoring of Direct Current (DC) to DC converters requires fault detection that is accurate, reproducible and early enough to act before conventional protection trips. This paper presents a Random Forest (RF) framework that fuses output-voltage, inductor-current and heatsink-temperature measurements of a 48 V/10 A synchronous buck converter (96 V input, 20 kHz switching, cascaded PI control). A fully specified averaged-model simulation with sensor models (10 kHz sampling) and per-run component tolerances generates 200 labelled runs (40 per class, 60 s each; 59,000 windows of 0.2 s) covering normal operation, overcurrent (13.8–15.2 A), overvoltage (55.5–59.0 V), overtemperature caused by cooling degradation, and a combined severe fault. Ten features are extracted per window, including ripple factors, ripple Total Harmonic Distortion (THD), temperature slope and a thermal-model residual. A five-class RF (128 trees, maximum depth 14) tuned by Bayesian optimisation under run-wise cross-validation achieves 97.9% accuracy and 98.1% macro-F1 on 60 independent test runs (16,843 windows), and $97.7 \pm 1.4\%$ accuracy in repeated group 5-fold cross-validation. A tuned support vector machine attains higher in-distribution accuracy (99.5%), whereas RF gives the highest mean accuracy (98.0%) under six unseen operating conditions. Fusing electrical and thermal features raises accuracy from 70.2% (electrical only) and 75.4% (thermal only) to 97.9%. With a three-window alarm rule, all 48 test faults are flagged before the conventional trip threshold is crossed, with mean lead times of 3.9 s (overcurrent), 7.5 s (overvoltage), 26.5 s (overtemperature) and 2.5 s (severe fault). A classifier-weighted Fault Severity Index (FSI) rises from 0.04 in normal operation to 2.62 under severe fault, providing a quantitative severity ranking.

Keywords: Anomaly Index, DC-DC converter, Early fault detection, Fault Severity Index, Random Forest classifier, Thermal-model residual, Sustainable Development Goal 7 (Affordable and Clean Energy), Sustainable Development Goal 9 (Industry, Innovation and Infrastructure).

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1. INTRODUCTION

DC-DC converters are a key enabling technology in renewable-energy interfaces, electric-vehicle charging, aerospace and defence electronics, industrial automation and microgrids, where monitoring must go beyond protection that acts after a major event and provide early warning for proactive maintenance [1-3]. Machine learning complements model- and

rule-based diagnosis of electrical faults, battery deviations and converter-side faults under time-varying conditions; combined electrical and thermal cues improve the visibility of abnormalities and classifiers such as SVM can extract latent fault signatures [4,5], while waveform quality, ripple and distortion remain fundamental diagnostic features [6,7]. AI-based methods are central to open-circuit fault classification in power converters [8], converter-level monitoring must remain compatible with efficiency and continuity [9], and methods developed for sensor-rich battery datasets or converter control [10-18] have not yet been combined into one compact converter-monitoring framework.

Despite these advances, three gaps remain. First, most converter-level studies classify switch open- or short-circuit faults from electrical waveforms alone [3,8,19,20], whereas thermally driven degradation such as loss of forced cooling produces almost no electrical signature until an over-temperature protection trips. Second, reported accuracies are rarely accompanied by the converter parameters, dataset size,

class distribution and data-splitting protocol needed to reproduce them, and random window-level splits can leak nearly identical samples of one run into both training and test sets. Third, classification of an already developed fault is seldom related to the instant at which threshold protection would act, so the early-warning value is not quantified. *Table 1* compares representative DC-DC converter fault-diagnosis studies with the present work.

The contributions are: (i) a fully specified 48 V/10 A synchronous buck converter simulation benchmark (*Tables 2–3*) with 200 labelled runs; (ii) a ten-dimensional electrical–thermal feature vector including a physics-based thermal residual (*Table 4*); (iii) a five-class RF classifier tuned by Bayesian optimisation under run-wise cross-validation with training-only normalisation; (iv) formal definitions of the anomaly index and a classifier-weighted Fault Severity Index (FSI); and (v) a quantitative evaluation including the numerical confusion matrix, SVM, KNN and DT baselines on identical splits, feature importance and ablation, detection lead time relative to trip thresholds, robustness to unseen conditions and inference cost.

Table 1. Comparison with related DC-DC converter fault-diagnosis studies

Ref.	Converter	Sensed signals	Fault types	Method	Data / validation	Performance
[19]	PSFB DC-DC	Transient V and I	IGBT open-circuit	Wavelet + deep feedforward network	Simulation; 30/70% split	Accuracy > 97%
[20]	PV boost	PV V, I; DC-bus V; output I	Switch/diode open/short; sensor attacks	RF (300 trees)	OPAL-RT HIL; 500 test cases	Accuracy 94.6%
[21]	PV buck-boost	I–V curve (400 features)	7 PV-side conditions	HHO + XGBoost	Experimental; 658 + 132 samples	Accuracy 99.49%
This work	Sync. buck 48 V/10 A	V, I, heatsink T	OC, OV, OT, combined severe	Bayesian-optimised RF, 10 features	Simulation; 200 runs; run-wise split; repeated group CV	Accuracy 97.9%; alarm 2.5–26.5 s before trip

2. CONVERTER CONFIGURATION, DATASET AND METHODOLOGY

Figure 1 is the measurement architecture, integrating sensing, signal conditioning and data pre-processing; its diagnostic output chain includes feature extraction, classification and maintenance-orientated functions. On the converter side, the sensors provide the output voltage, current, and temperature.

