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Research Article

A Project Management Framework for Implementing AI-Driven Fault Mitigation Systems

Isaac Buyondo*, Konstantinos Kiousis

Faculty of Computer Science, Berlin School of Business & Innovation, Barlin, Germany

Abstract

The research seeks to establish a Project Management Framework for the Implementation of AI-Driven Fault Mitigation Systems by utilizing quantitative methodologies such as machine learning, in conjunction with insights from telecommunications engineers. This study integrates empirical data with practical expertise. The research was conducted using data obtained from Savanna Fibre Limited, resulting in a dataset comprising fault logs. Hybrid AI models, specifically a combination of CNN-LSTM with certain physics-based modifications, were trained and tested to detect faults at an early stage, identify the nature of the problems, locate the source of the issues, and assess the potential severity of the faults. Data preprocessing pipelines were developed to tackle challenges including imbalanced classes and sparse records of submarine cable faults, while domain knowledge also played a crucial role in guiding feature engineering and model interpretation. The framework demonstrates impressive performance: it achieves a 94.3% F1-score in fault classification, forecasts issues up to 72 hours ahead with a 92% confidence level, and accurately identifies fault locations within ±25 meters. To enhance its practicality, a versatile deployment configuration integrates model outputs into real-world workflows through CI/CD pipelines and even utilizes AR tools to assist in field repairs, resulting in a 42% reduction in repair times during actual tests. This research indicates that AI-driven, proactive maintenance is not merely theoretical; it is achievable with the appropriate data, interdisciplinary collaboration, and practical testing. Looking forward, there is significant potential to expand this approach for 5G and IoT networks or to refine our management of uncertainty in critical systems.

Keywords

Mitigation, Fibre, Optical, Transmitters, Networks, Telecommunication, Techniques

1. Introduction

AI-powered fault mitigation systems are transforming the way we identify and address problems in intricate systems, shifting from reactive to proactive strategies. These systems utilize machine learning, deep learning, and various AI methodologies to examine data, forecast possible failures, and even automate responses, thereby improving reliability, decreasing downtime, and lowering costs [1]. On this note, AI - powered fault mitigation seeks to improve system reliability, minimize downtime, and optimize resource distribution by utilizing AI's capacity to analyze extensive datasets, recognize patterns, and automate responses.

Researchers globally have utilized a variety of methodologies to investigate and manage faults, integrating experimental, analytical, and simulation-based techniques as out-

*Corresponding author: buyondoisaac21@gmail.com (Isaac Buyondo)

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lined below:

Optical Time Domain Reflectometry (OTDR): This method transmits light pulses to identify faults with meter-level accuracy. OTDR is commonly used in field trials; however, it necessitates downtime and skilled personnel [2].

Power Monitoring: This technique assesses optical power at nodes to identify anomalies. Real-time systems are incorporated into network operations, yet they do not possess localization capabilities [3].

Distributed Sensing: This approach employs fibres as sensors to monitor strain, temperature, or vibration. Brillouin OTDR and fibre Bragg gratings have been evaluated in controlled experiments, demonstrating high sensitivity [3].

Simulation-Based Studies: Instruments such as Opti System, VPI Transmission Maker, or MATLAB simulate network performance to evaluate the effects of faults. These simulations are a cost-effective means for testing new methodologies [4].

Field Trials: Implement prototype systems within actual networks to assess the accuracy of fault detection. These trials yield practical insights, although they require significant resources [5].

Statistical Analysis: Utilizes probabilistic models (such as Weibull or Poisson distributions) to forecast fault occurrences based on past data. These models contribute to reliability studies [6].

Management Protocols: The Simple Network Management Protocol (SNMP) gathers performance data. Research investigates their integration with automated systems [4].

Nevertheless, all the aforementioned methodologies have enhanced fault management but encounter challenges related to scalability, cost, and reactivity, which has sparked interest in innovative solutions.

Objective of the Study

To design a project management-based implementation framework for AI-driven fault mitigation and to assess the effectiveness of the proposed framework through case studies and simulations.

2. Literature Review

2.1. AI and Predictive Maintenance: Conceptual Framework

Predictive maintenance utilizes artificial intelligence (AI) and machine learning (ML) to examine both historical and real-time data, enabling the prediction of equipment failures prior to their occurrence [7]. This proactive maintenance strategy employs data and analytics to foresee equipment failures, permitting maintenance activities to be conducted only when necessary. This method stands in contrast to reactive maintenance, which addresses equipment issues post-failure, and preventive maintenance, which adheres to a predetermined schedule irrespective of the equipment's actual condition. In the context of optical fibre networks, predictive maintenance entails the detection of potential faults (such as attenuation and cable cuts) through the analysis of performance metrics, environmental conditions, and equipment status, employing a deep learning framework capable of forecasting future fault incidents in real-time for Passive Optical Networks (PONs) with enhanced accuracy, precision, recall, and F1 score [8].

AI techniques for predictive maintenance encompass supervised learning (such as regression and classification), unsupervised learning (including clustering and anomaly detection), and reinforcement learning (for instance, optimizing maintenance schedules) [7]. Machine learning methods surpass conventional statistical models in forecasting the susceptibility of software and hardware to faults [9]. Deep learning, especially recurrent neural networks (RNNs) and convolutional neural networks (CNNs), is particularly adept at managing time-series data and spatial patterns, rendering it effective for network monitoring [10].

Key factors in predictive maintenance encompass the signal-to-noise ratio, bit error rate, optical power levels, temperature, strain, and historical fault records [5]. These factors are analyzed to create features for machine learning models, including time-series trends or anomaly scores. The AI-based predictive maintenance conceptual framework corresponds with the dissertation's aim to establish a proactive fault management system for optical fibre networks. However, its implementation in this field is still inadequately explored, as elaborated upon below.

2.2. AI Applications in Predictive Maintenance: Cross-Domain Insights

Although AI-driven predictive maintenance is well-established in sectors such as manufacturing, transportation, and energy, its use in optical fibre networks remains limited. Cross-domain research offers valuable insights into methodologies and models that can be applied to telecommunications.

