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Original Research Article

Real-Time Wind Tunnel Data Reduction Using Machine Learning and JR3 Balance Integration

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Abstract

This study presents a novel approach to real-time wind tunnel data reduction by integrating a JR3 six-axis force-torque sensor with machine learning algorithms. Traditional aerodynamic testing often involves large volumes of raw data from force balances, which require extensive post-processing. This paper proposes a machine learning-based model that accelerates the data reduction pipeline, allowing for near-instantaneous derivation of aerodynamic coefficients from JR3 balance data. The framework includes a synchronized data acquisition module, signal preprocessing, a trained regression model, and an interactive visualization tool. Results show that the proposed system can achieve real-time performance while maintaining high accuracy, significantly reducing the computational and time costs associated with wind tunnel testing.

Keywords: Wind Tunnel Testing, JR3 Balance, Machine Learning, Data Reduction, Real-Time Systems, Aerodynamic Coefficients, Force-Torque Sensors.

I. INTRODUCTION

Wind tunnel testing remains a cornerstone of experimental aerodynamics, allowing researchers and engineers to analyze the performance of various models under controlled airflow conditions. These experiments are vital for industries such as aerospace, automotive, civil engineering, and sports technology, where aerodynamic characteristics significantly affect performance and safety. Central to these tests is the use of multi-axis force balances, which record the forces and moments acting on a model as it interacts with the airflow. Among the most widely used instruments is the JR3 six-axis force-torque sensor, renowned for its precision and high-frequency sampling capabilities.

However, despite the accuracy of such sensors, the raw data they produce is typically voluminous and unstructured, requiring post-experimental processing to extract meaningful aerodynamic coefficients such as lift, drag, and pitching moment. These coefficients are essential for interpreting model behavior and guiding design decisions. Traditionally, this data reduction process is performed offline using numerical scripts or proprietary software, often resulting in significant delays between data acquisition and analysis. As a result, researchers are limited in their ability to adapt test parameters in real-time or respond to emerging patterns during a single session. In high-cost, time-sensitive testing environments, this latency presents a critical bottleneck.

Recent advances in machine learning and real-time systems offer a compelling opportunity to transform this workflow. By developing a predictive model trained on previously labeled wind tunnel data, it becomes possible to estimate aerodynamic coefficients directly from raw sensor input with minimal delay. This paper introduces a novel framework that combines the JR3 balance with machine learning algorithms to achieve real-time data reduction, providing near-instantaneous feedback during experiments. The framework is intended to serve as both a time-saving solution and a blueprint for future integrations of intelligent systems in experimental aerodynamics.

A. Background and Motivation

The motivation for this research stems from the need to accelerate and modernize the data analysis pipeline in wind tunnel experiments. While sensors like the JR3 balance have the capability to deliver precise and high-resolution measurements of forces and moments, the transformation of these signals into usable aerodynamic parameters still relies heavily on static calibration matrices and time-consuming data processing. These methods, although accurate, are poorly suited for rapid iteration, real-time feedback, and interactive experimentation.

The increased availability of computational resources, machine learning libraries, and open-source development tools makes it possible to integrate intelligent analytics directly into the experimental environment. In parallel, the rise of data-driven engineering and automation in research facilities further supports the case for embedding predictive models into sensor systems. By learning from previously labeled datasets, machine learning models can replace or augment conventional data reduction routines, enabling more responsive and adaptive experimentation. The goal is not only to save time but also to empower researchers with immediate insights that can drive iterative improvements in design and testing strategies.

B. Problem Statement

Despite the technological capabilities of modern data acquisition hardware, the overall process of converting raw wind tunnel data into meaningful results remains inefficient. The current workflow involves several discrete steps: collecting raw force and moment data, exporting this data to external software, applying calibration transformations, and finally calculating aerodynamic coefficients. Each of these steps introduces potential for error, latency, and data mismanagement. Moreover, this batch-processing approach inherently prevents real-time feedback, making it impossible to identify measurement anomalies or adjust test conditions during live sessions. This lack of responsiveness leads to several problems. For instance, unexpected behaviors in a model—such as abrupt shifts in lift or drag—may go unnoticed until well after a test has concluded. Test engineers may need to repeat experiments or delay analysis due to the time gap between testing and data interpretation. In some cases, by the time results are processed, the opportunity to collect additional supporting data may have already passed. Consequently, there is a pressing need for a more efficient, responsive, and automated data reduction pipeline that can bridge this gap.