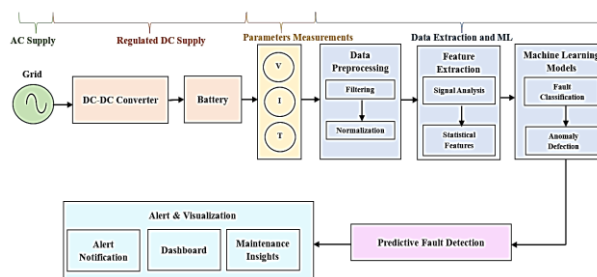


Figure 1. Overall Architecture of the Random Forest-Based Early Fault Detection System for the DC-DC Converter

2.1. Converter Configuration and Simulation Setup

The converter is a non-isolated synchronous buck converter that supplies a 48 V bus at 10 A (480 W) from a 96 V DC link produced by a three-phase transformer–rectifier (300 Hz six-pulse ripple, 6 V peak-to-peak per kW), *figure 2*. Two IRFP4668 MOSFETs switch at 20 kHz; a cascaded PI controller (outer voltage loop, inner inductor-current loop) regulates the output with a 16 A current limit, and the load is 50% resistive and 50% constant power. All parameters are listed in *Table 2*. The data were generated by simulation only: the state-space averaged model (including DCR, ESR, control, current limit, DC-link ripple, the loss model of *Eq. (10)* and the thermal model of *Eq. (9)*) was integrated with a 10 μ s forward-Euler step in Python 3.11 (NumPy, Numba) and decimated to the 10 kHz acquisition rate. The 2 kHz second-order anti-aliasing filter attenuates the unmodelled 20 kHz switching ripple by at least 40 dB. Sensor models include gain and offset errors, noise, 12-bit quantization and the NTC time constant; per-run component tolerances emulate unit-to-unit variation. Machine learning used scikit-learn 1.8 [23] and scikit-optimize 0.10.

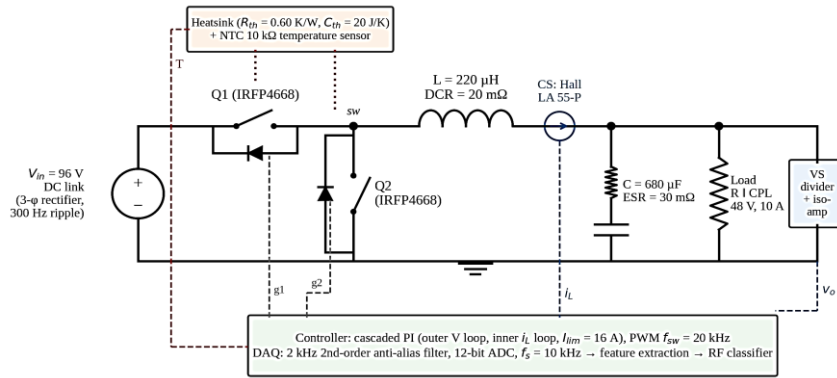


Figure 2. Synchronous buck converter with sensor placement, controller and data-acquisition chain

Table 2. Converter, control, thermal and sensing parameters used to generate the dataset.

Parameter	Value	Parameter	Value
Input voltage V_{in}	96 V (92–100 V per run)	Voltage sensor	Divider + isolated amplifier, 0–120 V
Output voltage V_{ref}	48 V	Current sensor (i_L)	Hall LEM LA 55-P, 0–50 A
Load current / power	10 A / 480 W (9–11 A per run)	Temperature sensor	NTC 10 kΩ on heatsink, $\tau = 1.5$ s
Switching frequency	20 kHz	Ambient sensor	NTC 10 kΩ
Q1, Q2	IRFP4668, 200 V, 8 mΩ, +0.7%/°C	Anti-aliasing / ADC	2 kHz 2nd order / 12-bit
$t_r + t_f; P_{fix}$	120 ns; 2.5 W	Sampling rate f_s	10 kHz
L (DCR); C (ESR)	220 μH (20 mΩ); 680 μF (30 mΩ)	Gain error (V / I)	0.5% / 0.65%
Voltage PI K_{pv}, K_{iv}	0.40 A/V, 60 A/(V·s)	Offset (V / I / T)	0.10 V / 0.10 A / 0.4 °C
Current PI K_{pi}, K_{ii}	0.020 A ⁻¹ , 20 (A·s) ⁻¹	Noise (V / I / T)	0.05 V / 0.04 A / 0.03 °C
Current limit I_{lim}	16 A	Tolerances (1σ)	L 5%, C 7%, R_{ds} 10%, R_{th} 8%
$R_{th}; C_{th}$	0.60 K/W; 20 J/K ($\tau = 12$ s)	Window / run length	0.2 s (2000 samples) / 60 s
Ambient T_{amb}	25 °C (23–27 °C per run)	Simulation step	10 μs forward Euler

2.2. Fault Classes, Dataset and Data Splitting

Five classes are defined before training (Table 3). Each fault starts at t_{on} (10–16 s), grows linearly over a ramp T_r (8–16 s) and is then held to 60 s, so the fault progress is $\rho(t) = \min\{\max[(t - t_{on})/T_r, 0], 1\}$. Normal runs contain one $\pm 10\%$ load step at a random instant so that legitimate load changes must not trigger alarms. Each run gives 295 non-overlapping 0.2 s windows after a 1 s start-up (59,000 windows in total). A window is labelled Normal before onset and with the fault class once $\rho \geq 0.3$; the 2,863 transition windows ($0 < \rho < 0.3$) are excluded from training and from the classification metrics but used in the detection analysis (Section 3.5).

To prevent leakage between adjacent windows, data are split by run, never by window: 28 runs per class form the training set and 12 runs per class the independent test set (fixed seed 42). Hyperparameters are tuned by stratified group 5-fold cross-validation within the training runs, with the run identifier as group. The normalization statistics of Eq. (3) are computed from the training folds only and frozen before any test prediction.

Table 3. Class taxonomy, fault injection and dataset (onset 10–16 s, ramp 8–16 s; windows of 0.2 s).

