ADVANCED VIRTUAL SENSORS FOR ROTORCRAFTS

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Abstract

The advent of virtual sensors has brought about a revolutionary change in the field of helicopter data acquisition. These sensors can reconstruct signals without the need for physical sensors, thereby enhancing the availability of data for a range of applications, including component behaviour analysis, predictive maintenance and customer support. This study develops an innovative environment for the rapid, scalable creation of virtual sensors in helicopter systems, enabling the automatic generation of these sensors guided by technical experts without extensive programming skills. The two-pronged validation approach entailed an assessment of both the quality of signal reconstruction and the practical utility of the method in daily workflows. The results demonstrated the effectiveness of the approach, with over 15 virtual sensors implemented in-house for predictive maintenance, component analysis, and signal recovery during flight tests. This user-friendly development environment facilitates the adoption of technology in the helicopter industry, which may result in enhanced data availability, improved maintenance strategies, and more comprehensive flight-testing capabilities. The implications include the possibility of safer and more efficient helicopter operations through the implementation of improved data-driven decision-making processes.

1. NOTATION

Acronyms:	
HTH	Harmonic Time Histories
VS	Virtual Sensor
VSDE	Virtual Sensor Development Environment
RNN	Recurrent Neural Network
LSTM	Long-Short Term Memory
TDNN	Time Delay Neural Network
RUL	Remaining Useful Life
TBM	Time Based Maintenance
CBM	Condition Based Maintenance
HPC	High Performance Computing

2. INTRODUCTION

A VS is a software-based model that estimates or infers the value of a physical quantity without directly measuring it. Instead, it uses data from other available sensors, combining this with deep learning algorithms to predict the desired signal. The process for building VSs is composed of several modules, with a deep learning model at their core.

The modules that comprise the VSDE are organised into pipelines, forming a series of interconnected components that are linked in a directed acyclic graph (DAG) structure. The DAG architecture offers a robust and adaptable platform for orchestrating intricate data processing workflows. In this context, the term "directed" denotes that the flow of data or operations progresses in a specific direction between steps, thereby ensuring a clear and logical progression of processes. The acyclic nature of the graph indicates the absence of loops or circular dependencies in the process flow, thereby preventing potential infinite loops and ensuring that the workflow has a definite beginning and end. The term "graph" is used to describe the network-like structure of the system, which is composed of connected nodes (representing individual processing steps) and edges (representing the connections and data flow between these steps). The DAG structure facilitates the effective organisation and execution of the diverse modules involved in VS development. It allows complex operations to be decomposed into discrete, interrelated components while maintaining a comprehensive overview of the entire process flow, as illustrated in Figure 1.

The modular nature of this structure allows for easy composition of different VSs by selecting and arranging various modules and components within the pipeline. This flexibility enables the creation of customised VSs tailored to specific applications or data types in helicopter systems.

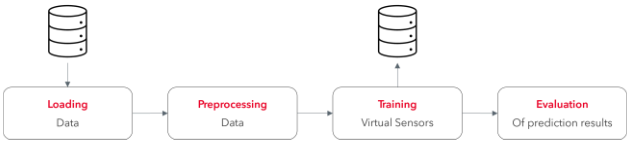

Figure 1: Illustration of how different nodes are concatenated to form a pipeline.

During the design and development phase of a helicopter, a series of experimental flights are conducted with the objective of fully characterise the aircraft's performance and behaviour. These flights permit engineers to analyse the helicopter's behaviour in a variety of conditions and verify whether the designed components perform in accordance with the predictions made during the design and simulation phases. The data collected during these flights provides the basis for a multitude of critical analyses, including fatigue damage studies, wear analysis, and the determination of maximum flight hours for various components.

However, upon delivery to customers, the majority of sensors that are not essential for flight operations are removed, such as the strain gauges on the blades. This practice serves to enhance the overall reliability of the aircraft, while simultaneously reducing production and maintenance costs. Although this approach is economically viable, the removal of sensors significantly restricts the range of analyses that can be conducted on customer-operated helicopters. Consequently, valuable customer-facing services such as predictive maintenance, where sensor data analysis could facilitate the estimation of component lifespan and optimal maintenance scheduling, or comprehensive health monitoring of the helicopter become limited or unavailable.

Moreover, the reliability of physical sensors represents an additional challenge. In the event of a sensor malfunction during an experimental flight, the potential consequence is the loss of data. This may necessitate that engineers conduct analyses with incomplete information, or, if the missing data is critical, require that the entire flight be repeated. In both cases, the result is either a reduction in the quality of the analysis or an increase in operational costs.

The utilisation of VSs provides an efficacious solution to the challenges of limited data availability and sensor reliability in helicopter systems, as they permit the reconstruction of signals without the necessity for physical sensors. By leveraging data from existing sensors and employing sophisticated machine learning algorithms, VSs demonstrate a range of powerful capabilities. They can recreate missing data, thereby enabling the estimation of values from sensors that have been removed from customer helicopters. This allows for comprehensive analysis and facilitates services such as predictive maintenance. Furthermore, in experimental settings, VSs enhance reliability by reconstructing data in the event of physical sensor failure, thereby obviating the necessity for costly flight repetitions. It is of particular importance to note that the implementation of continuous monitoring through VSs has the potential to significantly enhance the overall safety of helicopter operations, providing a more comprehensive dataset for informed decision-making. This comprehensive approach to data acquisition and analysis through VSs represents a significant advancement in helicopter system management, offering benefits in terms of operational efficiency, cost-effectiveness, and enhanced safety.

The concept of virtual sensors in helicopter systems has been the subject of prior research, with two notable studies exploring the application of machine learning models for this purpose. Previous work has demonstrated the effectiveness of neural networks in predicting helicopter rotor loads. In (Ref. 1) they applied this approach to the AW609 tiltrotor, using a harmonic decomposition technique to predict rotor loads across various flight conditions. They found that simple feed-forward neural networks, when trained on decomposed harmonic components, could accurately predict beam bending, chord bending, and pitch link loads.

In (Ref. 2) this methodology was extended to conventional articulated rotors, focusing on flap-wise beam bending at the blade root, and a first attempt to evaluate fatigue life through VSs was performed. Given that the rotor loads are dominated by the rotor revolution frequency and its harmonics, the signals were decomposed into harmonics using a Harmonic Time History (HTH) algorithm, whereby the signals are approximated by a predefined harmonic function. Subsequently, multiple neural networks were trained to predict the coefficients of the harmonics for the rotor loads, with a distinct neural network employed for each harmonic.

