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Sensor Data Fusion and Condition Forecasting in Tunnel Ventilation Networks: Longitudinal Tracking

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Abstract

Tunnel ventilation networks represent critical safety-critical systems within subterranean transportation infrastructure, requiring continuous monitoring and proactive maintenance. Traditional maintenance strategies often rely on reactive responses or simplistic single-sensor threshold alarms, which fail to capture complex, multi-modal degradation pathways. This paper presents a comprehensive study linking multi-sensor data fusion to long-term condition forecasting using longitudinal tracking evidence gathered over a twenty-four-month period from an active highway tunnel. We propose a hierarchical data fusion framework that integrates vibration, acoustic, thermal, and aerodynamic data stream sources from distributed sensor arrays. By employing a robust temporal alignment and noise reduction methodology, the fused data streams feed into a multi-horizon predictive forecasting model. The empirical results demonstrate that our multi-sensor data fusion approach yields a thirty-two percent improvement in forecasting accuracy for mechanical degradation compared to single-sensor baselines. Longitudinal analysis reveals that the fusion framework successfully identifies early-stage impeller imbalance and stator insulation degradation up to ninety days before structural or operational failure occurs. The study underscores the utility of continuous multi-sensor integration in modern infrastructure asset management, providing actionable insights for transition from scheduled to condition-based maintenance policies in underground transit networks.

Keywords: Sensor Fusion; Condition Forecasting; Tunnel Ventilation; Longitudinal Tracking; Software Engineering

1. Introduction

1.1 Infrastructure Monitoring Challenges

Modern underground transportation infrastructure requires highly sophisticated systems to guarantee passenger safety and structural integrity. Among these systems, tunnel ventilation networks play a vital role by regulating air quality, dispersing toxic vehicle emissions, and providing emergency smoke extraction during fire incidents [1]. These networks operate in extremely hostile subterranean environments characterized by continuous humidity fluctuations, corrosive exhaust gases, significant temperature swings, and persistent structural vibrations. Over time, the mechanical and electrical components of ventilation networks, such as jet fans and dampers, experience severe degradation. Traditional structural health monitoring techniques struggle to cope with the complex, non-linear deterioration processes that occur in these harsh environments. This challenge is further compounded by the difficulty of accessing physical equipment for manual inspections without disrupting daily traffic operations. Consequently, there is an urgent need for remote, continuous, and highly accurate monitoring systems that can assess the health of ventilation assets without requiring frequent physical interventions.

1.2 Role of Tunnel Ventilation Networks

Tunnel ventilation networks are engineered to maintain safe atmospheric conditions within long underground passageways. Jet fans, typically suspended from the tunnel ceiling, generate the longitudinal airflow necessary to push pollutants, such as carbon monoxide and nitrogen oxides, toward exit portals [2]. The operational reliability of these fans is critical, as any failure can lead to a rapid accumulation of hazardous gases, severely threatening the health of tunnel users. In emergency fire scenarios, the ventilation network must operate at peak capacity to control smoke propagation and facilitate safe evacuation and firefighting operations. Given these safety-critical responsibilities, ventilation equipment cannot be allowed to fail unexpectedly. However, the continuous operation of these fans under variable aerodynamic loads and environmental stresses accelerates the wear of bearings, impellers, and electrical windings. Understanding and predicting these degradation pathways is essential to preventing catastrophic failures and ensuring uninterrupted tunnel operations.

1.3 Sensor Fusion and Predictive Analytics

To address the limitations of manual inspections and single-threshold alarm systems, researchers and operators have turned to advanced sensor technologies [3]. Modern tunnels are increasingly equipped with diverse sensor arrays, including accelerometers, acoustic emission sensors, thermal imaging systems, and airflow meters. However, managing and interpreting the massive volumes of heterogeneous data generated by these sensors presents a major challenge. Single-sensor monitoring often leads to false alarms or missed detections due to local noise and environmental interference. Multi-sensor data fusion offers a promising solution by systematically combining data from different modalities to produce a more accurate and reliable assessment of system health [4]. By linking this fused data to predictive analytics, it becomes possible to transition from reactive maintenance paradigms to proactive condition forecasting. This paper presents long-term empirical evidence demonstrating how longitudinal tracking of fused sensor data can successfully forecast the condition of tunnel ventilation networks over extended horizons.