Class	Fault mechanism / modified parameter	Final magnitude	Runs (train/test)	Train windows	Test windows
Normal	None; one $\pm 10\%$ load step	48 V, 9–11 A	28/12	15,005	6,384
Overcurrent (OC)	Added load conductance (overload, partial short)	13.8–15.2 A (nominal 14.5 A)	28/12	6,023	2,613
Overvoltage (OV)	Voltage-feedback gain drift	55.5–59.0 V (nominal 57.5 V)	28/12	6,054	2,628
Overtemperature (OT)	Loss of forced cooling: $R_{th} \times 2.0$ –2.8	Electrical point unchanged	28/12	6,076	2,545
Severe fault	Combined: load demand 16.3–17.3 A, $R_{th} \times 1.8$ –2.4, C –40%, ESR $\times 3$	16 A current limit, voltage sag	28/12	6,136	2,673
Total	Trip thresholds (reference): 13.0 A, 55.0 V, 34.0 °C	–	140/60	39,294	16,843

2.3. Signal Processing and Feature Extraction

The measured converter state at the k -th sampling instant is represented by the sensor vector

$$\mathbf{x}(k) = \begin{bmatrix} v(k) \\ i(k) \\ T(k) \end{bmatrix} \in \mathbb{R}^3 \quad (1)$$

where $v(k)$, $i(k)$ and $T(k)$ are the output voltage, inductor current and heatsink temperature sampled at $f_s = 10$ kHz. To suppress switching noise and short-duration fluctuations, each signal is filtered by

$$\tilde{x}_m(k) = \frac{1}{L} \sum_{n=0}^{L-1} x_m(k-n), m \in \{v, i, T\} \quad (2)$$

where L is the smoothing window length ($L = 5$ samples, 0.5 ms; the 300 Hz ripple is attenuated by less than 4%). Each element of the feature vector (Table 4) is standardized as

$$\tilde{x}_m(k) = \frac{x_m(k) - \mu_m}{\sigma_m}, m \in \{v, i, T\} \quad (3)$$

where μ_m and σ_m are the mean and standard deviation computed from the training windows only and applied unchanged to test windows. The sequence is: sampling, filtering (Eq. 2), windowing, feature extraction (Eqs. 4–12), standardisation (Eq. 3). The RMS value over a window of $N = 2000$ samples is

$$X_{m,\text{rms}} = \sqrt{\frac{1}{N} \sum_{k=1}^N x_m^2(k)}, m \in \{v, i\} \quad (4)$$

and the thermal dispersion is quantified by the temperature standard deviation

$$\sigma_T = \sqrt{\frac{1}{N} \sum_{k=1}^N (T(k) - \mu_T)^2} \quad (5)$$

where μ_T is the window-mean temperature. The voltage and current ripple factors within the 0.2 s window are

$$r_v = \frac{V_{\max} - V_{\min}}{V_{\text{avg}}} \times 100 \quad (6)$$

$$r_i = \frac{I_{\max} - I_{\min}}{I_{\text{avg}}} \times 100 \quad (7)$$

The total harmonic distortion is

$$\text{THD} = \frac{\sqrt{\sum_{n=2}^{\infty} X_n^2}}{X_1} \times 100 \quad (8)$$

where X_1 is the fundamental and X_n the n -th harmonic magnitude. Here the fundamental is the 300 Hz ripple component (DC removed, Hann-windowed FFT, $n = 2-10$), so Eq. (8) gives the ripple THD (THD_v , THD_i), distinct from the ripple factors r_v , r_i . The first-order thermal dynamics are

$$C_{th} \frac{dT(t)}{dt} = P_{\text{loss}}(t) - \frac{T(t) - T_{\text{amb}}}{R_{th}} \quad (9)$$

where C_{th} , R_{th} , T_{amb} and P_{loss} are the thermal capacitance, thermal resistance, ambient temperature and power loss. eq. (9) generates the simulated heatsink temperature and, with nominal parameters, gives the healthy reference temperature $\hat{T}_h(k)$ for the thermal residual. The loss model is

$$P_{\text{loss}} = i_L^2 (2R_{ds}(T) + R_L) + \frac{1}{2} V_{in} i_L (t_r + t_f) f_{sw} + P_{fix} + i_C^2 \text{ESR} \quad (10)$$

where the factor 2 lumps the conducting MOSFET, $R_{ds}(T) = R_{ds,25}[1 + 0.007(T - 25)]$, and an equal PCB/sensor allowance. $\hat{T}_h(k)$ is obtained from Eqs. (9)–(10) with nominal R_{th} , C_{th} , driven by the measured current and ambient temperature. The thermal residual and the causal temperature slope (last five windows) are

$$r_T(k) = \bar{T}(k) - \hat{T}_h(k) \quad (11)$$

$$\dot{T}(k) = \frac{\bar{T}(k) - \bar{T}(k-5)}{5T_w} \quad (12)$$

where $\bar{T}(k)$ is the window-mean temperature and $T_w = 0.2$ s. A positive r_T indicates heating not explained by the electrical loading, i.e., cooling degradation. The RF input is the ten-dimensional vector

$$\mathbf{f}(k) = [V_{rms}, I_{rms}, r_v, r_i, \text{THD}_v, \text{THD}_i, \bar{T}, \sigma_T, \dot{T}, r_T]^T$$

(Table 4); raw samples, $A(k)$ and FSI are not RF inputs.

Table 4. Definition of the RF input feature vector $\mathbf{f}(k)$ (dimension 10; window 0.2 s unless stated)

No.	Feature	Source	Eq.	Unit	Purpose	No.	Feature	Source	Eq.	Unit	Purpose
1	V_{rms}	v	(4)	V	Voltage level	6	THD_i	i	(8)	%	Current ripple distortion
2	I_{rms}	i	(4)	A	Loading level	7	$\bar{T}$	T	mean	°C	Heatsink temperature
3	r_v	v	(6)	%	Voltage ripple	8	σ_T	T	(5)	°C	Thermal variability
4	r_i	i	(7)	%	Current ripple	9	$\dot{T}$	T	(12)	°C/s	Slope (1 s, causal)
5	THD_v	v	(8)	%	Voltage ripple distortion	10	r_T	T, i, T_{amb}	(11)	°C	Unexplained heating