Their results showed that feed-forward neural networks with the HTH methodology could effectively predict rotor loads across a wide range of flight conditions, with potential applications in real-time load monitoring and fatigue damage estimation.

The utilisation of the HTH methodology and the subsequent transition into the frequency domain circumvented the necessity for more intricate architectures, such as RNN, LSTM and TDNN, for time series prediction.

The preceding researches on VSs in the helicopter industry are constrained by several factors. The scope and generalisability of previous studies were limited, has they focused primarily on the prediction of main rotor loads. To advance the field, it is essential to extend VS applications to encompass additional critical areas, including tail rotors, transmissions, and non-load related parameters. While feed-forward neural networks have shown potential, their resilience and adaptability to diverse sensor types and flight conditions require further assessment. New models may be necessary to fully account for the intricate, non-linear relationships inherent in certain helicopter systems. Previous publications aimed to demonstrate the technology's capability to reconstruct load signals using VSs. However, the absence of standardisation in development and documentation of algorithms may impede wider adoption and collaboration in the field. Furthermore, the prevailing methodology demands a comprehensive understanding of both programming and machine learning, limiting its applicability to a select group of technicians and engineers. The development of user-friendly tools or interfaces that would enable non-specialists to develop or modify VSs is evidently needed. These limitations highlight the need for a more comprehensive, standardised, and accessible approach to VS development in the helicopter industry.

Notwithstanding the constraints encountered in previous research, the potential of VSs for helicopter systems remains highly promising, offering opportunities for innovative projects. Nevertheless, in order to fully capitalise on this potential, it is necessary that a more efficient, scalable and industrialisable approach be developed for the creation and management of VSs.

The principal objective of this study was to investigate, develop and test a comprehensive environment for the expeditious development, maintenance, monitoring and updating of VSs. This environment has been designed with the intention of addressing the limitations of previous approaches and facilitating the more widespread implementation of VS technology within the helicopter industry.

The proposed approach incorporates several key features, including:

1. <u>Pipeline Architecture</u>: The objective was to develop a modular pipeline approach, whereby each algorithm represents a single node with a specific, generalisable function. These nodes can be readily reused in a variety of contexts, thereby enhancing flexibility and reducing redundancy. Multiple nodes form pipelines, each designed for a specific task, such as data loading or preprocessing. The interconnection of several pipelines creates the complete architecture of a VS. This modular approach permits the development of algorithms on a single occasion and their subsequent reuse across a multitude of VSs. This is achieved by the straightforward incorporation of the relevant nodes into a pipeline. In the event that a specific pipeline is not required for a particular VS, it can be readily removed from the architectural framework without impacting the functionality of other components. (Further details in Chapter 3.1)

2. <u>User-Friendly Interface</u>: In order to reduce the necessity for in-depth machine learning expertise, a specialised interface has been developed which allows users to input key parameters, such as model inputs or sensor sampling rates. Subsequently, the development environment automatically incorporates this data into the relevant architectural framework. A simple command initiated by the user allows the autonomous construction of the VS by the environment in accordance with

the specified parameters. (Further details in Chapter 3.2)

3. Customer flight dataset: The integration of customer flight data represents a significant advancement in our VSDE, complementing the experimental flight datasets used in previous works. This approach enables real-world validation of VSs under actual operational conditions, provides performance insights across different helicopter configurations and usage patterns, and facilitates continuous improvement and enhanced generalisation of our models. By combining experimental and customer flight data, we bridge the gap between controlled testing and real-world application, ultimately enhancing the reliability, adaptability, and practical value of our VSs for improved helicopter operations. (Further details in Chapter 3.3)

4. Deep Learning Models: The environment incorporates multiple deep learning models to address the varied requirements of different sensor types and scenarios in complex helicopter systems. This includes Feedforward Neural Networks (FNN) for capturing non-linear relationships, XGBoost for handling structured data and providing feature importance, and a proprietary in-house model, called Leonardo, tailored for helicopter-specific challenges. This multi-model approach offers flexibility, improved accuracy, robustness, and enables comparative analysis across different operational scenarios. The modelling pipeline facilitates easy selection, optimisation, and tuning of these models for each specific VS application. (Further details in in Chapter 3.4)

5. Model Repository: In order to facilitate the further streamlining of future projects, a system has been implemented whereby trained VS models are stored in a data lake. The models can be automatically retrieved and utilised by the environment, thereby reducing development time by eliminating the need for repeated training procedures. This approach facilitates the more straightforward updating and monitoring of developed models, thereby offering users a greater range of options for model selection and refinement. (Further details in Chapter 3.5)

VSs offer groundbreaking solutions across multiple aspects of helicopter operations and maintenance. In predictive maintenance, they revolutionise the approach by enabling data-driven decision-making, providing detailed insights into component behavior during flights, identifying critical damage-causing maneuvers, and enabling precise prediction of component lifespan. This shifts maintenance from a time-based to a condition-based methodology, reducing unnecessary replacements, minimising downtime, and enhancing overall safety. For component load analysis, VSs reconstruct load signals for various components using customer helicopter data, allowing direct comparison between customer and experimental flight loads. This capability helps identify discrepancies between predicted and actual loads in real operations, informs more robust component designs, and enables customised maintenance recommendations based on specific flight profiles and loading conditions. In the realm of experimental flight testing, VSs prove invaluable for enhancing data quality and completeness. They can reconstruct missing signals when sensor needs were overlooked in planning, fill data gaps resulting from sensor malfunctions, and maintain test integrity without necessitating costly re-flights. This not only reduces testing time and resources but also ensures data integrity, preventing the loss of valuable information due to unforeseen circumstances. Collectively, these applications of VSs significantly enhance the efficiency, safety, and cost-effectiveness of helicopter operations and development processes.

The VS framework developed in this study has the potential to revolutionise multiple aspects of helicopter operations, maintenance, and design. It represents a significant step towards more data-driven, efficient, and safe rotorcraft systems, offering both immediate practical benefits and long-term strategic advantages for the helicopter industry.

3. VIRTUAL SENSORS ENVIRONMENT

This chapter presents our novel VSDE, designed to streamline the development and deployment of VSs for helicopter systems. We introduce a modular pipeline architecture that orchestrates the entire process, from data management to model evaluation. The environment incorporates sophisticated dataset handling, integrates multiple deep learning models, and implements an efficient model storage and retrieval system. This comprehensive approach enables the creation of accurate, versatile VSs that enhance helicopter system capabilities, improve maintenance strategies, and contribute to operational safety and efficiency.