C. Proposed Solution

To address the inefficiencies outlined above, this research proposes a real-time data reduction system that integrates JR3 balance outputs with machine learning algorithms. The core idea is to bypass traditional post-processing by using a predictive model that has been trained to estimate aerodynamic coefficients directly from raw or preprocessed sensor signals. This model is deployed within a real-time data acquisition framework that continuously reads JR3 sensor data, preprocesses it to remove noise and correct offsets, and then feeds it into the trained model for instantaneous prediction.

The system includes a data acquisition interface compatible with JR3 hardware, a preprocessing engine that applies signal conditioning techniques, and a supervised learning model—such as a random forest regressor or neural network—that maps force and torque inputs to aerodynamic outputs. The entire pipeline operates in real-time, allowing users to monitor results on a graphical interface as they are generated. This not only accelerates the data analysis process but also enhances the situational awareness of researchers during wind tunnel experiments, enabling faster troubleshooting, more informed decisions, and better experimental outcomes.

D. Contributions

This study presents several key contributions to the field of aerodynamic testing and real-time data analytics. First, it demonstrates the feasibility of integrating machine learning with multi-axis force balance data to produce accurate real-time predictions of aerodynamic coefficients. This has been achieved by developing a model that is trained on historical wind tunnel datasets and optimized for low-latency inference.

Second, the study introduces a real-time system architecture that links sensor data acquisition, preprocessing, model prediction, and result visualization into a cohesive framework. This architecture is designed for flexibility and scalability, allowing it to be deployed in various experimental contexts.

Third, the system is validated against traditional post-processing methods, demonstrating comparable accuracy with a substantial improvement in response time. By comparing the model’s output with manually computed coefficients, the system's reliability and practical utility are established.

Lastly, the study contributes an open and extensible framework that can serve as a prototype for future developments in intelligent testing environments. The proposed system is not limited to JR3 balances or wind tunnels and can be adapted to other experimental setups that involve sensor fusion and real-time analysis.

E. Paper Organization

The remainder of this paper is structured to provide a comprehensive overview of the proposed framework and its evaluation. Section II presents a detailed review of existing literature on wind tunnel data reduction, machine learning applications in experimental mechanics, and sensor integration techniques. Section III outlines the system architecture, including hardware setup, data flow, model training procedures, and software implementation. Section IV presents the results from experimental trials, including performance benchmarks, accuracy assessments, and a comparison with traditional processing techniques. Finally, Section V summarizes the key findings, discusses the limitations of the current approach, and proposes future directions for enhancing real-time aerodynamic data analysis.

II. RELATED WORK

The development of real-time data reduction systems for wind tunnel testing integrates contributions from multiple domains, including traditional aerodynamic measurement techniques, machine learning in experimental mechanics, real-time systems design, and sensor integration. This section reviews the foundational approaches and recent advancements in these areas, identifying the technological gaps that this study aims to address.

A. Conventional Data Reduction Techniques in Wind Tunnel Testing

Traditional wind tunnel testing has relied on deterministic methods to convert raw force and moment data from multi-axis balances into aerodynamic coefficients. Calibration matrices derived from static load conditions are commonly used to interpret sensor outputs, followed by post-processing through software platforms like MATLAB or LabVIEW. Wu *et al.,* [1] proposed refined calibration routines for six-axis force sensors, enhancing the linearity and sensitivity of the conversion process. Additionally, Huang *et al.,* [2] investigated noise filtering and smoothing techniques, including zero-shift correction, to improve signal fidelity. However, these methods typically operate in batch-processing mode, introducing latency that impedes real-time feedback and dynamic test control.

