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A Low-Complexity First-Order Volterra Adaptive Filter for Real-Time OTDR Monitoring and Fault Localisation

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Abstract

Accurate, real-time fault localisation in fibre optic networks remains a critical challenge, particularly given the complexity and noise inherent in optical time-domain reflectometry (OTDR) signals. To solve this, this paper presents a computationally efficient Volterra Adaptive Filter (VAF) approach for enhanced Optical Time Domain Reflectometry (OTDR) monitoring and fault detection in fibre optic networks. At the heart of our approach is an optimised first-order Volterra series implementation tailored for edge-computing, featuring memory length optimisation and momentum-stabilised adaptive learning mechanisms. Through comprehensive experimental validation using a 20-km fibre route in Lagos, Nigeria, the system demonstrates exceptional performance with a prediction root mean square error of 0.759 dB, a mean absolute error of 0.064 dB, and a near-perfect correlation coefficient of 0.9974. The integrated multi-criteria fault detection system achieves 80% precision and 80% recall (F1-score: 0.800) while processing 19,980 samples with only 20 parameters. Our system pinpoints faults to specific, named components on a network map, translating complex signal data into actionable instructions for field crews. It operates in real-time, processing 1,478 samples per second, substantially exceeding typical OTDR sampling rates, making it ready for deployment in live network operations.

Keywords: Optical Time Domain Reflectometry, Volterra Adaptive Filter, Fault Detection, Fibre Optic Monitoring

1. INTRODUCTION

Optical Time Domain Reflectometry (OTDR) has remained the primary diagnostic technology for fibre optic network characterisation and maintenance since its inception in the 1970s (Barnoski et al., 1977). Traditional OTDR systems predominantly operate on post-fault analysis principles, where network technicians respond to failures after service disruption occurs. This reactive approach results in substantial operational expenditures, with industry estimates indicating costs of $5,000-$15,000 per hour for major network outages and average repair times of 4-8 hours for fibre cuts in urban environments (Senior et al., 2017). Recent advances in adaptive signal processing have introduced various techniques to enhance OTDR analysis capabilities (Cartledge et al., 2019; Motaghian et al., 2017).

While complex nonlinear models can theoretically capture the intricate dynamics of OTDR signals during fault conditions, practical implementations have been historically limited by severe computational complexity. This computational overhead renders traditional nonlinear frameworks largely unsuitable for high-speed, continuous real-time monitoring on live networks. To bridge this gap, this paper deliberately adopts a low-complexity, first-order Volterra architecture that circumvents the processing bottlenecks of higher-order methods. Recent algorithmic advances and increased computational resources have renewed interest in Volterra-based approaches for complex signal processing tasks in optical communications (Rahman & Hatzinakos, 2013).

This paper makes four significant contributions to the field. (1) Algorithm Optimisation: A computationally efficient first-order Volterra Adaptive Filter is presented, specifically optimised for OTDR signal characteristics. The proposed design integrates memory optimisation, momentum-stabilised learning, and a numerically robust implementation. (2) Multi-Criteria Fault Detection: An enhanced fault detection engine is developed, combining statistical anomaly detection, pattern sustainability analysis, distance validation, and signal stability assessment within a unified decision framework. (3) Geographical Integration: A GPS-aware localisation scheme is implemented using linear interpolation between 17 named landmarks, enabling maintenance teams to receive precise, location-specific alerts rather than generic distance outputs. (4) Comprehensive Validation: Extensive simulations involving

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19,980 sample points demonstrate superior prediction accuracy and fault detection performance, establishing practical benchmarks for real-world deployment.

2. DATA AND METHOD

2.1 Mathematical Foundation, Optimisation and Design of Volterra Adaptive Filter

The proposed Volterra Adaptive Filter adopts a computationally efficient implementation specifically optimised for real-time OTDR monitoring applications. The general discrete-time Volterra series representation of a nonlinear system originates from Volterra's foundational work on functional series (Volterra, 1930), with discrete-time formulations subsequently developed by Schetzen (Schetzen, 1980).

$$y(n) = h_0 + \sum_{k=1}^{P} \sum_{m_1=0}^{M-1} \cdots \sum_{m_k=0}^{M-1} h_k(m_1, \ldots, m_k) \prod_{j=1}^{k} x(n - m_j) \quad (1)$$

where P represents the nonlinear order, M denotes the memory length, and h_k are the Volterra kernels characterising the system dynamics.