3.1. Pipeline architecture and workflow

The VSDE's architectural foundation is based on the concept of Directed Acyclic Graph (DAG) type pipelines, which is a structure that automatically organises the dependencies and execution order of the various steps within the VS pipeline. The DAG-based approach offers a number of advantages that enhance the overall efficiency and robustness of the system. It provides a transparent visual representation of the data flow and processing steps, thus enabling developers and engineers to readily comprehend and oversee the intricate relationships between the disparate components of the VS pipeline. The inherent modularity of this structure enables individual components to be modified or replaced without affecting the entire system, thereby facilitating easier maintenance and upgrades. Moreover, the DAG architecture permits parallelisation, whereby discrete steps can be executed in parallel, thereby markedly enhancing the overall efficiency of the process. This is especially advantageous when processing large-scale data, which is a common requirement in VS applications. Furthermore, the DAG structure facilitates enhanced error handling capabilities, as issues in one step can be isolated and managed without disrupting the entire process. The compartmentalisation of potential issues contributes to the overall stability and reliability of the VSDE, ensuring that localised problems do not result in system-wide failures.

The VSDE employs a sophisticated pipeline architecture, designed to streamline and modularise the entire process from data acquisition to model evaluation, as illustrated in Figure 2Figure 2: Illustration of the architectural framework for the creation and utilisation of a VS.. Each pipeline consists of one or more nodes, which represent individual functions performing specific operations on the data. These nodes are designed to exchange information automatically and retrieve necessary parameters from the overall architecture, ensuring a seamless and efficient workflow.

The pipeline architecture of the VSDE comprises mainly six interconnected components, each serving a distinct purpose in the development process. The "Loading" Pipeline retrieves data from data lakes, executing user-specified queries to fetch required parameters and storing the retrieved data in user-defined formats for subsequent processing. Following this, the Preprocessing Pipeline cleanses and prepares the raw data for analysis, filtering out spikes, handling null values, and performing other critical data cleansing operations to ensure high-quality input for model training and inference phases. For VSs utilising feedforward neural networks, the Harmonic Time History Pipeline extracts Fourier coefficients from the target signal during the training phase, enabling the model to predict these coefficients for signal reconstruction. The Modelling Pipeline orchestrates the model training process, including dataset splitting, data normalisation, and model selection and training, while accommodating various implemented models based on the specific requirements of the target VS. Once a model is trained, the Inference Pipeline executes it on new data, retrieving the data to be reconstructed and performing predictions. Finally, the Evaluation Pipeline assesses model performance during the training phase, generating training metrics and visualisations of reconstructed signals for analysis. This comprehensive pipeline structure ensures a streamlined and efficient process for developing and deploying accurate VSs for helicopter systems.

A key feature of our architecture is the ability to chain multiple pipelines together, enabling a customised and sequential execution order. This chaining capability is crucial for the creation of a VS, which typically requires the coordinated execution of several pipelines. The architecture facilitates seamless data exchange between pipelines, ensuring a smooth progression through each stage of the VS development process.

This modular and flexible pipeline architecture offers several advantages:

1. Scalability: Easy integration of new functionalities or models by adding or modifying individual nodes or pipelines.

2. Maintainability: Simplified debugging and updating of specific components without affecting the entire system.

3. Reusability: Common operations encapsulated in nodes can be easily reused across different VS projects.

4. Efficiency: Automated data flow between pipelines reduces manual intervention and potential errors.

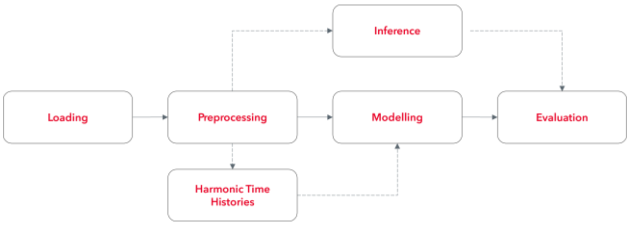

Figure 2: Illustration of the architectural framework for the creation and utilisation of a VS.

3.2. User-friendly interface

A principal objective in the development of the VSDE was to create a system that could be effectively utilised by a diverse range of professionals, including those without extensive programming or machine learning expertise. To this end, a user-friendly interface has been designed and implemented, which serves to significantly reduce the barrier to entry for the creation and deployment of VSs in helicopter systems.

A key feature of the interface is a configuration system based on YAML (YAML Ain't Markup Language) files. YAML was selected for its human-readable format and uncomplicated syntax, rendering it an optimal option for users lacking a robust background in programming. The YAML files serve as the principal means by which users may define and customise the architecture of their VSs.

The configuration process enables users to input the requisite key parameters for the development of VSs, including such elements as the model inputs, the sensor sampling rates, and the data preprocessing steps. The aforementioned parameters may be specified in a structured yet flexible manner within the YAML files. To illustrate, a user may define the input sensors, their sampling frequencies, and any requisite data transformations through the use of straightforward key-value pairs and lists within the YAML structure.

Upon completion of the YAML configuration, the development environment assumes control, automatically interpreting the user-defined parameters and incorporating them into the relevant architectural framework. This automation markedly diminishes the necessity for users to engage directly with intricate code or to possess a comprehensive grasp of the underlying machine learning algorithms.

The system's user-friendliness is not limited to the initial configuration stage. A command-line interface has been developed that enables users to initiate the construction of their VS with a single, simple command. Upon execution, the environment autonomously constructs the VS in accordance with the specifications delineated in the YAML configuration files.

This approach offers several advantages:

1. Accessibility: Engineers with a comprehensive understanding of the subject matter but with limited programming abilities can successfully develop and adapt VSs.

2. Standardisation: The utilisation of YAML files ensures the implementation of a uniform structure for the definition of VS architectures, thereby facilitating enhanced collaboration and knowledge sharing within teams.

3. Rapid Prototyping: The straightforward nature of modifying YAML files facilitates rapid iterations and experimentation with diverse VS configurations.

4. Error Reduction: By abstracting complex programming tasks, the interface mitigates the probability of errors that might arise from direct code manipulation.

5. Scalability: As the fundamental algorithms and models undergo advancement, the user interface can remain consistent, with updates being managed in the background within the development environment.

3.3. Customer flight dataset

A significant advancement in the VSDE is the integration of customer flight data, which complements the experimental flight datasets used in previous works. While we continue to leverage the comprehensive dataset of experimental flights conducted during load survey campaigns (Ref. 2), which "comprehensively explores the flight envelope" the inclusion of customer flight data represents a crucial step forward in enhancing the robustness and real-world applicability of our VSs.