In the transportation sector, AI is utilized to forecast equipment failures in aerospace systems. For instance, Liu et al. created an LSS model that integrates LSTM and statistical process analysis to effectively predict faults in aero-engine bearings, which exhibit multi-stage performance degradation, thereby enhancing reliability and safety [11].

The model's capability to analyze time-series data is pertinent to optical fibre networks, where metrics such as optical power vary over time. A deep neural network equipped with a multi-head attention mechanism successfully predicts optical fibre signals, providing benefits in computation time without compromising accuracy and achieving a favorable balance between prediction accuracy and distance generalization [12].

In the transportation field, AI is employed to anticipate failures in railway and aviation systems. Tang et al. implemented a random forest model to forecast railway track degradiation, utilizing factors such as load, speed, and weather conditions [13]. The analysis of feature importance within the model highlighted critical predictors, a method that can be applied to fibre networks for prioritizing variables such as strain or moisture ingress [2].

In the field of energy, artificial intelligence oversees the components of power grids. Bose implemented AI methodologies, including expert systems and fuzzy logic, which improved the design, simulation, estimation, fault diagnostics, and fault-tolerant control of smart grids and renewable energy systems [14] . These investigations illustrate the effectiveness of AI in predictive maintenance; however, they also reveal a deficiency: optical fibre networks, characterized by their distinct fault types and data attributes, necessitate customized models. The intricacy of fibre systems, encompassing DWD, M interactions, and long-distance transmission, demands adaptations specific to the domain [5].

2.3. AI in Telecommunications: Fault Prediction Studies

AI applications for fault prediction are becoming more prevalent, yet remain limited within the telecommunications sector, especially concerning optical fibre networks. Numerous studies offer valuable insights; however, the majority concentrate on wireless or copper-based systems.

P. Li introduced a supervised learning methodology utilizing Support Vector Machines (SVMs) to forecast faults in optical transport networks [15]. This model evaluated performance metrics (such as bit error rate and optical power) from a metropolitan Dense Wavelength Division Multiplexing (DWDM) network, achieving an accuracy of 79.8% in predicting attenuation and connector faults. Nonetheless, the research depended on historical data without incorporating real-time integration, which restricts its scalability for dynamic networks.

Xie et al. created an unsupervised learning model employing autoencoders for anomaly detection in fibre optic systems. His proposed unsupervised deep learning technique enhances anomaly detection in distributed optical fibre acoustic sensing, attaining a threat detection rate of 91.5% while minimizing false alarm rates. Although promising, this study was limited to laboratory-based simulations and did not validate its findings in real-world networks [16].

Li et al. suggested a CNN-LSTM neural network model to accurately predict changes in submarine cable burial depth trends, demonstrating greater prediction accuracy and efficiency compared to single convolutional neural network models and individual long-term and short-term memory neural network models. The model reached an accuracy of 90%, but its computational demands posed challenges for real-time implementation [17].

These studies emphasize the potential of AI while also highlighting certain limitations: small-scale datasets, absence of real-time processing capabilities, and a narrow focus on specific fault types (for instance, attenuation rather than cable cuts). The existing literature lacks comprehensive models that address the entire range of fibre faults, particularly in long-haul and access networks.

2.4. Gaps in the Literature

The existing literature identifies several deficiencies that this research intends to address:

Limited Application of AI in Optical Fibre Networks: Although AI is widely utilized in sectors such as manufacturing and transportation, its application in fibre networks is still in its early stages, with only a few studies exploring the complete spectrum of faults (e.g., dispersion, moisture ingress) [5, 18].

Absence of Real-Time Models: The majority of research, such as that by Li, relies heavily on historical data, which restricts the ability to predict faults in real-time a crucial requirement for mission-critical applications like 5G [17].

Challenges in Scalability: Models, including those proposed by Li, are computationally demanding and therefore not suitable for large-scale or resource-limited networks [17].

Limited Fault Focus: Current research tends to concentrate on specific faults (e.g., attenuation, splice losses), overlooking other significant issues such as cable cuts or equipment failures [2].

These deficiencies underscore the necessity for a comprehensive, scalable, and real-time AI framework for fault prediction in optical fibre networks, which this research seeks to create.

2.5. Project Management Frameworks for AI Deployment

Deploying AI solutions within the telecommunications sector necessitates strong project management frameworks to guarantee effective execution. The existing literature highlights various frameworks that can be tailored to AI-driven fault prediction systems.

2.5.1. PRINCE2 (Projects IN Controlled Environments)

PRINCE2 focuses on structured processes, risk management, and stakeholder involvement. It has been utilized for the deployment of network monitoring systems, demonstrating its appropriateness for telecommunications due to its emphasis on phased delivery and quality assurance [19].

2.5.2. Agile Frameworks

Agile methodologies, including Scrum, facilitate iterative development and are particularly suitable for AI projects that demand ongoing model enhancement. The integration of Scrum and Agile methodologies into project-based learning effectively imparts AI knowledge, improving problem-solving abilities, critical thinking, and teamwork skills among AI agents [20]. Agile methodologies are particularly effective in adapting AI models to changing network conditions.

2.5.3. PMBOK (Project Management Body of Knowledge)

PMBOK offers a thorough framework for overseeing scope, time, cost, and risk. Li et al. implemented PMBOK in a 5G network upgrade, highlighting the importance of stakeholder communication and resource distribution [17]. In the context of AI within fibre networks, PMBOK can facilitate alignment with operational objectives [21].

2.5.4. Hybrid Approaches

The integration of PRINCE2's structured methodology with the adaptability of Agile is becoming increasingly favored. Simonaitis et al. employed a hybrid strategy to implement IoT systems, effectively balancing long-term planning with iterative development [19]. This methodology is particularly well-suited for AI fault prediction, where data pipelines necessitate a structured approach, yet models require ongoing refinement.

Key considerations for AI deployment:

1) Data Governance: Ensuring data quality and compliance with regulations like GDPR [22].
2) Stakeholder Engagement: Involving network operators and technicians to align AI outputs with operational needs [21].
3) Scalability: Designing systems to handle large-scale networks without performance degradation [17].
4) Cost Management: Balancing computational costs with benefits, particularly for resource-constrained operate to optical fibre networks necessitates additional investigation, which is the primary focus of the study.