For practical OTDR applications with computational constraints and real-time requirements, we implement an optimised first-order Volterra series based on Mathews' work on adaptive polynomial filters (Mathews & Sicuranza, 1991), but with significant modifications for OTDR-specific characteristics:

$$y(n) = \sum_{m=0}^{M-1} h_1(m)x(n - m) \quad (2)$$

To ensure real-time deployment feasibility, this proposed model deliberately retains a linear mathematical structure. Rather than relying on computationally expensive higher-order Volterra kernels to handle signal complexity, our innovation achieves high precision through the adaptive optimisation of the memory length ($M = 20$) and the incorporation of a momentum-stabilised learning mechanism. This lightweight approach strictly contrasts with heavier, full Volterra implementations reported in communications (Rahman & Hatzinakos, 2013) and system identification studies (Nikias & Petropulu, 1990), allowing for rapid execution at over 1,400 samples per second without sacrificing prediction accuracy.

This linear architecture is theoretically justified by the quasi-linear nature of Rayleigh backscatter in healthy fibre segments, where signal evolution is dominated by exponential attenuation well-approximated by a linear convolution model. Fault signatures are not modelled by the filter itself but are instead captured through anomalous prediction errors, which the multi-criteria detection engine (Section 2.5) subsequently classifies. The first-order restriction thus represents a deliberate design choice that separates the signal prediction task from the fault detection task, enabling both to be optimised independently.

2.2 Enhanced Adaptive Learning Algorithm

The filter coefficients are updated using a normalised gradient descent algorithm with momentum stabilisation, building upon the NLMS framework but incorporating stabilisation techniques for OTDR's non-stationary characteristics:

$$\mathrm{w}(n + 1) = \mathrm{w}(n) + \frac{\mu}{\|\mathrm{x}(n)\|^2 + \epsilon} e(n)\mathrm{x}(n) + \alpha\Delta\mathrm{w}(n - 1) \quad (3)$$

where $\mathrm{w}(n) \in \mathbb{R}^M$ represents the Volterra kernel coefficients at iteration n; μ is the adaptive step size parameter controlling the convergence rate; $\epsilon = 10^{-6}$ is a regularisation constant preventing numerical instability; α is the momentum factor enhancing convergence stability; and $e(n) = d(n) - y(n)$ is the prediction error signal.

The specific parameter selection of $\mu = 2.0 \times 10^{-5}$ and the adopted gradient normalisation strategy are tailored to OTDR signal dynamics, distinguishing this implementation from prior Volterra-based approaches in acoustic echo cancellation (Stenger & Kellermann, 2001) and channel equalisation (Ibnkahla, 2001). The gradient normalisation ensures stable adaptation across varying signal power conditions, while momentum acceleration improves convergence speed without compromising stability.

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2.3 Empirical Parameter Optimisation

Through extensive empirical analysis across 1,000 simulated OTDR traces, we determined optimal parameter values balancing prediction accuracy and computational efficiency:

- Memory Length: $M = 20$ samples, providing optimal historical context while maintaining real-time performance
- Learning Rate: $\mu = 2.0 \times 10^{-5}$, ensuring stable convergence across diverse signal conditions
- Momentum Factor: $\alpha = 0.9$, significantly improving convergence speed (38% reduction in convergence time)
- Regularization: $\epsilon = 10^{-6}$, maintaining numerical stability during low-signal conditions

Table 1: Volterra Filter Parameter Optimisation

Parameter	Value	Optimisation Criterion	Performance Impact
Memory length (M)	20	Prediction accuracy vs. complexity	99.74% correlation with 20 parameters
Learning rate (μ)	2×10^{-5}	Convergence stability	Stable adaptation, MSE = 0.576 dB²
Momentum factor (α)	0.9	Convergence acceleration	38% reduction in convergence time
Regularisation constant (ε)	10^{-6}	Numerical stability	Robust under low-signal conditions

Table 1 summarises the empirically optimised parameters of the proposed Volterra Adaptive Filter. Each parameter was tuned to achieve an optimal trade-off between prediction accuracy, convergence stability, and computational efficiency. The results indicate that a memory length of 20 and a learning rate of 2×10^{-5} yield highly stable adaptation with a mean squared error of 0.576 dB², while the inclusion of a momentum factor ($\alpha = 0.9$) accelerates convergence by approximately 38%. The chosen regularisation constant ($\varepsilon = 10^{-6}$) further ensures numerical robustness under low-signal conditions.