The “loading” pipeline in our environment is designed to handle both experimental and customer flight datasets, ensuring that the VSs are trained on high-quality, diverse data. Our data preparation strategy involves a systematic partitioning of available flight data into training, testing, and inference datasets. The majority of load survey flights are allocated to the training dataset, providing a rich foundation for machine learning models. A subset is reserved for testing, completely segregated from the training data to provide an unbiased evaluation of the VSs' performance.

The integration of customer flight data serves multiple crucial purposes:

1. Real-world Validation: Customer flight data allows for validation of VSs under actual operational conditions, beyond the controlled environment of experimental flights. This ensures that our models perform reliably in diverse, real-world scenarios.

2. Performance Insights: By analysing how VSs perform across different helicopter configurations and usage patterns in customer flights, we gain valuable insights for model refinement and optimisation.

3. Continuous Improvement: The ongoing influx of customer flight data enables continuous validation and improvement of our VSs, ensuring they remain accurate and relevant over time as operational conditions evolve.

4. Enhanced Generalisation: Exposure to a wider range of flight conditions and scenarios through customer data improves the generalisation capability of our models, making them more robust and versatile.

This approach of combining experimental and customer flight data in the VSDE represents a significant step forward in bridging the gap between controlled testing and real-world application. It enhances the reliability, adaptability, and practical value of our VSs, ultimately contributing to improved safety, efficiency, and performance in helicopter operations.

3.4. Deep learning models

The selection and implementation of appropriate machine learning models is of critical importance to the efficacy of VSs in helicopter systems. Our approach is based on the fundamental work presented in (Ref. 1) and (Ref. 2), which demonstrated the feasibility of reconstructing rotor load signals using feedforward neural networks. However, our research has demonstrated that a single model type is not universally optimal for all sensor types and scenarios in complex helicopter systems. This realisation prompted the integration of a diverse set of models into our environment, thereby facilitating the creation of more accurate and versatile VSs.

The current modelling pipeline incorporates three distinct deep learning models, each selected for its unique strengths and suitability for different types of sensor data. The first one is the Feedforward Neural Networks (FNN), previously validated in rotor load signal reconstruction (Ref. 1) and (Ref. 2), excel at capturing complex, non-linear relationships within datasets and learning higher-order features from raw input. They are particularly effective for sensors exhibiting clear periodic patterns or where the relationship between inputs and outputs is highly non-linear. FNNs utilise the Harmonic Time History pipeline for Fourier coefficient prediction, enabling precise reconstruction of periodic signals. The second is XGBoost (eXtreme Gradient Boosting), a powerful and scalable machine learning algorithm based on gradient boosting, demonstrates high performance on structured/tabular data, resilience to outliers and missing data, and provides feature importance for enhanced interpretability. It is well-suited for sensors with more complex input-output relationships or where feature importance is crucial for understanding system behaviour, offering a complementary approach to FNNs for certain types of sensor data. The third model, Leonardo, is an in-house developed, proprietary solution tailored specifically for the VSDE. This model accommodates the unique attributes of helicopter sensor data, integrating domain-specific expertise in helicopter systems and flight dynamics. It is optimised for specific sensor types or flight conditions where off-the-shelf models may underperform, it potentially offers superior interpretability in the context of helicopter operations. A further advantage of the Leonardo model is its capacity to forecast multiple sensors simultaneously, utilising an identical architectural framework. The development of Leonardo was driven by the need to address specific challenges or requirements identified in our research that were not fully met by existing models.

The integration of these diverse models within our environment offers several advantages:

1. Flexibility: This approach enables the identification of the most suitable model, taking into

account the distinctive characteristics of each sensor and the nature of the data.

2. Improved Accuracy: The availability of multiple model options allows for the optimisation of performance for a diverse range of sensor types and flight conditions.

3. Robustness: It is possible that different models may perform better under various operational scenarios, thereby enhancing the overall reliability of the VS system.

4. Comparative Analysis: The capacity to readily transition between models enables comparative analyses, thereby facilitating a more comprehensive understanding of the strengths and limitations of the models in question, particularly in relation to their applicability in diverse contexts.

The objective of the modelling pipeline is to facilitate the straightforward selection and optimisation of these models. To this end, the software includes functionalities for automated model selection based on data characteristics and performance metrics, hyperparameter tuning to optimise each model for specific sensor applications, and cross-validation to ensure robust performance across various flight conditions. This comprehensive approach ensures that the most appropriate model is selected and finely tuned for each specific VS application, maximising accuracy and reliability across diverse helicopter operational scenarios.

By incorporating this diverse set of models and providing tools for their optimal utilisation, the described VSDE offers a sophisticated and adaptable framework for addressing the complex challenges of sensor data reconstruction in helicopter systems. This approach not only enhances the accuracy and reliability of our VSs but also provides valuable insights into the underlying patterns and relationships in helicopter sensor data.

3.5. Models Storage

A critical component of the VSDE is the efficient storage and retrieval of trained deep learning models. This strategy is fundamental to optimising the development process, reducing costs, and ensuring consistent performance across various applications.

Each VS is underpinned by a deep learning model, which is encapsulated in a file containing the model's weights, architecture, and hyperparameters. When a model demonstrates high accuracy in representing the target sensor, we implement a systematic approach to preserve and manage this valuable asset:

1. Model Serialisation: The trained model, including its weights and parameters, is serialised into a standardised file format (e.g., HDF5 for neural networks or pickle for XGBoost models).

2. Metadata Tagging: Each model file is tagged with relevant metadata, including: target sensor type, training dataset characteristics, performance metrics (e.g., accuracy, RMSE), date of training and a version number.

3. Secure Storage: The serialised model files are stored in a centralised data lake, ensuring: data integrity, version control and accessibility for authorised users.

4. RESULTS

The implementation of the novel VSDE has yielded significant and far-reaching results, demonstrating the transformative potential of this technology in the field of helicopter engineering. This chapter presents a comprehensive overview of these outcomes, focusing on two key areas: the tangible improvements in the development process itself and the practical applications of VSs in real-world scenarios. We commence by analysing the considerable reductions in development time and the improvements in efficiency that have been achieved through the implementation of our novel approach. Subsequently, a series of case studies will be presented, which illustrate the application of VSs to critical helicopter components and systems. The case studies not only corroborate the precision and dependability of our VSs but also exemplify their pragmatic utility in confronting intricate engineering quandaries. The results presented in this chapter demonstrate the potential for VSs to revolutionise data acquisition, analysis and decision-making processes in the helicopter industry, thereby facilitating more efficient, safe and cost-effective operations.