2.4. Anomaly Index and Fault Severity Index

A tolerance-normalised anomaly index combining voltage, current and temperature deviations

$$iA(k) = w_v \frac{|V_{rms}(k) - V_{ref}|}{\delta_v V_{ref}} + w_i \frac{|I_{rms}(k) - I_{ref}|}{\delta_i I_{ref}} + w_T \frac{|\Delta T(k) - \Delta \hat{T}_h(k)|}{\delta_T \Delta \hat{T}_h(k)} \quad (13)$$

where $V_{ref} = 48$ V, $I_{ref} = 10$ A, $\Delta T = \bar{T} - T_{amb}$, $\Delta \hat{T}_h = \hat{T}_h - T_{amb}$, tolerance bands $\delta_v = 0.05$, $\delta_i = 0.20$, $\delta_T = 0.50$ and $w_v = w_i = w_T = 1/3$, so $A(k) = 1$ corresponds to an average deviation equal to the tolerance band. The Fault Severity Index weights $A(k)$ by the classifier's confidence that the window is not healthy and adds the unexplained heating:

$$FSI(k) = [1 - \hat{p}_N(k)]A(k) + w_r \frac{\max[0, r_T(k)]}{\Delta T_{nom}} \quad (14)$$

where $\hat{p}_N$ is the classifier posterior of the Normal class, $w_r = 0.25$ and $\Delta T_{nom} = 4.35$ °C (mean healthy rise of the training windows). $FSI < 0.1$ indicates healthy operation and $FSI > 1$ a deviation beyond the tolerance bands; because it depends on $\hat{p}_N$, FSI is computed for each classifier. Six anomaly states are used: N (normal), AN1 (incipient, $0.3 \leq \rho < 0.6$, any fault) and AN2–AN5 (fully developed OC, OV, OT and severe fault).

2.5. Random Forest Classifier, Optimisation and Evaluation Protocol

The RF [22] is a supervised five-class classifier (Normal is one of the classes, so no separate anomaly detector precedes it) formed by B trees grown on bootstrap samples with random feature subsets:

$$\hat{p}_c(k) = \frac{1}{B} \sum_{b=1}^B \hat{p}_{b,c}(\mathbf{f}(k)), \quad \hat{c}(k) = \operatorname{argmax}_c \hat{p}_c(k) \quad (15)$$

where $\hat{p}_{b,c}$ is the class- c leaf frequency of tree b . Hyperparameters were selected by Bayesian optimisation [24] (Gaussian-process surrogate, expected improvement, 10 randoms + 20 guided evaluations) minimising $1 - \text{macro-F1}$ of the group 5-fold CV on every third training window; the final model was refitted on all 39,294 training windows (Table 5). Baselines (SVM, KNN, DT) were grid-searched on the same folds and splits; Figure 3 shows the workflow. Per-class metrics follow from the one-versus-rest counts:

$$P_c = \frac{TP_c}{TP_c + FP_c}, \quad R_c = \frac{TP_c}{TP_c + FN_c}, \quad S_c = \frac{TN_c}{TN_c + FP_c} \quad (16)$$

$$F1_c = \frac{2P_c R_c}{P_c + R_c}, \quad \text{Accuracy} = \frac{1}{N_w} \sum_{c=1}^5 T P_c \quad (17)$$

where N_w is the number of test windows; macro averages are unweighted class means. Stability is assessed by five repetitions of group 5-fold CV on the training runs (mean $\pm$ SD). For early detection, the RF is applied to the complete test time series; an alarm is raised when the same fault class is predicted with maximum posterior ≥ 0.60 in three consecutive windows (rule chosen beforehand on out-of-fold training predictions as the

setting with no missed detection and minimum latency). With t_{trip} the first crossing of a trip threshold (Table 3),

$$\tau_d = t_{alarm} - t_{on}, \quad \tau_{lead} = t_{trip} - t_{alarm} \quad (18)$$

Robustness is tested on 204 extra runs under unseen conditions: $V_{in} = 88/104$ V, load 8/12 A, $T_{amb} = 18/32$ °C (30 runs each) and 75% fault severity (24 runs).

Table 5. RF hyperparameters (Bayesian Optimisation) and baseline configurations

Model	Hyperparameter: search space $\rightarrow$ selected value
RF	Trees 50–500 $\rightarrow$ 128; max. depth 4–30 $\rightarrow$ 14; min. samples/leaf 1–20 $\rightarrow$ 4; min. samples/split 2–20 $\rightarrow$ 16; features/split 1–10 $\rightarrow$ 5; criterion Gini/entropy $\rightarrow$ Gini; bootstrap, balanced class weights, seed 42
SVM	RBF kernel; $C \in \{1, 10, 100, 1000\} \rightarrow 10$; $\gamma \in \{0.01, 0.1, 1\} \rightarrow 0.01$; balanced weights
KNN	$k \in \{3, 5, 7, 11, 15, 21\} \rightarrow 5$; weighting uniform/distance $\rightarrow$ distance
DT	Depth $\{5, 10, 15, 20, \text{none}\} \rightarrow 15$; min. leaf $\{1, 5, 10\} \rightarrow 10$; Gini/entropy $\rightarrow$ Gini; balanced

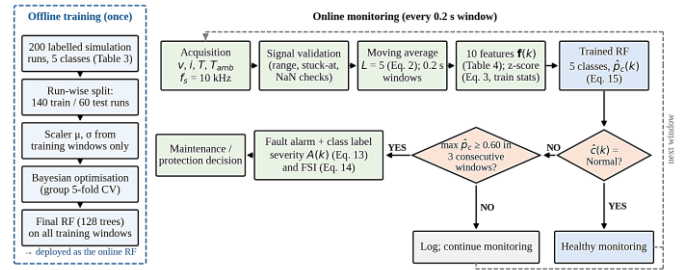


Figure 3. Revised workflow: offline training (left) and online supervised RF classification, alarm and severity assessment