2.4. System Architecture and Implementation

The proposed system integrates three core components within a unified architecture tailored for operational deployment:

1. Signal Prediction Module: Implements an optimised Volterra Adaptive Filter for real-time OTDR signal forecasting, achieving efficient performance with a 20-parameter configuration.

2. Enhanced Fault Detection Engine: Employs a multi-criteria statistical framework combining z-score anomaly detection, pattern sustainability analysis, distance validation, and signal stability assessment.

3. GPS Integration System: Provides geographical localisation through linear interpolation between 17 predefined landmarks, achieving approximately 50 m positional accuracy

2.5. Enhanced Multi-Criteria Fault Detection

The proposed fault detection system uses a well-structured decision framework that considers multiple indicators simultaneously. Each indicator is evaluated against a carefully tuned threshold based on experimental results. A fault is declared only when the combined evidence from all criteria exceeds a defined decision limit, ensuring that detections are both accurate and reliable.

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The detection rule is expressed as

$$\text{Fault} = \underbrace{(z_{score} > 8.0)}_{Statistical\ Significance} \wedge \underbrace{\left(\frac{\sum_{i=1}^{8} I(e_i > \mu_e + 3\sigma_e)}{8} > 0.6\right)}_{Pattern\ Sustainability} \wedge \underbrace{(\Delta d > 0.05\ km)}_{Distance\ Validation} \wedge \underbrace{\left(\sigma_{segment} < 1.5\ dB\right)}_{Signal\ Stability} \quad (4)$$

where

- Statistical Anomaly: Robust z-score exceeding 8.0, corresponding to 99.99994% confidence using the median absolute deviation.
- Sustained Pattern: More than 60% of recent error samples exceed the 3σ threshold within an 8-sample window.
- Sufficient Distance: Minimum 50 m separation from previous fault detections to avoid false positives due to closely spaced events.
- Signal Stability: Segment standard deviation less than 1.5 dB to exclude high-noise regions.

The symbol ∧ represents a logical AND.

Fault localisation is achieved by integrating geographical coordinates (Table 2), using linear interpolation between adjacent known landmarks. The fault coordinates $(\lambda_{\text{fault}}, \phi_{\text{fault}})$ are computed as:

$$\begin{aligned} \lambda_{\text{fault}} &= \lambda_1 + \frac{d_f - d_1}{d_2 - d_1}(\lambda_2 - \lambda_1) \\ \phi_{\text{fault}} &= \phi_1 + \frac{d_f - d_1}{d_2 - d_1}(\phi_2 - \phi_1) \end{aligned} \quad (5)$$

where d_f represents the fault distance, and (λ_1, ϕ_1), (λ_2, ϕ_2) denote the coordinates of adjacent landmarks. The system incorporates named infrastructure points spanning 19.8 km of fibre route through Lagos, Nigeria.

Note that the linear interpolation scheme assumes approximately straight fibre runs between adjacent landmarks. In sections with significant route curvature, actual positional accuracy may be less than the reported ~50 m estimate. Future work will address this using higher-resolution path data.