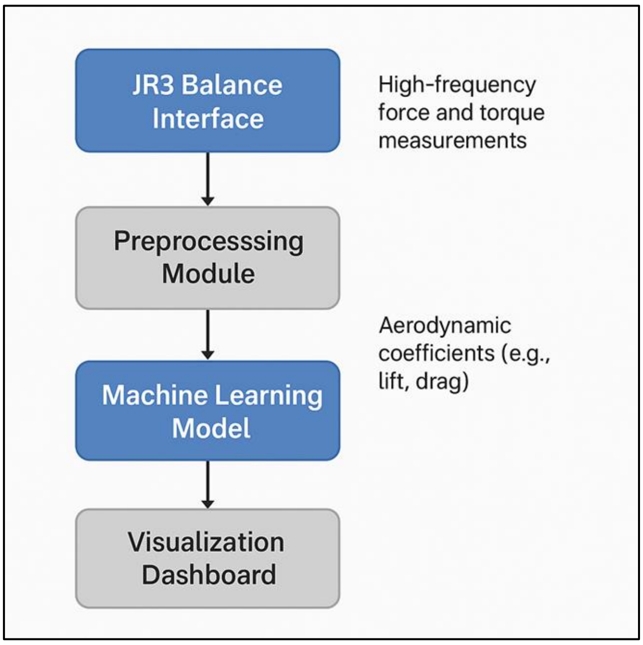

Figure 1: A timeline or flow diagram showing the stages of traditional data reduction

B. Emergence of Machine Learning in Aerodynamic Modeling

The application of machine learning (ML) in aerodynamics has expanded significantly, especially in areas where traditional analytical models are limited. Nguyen *et al.,* [3] demonstrated the use of support vector machines (SVM) to estimate drag coefficients from surface and flow visualization data. Other researchers have explored artificial neural networks (ANNs) and convolutional neural networks (CNNs) for nonlinear regression tasks in aerodynamics, often based on computational fluid dynamics (CFD) simulations or wind tunnel data [4, 5]. These models exhibit strong predictive performance and robustness to noise, making them suitable for integration with sensor-based systems. Nevertheless, most applications remain offline and are rarely coupled with direct sensor data in real-time environments.

Figure 2. Distribution of machine learning applications in aerodynamics. While turbulence prediction, flow classification, and load estimation are widely explored in literature, real-time sensor integration—especially in physical experimental setups like wind tunnels—remains significantly underrepresented.