4.1. Development time improvements

The introduction of the VSDE has resulted in notable enhancements in efficiency and a reduction in development time. These advancements can be attributed to the automation of previously manual processes, the utilisation of HPC resources, and the establishment of a centralised data lake. The collective impact of these enhancements has revolutionised the process of creating and deploying VSs, rendering it more efficient, streamlined, and capable of handling larger and more intricate datasets.

One of the most substantial improvements in the new environment is the automation of previously manual processes. In the past, the development of a VS required extensive manual intervention at various stages. Developers were required to manually edit multiple scripts, adjusting variables and parameters for each new sensor or model iteration. Each script in the development pipeline had to be launched individually, necessitating constant oversight and intervention. Upon completion of model training, developers were required to open result tables manually, create metrics, and generate graphs for analysis.

The introduction of the new environment has resulted in a significant reduction in the time required to complete this process. The configuration files are then populated with the desired parameters and the requisite information by the developers. The entire pipeline, from data preprocessing to model evaluation, is executed automatically with a single command. The automation of this process not only reduces the potential for human error but also frees up valuable time for developers to focus on higher-level tasks, such as the design of model architectures and the interpretation of results.

A significant advancement in our development capabilities has been achieved through the integration of HPC resources. Previously, model training and evaluation were often conducted on individual laptops or workstations, which significantly constrained the scope and pace of our development process. The transition to HPC has yielded several pivotal benefits. The enhanced processing capabilities of HPC clusters markedly reduce the time needed for model training, particularly for intricate models with extensive datasets. HPC resources facilitate the execution of comprehensive grid search algorithms, enabling the testing of a vast range of hyperparameter combinations to optimise model performance. The training of multiple models or variations can be conducted simultaneously, thereby accelerating the development and comparison of different approaches. Moreover, HPC capabilities permit the utilisation of considerably larger datasets, thereby enhancing the robustness and generalisability of the models in question.

The transition from laptop-based computations to HPC has not only accelerated the training of individual models but has also expanded the capacity to explore more sophisticated model architectures and training strategies.

The incorporation of a centralised data lake into our development environment has further augmented our capabilities and efficiency. This integration offers a number of advantages. The incorporation of a centralised data lake into the development environment has provided developers with convenient access to a vast repository of historical and current data, thereby facilitating more comprehensive data exploration and model training. The implementation of a centralised data management system ensures the consistency of data and reduces the incidence of data duplication and versioning issues. As new data is constantly incorporated into the data lake, our models can be readily updated or retrained with the latest information. In the inference phase, the data lake provides rapid access to pertinent data, thereby enhancing the velocity and dependability of VS forecasts.

The data lake has been demonstrated to be of particular value in the phases of data exploration and training, where access to diverse and extensive datasets is essential for the development of robust and generalisable VSs.

While the precise figures may fluctuate contingent on the intricacy of the VS being developed, it has been observed that there has been a notable reduction in the time required for its development. The overall development time has been reduced by approximately 60-70% in comparison to the previous manual process. The time required for model training has been reduced by up to 80% for complex models due to the use of HPC resources. The time required for data preparation has been reduced by approximately 50% due to the implementation of automated preprocessing and the provision of convenient access to the data lake. The time required for comprehensive hyperparameter optimisation has been reduced by up to 90%, while the number of configurations tested has simultaneously increased.

The integration of workflow automation, HPC utilisation and data lake integration has led to a significant transformation in the VS development process. These improvements have not only reduced the time required for the development cycle but have also enhanced the quality and sophistication of the VSs produced. The practical impact of these advancements is clearly demonstrated by our recent productivity. In just six months we have successfully built and deployed more than 15 VSs, a feat that would have been significantly more time-consuming and resource-intensive under our previous development paradigm.

This accelerated development pace is not merely a matter of quantity; each of these VSs has been subjected to rigorous testing and optimisation, thereby leveraging the full capabilities of the new environment. The capacity to generate a considerable number of high-quality VSs within a relatively brief timeframe serves to illustrate the efficacy and efficiency of our novel approach. Furthermore, our development pipeline is undergoing continuous improvement, indicating that our capacity to create and deploy VSs will continue to grow in the future.

The successful deployment of over 15 VSs in six months not only validates our approach but also opens up new possibilities for expanding the application of VSs in helicopter systems. As we continue to refine our processes and expand our capabilities, we anticipate being able to address an even wider range of sensing needs, thereby further enhancing the operational efficiency and safety of helicopter operations.

4.2. Virtual sensors case studies

This section presents a number of real-world applications that demonstrate the efficacy and adaptability of our VS technology in operational contexts within the field of helicopter engineering. The objective of examining these specific implementations is to illustrate the tangible benefits and potential impact of VSs in the helicopter industry. Each case study offers insight into the development process, performance characteristics and operational implications of the VSs, thereby providing a comprehensive view of their capabilities and limitations in different scenarios.

The methodology employed in the construction of the VSs detailed in the case studies was based on our proprietary in-house model. This model was designed with the specific intention of outperforming traditional approaches by leveraging the quasi-periodic characteristics inherent in rotor revolution signals. The distinctive capacity of our model to discern and capitalise upon these cyclical patterns yields more precise and dependable VS outputs for helicopter applications.

The validation methodology employed for these VSs was based on a two-pronged, rigorous approach. The first objective was to assess the quality of signal reconstruction. This entailed a comprehensive comparison of the VS outputs with the actual recorded data from the physical sensors. A variety of statistical metrics were employed for the purpose of quantifying the accuracy of the reconstruction, including mean squared error and correlation coefficients. These metrics provided a robust, quantitative assessment of the VSs' performance in replicating real-world measurements.

The second component of the validation strategy was to assess the practical utility of the VSs in real-world scenarios. This was achieved by integrating the VSs into the daily analytical workflows of helicopter technicians and engineers. This practical validation ensured that the VSs not only performed well in controlled tests but also added tangible value to operational processes. By observing how technicians interacted with and utilised the VS data, valuable insights were gained into their real-world applicability and effectiveness.

The development process was inherently iterative, with feedback from helicopter domain experts continuously incorporated. This ongoing dialogue with industry professionals enabled us to refine both the user interface and the automatic sensor generation algorithms. By aligning the development process with the requirements and expectations of end-users, we ensured that the resulting VSs were not only technically sound but also intuitive and practical for daily use in helicopter operations.