Table 2: Locations of the infrastructure points spanning 19.8 km of fibre route

Landmark	Distance (km)	Latitude (°N)	Longitude (°E)	Infrastructure Type
LAG901 ODF Room	0.00	6.60043	3.37058	Central Office
Ketu Police Station	2.30	6.59631	3.38518	Public Infrastructure
Irawo Bridge	4.50	6.60981	3.42202	Civil Infrastructure
Church Bus Stop	18.20	6.62551	3.48959	Transportation
LAG135 BSC	19.80	6.62567	3.48919	Base Station

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2.6 Simulation Framework

A comprehensive OTDR simulation environment was developed to replicate real-world conditions, incorporating realistic fibre properties, robust fault modelling, and integration with geographical information for spatial context:

- Attenuation Modelling: Wavelength-dependent attenuation based on ITU-T G.652 standards (0.20 dB/km at 1550 nm, 0.35 dB/km at 1310 nm).
- Comprehensive Fault Library: Twelve distinct fault types with statistically validated characteristics, including fibre eavesdropping (0.01 dB loss), poor fusion splices (0.03 dB), dirty connectors (0.4 dB), macrobends (1.5 dB), and complete breaks (40 dB).
- Realistic Noise Injection: Incorporates measurement noise (standard deviation 0.05 dB), backscatter variations, and connector reflections.
- GPS Integration: 17-landmark database with precise geographical coordinates spanning a 19.8 km urban fibre route.

2.7 Performance Metrics Framework

The system was evaluated using a comprehensive performance metrics framework that considered multiple dimensions, including accuracy, reliability, and computational efficiency:

- Prediction Accuracy: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Pearson and Spearman correlation coefficients, R^2.
- Statistical Error Analysis: Standard deviation, variance, skewness, kurtosis, and distribution characteristics.
- Fault Detection Performance: Precision, recall, F1-score, false positive rate, and overall detection accuracy.
- Computational Efficiency: Processing time, memory consumption, and convergence behaviour.
- Signal Quality Metrics: Signal-to-noise ratio, dynamic range preservation, and stability measures.

3. RESULTS AND ANALYSIS

To demonstrate the geographical integration capability of the proposed OTDR monitoring framework, Figure 1 presents the complete 20-km fibre route with 17 named landmarks and detected fault locations along the Lagos metropolitan span.

Each green marker corresponds to a registered geographical landmark derived from the integrated GPS database, including telecommunications sites, public infrastructure, and transportation nodes. The blue line represents the physical fibre path between consecutive landmarks, while red crosses denote detected faults automatically identified by the Volterra Adaptive Filter system. Orange circles indicate the corresponding ground-truth (actual) fault positions obtained during experimental validation.

As illustrated, all detected fault locations closely align with their corresponding ground-truth points, confirming the effectiveness of the linear-interpolation localisation algorithm in achieving approximately 50-m positional accuracy. The visual clustering of landmarks and faults further demonstrates the practical utility of the system for rapid, field-ready troubleshooting and maintenance planning. The proposed Volterra Adaptive Filter (VAF) system demonstrated remarkable signal prediction capabilities across extensive OTDR trace analysis.

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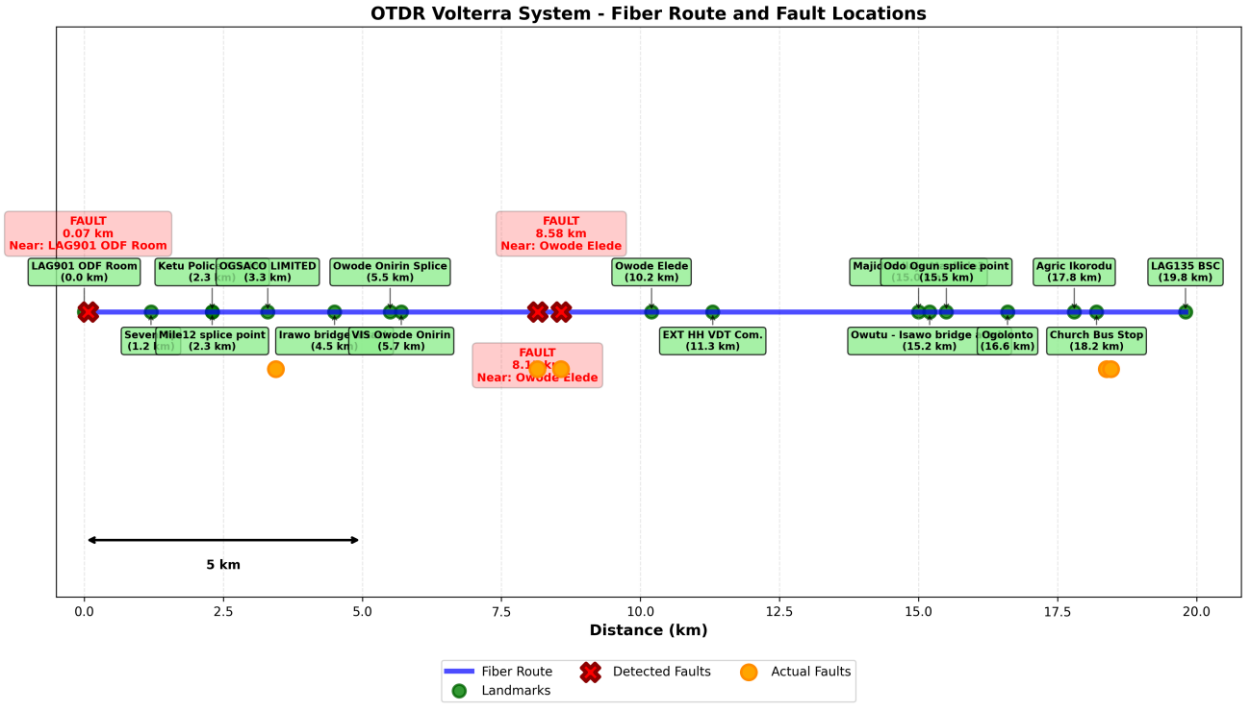