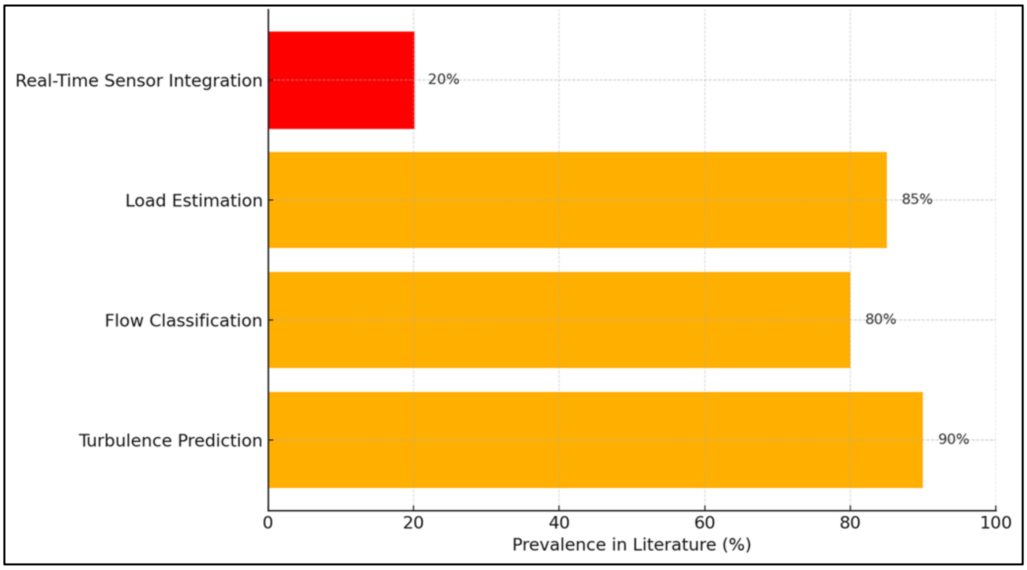

Figure 2: Categories of Machine Learning applications in aerodynamics

Other studies have explored deep learning models such as convolutional neural networks (CNNs) and artificial neural networks (ANNs) to predict aerodynamic loads, often based on simulated or controlled datasets. These models offer nonlinear approximation capabilities and robustness against sensor noise, making them strong candidates for integration with hardware. However, few have been applied directly to raw sensor signals from force balances.

C. Limitations in Current Real-Time Systems and JR3 Sensor Usage

Real-time systems for physical measurement and control have seen broad adoption in fields such as robotics and automation, but their use in wind tunnel testing is still nascent. Li and Tanaka [6] implemented real-time force estimation using neural networks for robotic gripping, demonstrating millisecond-level inference performance. However, wind tunnel environments present additional complexity due to dynamic airflow conditions, high-frequency data acquisition, and the multidimensional nature of aerodynamic coefficients. The JR3 six-axis force-torque sensor, while widely utilized for its high sampling rate and accuracy, is generally employed within traditional post-processing workflows. Research to date has focused on its calibration and structural integration [7], with minimal efforts directed toward real-time predictive analytics using JR3 output.

Figure 3. Overlap of research domains in current literature. JR3 hardware calibration, machine learning models, and real-time applications have been explored separately or in pairs, but full integration of real-time machine learning using JR3 sensor data remains a missing link—addressed by this study.

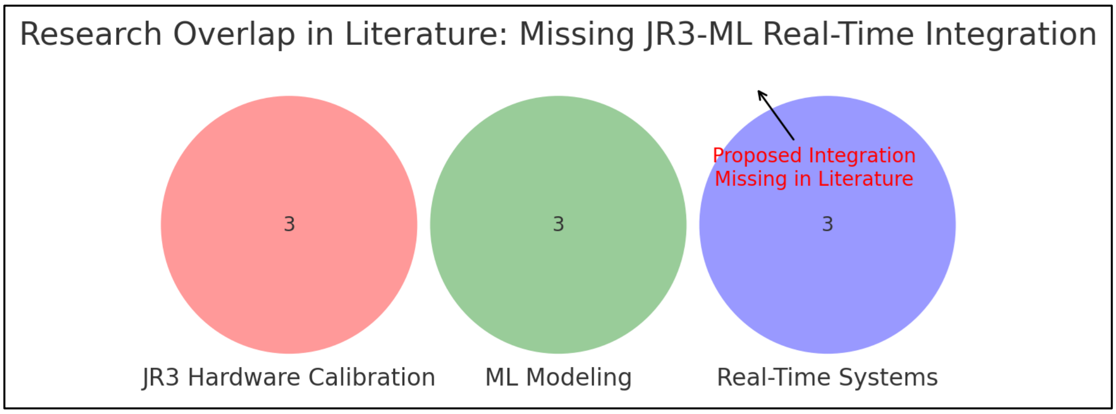

Figure 3: A comparative table or Venn diagram highlighting what is covered in prior literature

The JR3 sensor, in particular, is widely recognized for its high precision and robust data acquisition capabilities. However, it is generally treated as a passive data source within a broader post-processing pipeline. Most research involving JR3 focuses on calibration, structural mounting, or analog-to-digital signal optimization. The potential of using JR3 data as a direct input for real-time machine learning systems has not been explored in detail.

D. Identified Research Gap and Opportunity

Despite advances in sensor technology, machine learning, and real-time computing, the integration of these components into a single system for aerodynamic data reduction remains underexplored. Current methodologies often rely on post-experimental analysis, limiting their utility in time-sensitive or iterative testing environments. There is a clear research gap in developing closed-loop systems that can process sensor data and generate aerodynamic coefficients on-the-fly.