In summary, the section has examined specific literature regarding AI and predictive maintenance. Cross-domain research in sectors such as manufacturing, transportation, and energy illustrates the effectiveness of AI, while studies in telecommunications reveal new applications in fault prediction. The literature reveals gaps, including the limited application of AI in fibre networks, the absence of real-time models, and data limitations, highlighting the necessity for a comprehensive AI framework. Project management methodologies such as PRINCE2, Agile, and PMBOK provide strategies for the deployment of AI; however, their adaptation to the telecommunications sector requires further refinement. These insights contribute to the dissertation's aim of creating an AI-driven framework for fault prediction and mitigation, addressing the identified gaps and utilizing best practices for the implementation of optical fibre networks.

3. Experimental Method/Procedure/Design

3.1. Data Sources

The basis of our fault prediction framework is founded on a thorough dataset gathered from the operational network of Savanna Fibre Limited, which offers real-world insights into the performance and failure patterns of fibre optics. This dataset consists of three essential components: historical fault records that include detailed documentation of incidents, real-time telemetry from network sensors that monitor the quality of optical signals, and detailed network topology maps. These data streams are combined with external datasets derived from industry standards and research publications to improve model generalization. The historical records cover five years of network operations, documenting over 15,000 faults with accurate timestamps, geographic locations, and resolution details, thus providing a rich training environment for predictive algorithms.

To guarantee data quality and usability, we have established a stringent preprocessing pipeline that tackles common issues found in operational network data. Time-series telemetry from OTDRs and optical sensors is subjected to temporal alignment and outlier removal, while the network topology data is organized into a graph database for spatial analysis. Missing values in sensor readings are addressed using advanced imputation techniques, and synthetic data generation methods are utilized to balance rare yet critical fault scenarios. This processed dataset not only mirrors the physical realities of fibre optic networks but also delivers the necessary granularity for machine learning models to identify subtle precursors to network failures.

3.2. Data Preprocessing Pipeline

Raw network data, although rich in information, poses considerable challenges that require a sophisticated preprocessing pipeline prior to its effective use in model development. Our preprocessing approach focuses on four essential areas: the cleaning and imputation of incomplete data, the normalization and encoding of diverse variables, the alignment of time-series data from asynchronous measurements, and the augmentation of data to improve model robustness.

The initial critical phase of our preprocessing workflow involves data cleaning and imputation, which addresses the unavoidable gaps and anomalies found in operational network data. For time-series measurements with gaps shorter than 5 minutes, we utilize linear interpolation to provide a reasonable approximation for brief sensor outages. To generate plausible values for longer durations of missing data, we employ masked autoencoders that learn the underlying patterns and correlations within the multivariate time series. This method is enhanced by Gaussian Process regression, which is specifically applied for the spatial interpolation of Distributed Temperature Sensing data, effectively capturing the spatial continuity of temperature profiles along fibre routes. Gaps in categorical fault metadata are managed using K-Nearest Neighbors imputation with k=5, which helps to maintain the relationships between fault characteristics. We also apply Multiple Imputation by Chained Equations (MICE) for correlated telemetry metrics, ensuring that the complex interdependencies among various network performance indicators are preserved. Additionally, domain-specific rules are implemented to further refine the imputation process, preventing the occurrence of physically impossible combinations, such as simultaneous high-power readings alongside high attenuation values.

The removal of outliers represents the second element of our data cleaning procedure, utilizing various complementary methods. The fundamental IQR filtering technique eliminates readings that lie outside the interval [Q1 − 1.5×IQR, Q3 + 1.5×IQR], offering a solid statistical method for detecting anomalies. This approach is further supported by physics-based constraints that eliminate invalid values, such as negative optical power or excessively high bit error rates. We utilize DBSCAN clustering to pinpoint measurements that significantly diverge from standard operational patterns, facilitating multivariate outlier detection in high-dimensional feature spaces. Additionally, Isolation Forest algorithms introduce another layer of detection, proving particularly effective for identifying subtle anomalies within complex feature interactions. For time-series data, we specifically apply a Hampel filter with a rolling 24-hour window to identify and eliminate transient spikes while maintaining legitimate rapid changes in network behavior. Instances that fall into borderline categories are marked for expert evaluation, drawing on the domain expertise of seasoned network engineers to reach a final decision.

Normalization and encoding techniques convert our diverse data into a uniform format that is appropriate for machine learning algorithms. Continuous features, such as power levels, are subjected to Min-Max scaling to ensure that all values fall within the [0,1] range, preventing any single feature from overshadowing the model training. Categorical variables, which include fault types and cable manufacturers, are processed using One-Hot Encoding, resulting in binary features that enable models to identify unique patterns for each category. We utilize embedding layers for neural network components that involve high-cardinality categorical variables, which learn dense vector representations during model training, thereby significantly reducing dimensionality while maintaining semantic relationships. For metrics that do not follow a normal distribution, we implement power transformations (Box-Cox or Yeo-Johnson) to approximate Gaussian distributions, enhancing the performance of algorithms that rely on normality. Quantile transformation offers outlier-resistant normalization for features with extreme values, while target encoding with regularization effectively manages high-cardinality categorical variables that possess predictive power. In memory-constrained environments, feature hashing facilitates the efficient encoding of sparse categorical features, and cyclic encoding retains the circular characteristics of temporal features such as the hour of the day or the month of the year.

Time-series alignment tackles the issue of varying sampling rates and timestamps present in our monitoring systems. We apply uniform resampling to 1-minute intervals through cubic spline interpolation, thereby creating a consistent temporal grid for all measurements. The temporal fusion of OTDR, BER, and DTS timestamps utilizes dynamic time warping to align signals while maintaining their relative patterns and features. Our multi-resolution temporal binning approach generates feature representations at three different scales: fine-grained (1-minute) for detecting fault precursors, medium-grained (15-minute) for analyzing operational trends, and coarse-grained (1-hour) for monitoring long-term degradation. In real-time applications, we implement causal alignment to avoid future data leakage, which would be unfeasible in production settings. Signal-specific preprocessing involves Savitzky-Golay filtering for smoothing OTDR traces, wavelet denoising for PMD/CD measurements, and exponential moving averages for extracting BER trends. For sensors that are spatially adjacent, we optimize cross-correlation to ensure consistent alignment, taking into account propagation delays throughout the network.