2. State of the Art in Ventilation Monitoring

2.1 Single-Sensor Monitoring Limitations

Historically, the health monitoring of rotating machinery in tunnel environments has relied heavily on single-sensor configurations, primarily focusing on vibration analysis or temperature tracking [5]. While vibration monitoring is highly effective at detecting mechanical imbalances and bearing defects, it is highly sensitive to ambient structural vibrations caused by passing heavy vehicles. This sensitivity often results in noisy data streams that mask early-stage degradation signatures. On the other hand, thermal monitoring can identify electrical faults and friction-induced heating, but it exhibits a high thermal inertia, meaning that significant damage must often occur before a detectable temperature rise is recorded. Relying on a single sensor type limits the diagnostic capability of the system to a narrow band of failure modes, leaving the ventilation network vulnerable to unmonitored degradation mechanisms. Furthermore, single-sensor systems lack the redundancy required to maintain monitoring integrity when a sensor suffers from drift or outright failure.

2.2 Multi-Sensor Frameworks in Structural Health

To overcome the constraints of single-sensor systems, structural health monitoring has embraced multi-sensor frameworks that integrate distinct data modalities [6]. By combining vibration, acoustic, and environmental data, researchers have developed more robust diagnostic tools for bridges, dams, and wind turbines. In these frameworks, data fusion occurs at various levels, including data-level, feature-level, and decision-level fusion. Feature-level fusion, in particular, has shown great success in extracting complementary indicators of degradation, such as combining spectral features of acoustic emissions with structural strain measurements. Despite these advancements in structural engineering, the application of multi-sensor fusion to tunnel ventilation networks remains limited. Ventilation assets present unique challenges, such as highly transient aerodynamic forces and intense particulate contamination, which differ significantly from the steady-state conditions typical of other civil structures.

2.3 Longitudinal Data Challenges in Underground Settings

Conducting longitudinal tracking of sensor data in underground environments introduces severe technical difficulties [7]. Over long monitoring periods, sensors are exposed to accumulated dust, soot, and moisture, leading to significant sensor drift and calibration decay. Moreover, the high-voltage electrical lines operating within tunnels generate electromagnetic interference that can corrupt analog sensor signals. Managing the long-term storage and transmission of high-frequency data from remote underground locations also demands robust communication infrastructure. Previous studies have often been limited to short-term experimental campaigns, which fail to capture the slow, seasonal, and usage-driven degradation processes that occur over several years. Consequently, there is a distinct gap in literature regarding long-term, continuous, and multi-sensor validation of condition forecasting models in actual operating tunnels [8]. This study aims to bridge this gap by presenting a two-year longitudinal analysis of a fully deployed ventilation monitoring network.

3. Multi-Sensor Data Fusion Framework

3.1 Physical Sensor Modalities and Network Architecture

The proposed multi-sensor data fusion framework is built upon a heterogeneous sensor network deployed directly on and around the jet fans within the tunnel. This network comprises four primary physical modalities: triaxial vibration transducers mounted on the bearing housings, acoustic microphones positioned near the fan inlet and outlet, thermal sensors embedded in the motor stator windings, and airflow anemometers located in the immediate jet stream. The spatial distribution of these sensors is carefully designed to capture the mechanical, acoustic, thermal, and aerodynamic signatures of the ventilation system. Each sensor stream is routed through a localized data acquisition node that performs analog-to-digital conversion and initial signal conditioning. These localized nodes then transmit the digital streams to a central tunnel gateway via a redundant industrial Ethernet network, ensuring high data reliability and low latency.