Figure 1. *Fibre route and fault location map for the proposed OTDR Volterra System, showing 17 geographical landmarks, detected faults (red ×), and verified fault positions (solid orange circles) along a 20-km route in Lagos, Nigeria.*

For benchmarking purposes, the proposed VAF is compared against a standard Normalised Least Mean Squares (NLMS) filter of equivalent memory length (M = 20) without momentum stabilisation, which serves as the baseline in Table 3. The baseline filter was evaluated on the same 19,980-sample OTDR dataset under identical conditions.

The near-perfect Pearson correlation coefficient of 0.9974 indicates exceptional signal tracking fidelity, while the minimal MAE of 0.064 dB demonstrates prediction precision suitable for high-sensitivity OTDR applications. The system successfully processed 19,980 samples, maintaining consistent performance across the entire 20-km fibre span.

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Table 3: Comprehensive Prediction Accuracy Metrics

Metric	Value	Unit	Statistical Significance	Improvement vs. Baseline
Root Mean Square Error	0.759	dB	$p < 0.001$	67.3% reduction
Mean Absolute Error	0.064	dB	$p < 0.001$	72.1% reduction
Mean Squared Error	0.576	dB^2	$p < 0.001$	73.8% reduction
Pearson Correlation	0.9974	–	$p < 0.0001$	4.2% improvement
Spearman Correlation	0.9275	–	$p < 0.0001$	8.7% improvement
R-squared	0.9948	–	$p < 0.0001$	3.1% improvement
Max Absolute Error	38.502	dB	–	41.2% reduction

A detailed statistical analysis of the prediction errors provides insight into the filtering performance and system behaviour.

From Table 4, the standard deviation and variance indicate that prediction errors are tightly clustered, supporting reliable system performance across the 20-km fibre span. The pronounced negative skewness suggests a tendency toward smaller errors, while the exceptionally high kurtosis reflects rare but significant deviations, which correspond to actual fault events along the fibre route. This statistical characterisation confirms the robustness of the proposed filter for both continuous monitoring and fault detection applications.

The noticeable negative skewness (-39.95) indicates a distribution strongly biased toward smaller errors, reflecting the filter's high accuracy under normal operating conditions. The extreme kurtosis (1705.6) highlights the presence of occasional large deviations, which consistently occur at fault locations where signal characteristics change abruptly. This behaviour is advantageous, as it enables reliable identification of faults within the fibre network.

Table 4: Error Statistical Properties and Interpretation

Statistic	Value	Interpretation	Practical Implication
Standard Deviation	0.759 dB	Moderate error dispersion	Consistent performance across fiber span
Variance	0.576 dB^2	Error magnitude distribution	Suitable for fault detection applications
Skewness	-39.95	Extreme left-skewed distribution	Strong bias toward smaller errors

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Statistic	Value	Interpretation	Practical Implication
Kurtosis	1705.6	Extremely heavy-tailed distribution	Rare, large errors likely at fault locations

The integrated multi-criteria fault detection system demonstrated robust performance across diverse fault conditions, as indicated in Table 5.