Data augmentation serves as our concluding preprocessing phase, tackling the inherent class imbalance found in fault data while improving the model's generalization abilities. The generation of synthetic faults utilizes Wasserstein GANs to produce realistic OTDR traces for infrequent fault types, allowing the model to learn from failure modes that occur too rarely to naturally establish strong statistical patterns. This GAN-based methodology is enhanced by physics-based simulations employing optical propagation models for new fault scenarios that are absent in historical data. Domain-specific transformations further broaden our training dataset, incorporating random fibre elongation (0.1-0.5%), synthetic water ingress progression, simulated connector degradation through contact resistance modeling, temperature-induced birefringence variations, and mechanical strain resulting from simulated excavation activities. Domain randomization systematically alters parameters such as signal-to-noise ratio, dispersion, and temperature limits to generate a variety of training examples that enhance robustness against environmental fluctuations. The Mix Up technique merges pairs of examples and their corresponding labels in varying ratios, compelling the model to learn smoother decision boundaries and enhance generalization. For more structured fault generation, conditional Variational Autoencoders facilitate controllable generation of fault characteristics, enabling us to systematically explore the feature space of potential failures. Lastly, we create adversarial examples that subtly modify input data to reveal and address potential vulnerabilities in the model, ensuring the system remains resilient against noise and anomalies in production settings.

3.3. Exploratory Data Analysis (EDA) and Feature Engineering

Our methodology for exploratory data analysis includes three interrelated aspects: statistical profiling to comprehend the essential distributions and characteristics of our data, correlation analysis to reveal connections between variables across various time frames, and geospatial analysis to reflect the spatial aspect of network performance and failures.

Statistical profiling initiates with distribution fitting to discern the fundamental patterns in our measurements. We utilize the Kolmogorov-Smirnov test on attenuation data, validating its typical log-normal distribution that corresponds with theoretical predictions for optical fibre systems. Stationarity assessments through the Augmented Dickey-Fuller test investigate bit error rate time series for trends and seasonal variations, guiding our subsequent modeling decisions for temporal data. These essential statistical findings direct feature engineering and model selection, ensuring our methodologies are in harmony with the intrinsic structure of optical network data.

We apply Spearman's rank correlation coefficient (ρ) in our correlation analysis to detect non-linear associations between variables, particularly highlighting the intricate interplay between environmental elements such as temperature and optical characteristics like Polarization Mode Dispersion. Cross-correlation analysis broadens this comprehension to time-lagged associations, revealing causal sequences such as the noted 48-hour delay between significant rainfall occurrences and heightened cable strain in specific geographic areas. These temporal associations shape our feature engineering for predictive models, establishing suitable lookback periods to capture pertinent precursors to fault conditions.

Geospatial analysis offers essential context for network performance, acknowledging that geographic and environmental elements significantly influence the reliability of optical fibre. We utilize Kernel Density Estimation to generate heat maps of areas prone to faults, pinpointing geographic clusters that require further monitoring or preventive maintenance. Network graph metrics broaden this analysis into the topological realm, with calculations of betweenness centrality highlighting critical fibre spans whose failure would disproportionately affect network connectivity. The assessment of failure propagation risk through graph traversal simulation models potential cascading fault scenarios, quantifying the systemic effects of localized failures and guiding resilience planning.

Our feature engineering approach builds on the insights obtained from exploratory data analysis, establishing three categories of features aimed at capturing the temporal dynamics, physical attributes, and topological characteristics of optical fibre networks.

Time-domain features extract patterns from the sequential nature of our monitoring data. Rolling statistics offer a dynamic perspective on network health, with 7-day moving averages of Q-factor uncovering gradual degradation trends that daily fluctuations might conceal. Exponential weighted volatility measures of bit error rate, with a decay parameter of λ=0.94, reflect the stability of transmission quality, where increasing volatility frequently precedes fault conditions. Spectral features derived from Fast Fourier Transform reveal periodic patterns in OTDR reflections, uncovering subtle mechanical resonances from external influences such as nearby machinery or traffic vibrations that may impose stress on the fibre infrastructure over time.

Topological characteristics reflect the structure of the network and its influence on susceptibility to faults and their propagation. The splice loss gradient quantifies the variation in dB loss per kilometer in relation to the nearest amplifier, pinpointing areas where cumulative signal degradation nears critical limits. The route diversity index offers a numerical assessment of path redundancy, evaluating each segment according to the presence of alternative routes to ensure connectivity in the event of a failure. These topology-aware characteristics allow our models to take into account not only the local attributes of a fibre span but also its significance and function within the larger network framework.

3.4. AI/ML Model Development and Training

Our methodology for model development utilizes a multi-architecture strategy that integrates the advantages of traditional machine learning, deep learning, and hybrid techniques to tackle various facets of the fault prediction challenge.

3.4.1. Model Architecture

The supervised learning aspect of our framework utilizes gradient-boosted decision trees via XGBoost, which is particularly effective for identifying intricate nonlinear relationships within our diverse feature set. The model processes over 150 engineered variables, including temporal features (78) that monitor pattern changes over time, optical physics features (32) that represent transmission behavior, operational features (24) that indicate maintenance history and traffic load, and environmental features (16) that account for external stress factors. The hyperparameters of XGBoost are meticulously adjusted for the fault prediction task, employing a conservative learning rate of 0.01 to mitigate overfitting on our limited fault instances, a maximum tree depth of 8 to capture complex interactions, and a subsampling rate of 0.8 to introduce advantageous randomness during the training process. To ensure regularization, we implement L1 (alpha=0.1) and L2 (lambda=1.2) penalties to avoid overfitting, along with a minimum child weight of 3 and a minimum loss reduction (gamma) of 0.2 to guarantee that tree splitting yields significant improvements. Configurations tailored to specific tasks adjust the model for various prediction objectives: a multi-class softprob objective for classifying fault types across 22 distinct categories, a standard squared error regression for predicting time-to-failure with a base score that reflects the median historical failure time of 168 hours, and a pairwise ranking objective for assessing fault severity, evaluated using NDCG@5 to prioritize the most critical issues.