3. RESULTS AND DISCUSSION

3.1. Operating Characteristics

Table 6 replaces the former parameter table and reports, per class, the mean $\pm$ SD of every quantity over the fully developed fault windows ($\rho = 1$) of all runs (all windows of the normal runs); fault thresholds and classification metrics are reported separately (Tables 3 and 7). In healthy operation the converter delivers 47.98 V and 10.16 A with ripple factors of 1.06% (voltage) and 6.10% (current). Overcurrent raises the current to 14.41 A with a regulated voltage; overvoltage raises the output to 57.27 V and the current ripple to 8.09%. Overtemperature leaves voltage (47.94 V) and current (9.98 A) unchanged and is visible only thermally: the slope rises from 0.002 to 0.102 °C/s and the residual from 0.12 to 3.12 °C. The severe fault drives the converter into current limit (15.98 A), causing a sag to 41.01 V and a temperature rise of 11.7 °C. The ripple THD stays within 17.0–17.9% (voltage) and 33.8–36.1% (current) and is a weak discriminator. Figure 4 shows waveforms at nominal fault levels; there is no 5 A condition in this study.

Table 6. Measured characteristics of each operating condition (mean $\pm$ SD, simulated data)

Quantity (unit)	Normal	Overcurrent	Overvoltage	Overtemperature	Severe fault
Windows (n)	11,800	6,980	6,957	6,962	7,185
V_{rms} (V)	47.98 ± 0.26	47.97 ± 0.23	57.27 ± 0.93	47.94 ± 0.21	41.01 ± 2.58
I_{rms} (A)	10.16 ± 0.92	14.41 ± 0.38	10.18 ± 0.55	9.98 ± 0.61	15.98 ± 0.11
Voltage ripple factor r_v (%)	1.06 ± 0.21	1.36 ± 0.08	1.17 ± 0.09	1.04 ± 0.08	1.76 ± 0.13
Current ripple factor r_i (%)	6.10 ± 0.67	5.73 ± 0.27	8.09 ± 0.43	6.11 ± 0.29	3.72 ± 0.44
Voltage ripple THD (%)	17.8 ± 1.2	17.6 ± 0.9	17.0 ± 0.9	17.9 ± 1.1	17.8 ± 0.8
Current ripple THD (%)	33.8 ± 1.1	35.0 ± 1.1	33.9 ± 1.0	34.0 ± 1.3	36.1 ± 1.1
Mean temperature $\bar{T}$ ($^{\circ}\text{C}$)	29.4 ± 1.3	31.5 ± 1.4	29.7 ± 1.2	32.5 ± 1.7	36.8 ± 2.8
Temperature rise $\bar{T} - T_{amb}$ ($^{\circ}\text{C}$)	4.5 ± 0.7	6.5 ± 0.8	4.5 ± 0.6	7.5 ± 1.4	11.7 ± 2.6
Thermal deviation σ_T ($^{\circ}\text{C}$)	0.013 ± 0.000	0.014 ± 0.001	0.013 ± 0.000	0.015 ± 0.001	0.019 ± 0.004
Temperature slope $\dot{T}$ ($^{\circ}\text{C/s}$)	0.002 ± 0.013	0.054 ± 0.041	0.002 ± 0.002	0.102 ± 0.037	0.236 ± 0.091
Thermal residual r_T ($^{\circ}\text{C}$)	0.12 ± 0.63	0.15 ± 0.67	0.12 ± 0.54	3.12 ± 1.29	4.43 ± 1.97
Anomaly index $A(k)$	0.24 ± 0.11	0.82 ± 0.07	1.44 ± 0.14	0.59 ± 0.20	2.36 ± 0.39
Fault Severity Index (RF)	0.04 ± 0.06	0.84 ± 0.08	1.45 ± 0.15	0.77 ± 0.27	2.62 ± 0.45