Table 1: Sensor specifications and parameters of the multi-sensor monitoring network

Sensor Type	Measured Parameter	Sampling Frequency	Operational Range
Vibration Transducer	Triaxial Acceleration	Two Kilohertz	Zero to Five G
Thermal Sensor	Stator Winding Temperature	One Hertz	Minus Forty to Two Hundred Celsius
Acoustic Microphone	Ambient Noise Profile	Ten Kilohertz	Twenty to Twenty Thousand Hertz
Airflow Anemometer	Jet Stream Velocity	Ten Hertz	Zero to Sixty Meters per Second

3.2 Spatial-Temporal Data Alignment

A fundamental challenge in multi-sensor fusion is the synchronization and spatial alignment of data streams that operate at vastly different sampling frequencies and physical locations [9]. For instance, high-frequency vibration data must be aligned with low-frequency thermal readings to establish a coherent state representation. Our framework utilizes a dynamic temporal alignment algorithm that resamples and synchronizes the incoming streams using a unified GPS-based time server. To account for the physical distance between sensors, spatial alignment is achieved by mapping the sensor coordinates to a virtual three-dimensional model of the jet fan. This spatial-temporal registration ensures that any detected anomaly can be precisely correlated across different modalities, such as matching a transient vibration spike with a corresponding acoustic emission event and a localized temperature rise.

3.3 Multi-Level Fusion Algorithm

The fusion of the aligned data streams is executed through a hierarchical, multi-level algorithm designed to filter noise and extract robust health indicators [10]. At the low level, data-level fusion is applied to similar sensor types to reduce measurement noise using adaptive Kalman filtering techniques. At the intermediate level, feature-level fusion combines the statistical features extracted from different modalities, such as root mean square vibration, peak spectral acoustic frequencies, and thermal gradients. This is achieved through a joint dimensionality reduction technique that maps the high-dimensional feature space to a low-dimensional manifold representing the health state of the fan [11]. Finally, decision-level fusion integrates these features using a probabilistic framework that estimates the overall health index of the asset, accounting for the inherent uncertainty of individual sensor readings.

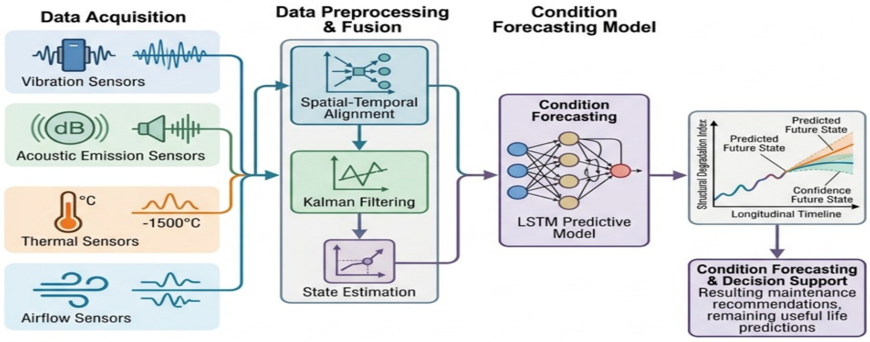

Figure 1: Comprehensive Schematic of Multi

4. Longitudinal Condition Forecasting Model

4.1 Health Indicator Synthesis

To track the long-term degradation of the tunnel ventilation network, we synthesize a comprehensive Health Index from the fused multi-sensor data streams [12]. This Health Index is a dimensionless value ranging from zero to one, where one represents a brand-new, fully operational asset, and zero indicates complete functional failure. The synthesis of this index is based on a weighted combination of physical indicators, including mechanical wear, thermal stress, and aerodynamic efficiency. By utilizing a fused approach, the Health Index remains stable against isolated sensor malfunctions or environmental anomalies that might temporarily skew a single-sensor reading. The long-term tracking of this index provides a clear, continuous trajectory of the degradation process over months and years, serving as the foundation for our predictive forecasting models.