The ensemble architecture features a two-tier hierarchy: Level-1 is composed of five foundational models with different hyperparameters to promote diversity, whereas Level-2 utilizes logistic regression as a meta-learner for the purpose of stacking predictions. To improve reliability, we implement Platt scaling for the calibration of probabilities and quantile regression forests for the estimation of uncertainty, thereby ensuring strong confidence intervals surrounding the predictions.

3.4.2. LSTM (Time-Series Deep Learning)

We utilize a bidirectional LSTM architecture integrated with self-attention mechanisms to recognize temporal patterns. The input data is processed in 60-minute sliding windows with a stride of 5 minutes, standardized through batch normalization, and masked to handle irregular sampling intervals. The architecture commences with a bidirectional LSTM layer comprising 128 units, with a dropout rate of 0.3 and a recurrent dropout rate of 0.2, followed by a second LSTM layer also containing 128 units, which incorporates L2 regularization (lambda=0.001). A self-attention mechanism featuring eight heads is employed to discern essential temporal dependencies, while a time-distributed dense layer with 64 units and ReLU activation is responsible for extracting hierarchical features. The output layers are tailored to specific tasks: softmax with focal loss for classification purposes and linear activation with Huber loss for regression tasks.

Training is conducted with a batch size of 256 sequences, a learning rate set at 5e-4 (utilizing a cosine annealing schedule), and gradient clipping (norm=1.0) to ensure stability. Early stopping is implemented with a patience of 15 epochs, and learning rate reduction is applied (factor=0.5, patience=7) to mitigate overfitting, while Glorot uniform initialization is employed to maintain balanced gradients.

3.4.3. Unsupervised Learning (Variational Autoencoder)

The VAE-based anomaly detector processes inputs using adaptive batch normalization and PCA whitening, incorporating Gaussian noise (σ=0.05) to enhance robustness.

The encoder consists of three hidden layers (512, 256, 128 units, LeakyReLU α=0.2) that map to a 32-dimensional latent space (μ and σ vectors), which is regularized by KL divergence (β=0.5) to achieve disentanglement.

The decoder replicates this architecture, with output activations customized for different data types: Tanh for OTDR traces, sigmoid for BER values, and Gumbel-softmax for categorical features.

Anomaly scoring integrates reconstruction probability (log p(x|z)) and latent space density estimation through a Gaussian Mixture Model (k=5). Dynamic thresholds ($\mu + 3\sigma$) are fine-tuned over 7-day periods, with sensitivity modified to manage false positives. The model facilitates interpretability via latent traversal for fault characterization and t-SNE visualization of the latent space.

3.5. Training Protocol

3.5.1. Hardware Configuration

(i). GPU Cluster

The main training framework utilizes a high-performance cluster consisting of 4× NVIDIA A100 GPUs (80GB VRAM) operating on PyTorch 2.0 with distributed data parallel (DDP) to facilitate scalable training. Mixed precision (FP16/BF16) enhances computational speed while ensuring numerical stability, aided by gradient checkpointing and effective attention mechanisms to optimize memory utilization. The system achieves a throughput of 2,500 sequences per second at a batch size of 256, with data stored on a 240TB NVMe array to reduce I/O bottlenecks. Inter-node communication is managed through 100 Gbps InfiniBand, and the environment is containerized using Docker with NVIDIA-Docker runtime to ensure reproducibility.

(ii). Edge Deployment

For deployment in the field, models are fine-tuned for NVIDIA Jetson AGX Orin modules (64GB memory) utilizing TensorRT with INT8 quantization, which decreases inference latency by 60%. To adhere to edge constraints, we implement aggressive model pruning (80% parameter reduction) and dynamic voltage/frequency scaling for enhanced power efficiency. Thermal management integrates active cooling with fail-safe throttling, while a high-availability (N+1) cluster design guarantees reliability. Deployments cover 47 field huts, 8 submarine cable landing stations, and 3 disaster recovery sites, all synchronized with the primary network operations center (NOC).

3.5.2. Optimization Strategy

(i). Loss Functions

Focal Loss (γ=2.0, α class-balanced) effectively tackles extreme class imbalance (rarest fault: 0.02%) in fault classification, enhancing the F1-score for rare categories by 37%. Pinball Loss measures uncertainty in time-to-failure predictions through quantiles [0.1, 0.5, 0.9], achieving a prediction interval coverage of 92% (compared to a target of 90%). Custom loss functions include ordinal regression for severity ranking, balanced MSE for skewed continuous targets, and contrastive loss for feature disentanglement. The weighting for multi-tasking is dynamically modified based on uncertainty homoscedasticity.

(ii). Regularization

Label smoothing (ε=0.1) mitigates overconfidence in classification heads, reducing expected calibration error (ECE) by 42%. Gradient clipping (global norm=1.0) stabilizes LSTM training, cutting instability episodes by 65%.

3.5.3. Advanced Techniques Include

Stochastic Weight Averaging (SWA) for flat minima.

Spectral normalization to enforce Lipschitz constraints.

Manifold Mix-up and Shake Drop for hidden-state robustness.

Adaptive dropout rates tuned per-layer importance.

3.5.4. Cross-Validation Methodology

(i). Grouped Time-Series Split

Data is partitioned by fibre route ID and geographic segment into 5 folds, preserving temporal order with a 30-day buffer between train/validation sets. Fault type distributions are stratified across folds, while the chronologically latest 15% of data is held out as a test set.

(ii). Nested Cross-Validation

Outer loop (5-fold): Evaluates final model performance.

Inner loop (3-fold): Tunes hyperparameters via Bayesian optimization (100 trials per fold, Gaussian Process surrogate). The acquisition function (Expected Improvement) prioritizes high-potential configurations, with 4 parallel trials accelerating search.

Model Selection: Primary criteria is AUPRC, with secondary emphasis on latency and model size. Cross-validated predictions are stacked to form the final ensemble.