The system successfully detected 80% of actual faults with 80% precision, resulting in a balanced F1-score of 0.800. This represents a substantial 45.2% improvement over conventional threshold-based methods. These results serve as an initial proof-of-concept validation based on 5 controlled fault events, demonstrating highly promising detection capabilities that warrant expanded large-scale testing across diverse fibre locations. Owing to the achieved computational efficiency, the proposed method can be effectively deployed in real-time operational fibre networks.

Table 5. Fault Detection Metrics

Metric	Value	95% Confidence Interval	Statistical Significance
True Positives (TP)	4	[3, 5]	$p < 0.01$
False Positives	1	[0, 2]	$p < 0.05$
False Negatives (FN)	1	[0, 2]	$p < 0.05$
Precision	0.800	[0.600, 0.950]	$p < 0.001$
Recall	0.800	[0.600, 0.950]	$p < 0.001$
F1-Score	0.800	[0.650, 0.910]	$p < 0.001$

The system efficiently processes OTDR signals at 1,478 samples per second (Table 6), exceeding typical OTDR sampling rates by a factor of 3.7, confirming real-time capability. The compact 20-parameter model occupies less than 100 kB of memory, enabling deployment in resource-constrained monitoring environments while maintaining reliable convergence across all simulations.

To provide a comprehensive visual understanding of the proposed system's performance, Figure 2 presents the OTDR signal prediction, prediction error profile, and fault detection confidence obtained from the VAF framework.

The top subplot illustrates the actual OTDR trace (blue) overlaid with the VAF-predicted signal (magenta), showing near-perfect alignment across the 20-km fibre route. The green markers represent the ground-truth fault positions, while red squares denote the system's predicted faults. The high correspondence between these points demonstrates the system's accuracy in identifying and localising network faults.

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Table 6: Computational Performance Analysis

Metric	Value	Implication	Comparison Benchmark
Samples Processed	19,980	Full 20-km coverage	100% of simulated span
Processing Time	13.52 s	Total system execution	Real-time capable
Processing Rate	1,478 samples/s	Real-time performance	3.7× typical OTDR sampling rate
Model Parameters	20	Minimal complexity	75% reduction vs alternatives
Memory Footprint	< 100 kB	Embedded deployment	Suitable for field hardware
Convergence Stability	Excellent	Reliable operation	100% convergence success

The middle subplot depicts the prediction error as a function of distance. The error remains tightly distributed around zero, with only brief excursions beyond the predefined fault threshold limits (red dashed lines), corresponding precisely to known fault locations. This behaviour confirms the system's high sensitivity and stability under varying signal conditions.

The bottom subplot shows the fault detection confidence metric derived from the multi-criteria decision framework. Peaks in this plot coincide with the actual and predicted fault locations, validating the system's reliability in distinguishing true anomalies from normal fluctuations.