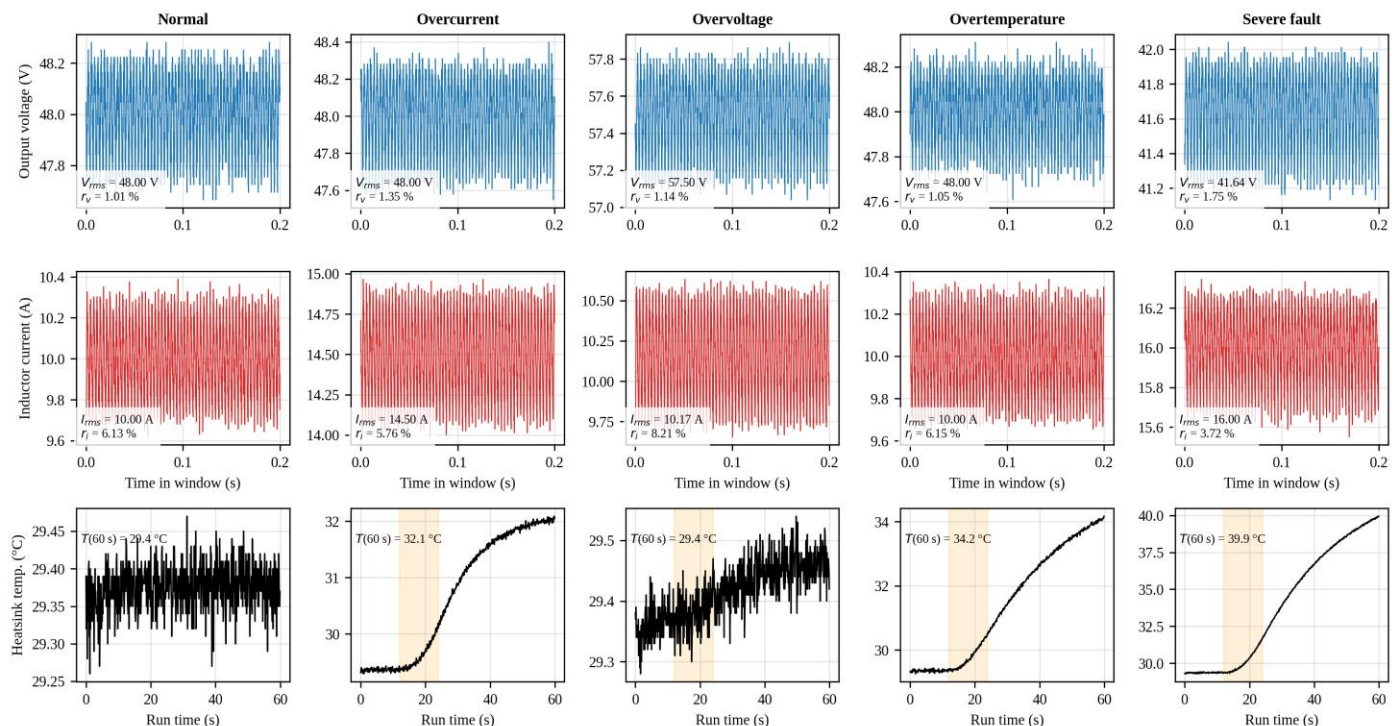


Figure 4. Voltage and current windows (0.2 s, at $t = 55$ s) and heatsink temperature over the 60 s run for the five classes at nominal conditions (shaded: fault ramp)

3.2. Hyperparameter Optimisation and Classification Performance

The Bayesian optimization (figure 5a) reduced the objective from 0.0171 to 0.0147 (CV macro-F1 98.5%) at evaluation 8, with no further improvement (281 s in total). figure 5b is a two-dimensional projection only: OC and severe-fault windows separate along I_{rms} , OT along r_T , while OV overlaps normal windows because it is separated by V_{rms} (not shown).

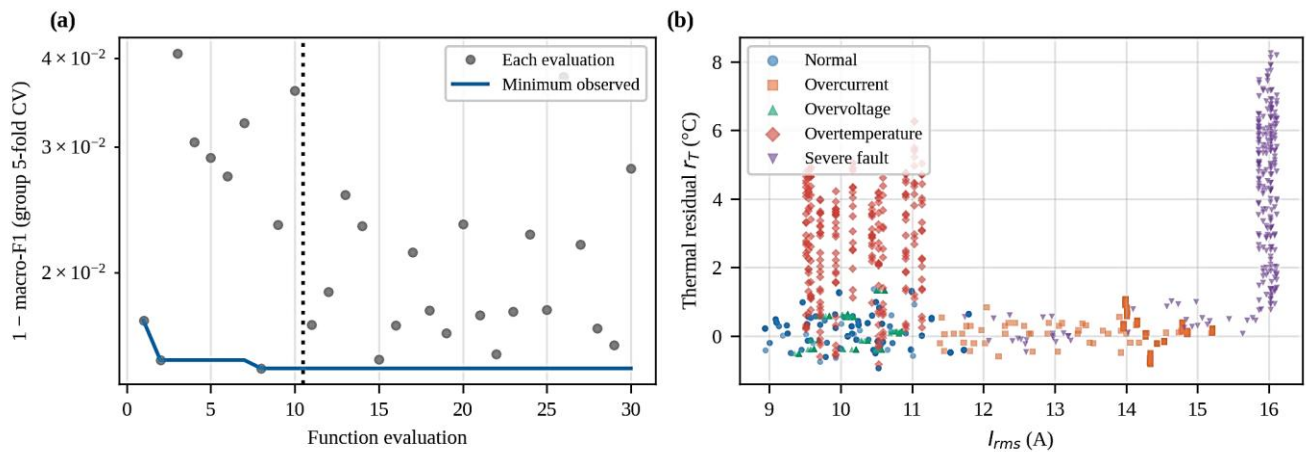


Figure 5. (a) Convergence of the Bayesian optimization of the RF; (b) two-dimensional projection of test windows on I_{rms} and r_T (visualisation only; the RF uses all ten features)

On the 16,843 test windows (Figure 6, Table 7) the RF reaches an overall accuracy of 97.91% (16,491 correct), macro precision, recall, specificity and F1 of 97.57%, 98.67%, 99.50% and 98.07%, with 100% recall for OV and OT and 99.81% for the severe fault. The dominant error is 294 normal windows (4.6%) classified as OC after upward load steps to 11.4–11.9 A, close to the incipient-overcurrent region ($\rho = 0.3 \approx 11.3$ A), which lowers OC precision to 89.57%. Repeated group CV gives $97.74 \pm 1.40\%$ accuracy and $97.82 \pm 1.33\%$ macro-F1, consistent with the test result.

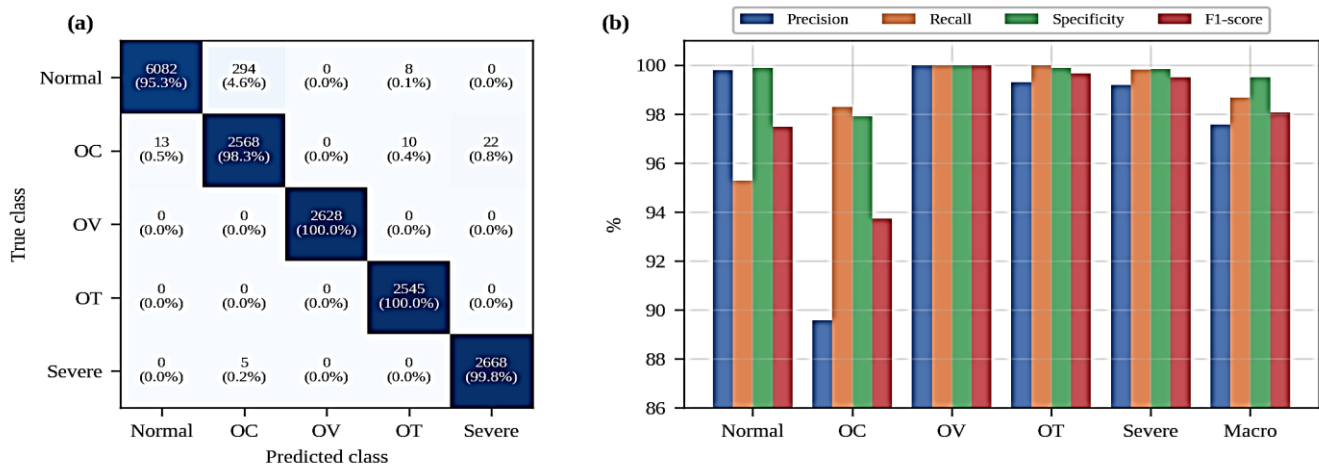


Figure 6. (a) Confusion matrix of the RF on the test set (counts and row %; 16,843 windows); (b) class-wise metrics

Table 7. Numerical confusion-matrix counts and class-wise metrics of the RF on the test set.