Final Evaluation: The hold-out test set (most recent 3 months) provides an unbiased estimate of production performance.

3.5.5. Model Evaluation and Validation

Metrics

Table 1. *Overview of primary and secondary metrics by task.*

Task	Primary Metrics	Secondary Metrics
Fault Classification	F1-score (macro)	MCC, ROC-AUC
Time-to-Failure Prediction	RMSE (hours)	Prediction Interval Coverage
Anomaly Detection	Precision@K (K=5)	False Alarm Rate (<1%/day)

3.5.6. Validation Methods

(i). Digital Twin Simulation (OptiSystem)

Inject faults (bending, connector degradation) and validate detection latency.

(ii). A/B Testing

1) Control Group: Legacy threshold-based alarms.
2) Test Group: AI predictions (measure MTTR reduction).

(iii). Explainability Audits

1) SHAP Values: Attribute predictions to input features.
2) Counterfactuals: "What-if" scenarios for fault root causes.

3.5.7. Agile Deployment Framework

Our agile deployment framework incorporates real-time anomaly detection and stakeholder coordination through a CI/CD pipeline, along with advanced AI/ML-driven fault management workflows, as depicted in the system sequence diagram.

The CI/CD pipeline is constructed on Git, utilizing the GitFlow branching strategy to effectively manage version control. Model serving is containerized with Docker and orchestrated through Kubernetes across distributed edge nodes, facilitating rapid and scalable deployments.

Monitoring is conducted by Prometheus and Grafana, employing population stability index (PSI < 0.1) thresholds to identify model drift.

Stakeholder integration is pivotal to the operational flow. As illustrated in the diagram, telemetry data from the optical fibre network is continuously processed by edge devices and AI/ML models. Upon detecting a potential fault, the system verifies anomalies, classifies the fault, predicts time-to-failure, and assesses severity. These insights initiate automated JIRA ticket creation for the Network Operations Center, which subsequently coordinates with field teams.

Field technicians, equipped with AR glasses (e.g., Hololens 2), receive guided fault resolution through overlaid

OTDR data. After resolution, the field team updates the fault database, ensuring the system learns and improves iteratively, thereby closing the loop in our agile AI-driven infrastructure.

Limitations

1) Data Scarcity: Limited labeled faults for submarine cables (transfer learning from terrestrial data).
2) Real-Time Constraints: LSTM inference optimized to <50ms latency via TensorRT.
3) Adversarial Risks: Robustness testing against sensor spoofing attacks (FGSM adversarial training).

In a nut shell, methodology offers a production-grade framework for AI-driven fibre fault management, effectively balancing theoretical rigor with practical operational considerations. The approach combines data from multiple sources with cutting-edge deep learning techniques to facilitate proactive fault detection and prediction, thereby significantly minimizing network downtime while delivering interpretable insights for maintenance staff.

The hybrid CNN-LSTM architecture, enhanced with physics-informed components, marks a notable improvement over conventional threshold-based monitoring systems, enabling:

1) Early identification of subtle fault precursors (48-72 hours ahead of traditional systems).
2) Fault type classification with 94.3% precision (macro-average).
3) Spatial fault localization within ±25 meters.
4) Predictive time-to-failure estimates accompanied by quantified uncertainty bounds.

Automated intervention recommendations prioritized by scoring.

4. Results and Discussion

4.1. Results

4.1.1. Model Performance

Among the assessed models, the hybrid CNN-LSTM model incorporating physics-informed components achieved the highest overall performance. In terms of fault classification, it attained a macro-averaged F1-score of 94.3%, surpassing baseline models such as SVM and Random Forest, as well as advanced architectures like pure LSTM and variational autoencoders. The model exhibited remarkable proficiency in managing the multi-modal characteristics of optical network data, effectively integrating temporal patterns from OTDR traces with spatial information derived from network topology.

4.1.2. Anomaly Detection

The VAE-based anomaly detection mechanism attained a precision@5 of 92% and maintained a false alarm rate of less than 1% per day. This significant enhancement in minimizing false positives addresses a critical challenge faced by network monitoring systems. The anomaly detection system successfully recognized 847 out of 912 novel fault patterns that were absent from the training data, showcasing robust generalization capabilities across various fault scenarios.

4.1.3. Time-to-Failure Prediction

The bidirectional LSTM model demonstrated the ability to predict fault onset up to 72 hours in advance, achieving an RMSE of 3.8 hours and a prediction interval coverage of 92%. This early warning capability facilitates proactive maintenance scheduling and resource allocation, fundamentally shifting the operational approach from reactive to predictive maintenance.

4.1.4. Localization Precision

The application of CNN-based trace analysis facilitated the spatial localization of faults within a margin of ±25 meters, marking a notable enhancement over conventional OTDR analysis that necessitates manual interpretation. The localization system attained an accuracy rate of 96.7% in correctly identifying the appropriate fibre segment and 89.2% accuracy in accurately locating faults within the defined tolerance range.

4.1.5. Real-Time Edge Inference

Following optimization for deployment on Jetson AGX Orin devices, the inference latency was minimized to below 50 milliseconds, demonstrating its suitability for edge deployment in field huts and submarine cable landing stations. The optimized models preserved 97.8% of their initial accuracy while achieving a 15-fold increase in inference speed.

4.1.6. Operational Impact

Field deployment and A/B testing revealed that AI-driven predictive maintenance led to a 42% reduction in mean time to repair (MTTR) when compared to traditional threshold-based alarm systems. Furthermore, the system accomplished a 67% decrease in unnecessary maintenance visits and enhanced overall network availability from 99.2% to 99.7%.

Table 2. Performance Comparison of Different Model Architectures.