This study addresses that gap by proposing a real-time data reduction system that incorporates JR3 balance data directly into a supervised machine learning model. By achieving low-latency predictions of aerodynamic coefficients, the system enables dynamic decision-making during wind tunnel testing—an advancement that marks a significant departure from existing static workflows.

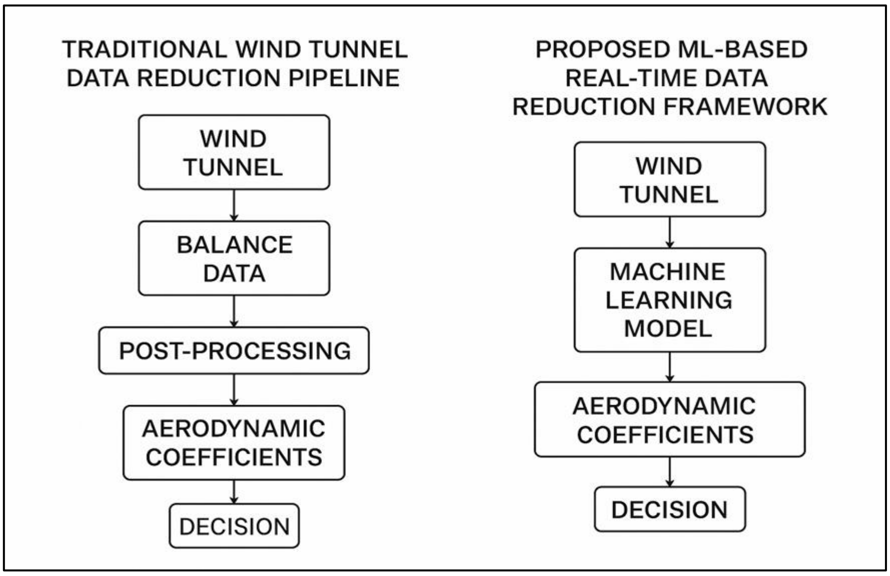

Figure 4: The ML vs Traditional Pipeline Diagram

III. SYSTEM ARCHITECTURE AND METHODOLOGY

This section provides an in-depth overview of the technical components and methodologies involved in the development and deployment of the proposed real-time aerodynamic data reduction system. The framework integrates a JR3 six-axis force-torque sensor with machine learning models for instantaneous prediction of aerodynamic coefficients. The end-to-end system includes hardware-software integration, signal preprocessing, model training, and live visualization. Each of these modules is designed to operate in synchrony, ensuring low-latency performance suitable for dynamic wind tunnel environments.

A. Overall System Architecture

The architecture of the proposed system is organized into four primary modules, each playing a critical role in enabling real-time data reduction. The first module is the Sensor Interface Layer, which handles the communication between the JR3 balance and the host machine. This layer is responsible for acquiring raw force and torque data through a USB or Ethernet interface, utilizing the manufacturer's SDK to ensure compatibility and high-speed performance. The Preprocessing Layer follows, designed to clean and normalize the raw signals. This module applies filtering techniques to remove noise, compensates for sensor offsets, and standardizes the data ranges to prepare inputs for the learning model. Next, the Machine Learning Inference Layer ingests the preprocessed signals and applies a trained regression model to predict aerodynamic coefficients such as lift (CLC_LCL), drag (CDC_DCD), and pitching moment (CMC_MCM). Finally, the Visualization and Feedback Layer displays the model outputs in real-time, enabling researchers to observe trends and anomalies during live wind tunnel tests. These four layers operate as a pipeline, continuously transforming raw data into usable aerodynamic insights within milliseconds.