Class	Support	TP	FP	FN	TN	Precision (%)	Recall (%)	Specificity (%)	F1 (%)
Normal	6,384	6,082	13	302	10,446	99.79	95.27	99.88	97.48
Overcurrent	2,613	2,568	299	45	13,931	89.57	98.28	97.90	93.72
Overvoltage	2,628	2,628	0	0	14,215	100.00	100.00	100.00	100.00
Overtemperature	2,545	2,545	18	0	14,280	99.30	100.00	99.87	99.65
Severe fault	2,673	2,668	22	5	14,148	99.18	99.81	99.84	99.50
Macro average	16,843	—	—	—	—	97.57	98.67	99.50	98.07
Overall accuracy	16,843	16,491	—	—	—	—	—	—	97.91

3.3. Baseline Comparison and Robustness

Under identical splits (Table 8), the tuned SVM is the most accurate in distribution (99.46%), followed by KNN (98.65%), DT (98.27%) and RF (97.91%); the earlier claim of superior RF performance has therefore been withdrawn. The RF, however, generalizes best to unseen operating conditions (*table 9*): its mean accuracy over the six scenarios within the training envelope is 98.00%, versus 96.28% (SVM), 96.13% (DT) and 95.10% (KNN), and it is least affected by ambient shifts (98.58% at 18 °C versus 92.99% for SVM). It also supplies the posteriors used by the FSI. All models fail at a 12 A base load (57.5–78.0%), which lies above the 9–11 A training range and inside the incipient-OC region; training data must therefore cover the full load envelope.

Table 8. Comparison with baseline classifiers on identical splits (test: 60 runs; repeated CV: 140 training runs)

Model	Test Acc. (%)	Macro P (%)	Macro R (%)	Macro S (%)	Macro F1 (%)	Rep. CV Acc. (%)	Rep. CV F1 (%)	Train (s)	Infer. (ms)
RF	97.91	97.57	98.67	99.50	98.07	97.74 ± 1.40	97.82 ± 1.33	5.29	5.51
SVM	99.46	99.51	99.42	99.85	99.46	99.43 ± 0.32	99.44 ± 0.29	6.58	0.11
KNN	98.65	98.87	98.51	99.61	98.69	98.75 ± 0.32	98.73 ± 0.35	0.04	0.34
DT	98.27	97.96	98.74	99.58	98.33	96.23 ± 2.47	95.99 ± 2.91	0.27	0.04

P/R/S = precision/recall/specificity; Rep. CV = 5 × stratified group 5-fold CV (mean ± SD); Infer. = single-window time, scikit-learn, one core of an Intel Xeon 2.1 GHz.

Table 9. Accuracy (%) under operating conditions not used for training

Scenario (runs)	RF	SVM	KNN	DT	Scenario (runs)	RF	SVM	KNN	DT
$V_{in} = 88 \text{ V}$ (30)	96.44	94.15	92.97	87.82	$T_{amb} = 32 \text{ °C}$ (30)	98.15	97.27	91.94	97.45
$V_{in} = 104 \text{ V}$ (30)	99.04	99.02	98.24	98.89	75% severity (24)	98.52	95.83	93.44	98.16
Load 8 A (30)	97.26	98.45	97.80	96.04	Mean of six (174)	98.00	96.28	95.10	96.13
$T_{amb} = 18 \text{ °C}$ (30)	98.58	92.99	96.20	98.40	Load 12 A (30) *	66.04	73.93	77.98	57.49

(*Outside the 9–11 A training range; not included in the mean)

3.4. Fault Severity Index, Feature Importance and Ablation

Figure 7a shows the FSI per anomaly state. With RF posteriors it is 0.05 (N), 0.47 (AN1), 0.81 (AN2, OC), 1.42 (AN3, OV), 0.80 (AN4, OT) and 2.60 (AN5, severe); SVM, KNN and DT differ only in N (0.02–0.05) and AN1 (0.43–0.48), where classifier confidence matters. The factor $1 - \hat{p}_N$ suppresses the healthy baseline of $A(k)$ (0.20), and the residual term raises AN4 and AN5 above $A(k)$. FSI is not monotonic across AN2–AN4 because these are different fault types, but it increases from normal to incipient, developed and combined faults (0.04 ± 0.06 to 2.62 ± 0.45 , Table 6).

By permutation importance (figure 7b) the most discriminative features are I_{rms} (0.382), V_{rms} (0.249) and $\dot{T}$ (0.190); the ripple THD and absolute temperature contribute < 0.001, and r_T is partly redundant with $\dot{T}$. The ablation (Table 10) shows that electrical-only features cannot detect cooling degradation (OT recall 4.8%) and thermal-only features confuse OV (30.5%), while the combined V–I–T vector raises accuracy to 97.9%, which substantiates the benefit of multi-sensor fusion.