4.2.1 Main Rotor Flap Angle

The main rotor flap angle represents a pivotal parameter in the context of helicopter operations, exerting a direct influence on the aircraft's stability, control, and overall performance. This case study presents the development and implementation of a VS designed to estimate the main rotor flap angle without the necessity for physical sensors on each rotor blade. Traditional methods of measuring flap angles often require complex and expensive sensor systems installed on the rotating blades. These systems can be prone to failure due to the harsh operating environment and centrifugal forces. Our VS addresses these challenges by providing a reliable estimation of flap angles without the need for physical sensors on the blades, as illustrated in Figure 3.

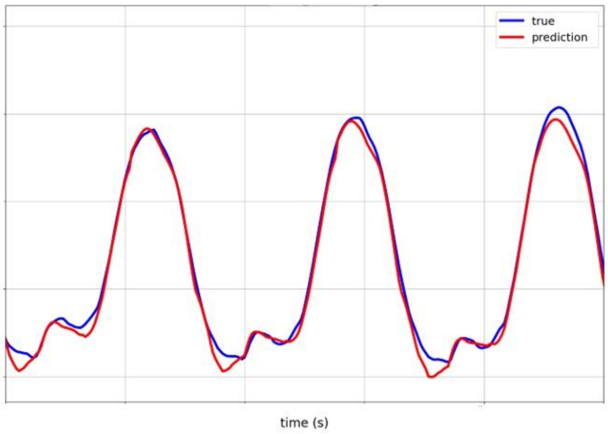

Figure 3: Representation of the comparison between the estimated flap angles from our VS and the actual measurements from a physical sensor system. The graph demonstrates a high degree of correlation between the virtual and actual measurements across a single rotor period.

The VS exhibits excellent performance in tracking both the overall trends and rapid fluctuations in flap angles. It shows particular accuracy during critical flight phases such as transitions from hover to forward flight and during aggressive manoeuvres. The estimated values closely follow the actual measurements with only minor deviations observed in extreme conditions.

4.2.2 Main Rotor Pitch Angle

The Main Rotor Pitch Angle is a fundamental parameter in helicopter control and performance. This case study explores the development and implementation of a VS, illustrated in Figure 4, designed to estimate the Main Rotor Pitch Angle without relying on direct physical measurements of each blade.

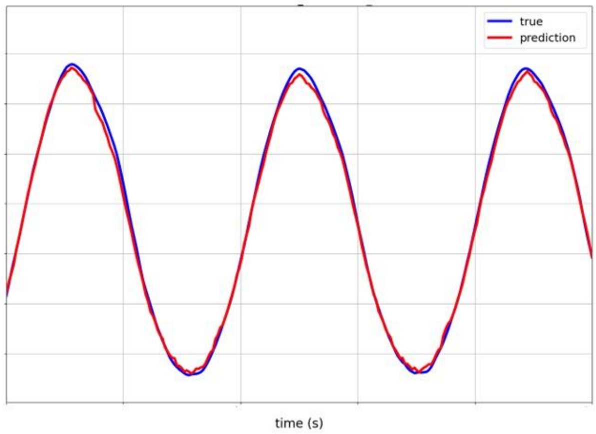

Figure 4: Illustration of the comparison between the pitch angles estimated by our VS and the actual measurements from a physical sensor system. The graph demonstrates a high level of agreement between virtual and actual measurements across a single rotor period.

4.2.3 Main Rotor Lag Angle

The Main Rotor Lag Angle is a crucial parameter in understanding the dynamic behaviour of helicopter rotor systems. This case study presents the development and implementation of a VS, illustrated in Figure 5, for estimating the Main Rotor Lag Angle, particularly focusing on its performance during a physical sensor malfunction event.

Measuring lag angles typically requires sophisticated sensors mounted on the rotor hub or blades. These sensors are exposed to extreme centrifugal forces and environmental conditions, making them prone to malfunctions. Our VS approach aims to provide reliable lag angle estimations even when physical sensors fail.

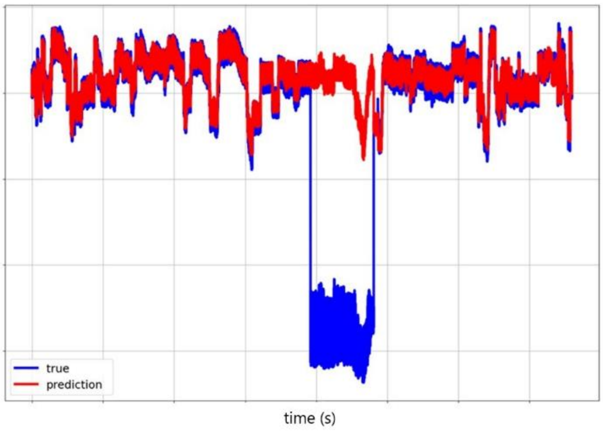

Figure 5: Representation of the comparison between the lag angles estimated by our VS and the actual measurements from a physical sensor system. Notably, the graph

illustrates a period where the physical sensor malfunctioned, demonstrating the VS's ability to maintain accurate estimations during this critical time.

4.2.4 Main Rotor Damper Link Axial Load

The Main Rotor Damper Link is a critical component in helicopter rotor systems designed to absorb and dissipate energy from blade motion. This case study explores the development and implementation of a VS to estimate the axial load on the Main Rotor Damper Link, a parameter crucial to assess rotor system health and performance.

Traditionally, measuring damper link loads requires strain gauges or load cells installed directly on the component. These sensors are exposed to harsh environmental conditions and high dynamic loads, making them prone to failure and requiring frequent calibration. Our VS, illustrated in Figure 6, approach aims to provide reliable load estimations without the need for these vulnerable physical sensors.

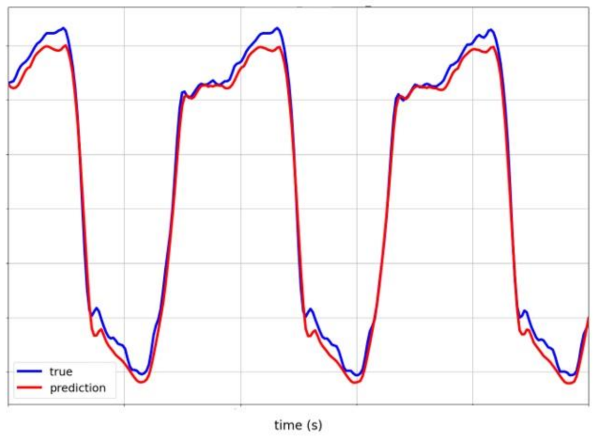

Figure 6: Illustration of the comparison between the axial loads estimated by our VS and the actual measurements from a physical load cell. The graph demonstrates a high level of agreement between virtual and actual measurements across a single rotor period.