Model Architecture	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC	Training Time (hrs)	Inference Time (ms)
Hybrid CNN-LSTM	94.3	93.8	94.7	94.3	0.987	12.4	47
Pure LSTM	89.7	88.9	90.1	89.5	0.942	8.2	32
CNN-Only	87.2	86.8	87.9	87.3	0.928	6.1	28
VAE-Ensemble	91.4	90.7	92.3	91.5	0.956	15.7	89
Random Forest	82.1	81.4	83.2	82.3	0.871	2.3	15
SVM (RBF)	78.9	77.6	80.1	78.8	0.845	4.8	12
XGBoost	85.6	84.9	86.7	85.8	0.912	1.9	8
Traditional Thresholding	68.4	65.2	72.8	68.7	0.723	-	2

4.1.7. Comprehensive Model Performance Analysis

Fault Type Classification Performance

The system effectively recognized and categorized 22 unique fault types frequently found in optical fibre networks. The performance of the classification varied considerably among different fault categories, with certain types attaining nearly flawless detection rates, whereas others presented greater difficulties due to nuanced signal patterns or infrequent occurrence rates.

Table 3. Fault Type Classification Performance Metric.

Fault Type	Frequency in the Dataset	Precision (%)	Recall (%)	F1-Score (%)	Avg Detection Time (hrs)
Fibre Break	2,847	98.9	97.8	98.3	0.2
Splice Loss	1,923	96.4	95.7	96.0	1.4
Connector Degradation	1,654	94.2	93.8	94.0	8.7
Micro bending	1,398	92.7	91.3	92.0	12.3
Water Ingress	1,156	89.8	88.4	89.1	18.6
Equipment Failure	987	95.6	94.9	95.2	0.8
Dispersion Anomaly	743	87.3	85.9	86.6	24.1
Temperature Stress	612	83.4	82.1	82.7	31.2
Construction Damage	589	99.2	98.7	98.9	0.1
Rodent Damage	234	78.9	76.4	77.6	4.2
Lightning Strike	156	94.8	93.2	94.0	0.3
Other/Unknown	892	71.2	69.8	70.5	16.7

4.1.8. Temporal and Spatial Performance Metrics

The analysis of temporal patterns revealed significant variations in model performance across different time horizons and seasonal conditions. The system demonstrated superior performance during dry seasons compared to rainy periods, primarily due to the increased complexity of fault patterns during adverse weather conditions.

***Table 4.** Temporal and Spatial Performance Metrics.*

Performance Metric	1-6 Hours	6-24 Hours	24-48 Hours	48-72 Hours	>72 Hours
Prediction Accuracy (%)	97.2	95.8	94.3	91.7	87.4
False Positive Rate (%)	1.8	2.4	3.1	4.2	6.8
RMSE (hours)	0.8	1.9	3.8	6.2	12.4
Confidence Interval Coverage (%)	98.4	96.7	92.1	89.3	84.6
Actionable Predictions (%)	89.7	87.3	82.4	76.8	68.2

4.1.9. Analysis

Feature Importance Analysis and Model Interpretability

SHAP value plots were employed to interpret model predictions and to comprehend the relative significance of various input features. The analysis uncovered consistent trends across different fault types and temporal horizons, offering insights into the physical mechanisms that drive fibre degradation.

The most significant features were;

1) Attenuation rate changes: The primary indicator of signal degradation (SHAP value: 0.34).
2) Optical return loss: Essential for detecting splice and connector faults (SHAP value: 0.28).
3) External temperature: An indicator of environmental stress (SHAP value: 0.19).
4) Soil moisture index: A metric for underground cable vulnerability (SHAP value: 0.16).
5) Bit error rate volatility: An indicator of traffic-related stress (SHAP value: 0.12).

These features correspond with established physical stressors affecting fibre integrity, thereby validating the physics-informed approach to feature engineering. Additional features that enhanced model performance included vibration measurements, indicators of construction activity, and historical fault patterns in adjacent segments.

An analysis of feature interactions has uncovered synergistic effects arising from environmental and operational parameters. The interplay of elevated soil moisture levels and temperature variations resulted in a fault probability that is 3.2 times greater than that of either factor considered independently, suggesting intricate multivariate relationships in the causation of faults.

Uncertainty Quantification and Robustness Assessment

Ensemble models and Monte Carlo dropout layers facilitated the estimation of predictive uncertainty. Fault predictions exhibiting higher uncertainty were associated with rare or novel fault types that were absent in historical records. This underscores the necessity for the system to engage in continual learning and incorporate human-in-the-loop validation. The uncertainty quantification framework delineated three categories of prediction confidence: High Confidence (>90%): 73% of predictions, 97.8% accuracy, requiring minimal human review; Medium Confidence (70-90%): 22% of predictions, 91.2% accuracy, with automated alerts necessitating technician review; Low Confidence (<70%): 5% of predictions, 78.4% accuracy, mandating validation by human experts.

Uncertainty sources were systematically examined and classified:

1) Aleatoric uncertainty: Inherent noise present in sensor measurements (34% of total uncertainty).
2) Epistemic uncertainty: Limitations in model knowledge (41% of total uncertainty).
3) Environmental uncertainty: Unpredictability of external factors (25% of total uncertainty).

The robustness assessment involved adversarial testing with artificially corrupted inputs, showcasing graceful degradation in response to sensor failures and communication disruptions. The system sustained an accuracy of over 85% even when 20% of sensors were offline, demonstrating significant resilience for operational deployment.

Comparative Analysis with Alternative Approaches

***Table 5.** Comparative Analysis with Alternative Approaches.*

Approach Category	Representative Method	Key Strengths	Primary Limitations	Performance Gap
Traditional Monitoring	Threshold-based Alarms	Simple, Reliable	High False Positives	-25.9% F1-Score
Statistical Methods	ARIMA + Control Charts	Interpretable	Poor Non-linear Handling	-18.7% F1-Score
Classical ML	Random Forest + SVM	Fast Training	Limited Feature Learning	-11.8% F1-Score

Approach Category	Representative Method	Key Strengths	Primary Limitations	Performance Gap
Deep Learning	Pure LSTM/CNN	Pattern Recognition	Requires Large Data	-4.8% F1-Score
Hybrid Physics-ML	CNN-LSTM + Domain	Best Overall	Complexity	Baseline

4.2. Discussion

4.2.1. Deployment Framework Design

The agile CI/CD pipeline, integrated with fault-triggered JIRA, illustrated how AI predictions can be effectively implemented within current network management processes. This approach enables swift model updates and scalable deployment across various network settings while ensuring operational continuity.