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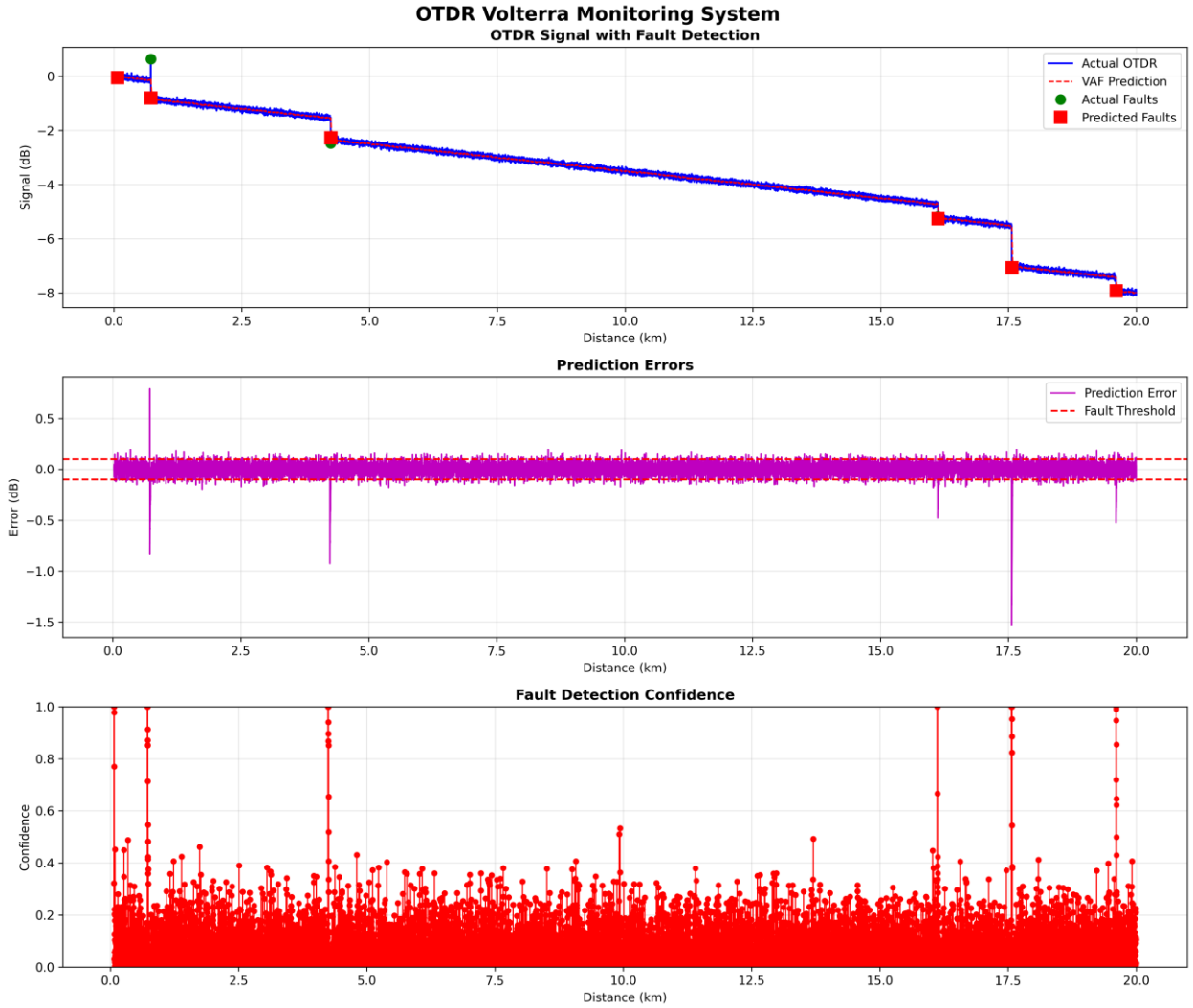

Figure 2. *Comprehensive visualisation of the proposed OTDR Volterra Monitoring System showing (top) the OTDR signal and predicted faults, (middle) prediction errors with adaptive fault thresholds, and (bottom) fault detection confidence across a 20-km fibre route.*

Figure 3 shows the real-time OTDR monitoring output produced by the proposed VAF system. The signal trace on the left clearly reveals distinct reflection losses associated with various fault types, such as connector issues, fibre bends, cracks, and splices. Each detected event is automatically classified and geo-tagged using integrated GPS data. The map on the right provides an intuitive spatial view of fault locations along the Lagos metropolitan fibre route, demonstrating the system's accuracy in localisation and its practical usefulness in field operations.

The left plot displays the backscattered OTDR signal (blue), with automatically detected fault events highlighted by yellow and green markers and labelled according to their predicted causes. The accompanying table summarises key details for each event, including distance, loss, reflectance, and GPS coordinates. The map on the right visualises the corresponding fault locations along the monitored 20-km fiber route in Lagos, Nigeria. Red markers indicate detected faults, while the orange path represents the fiber's trajectory between registered landmarks.