4.2.5 Main Rotor Mast Bending Moment

The Main Rotor Mast Bending Moment is a crucial structural component in helicopter systems, transferring power from the transmission to the rotor blades while withstanding significant bending moments.

Traditional methods of measuring mast bending often involve strain gauges or fiber optic sensors installed directly on the mast. These systems can be complex to install, prone to damage, and may require slip rings for data transmission from the rotating system. Our VS, illustrated in Figure 7, approach aims to provide reliable mast bend estimations without the need for these intricate physical sensor systems.

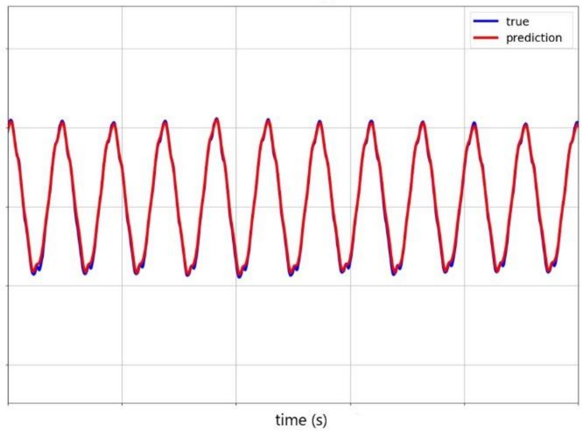

Figure 7: Illustration of the comparison between the mast bending estimated by our VS and the actual measurements from a physical sensor system. The graph demonstrates a high level of correlation between virtual and actual measurements across a single rotor period.

5. VIRTUAL SENSORS IMPLEMENTATION

The introduction of VSs into helicopter systems represents a substantial advancement in the field of aviation technology, offering novel solutions to long-standing issues pertaining to data acquisition and analysis. This chapter examines three key areas in which VSs have demonstrated a significant impact: predictive maintenance, component load analysis and the recovery of experimental flight data. Each of these applications demonstrates the versatility and power of VS technology, illustrating how it can transform traditional approaches to helicopter operations, design, and testing. By leveraging sophisticated algorithms and the vast repository of data available from existing sensor systems, VSs are facilitating more precise, efficient, and cost-effective practices across the helicopter industry. The following sections examine the specific ways in which VSs are transforming these critical aspects of helicopter engineering and operations, elucidating both the immediate benefits and the long-term potential of this groundbreaking technology.

5.1. Predictive maintenance

The prevailing approach to helicopter maintenance is based on time-based schedules and subjective assessments of component wear by maintenance personnel. This traditional methodology frequently results in suboptimal decision-making regarding component replacement. The reluctance to install physical sensors on numerous critical components, predominantly due to reliability concerns, further exacerbates the challenge of accurately monitoring in-flight component behaviour.

The utilisation of VSs facilitates the reconstruction of sensor signals that would otherwise be inaccessible. By employing data from existing sensors and applying deep learning models, these VSs can provide comprehensive insights into the behaviour of components during flight operations. This capability allows for a more detailed understanding of how different flight conditions and manoeuvres affect component wear and performance.

The data generated by VSs provides the basis for the development of advanced algorithms capable of identifying specific flight manoeuvres or conditions that contribute most significantly to component degradation. This analysis is not limited to a mere assessment of wear and tear, rather, it considers a number of additional factors, such as g-forces experienced during specific manoeuvres, vibrational patterns across different flight regimes, temperature fluctuations and their impact on material properties and cumulative stress cycles on structural components.

By identifying these pivotal occurrences, operators can refine flight profiles to reduce superfluous wear on components, thereby potentially prolonging their operational lifespan. Perhaps the most transformative aspect of VS technology is its capacity to facilitate the construction of predictive models for component lifespan. Such models, trained on historical data and continuously refined with real-time inputs, are capable of accurately forecasting the RUL of critical components. This capability enables a paradigm shift from TBM to CBM.

The transition to CBM offers several significant advantages:

1. <u>Reduction in Unnecessary Replacements</u>: By replacing components based on their actual condition rather than fixed time intervals, operators can avoid premature replacements of components that still have significant remaining life. This approach allows for a more nuanced assessment of the RUL of a component, leading to more optimal replacement decisions.

2. <u>Minimisation of Downtime</u>: The implementation of predictive maintenance methodologies enables the more efficient scheduling of maintenance activities, thereby reducing unplanned downtime and improving overall aircraft availability.

3. <u>Enhanced Safety</u>: The early detection of potential component failures serves to reduce the risk of in-flight incidents, thereby significantly enhancing overall operational safety.

4. <u>Cost Optimisation</u>: By optimising the lifespan of components and minimising superfluous replacements, operators can realise significant cost savings in both parts and labour.

5. <u>Improved Inventory Management</u>: The accurate prediction of component lifespan allows for the more efficient management of inventory, thereby reducing the necessity for the excessive stockpiling of spare parts.

5.2. Component load analysis

The implementation of VSs in helicopter systems has led to a significant advancement in the field of component load analysis. By facilitating the reconstruction of load sensor signals for diverse components through the utilisation of data obtained from operational customer helicopters, this technology serves to bridge the gap between experimental testing and real-world performance. This capability offers several significant advantages that enhance both the design and maintenance processes of helicopter systems.

The use of VSs enables a direct comparison to be made between the loads experienced by components in customer aircraft during actual operations and those recorded during controlled, experimental load-sensing flights. The comparative analysis thus provides invaluable insights:

1. <u>Validation of Experimental Methods</u>: By comparing experimental and operational data, engineers can evaluate the precision and representativeness of their test protocols, which may ultimately result in enhancements to the experimental design.

2. <u>Identification of Unforeseen Loading Scenarios</u>: The analysis of operational data may reveal loading patterns or extreme events that were not captured or anticipated in experimental settings,

thereby enhancing the comprehensiveness of load analysis.