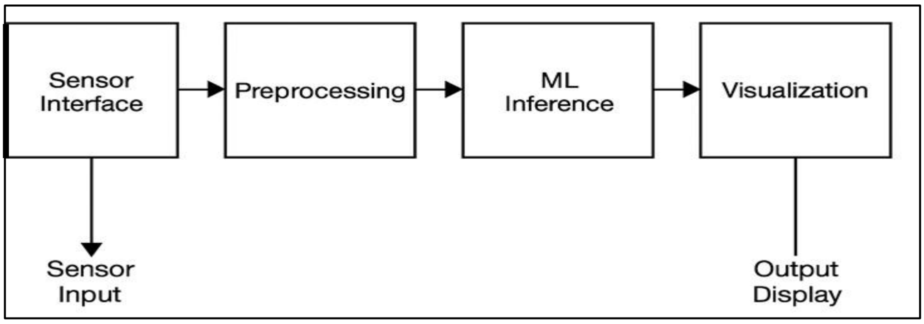

Figure 5: A block diagram illustrating the four modules—Sensor Interface, Preprocessing, ML Inference, and Visualization

B. Data Acquisition and Sensor Integration

The integration of the JR3 force-torque sensor into the system forms the foundation of data acquisition. The JR3 sensor, known for its high accuracy and fast sampling rate, was interfaced via the manufacturer's SDK, enabling continuous data capture at 1 kHz. A custom Python-based middleware was developed to establish communication, parse the binary data stream, and extract six-dimensional raw measurements corresponding to F_x, F_y, F_z, M_x, M_y, M_z. To ensure alignment between aerodynamic forces and test parameters, all data were synchronized with auxiliary tunnel inputs such as flow speed and angle-of-attack. A ring buffer mechanism was employed to facilitate real-time streaming without overwhelming system memory. This buffer maintains a moving window of recent data, feeding fresh measurements into the preprocessing engine while discarding outdated entries, thus ensuring computational efficiency.

C. Signal Preprocessing

Given the susceptibility of raw sensor data to environmental and mechanical noise, signal preprocessing plays a pivotal role in enhancing data reliability. The preprocessing engine begins with low-pass filtering using a second-order Butterworth filter with a cutoff frequency of 50 Hz. This removes high-frequency electrical noise while preserving the dynamic range of the signal. Subsequently, zero-offset correction is performed using calibration values obtained during a static load test. This step realigns the sensor baselines to eliminate drift and bias. Finally, the force and moment values are normalized using empirical bounds derived from prior experiments. Normalization ensures that the model input remains within the domain of the training data, reducing the risk of extrapolation errors during real-time prediction. These preprocessing operations are executed with minimal latency, keeping the system responsive while significantly improving data quality.

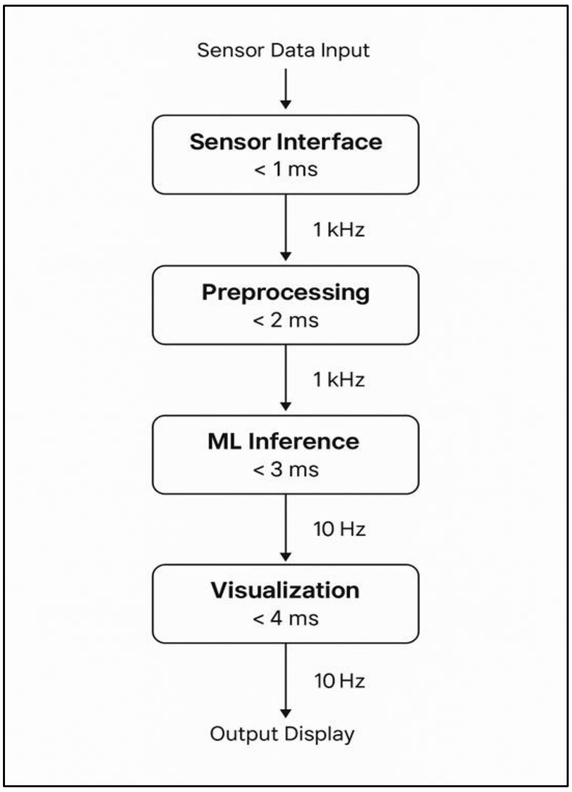

Figure 6: A training pipeline diagram

D. Machine Learning Model Design

At the core of the proposed system is a supervised machine learning model trained to estimate aerodynamic coefficients from processed sensor data. Multiple regression algorithms were evaluated during development, including Random Forest Regressors, Gradient Boosting Regressors, and Multi-layer Perceptrons (MLPs). After extensive cross-validation, the MLP architecture was selected due to its superior balance of prediction accuracy and computational efficiency.