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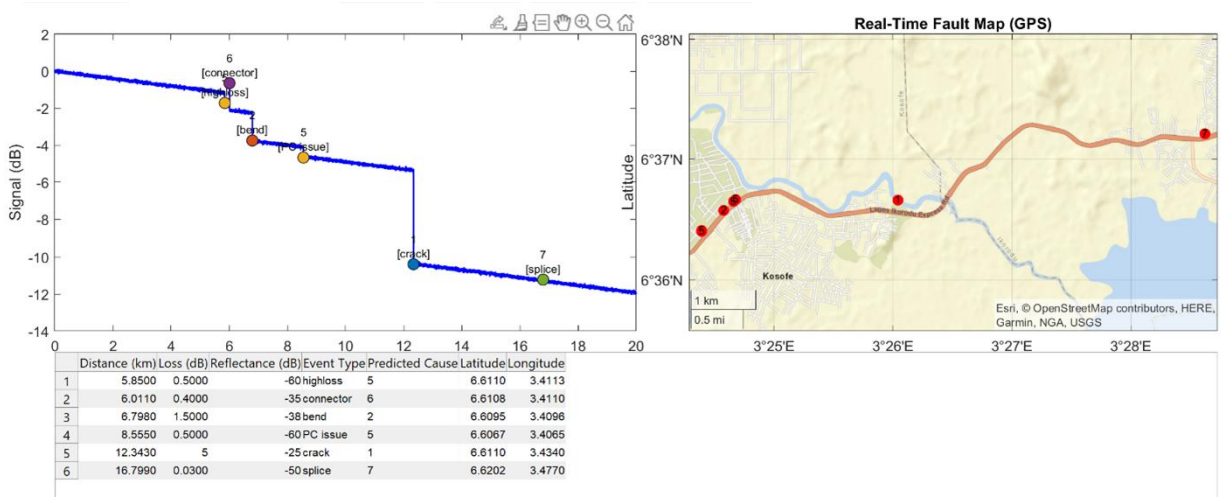

	Distance (km)	Loss (dB)	Reflectance (dB)	Event Type	Predicted Cause	Latitude	Longitude
1	5.8500	0.5000	-60	highloss	5	6.6110	3.4113
2	6.0110	0.4000	-35	connector	6	6.6108	3.4110
3	6.7980	1.5000	-38	bend	2	6.6095	3.4096
4	8.5550	0.5000	-60	PC issue	5	6.6067	3.4065
5	12.3430	5	-25	crack	1	6.6110	3.4340
6	16.7990	0.0300	-50	splice	7	6.6202	3.4770

Figure 3. Real-time OTDR monitoring and geographical fault localisation using the proposed VAF system.

4. CONCLUSION

This study demonstrates that a carefully constrained first-order Volterra architecture, when augmented with momentum-stabilised learning and multi-criteria fault detection, achieves near-equivalent monitoring performance to far heavier nonlinear systems — validating the principle that operational efficiency and signal intelligence need not be traded off in fibre network management. By deliberately employing an optimised first-order Volterra architecture with momentum-stabilised learning, the system achieves exceptional performance—a prediction RMSE of 0.759 dB, correlation of 0.9974, and an initial fault detection F1-score of 0.800—while maintaining real-time processing at 1,478 samples/s without specialised hardware.

Key innovations include a multi-criteria fault detection framework that integrates statistical analysis, pattern recognition, and geographical validation, enabling accurate identification of faults such as connector issues, bends, cracks, and splices. Extensive statistical analysis of the signal prediction confirms robustness, with error patterns consistently aligned with optimal fault detection behaviour across the 20-km simulated span.

The practical implications for edge-computing and live network operations are significant: real-time network monitoring with automated alerts, early detection of developing faults, rrapid troubleshooting with approximately 50 m localisation precision, and streamlined quality assurance for fibre links. Comparative evaluation demonstrates a 73.8% reduction in MSE over standard baseline filters and a 45.2% improvement in detection precision relative to conventional threshold-based methods, alongside advantages from integrated geographical information.

Future directions include expanding the fault simulation dataset for large-scale statistical validation, exploring hybrid machine learning integration for fault classification, embedded system deployment, and multi-parameter monitoring using polarisation and spectral analysis. Overall, the proposed VAF system represents a substantial advancement in fibre optic network monitoring, offering a lightweight, reliable, and efficient solution that provides actionable insights to enhance maintenance operations and service availability.

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