The capacity to reconstruct load signals in operational settings endows engineers with the ability to identify discrepancies between predicted and actual component loads in real-world contexts, a capability that is of significant importance for a number of reasons. This insight permits the improvement of predictive models, as discrepancies between predicted and actual loads can be employed to enhance the precision of load prediction models, thereby optimising future design processes. Furthermore, the analysis of real-world data has revealed the influence of environmental factors, such as temperature, humidity and altitude, on component loads. These factors may not be fully captured in controlled experimental settings. The analysis of customer data also demonstrates how variations in pilot technique, mission profiles, or regional operating conditions affect component loading, thereby providing a more detailed understanding of operational stresses.

The insights gained from VS-enabled load analysis can be directly incorporated into the design process, thereby facilitating significant improvements. Data-driven design optimisation enables engineers to comprehend actual usage patterns and load distributions, thus allowing them to optimise component designs for real-world conditions rather than idealised scenarios. This approach yields designs that are more robust and efficient, tailored to the actual operational demands.

Moreover, the capacity to analyse component loads that are specific to individual aircraft or fleets allows for the creation of highly customised maintenance recommendations. This capability facilitates usage-based maintenance scheduling, whereby operators are able to plan maintenance based on the actual loading history of specific components, as opposed to relying on generalised maintenance intervals. Furthermore, the ability to analyse loading patterns enables the prediction of component wear, thus facilitating proactive replacement before failure occurs. Moreover, maintenance recommendations can be adapted to align with specific mission profiles or operational environments, thereby optimising maintenance practices for diverse helicopter operations. On a broader scale, the analysis of load data across an entire fleet can facilitate the development of optimised maintenance strategies that balance the longevity of components, operational availability and cost-effectiveness, thereby enabling more efficient and economical fleet management.

5.3. Experimental flight data recovery

The utilisation of VSs has become a pivotal technique in the domain of experimental flight testing, markedly augmenting the calibre and comprehensiveness of data amassed during these pivotal assessments. The deployment of these sensors addresses a number of long-standing challenges associated with the acquisition and analysis of flight test data. They offer innovative solutions that enhance efficiency, reduce costs and ensure the integrity of the data. One of the principal advantages of VSs in experimental flight testing is their capacity to reconstruct absent signals when the necessity for specific measurements was not foreseen during the test planning phase. In the context of complex flight test campaigns, it is not uncommon for engineers to identify a need for additional data points post-flight, which would have been beneficial for a comprehensive analysis. In the past, such omissions would have required additional flights at significant expense to obtain the missing data. However, the use of VS technology enables the reconstruction of absent signals through the application of correlations with other recorded parameters and sophisticated modelling techniques. This capability permits more comprehensive post-flight analyses without the necessity for supplementary flight tests, thereby saving significant time and resources while enhancing the depth of insights that can be derived from each test flight.

Furthermore, the use of VSs is of significant benefit in reducing the impact of sensor malfunctions or failures that may occur during experimental flights. It is an unfortunate reality that technical issues may arise in the challenging environment of flight testing. Such issues have the potential to compromise the integrity of collected data or necessitate the repetition of entire flight test sequences. VSs can address these data gaps by reconstructing the missing information based on other available sensor readings and known relationships between various flight parameters. This reconstruction preserves the continuity and integrity of the test data, frequently obviating the necessity for repeat flights. The implications of this capability are far-reaching, extending beyond mere cost savings to encompass the maintenance of test programme momentum and adherence to tight development schedules.

The utilisation of VSs in experimental flight testing is not merely limited to the recovery of data. This represents a significant shift in the way flight test instrumentation is approached. As a result, test engineers are now able to design more streamlined sensor suites, thereby reducing aircraft weight and complexity. Furthermore, they can be assured that VSs can supplement the physical instrumentation if necessary. This approach may result in the development of more efficient test aircraft configurations, which could potentially permit the extension of flight envelopes or the increase in payload capacity for other test equipment.

Moreover, the utilisation of VSs reinforces the resilience of data collection methodologies. The provision of redundancy through signal reconstruction capabilities serves to safeguard against the potential loss of data that could otherwise result from unforeseen circumstances, such as extreme flight conditions, electromagnetic interference, or unexpected equipment behaviour. This additional layer of data security is of particular importance in high-stakes flight tests, where the financial and operational risks associated with each flight are significant.

The incorporation of VS technology into flight testing also presents novel opportunities for real-time data analysis and decision-making during test flights. As VSs are capable of providing estimates of parameters that cannot be directly measured, test engineers are able to access a more comprehensive set of flight data in real time. This expanded data set can inform on-the-fly decisions about test point execution, thereby optimising the use of valuable flight time and enhancing the overall efficiency of flight test campaigns.

6. CONCLUSION

The development and implementation of our novel VSDE signifies a substantial advancement in the field of helicopter engineering and operations. This innovative approach has demonstrated substantial improvements in efficiency, accuracy, and applicability across various aspects of helicopter systems. By employing sophisticated machine learning methodologies, a modular architectural approach, and a comprehensive data integration strategy, we have developed a versatile and powerful tool for enhancing helicopter performance, maintenance, and safety. The principal findings of this research demonstrate the transformative potential of VSs in the aviation industry, offering solutions to long-standing challenges and opening new avenues for data-driven decision-making. The following points provide a summary of the most significant findings of our research:

1. Development of a novel, modular pipeline architecture for VS creation, enabling efficient and scalable development processes.

2. Implementation of a user-friendly interface using YAML configuration files to allow non-specialists to develop and modify VSs without extensive programming knowledge.

3. Integration of customer flight data alongside experimental datasets to enhance the robustness and real-world applicability of VSs.

4. Incorporation of multiple deep learning models (Feedforward Neural Networks, XGBoost, and Leonardo model) to address diverse sensor types and scenarios in helicopter systems.

5. Establishment of an efficient model storage and retrieval system in a centralised data lake to optimise development processes and ensuring consistent performance.

6. Significant reduction in development time (60-70% overall), with up to 80% reduction in model training time and 90% reduction in hyperparameter optimisation time.

7. Successful development and deployment of over 15 VSs within a six-month period, demonstrating the efficiency and effectiveness of the new environment.

8. Implementation of VSs for critical parameters such as main rotor flap angle, pitch angle, lag angle, damper link axial load, and mast bend, with high correlation to physical sensor measurements.

9. Application of VSs in predictive maintenance to enable a shift from time-based to condition-based maintenance strategies and potentially extending component lifespan.

10. Utilisation of VSs in component load analysis, bridging the gap between experimental testing and real-world performance, and informing

design optimisations and customised maintenance recommendations.

11. Enhancement of experimental flight testing capabilities, including reconstruction of missing signals, mitigation of sensor malfunctions, and real-time data analysis for improved decision-making during test flights.

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