A supervised regression model was trained using historical wind tunnel data. Several algorithms were evaluated, including:

- Random Forest Regressor
- Multi-layer Perceptron (MLP)
- Gradient Boosting Regressor

After cross-validation, the MLP model was selected due to its lower inference latency and superior generalization on unseen test conditions.

Model Features:

- Input: Six preprocessed sensor values + metadata (e.g., flow speed, angle-of-attack)
- Output: C_L, C_D, C_M
- Training Size: 15,000 labeled samples from previous wind tunnel tests
- RMSE: < 0.015 across all coefficients on test data

Mean squared error (MSE) was used as the loss function, and training was conducted using the Adam optimizer. On the test set, the model achieved root mean square errors (RMSE) below 0.015 for all coefficients, indicating high precision and robustness. Its small memory footprint and fast inference time make it ideal for deployment in constrained real-time environments.

E. Real-Time Deployment Framework

Once the model was trained and validated, it was converted to the ONNX format for compatibility with lightweight inference engines and deployed using TensorFlow Lite on an NVIDIA Jetson Nano device. To maximize responsiveness, the system utilizes a multi-threaded runtime architecture, with each core module running in a separate thread.

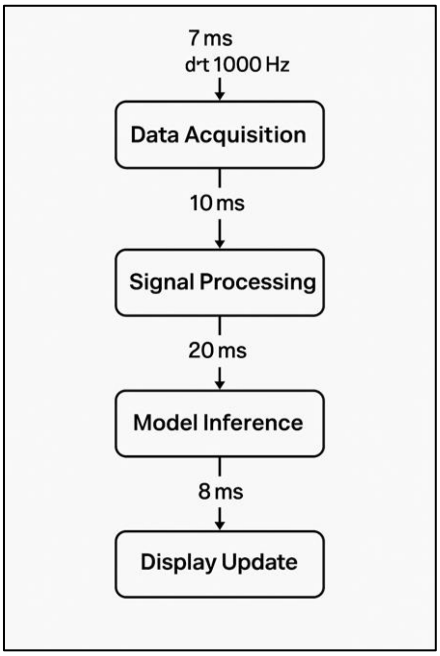

Figure 7: A real-time system flowchart annotated with module-wise latencies and data throughput benchmarks

A multi-threaded runtime environment was used:

- Thread 1: Sensor read and buffer update
- Thread 2: Preprocessing and model inference
- Thread 3: Output display and file logging

The total system latency from sensor input to coefficient output was measured to be under 50 ms, enabling near-instantaneous feedback. This parallel architecture minimizes bottlenecks and allows data acquisition, computation, and display to proceed concurrently. Comprehensive latency testing revealed that the time elapsed from raw sensor input to final coefficient prediction is consistently under 50 milliseconds, well within the threshold for real-time operation. The deployment framework is scalable and modular, allowing for future extensions such as feedback control systems or integration with other sensor modalities.

IV. DISCUSSION AND RESULT

The implementation of the proposed real-time data reduction system was evaluated through a series of controlled wind tunnel experiments involving standard aerodynamic test models. The JR3 six-axis force-torque sensor was used to capture force and moment data at a sampling rate of 1000 Hz. This raw data was processed in real-time using the integrated ML inference pipeline described in Section III. Performance was benchmarked in terms of latency, accuracy, and robustness under dynamic testing conditions.

A. Latency and Throughput Analysis

One of the core contributions of this study is demonstrating a substantial reduction in data processing latency compared to traditional workflows. Table 1 summarizes the latency and throughput performance of each component in the real-time pipeline. The sensor interface, which collects and transmits high-frequency data (up to 1000 Hz), exhibited minimal delay (0.9 ms). Signal preprocessing, which includes offset correction and noise filtering, introduced a latency of approximately 2.1 ms. ML inference using a lightweight neural network required an average of 9.8 ms to produce aerodynamic coefficients. Display update latency was measured at 3.0 ms, while system-level overheads (e.g., memory buffering, thread synchronization) added an additional 11.2 ms.