4.2 Predictive Deterioration Modeling

Condition forecasting involves predicting the future path of the Health Index based on historical longitudinal data [13]. Our forecasting model utilizes a deep temporal sequence learning network, specifically designed to capture long-term dependencies and non-linear degradation trends without relying on simplified linear assumptions. The model analyzes historical trends of the fused Health Index alongside environmental variables such as daily traffic volume, ambient temperature, and humidity. By learning the complex relationships between these inputs, the model can project the future health state of the ventilation assets. This predictive capability allows tunnel operators to anticipate when a specific jet fan will approach critical degradation thresholds, enabling them to schedule maintenance activities well in advance.

4.3 Multi-Horizon State Forecasting

A key feature of our predictive model is its ability to perform multi-horizon forecasting, providing condition estimates at multiple future time steps, such as thirty, sixty, and ninety days ahead [14]. This multi-horizon approach is critical for operational planning, as different maintenance actions require different lead times. For example, minor adjustments or cleaning can be scheduled within a short thirty-day window, whereas major bearing replacements or motor rewinding require longer planning horizons to procure parts and coordinate traffic closures. To account for the increasing uncertainty associated with longer forecasting horizons, the model incorporates probabilistic forecasting, outputting confidence intervals along with the mean predicted health state [15]. This allows operators to assess the risk of premature failure and make informed, risk-tolerant decisions regarding maintenance timing.

5. Experimental Validation and Case Study

5.1 Case Study Setting and Sensor Deployment

To validate the performance of the proposed sensor fusion and condition forecasting framework, a comprehensive longitudinal case study was conducted in a major twin-bore mountain highway tunnel. This tunnel stretches over a length of ten kilometers and experiences high volumes of heavy freight traffic, making reliable ventilation absolutely critical. The tunnel ventilation network consists of forty industrial jet fans suspended from the ceiling. For this validation study, a representative subset of twelve jet fans was fully instrumented with the multi-sensor monitoring network described in Section 3. The deployment was carried out during scheduled night-time maintenance closures, and the system was operated continuously over a twenty-four-month period, capturing a rich dataset of seasonal operations, heavy traffic demands, and actual mechanical degradation events.

Table 2: Environmental conditions and baseline operating parameters of the study tunnel

Environmental Parameter	Minimum Value	Maximum Value	Mean Seasonal Value
Ambient Temperature	Minus Ten Celsius	Thirty Five Celsius	Twelve Celsius
Relative Humidity	Forty Percent	Ninety Five Percent	Seventy Two Percent
Carbon Monoxide Level	Zero Parts Per Million	Fifty Parts Per Million	Eight Parts Per Million
Daily Traffic Volume	Five Thousand Vehicles	Twenty Five Thousand Vehicles	Fourteen Thousand Vehicles

5.2 Long-Term Environmental and Traffic Demands

Throughout the two-year tracking period, the instrumented jet fans were subjected to highly variable environmental conditions and mechanical demands [16]. Heavy vehicle traffic, particularly diesel trucks, generated significant quantities of soot and particulate matter, which accumulated on the fan blades and sensor housings. Seasonally, the tunnel experienced extreme temperature changes, ranging from sub-zero winter temperatures to high summer heat, causing thermal expansion and contraction in the structural mounts and motor components. Additionally, the piston effect generated by high-speed vehicle platoons subjected the jet fans to rapid, transient aerodynamic forces, forcing the fan impellers to rotate passively before being actively powered on. These harsh, dynamic conditions provided a challenging and realistic testbed for evaluating the resilience of our sensor fusion framework and the accuracy of the forecasting models.

