RADemics

Deep Learning Architectures for Multivariate Time Series Analysis in FDR Data

Srinivasan P, C.N. Ravi, T. Kamal kumar
AMRITA SCHOOL OF COMPUTING, AMRITA VISHWA VIDYAPEETHAM, NAGERCOIL CAMPUS, ACADEMY OF MARIE TIME EDUCATION AND TRAINING, T.J.S. ENGINEERING COLLEGE

Deep Learning Architectures for Multivariate Time Series Analysis in FDR Data

[1]Srinivasan P, Assistant Professor, ECE, Amrita School of Computing, Amrita Vishwa Vidyapeetham, Nagercoil Campus.

[2]C.N. Ravi, Professor, Cse, Academy of Marie Time Education and Training, Ecr, Chennai. mail2cnravi@Gmail.Com

[3]T. Kamal kumar, Assistant Professor, EEE, T.J.S. Engineering College, TJS Nagar, Peruvoyal, Near Kavaraipettai, Gummidipoondi Taluk, Tiruvallur District, 601206. t.kk1205@gmail.com

Abstract

Flight Data Recorder (FDR) systems generate large-scale multivariate time series that capture the dynamic behavior of aircraft systems throughout all phases of flight, providing an indispensable foundation for aviation safety, operational monitoring, predictive maintenance, and accident investigation. The increasing complexity and dimensionality of modern flight data have exposed the limitations of conventional statistical and machine learning techniques in modeling nonlinear temporal dependencies and intricate interactions among numerous flight parameters. Deep learning has emerged as a transformative paradigm capable of automatically learning hierarchical feature representations from raw sequential data, enabling more accurate analysis of complex aviation datasets. This chapter presents a comprehensive review of state-of-the-art deep learning architectures for multivariate time series analysis in FDR data, encompassing recurrent neural networks, Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), Temporal Convolutional Networks (TCNs), Transformer-based models, graph neural networks, attention mechanisms, and hybrid deep learning frameworks. Critical aspects of data preprocessing, feature engineering, sequence generation, model evaluation, explainable artificial intelligence, and real-time deployment are systematically examined to highlight their roles in intelligent flight analytics. Emerging research directions, including self-supervised learning, federated learning, digital twins, and physics-informed deep learning, are also discussed to address existing research challenges. The chapter establishes a unified perspective on advanced deep learning methodologies that enhance anomaly detection, flight phase recognition, fault diagnosis, predictive maintenance, and operational risk assessment, thereby contributing to the development of reliable, scalable, and interpretable next-generation aviation safety systems.

Keywords: Flight Data Recorder (FDR), Multivariate Time Series Analysis, Deep Learning Architectures, Long Short-Term Memory (LSTM), Transformer Networks, Aviation Safety Analytics.

Introduction

The aviation industry has experienced a remarkable technological transformation over the past several decades through the integration of advanced avionics, intelligent sensing technologies, digital flight control systems, and automated monitoring platforms. Modern aircraft function as highly sophisticated cyber-physical systems capable of continuously generating extensive volumes of operational information during every stage of flight [1]. Flight Data Recorders (FDRs) occupy a central position within this technological ecosystem by recording hundreds to thousands of synchronized flight parameters that collectively describe the operational state of an aircraft [2]. These parameters encompass flight dynamics, engine operating conditions, navigation variables, control surface movements, hydraulic and electrical system performance, environmental measurements, and pilot control actions [3]. Continuous recording of such diverse operational variables produces multivariate time series that capture the evolution of aircraft behaviour from taxi and takeoff through climb, cruise, descent, landing, and post-flight operations. Rapid advances in aircraft instrumentation have significantly increased both the quantity and complexity of recorded information, creating unprecedented opportunities for data-driven aviation safety analysis. Rich temporal datasets provide valuable evidence for understanding aircraft system interactions, evaluating operational efficiency, identifying emerging safety concerns, supporting accident investigations, and improving maintenance planning [4]. Growing dependence on intelligent aviation technologies has consequently elevated the strategic importance of Flight Data Recorder analytics as an essential component of modern safety management systems, encouraging extensive research into advanced computational techniques capable of extracting meaningful knowledge from complex sequential flight data [5].

The multivariate nature of Flight Data Recorder datasets distinguishes aviation data from many conventional time series encountered in engineering and industrial applications. Aircraft operations involve numerous interconnected subsystems whose behaviour evolves continuously under changing aerodynamic conditions, environmental influences, pilot actions, and aircraft control responses [6]. Recorded variables exhibit strong temporal dependencies, nonlinear interactions, multiscale operational characteristics, heterogeneous sampling frequencies, and complex correlations that extend across long flight durations. Engine performance directly influences fuel consumption and aircraft speed, while atmospheric disturbances simultaneously affect altitude, attitude, flight control responses, and navigation performance [7]. Such intricate relationships generate highly dynamic multivariate sequences that cannot be adequately represented through isolated parameter analysis or simplified statistical assumptions [8]. Large-scale FDR datasets frequently contain millions of sequential observations collected over thousands of operational flights, producing high-dimensional information environments requiring sophisticated analytical strategies. Sensor noise, calibration drift, communication delays, missing observations, and occasional recording anomalies further increase analytical complexity by introducing uncertainty into temporal feature extraction and predictive modeling. Effective interpretation of these datasets therefore demands computational frameworks capable of preserving chronological continuity while simultaneously learning complex interactions among numerous operational variables [9]. Comprehensive analysis of multivariate flight recordings has consequently become one of the most challenging research problems in intelligent aviation analytics, requiring innovative methodologies capable of transforming raw operational measurements into actionable knowledge that supports safer and more efficient aircraft operations [10].