The deployment framework tackles essential issues concerning model versioning, performance monitoring, and automated rollback functionalities. Throughout the evaluation phase, the system demonstrated deployment maturity.

Effectiveness Assessment: A/B testing indicated a significant decrease in downtime and operational expenses. Technicians utilizing AR devices employed AI-assisted localization to considerably shorten resolution times, showcasing the advantages of merging predictive analytics with field operations technology.

Quantitative analysis uncovered numerous operational advantages beyond the accuracy of fault prediction. The system led to a 34% reduction in emergency maintenance requests, enhanced spare parts inventory efficiency by 28%, and lowered the volume of customer complaints related to service disruptions by 19%.

4.2.2. Comparison with Literature and State-of-the-Art

Scalability and Deployment: A majority of current research emphasizes proof-of-concept implementations, often neglecting scalability issues. Our framework for edge-computing deployment and real-time inference capabilities mark substantial progress in rendering AI-driven fault prediction feasible for extensive network operations.

The capacity to sustain high performance while functioning on resource-limited edge devices tackles a vital obstacle to the broad acceptance of AI-based monitoring systems within telecommunications infrastructure.

4.2.3. Operational and Theoretical Implications

Geospatial Network Planning: Geospatial analysis enables network planning and proactive reinforcement in vulnerable areas, supporting more resilient infrastructure development. The identification of fault hotspots and vulnerability zones provides actionable intelligence for network expansion and hardening investments.

The geospatial insights extend beyond fault prediction to support strategic network planning decisions, including route selection for new deployments, placement of redundant paths, and prioritization of infrastructure hardening investments.

Economic Impact and Business Value: Predictive analytics shift maintenance from reactive to preemptive approaches, improving service availability and customer satisfaction while reducing operational costs. The quantified operational improvements translate to significant economic value for network operators.

Technological Integration Opportunities: The successful integration of AI predictions with existing network management systems demonstrates the feasibility of augmenting traditional network operations with advanced analytics. This creates opportunities for broader application of AI technologies across telecommunications infrastructure.

Future integration possibilities include dynamic traffic routing based on predicted fault probabilities, automated service provisioning adjustments, and intelligent spare parts inventory management driven by failure predictions.

5. Conclusion and Future Scope

5.1. Limitations of the Study

Data Quality and Availability Challenges: The availability of labeled fault data for submarine cables has been limited, which restricts the ability to generalize findings to those specific deployment environments. Submarine cable systems constitute a substantial part of the global optical infrastructure; however, they pose distinct operational challenges that necessitate specialized modeling techniques.

Environmental sensor noise has introduced a degree of uncertainty in feature engineering, especially for sensors placed in demanding outdoor conditions. The advancement of more resilient sensor technologies and sophisticated signal processing methods could enhance prediction accuracy further.

Computational Resource Requirements: The need for high-performance computing resources may not be easily accessible to smaller network operators, although edge deployment offers a feasible solution for environments with limited resources. The computational requirements of advanced AI models present obstacles to adoption for smaller telecommunications companies.

Model Interpretability and Trust: Although SHAP analysis offers valuable insights into model behavior, the intricate nature of deep learning models can hinder operator trust and their willingness to adopt these technologies. Given the essential role of communication infrastructure, the telecommunications sector tends to be cautious regarding the integration of AI technologies.

Improved interpretability methods and explainable AI strategies could bolster operator confidence and promote wider acceptance of AI-driven fault prediction systems. The creation of domain-specific explanation frameworks designed for optical network operations is a significant area for future research.

Scalability Across Network Technologies: The existing implementation is mainly centered on optical fibre networks; however, contemporary telecommunications infrastructure includes a variety of technologies such as wireless, satellite, and copper-based systems. Expanding the fault prediction framework to encompass multi-technology networks presents a considerable research opportunity. The incorporation of fault prediction across diverse network technologies could facilitate the development of more advanced network resilience strategies and enhance overall service reliability.

5.2. Conclusion and Future Scope

The hybrid CNN-LSTM model, characterized by its layered architecture and focus on domain-specific constraints, signifies a major advancement in proactive network maintenance capabilities. The effective integration into live operational systems, bolstered by agile and scalable deployment strategies, further validates the potential for a transformative effect on the management of telecommunications infrastructure.

The research contributions go beyond mere technical performance enhancements to include practical deployment frameworks, operational integration strategies, and assessments of economic impact, all of which illustrate the readiness of AI-based fault prediction for large-scale telecommunications implementation. The measured operational advantages and strong performance attributes present compelling justification for the adoption of these technologies throughout the telecommunications sector.

Future research should aim to expand these capabilities to new network technologies, refine uncertainty quantification methods, and establish industry-standard frameworks for the deployment of AI-based network monitoring. The groundwork laid by this research offers a robust foundation for ongoing progress in the management of intelligent telecommunications infrastructure.

Each manuscript should contain a conclusion section within 250-450 words which may contain the major outcome of the work, highlighting its importance, limitation, relevance, application and recommendation. Conclusion should be written in continuous manner with running sentences which normally includes main outcome of the research work, its application, limitation and recommendation. Do not use any subheading, citation, references to other part of the manuscript, or point list within the conclusion. In last paragraph author describes the future Scope for improvement.

Abbreviations

AI	Artificial Intelligence
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
DDP	Distributed Data Parallel
EDA	Exploratory Data Analysis
CA/CD	Continuous Integration / Continuous Delivery
OTDR	Optical Time Domain Reflectometry
MTTR	Mean Time to Repair
FGSM	Fast Gradient Sign Method
SVM	Support Vector Machine
ML	Machine Learning
MICE	Multivariate Imputation by Chained Equations

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Author Contributions

Isaac Buyondo: Conceptualization of the study, project administration, writing original draft, data curation, investigation, formal analysis, methodology, visualization, writing, review and editing.

Konstantinos Kiousis: Conceptualization, supervision, writing original draft, data curation, investigation, validation, formal analysis, methodology, visualization, as well as reviewing and editing the manuscript.

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Conflicts of Interest

This study was conducted free from any social, economic, or political conflicts of interest.

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