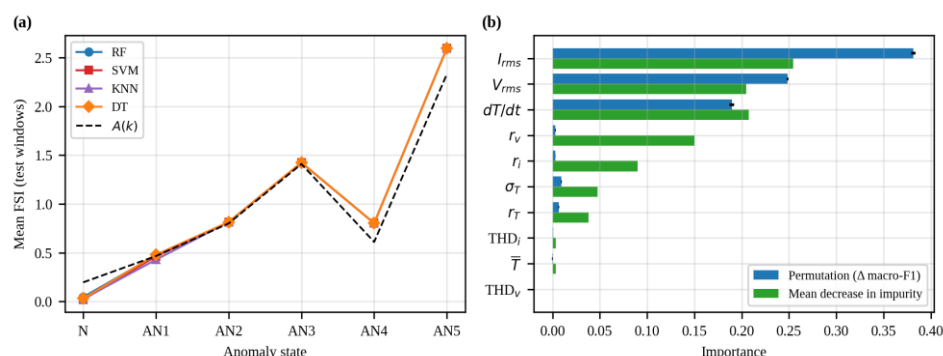


Figure 7. (a) Mean FSI per anomaly state for RF, SVM, KNN and DT posteriors; (b) RF feature importance

Table 10. Ablation of Sensor Modalities and Feature Groups (RF, Test Set)

Feature set (no.)	Acc. (%)	Macro-F1 (%)	Recall N / OC / OV / OT / Severe (%)
V only: V_{rms} , r_v , THD _v (3)	68.6	68.7	63.6 / 67.9 / 100 / 22.5 / 94.3
I only: I_{rms} , r_i , THD _i (3)	73.9	70.9	73.2 / 88.4 / 95.9 / 12.8 / 97.6
T only: $\bar{T}$ (1)	40.3	41.3	36.0 / 34.2 / 31.8 / 44.5 / 60.7
Thermal only: $\bar{T}$, σ_T , $\dot{T}$, r_T (4)	75.4	74.3	76.6 / 78.6 / 30.5 / 92.8 / 97.0
Electrical only: V + I (6)	70.2	67.8	65.7 / 87.4 / 100 / 4.8 / 97.3
Raw levels: V_{rms} , I_{rms} , $\bar{T}$ (3)	75.4	76.9	58.3 / 68.7 / 100 / 81.8 / 92.4
Combined V–I–T (10)	97.9	98.1	95.3 / 98.3 / 100 / 100 / 99.8

3.5. Early Detection Relative to Threshold Protection

All 48 test faults were flagged after onset and before the trip threshold was crossed (table 11, figure 8), at 22–38% of the final fault magnitude. Mean lead times were 3.87 s (OC), 7.45 s (OV), 26.54 s (OT; 7 of 12 runs crossed 34 °C within the record) and 2.48 s (severe). For the severe fault the first alarm reported OC in 11 of 12 runs, because the overload appears first; the Severe label followed 3.99 ± 0.49 s after onset, still before threshold crossing (5.04 s). Three of 12 normal runs raised an OC alarm after load steps to 119% of nominal current. Lead times would be shorter for abrupt faults.

Table 11. Detection latency and lead time relative to conventional trip thresholds (RF, 60 test runs)

Class	Detected before trip	First alarm corrects	Latency (s)	Progress at alarm (%)	Trip after onset (s)	Lead time (s), mean $\pm$ SD (min)
Over Current	12/12	10/12	4.50 ± 0.80	38.1	8.37	3.87 ± 0.98 (2.0)
Over Voltage	12/12	12/12	2.67 ± 0.29	21.9	10.12	7.45 ± 1.52 (5.2)
Over Temperature	12/12	12/12	3.33 ± 0.34	28.3	29.78 (7 runs)	26.54 ± 6.59 (18.0)
Severe Fault	12/12	1/12 *	2.56 ± 0.54	23.7	5.04	2.48 ± 0.70 (1.2)
Normal	—	3/12 false alarms	—	—	0/12 crossings	—

(Alarm: same class with posterior ≥ 0.60 in 3 consecutive windows.)
 (*Severe label confirmed 3.99 ± 0.49 s after onset.)

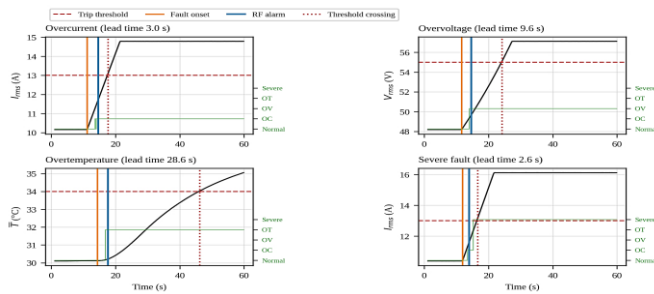


Figure 8. Early detection on test runs: monitored quantity, trip threshold, fault onset, RF alarm, threshold crossing and RF predicted class (right axis)

3.6. Computational Cost and Limitations

Feature extraction takes 1.0 ms and RF inference 5.51 ms per window (3.7 μ s per window in batch) on one Xeon core; the forest has 20,946 nodes (2.2 MB). This is far below the 200 ms window period, so on-line operation on a PC-class monitoring unit is feasible. The main limitations are the simulated averaged-model data, parametric faults without switch open/short-circuit cases, sensitivity to loads outside the training envelope and the alarms after large load steps.

4. CONCLUSIONS

A reproducible RF framework for early fault detection and classification in a 48 V/10 A synchronous buck converter using voltage, current and temperature was presented, with the converter, sensors, fault injection, dataset, features, classifier and run-wise evaluation fully specified and all values computed from one simulated dataset of 200 runs. Overcurrent raised the current to 14.41 A, overvoltage the output to 57.27 V, overtemperature produced a 3.12 °C thermal residual without electrical change, and the severe fault caused current limiting at 15.98 A with a sag to 41.01 V. The RF achieved 97.9% accuracy and 98.1% macro-F1 on independent test runs ($97.7 \pm 1.4\%$ in repeated CV); a tuned SVM was more accurate in distribution (99.5%), whereas the RF was the most robust under unseen conditions (98.0%). Electrical–thermal fusion raised accuracy from at most 75.4% for single modalities to 97.9%, all 48 test faults were flagged 2.5–26.5 s before the trip threshold, and the FSI rose from 0.04 to 2.62. Hardware validation, embedded implementation, switch-level faults and a wider load envelope are future work.

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Data Availability Statement: The simulation model, dataset-generation and analysis scripts used to produce all results in this paper are available from the corresponding author on reasonable request.

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