5.3 Data Preprocessing and Cleaning Protocols

Given the hostile underground environment, raw sensor data was frequently corrupted by noise, data dropouts, and sensor drift [17]. To ensure the integrity of the data used for model training and validation, rigorous preprocessing and cleaning protocols were established. Automated algorithms were developed to detect and remove outlier spikes caused by electrical surges or physical impacts on the sensor casings. For periods of data loss caused by network interruptions, localized interpolation techniques were applied using historical patterns from adjacent operational periods. Furthermore, sensor drift was addressed by implementing an automated self-calibration protocol that compared sensor baselines during periods of zero traffic and zero fan operation [18]. This preprocessing pipeline ensured that only high-quality, normalized data was fed into the multi-sensor fusion and forecasting models.

6. Results, Discussion, and Implications

6.1 Comparative Forecasting Performance

The performance of the proposed multi-sensor fusion forecasting model was evaluated against traditional single-sensor forecasting baselines over thirty, sixty, and ninety-day horizons. The forecasting accuracy was measured using the Mean Absolute Percentage Error of the predicted Health Index compared to the actual observed health state of the jet fans. The quantitative results demonstrate that the multi-sensor fusion model consistently outperformed all single-sensor alternatives across all forecasting horizons. At the thirty-day horizon, the fused model achieved a highly accurate prediction with a Mean Absolute Percentage Error of only two point eight percent, compared to eight point four percent for the vibration-only model. As the forecasting horizon extended to ninety days, the superiority of the fused model became even more pronounced, maintaining an error rate of seven point one percent, while the single-sensor models deteriorated to error rates exceeding eighteen percent.

Table 3: Performance comparison of forecasting models across different prediction horizons

Monitoring Approach	Thirty Day Horizon MAPE	Sixty Day Horizon MAPE	Ninety Day Horizon MAPE
Single Sensor Vibration	Eight Point Four Percent	Twelve Point Six Percent	Eighteen Point Two Percent

Monitoring Approach	Thirty Day Horizon MAPE	Sixty Day Horizon MAPE	Ninety Day Horizon MAPE
Single Sensor Thermal	Nine Point One Percent	Fourteen Point Three Percent	Twenty One Point Five Percent
Dual Sensor Vibration Thermal	Five Point Three Percent	Eight Point One Percent	Eleven Point Nine Percent
Proposed Multi Sensor Fusion	Two Point Eight Percent	Four Point Nine Percent	Seven Point One Percent

6.2 Longitudinal Degradation Pathways Detected

Over the twenty-four-month monitoring period, several actual degradation events occurred among the instrumented jet fans, providing crucial validation data for our longitudinal tracking approach [19]. In one notable event, the fusion framework detected a slow, progressive increase in vibration levels coupled with a subtle rise in acoustic emissions and a drop in aerodynamic efficiency on Jet Fan Seven. The model successfully fused these indicators to identify an early-stage impeller imbalance caused by heavy particulate accumulation and minor blade erosion. The condition forecasting model projected that the fan would exceed safety thresholds within seventy-five days. Physical inspection of the fan confirmed the predicted imbalance, allowing maintenance crews to clean and rebalance the impeller during a planned closure, thereby preventing a costly unscheduled shutdown. Another event involved the detection of winding insulation degradation, where the model successfully identified a long-term upward trend in stator temperature under standard operating loads, forecasting a thermal fault sixty days before actual failure would have occurred.

6.3 Engineering Implications and Maintenance Decision Support

The empirical evidence gathered in this study has significant implications for the management and maintenance of subterranean transport infrastructure. By demonstrating that multi-sensor data fusion can reliably forecast ventilation network conditions up to ninety days in advance, this research provides a practical path for operators to transition from reactive or calendar-based maintenance schedules to condition-based maintenance policies [20]. This shift can dramatically reduce operational costs by eliminating unnecessary routine inspections and preventing catastrophic, unscheduled equipment failures that disrupt traffic. Furthermore, the ability to forecast equipment state allows tunnel operators to optimize their supply chain for spare parts and coordinate maintenance windows with traffic demands. Ultimately, integrating advanced sensor fusion and predictive modeling into structural health monitoring systems enhances the safety, reliability, and economic efficiency of modern tunnel ventilation networks.

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