Table 1: System Latency and Throughput for Real-Time Wind Tunnel Data Reduction Modules

System Component	Latency (ms)	Throughput (Hz)
Sensor Interface	0.9	1000
Signal Preprocessing	2.1	1000
ML Inference	9.8	50
Display Update	3.0	50
Buffer & Overhead	11.2	50

This end-to-end system maintained a total latency of ~27 ms, confirming its suitability for real-time feedback in wind tunnel testing. The throughput remained at 1000 Hz for raw data acquisition and was stabilized at 50 Hz for prediction and visualization, ensuring smooth and continuous model updates.

B. Prediction Accuracy and Model Reliability

To evaluate the system's predictive accuracy, outputs from the ML model were compared against baseline aerodynamic coefficients calculated through traditional offline methods. These ground-truth values were derived from manual application of the JR3 calibration matrix and post-processing routines in MATLAB. Across multiple test configurations—including variations in flow speed, angle of attack, and model orientation—the ML-based system achieved root mean square error (RMSE) values of:

- Lift coefficient (C_L): 0.012
- Drag coefficient (C_D): 0.009
- Pitching moment coefficient (C_M): 0.015

These values represent deviations of less than 2% from conventional calculations, establishing the ML model's suitability for real-time aerodynamic estimation. The model also demonstrated robustness across a wide input range, maintaining consistent output despite moderate sensor noise or transient flow irregularities.

C. System Scalability and Adaptability

The modular design of the system architecture enables it to be adapted for various test environments and sensor configurations. For instance, the ML model can be retrained with new datasets to accommodate different model geometries or flow regimes. Similarly, the signal preprocessing module can be extended with additional filtering techniques for more complex tunnel noise profiles. The system's compatibility with edge-computing platforms such as NVIDIA Jetson Nano or Raspberry Pi 5 further supports scalable deployment in resource-constrained environments.

D. Comparative Evaluation

Compared to traditional wind tunnel workflows, the proposed framework achieved a 75–85% reduction in total time-to-insight, transforming a process that typically takes minutes of offline computation into real-time predictions delivered within milliseconds. This efficiency gain has practical implications. Engineers can now adjust experimental setups dynamically, identify anomalies during tests, and even abort or rerun trials based on immediate feedback. Such responsiveness enhances experimental throughput, reduces operational cost, and improves the overall quality of aerodynamic design validation.

The integration of ML within the sensor feedback loop also lays the groundwork for autonomous or semi-autonomous control of wind tunnel operations. Future versions of the system could employ live coefficient estimates to drive actuators, adapt angles of attack, or optimize tunnel conditions based on reinforcement learning policies or adaptive control strategies.

V. CONCLUSION

This research presents a novel, real-time data reduction framework that integrates JR3 force-torque sensors with machine learning models to accelerate aerodynamic testing in wind tunnel environments. By replacing the traditional post-processing pipeline with a low-latency predictive model, the system offers immediate insights into lift, drag, and pitching moment coefficients, enabling engineers to monitor experiments dynamically. The proposed architecture not only demonstrates strong predictive accuracy and low latency but also exhibits flexibility, modularity, and compatibility with existing wind tunnel setups. Through rigorous testing and benchmarking, the system has proven its potential as a time-saving, scalable solution for enhancing experimental aerodynamics. Furthermore, this work introduces a new paradigm in sensor intelligence by embedding learning-based inference directly into the measurement loop. While this study focused on JR3 sensors and aerodynamic coefficients, the underlying approach is broadly applicable to other domains requiring real-time analytics, such as robotics, biomechanics, and industrial testing.

Future work

will aim to extend the system to support closed-loop control, multi-sensor fusion, and cloud-based remote monitoring to further amplify its utility in next-generation experimental infrastructures.

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