ATMOSPHERIC VISIBILITY AND CLOUD COVER FORECASTING WITH NOVEL ARTIFICIAL INTELLIGENCE METHODS FOR FIJI’S AVIATION SECTOR

A Thesis submitted by

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ABSTRACT

Visibility and ceiling are two important meteorological parameters affecting the operation of aircraft, especially during the critical phases of take-off and landing at airports. Apart from being a key factor in safe and efficient flight operations, accurate forecasts of these two meteorological parameters also contribute to improving the economics of air transportation. This Master of Research (MRES) study aims to develop a new forecasting model based on the latest artificial intelligence methods to predict atmospheric visibility and cloud cover (or 'ceiling'). This study will address existing gaps in the area by advancing the practical application of deep learning with the following three objectives. Firstly, the study adopts the Iterative Input Selection (IIS) feature selection technique to deduce the optimum features for the proposed model from a global pool of features. Secondly, it aims to design and implement the proposed hybrid IIS-LSTM integrated model for a 1-hour forecast horizon and further compare the outcomes with four alternative AI models. Thirdly, the performance of the hybrid IIS-LSTM model is compared with the alternative models using performance evaluation metrics and graphical analysis. The study also elaborates on the suitability of the objective model for practical visibility and ceiling forecasts and discusses limitations to provide recommendations for future research. The objectives are achieved by using aeronautical meteorological data from two international airports in Fiji from 2012 to 2021. The proposed hybrid IIS-LSTM integrated model combines the feature selection characteristics of the IIS algorithm and the effective time series forecasting LSTM model. The model achieved the desired outcomes of the research by isolating key features for each study site. These optimum features maximised the efficiency of the forecasting component of the algorithm by reducing dimensionality and increasing generalisability of the model. The performance of this model showed its reliability in making accurate forecasts and was consistent for both study sites and for both target variables. It achieved the highest agreement metrics (Willmott's Index) against the comparison model and the lowest error metrics (RMSE). The model's performance against these benchmark models demonstrated its superiority over these models and further endorses it as a reliable practical tool. Therefore, the research outcomes present the proposed model as a useful practical tool for future implementation in the aviation industry and could enable a better understanding of the visibility and ceiling parameter predictions for this study region in the future.

CERTIFICATION OF THESIS

I Shiveel Raj declare that the Thesis entitled *Atmospheric Visibility and Cloud Cover Forecasting with Novel Artificial Intelligence Methods for Fiji's Aviation Sector* is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. This Thesis is the work of Shiveel Raj except where otherwise acknowledged, with the majority of the contribution to the papers presented as a Thesis by Publication undertaken by the student. The work is original and has not previously been submitted for any other award, except where acknowledged.

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STATEMENT OF CONTRIBUTION

This MRES thesis by publications has produced a high-quality (Quartile 1) publication during the candidature. The details of joint authorship and agreed share of these contributions are detailed as follows:

Article 1: Chapter 4

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Shiveel Raj contributed 70% to this paper. Collectively Ravinesh C. Deo, Ekta Sharma, Toan Dinh, Sancho Salcedo-Sanz and Ramendra Prasad contributed the remainder.

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ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
CCF	Cross-Correlation Functions
CNN	Convolutional Neural Network
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
DL	Deep Learning
ELM	Extreme Learning Machine
E_{NS}	Nash-Sutcliffe Efficiency
FMS	Fiji Meteorological Services
GEM	General Equivalent Markov
ICAO	International Civil Aviation Organisation
IIS	Iterative Input Selection
KGE	Kling Gupta Efficiency
LAMP	Localised Aviation Model Output Statistics Program
LASSO-MLP	Least Absolute Shrinkage and Selection Operator – Multilayer Perceptron
LM	Legates-McCabe Efficiency
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
METAR	Aerodrome routine meteorological reports
ML	Machine Learning
MLP	Multi-Layer Perceptron
MOS	Model Output Statistics
N-BEATS	Neural Basis Expansion Analysis for interpretable time series forecasting
NCVA	National Ceiling and Visibility Analysis
NWP	Numerical Weather Predictions
OBS	Observation Based System
PACF	Partial Auto Correlation Function
r	Pearson's Correlation Coefficient

R^2	Coefficient of Determination
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RTMA	Real-Time Mesoscale Analysis
RTMA-RU	Real-Time Mesoscale Analysis Rapid Updates
SPCZ	South Pacific Convergence Zone
TabNet	Attentive Interpretable Tabular Learning
TCN	Temporal Convolutional Network
WI	Willmott’s Index
WMO	World Meteorological Organisation

Chapter 1: INTRODUCTION

1.1. Background

Meteorological forecasting is an important element in aviation which significantly contributes to the planning, decision-making and contingency actions taken in the industry. Accurate and reliable information on meteorological parameters is essential for the safe and efficient operation of flights. Two of the meteorological parameters that are most useful in the aviation industry are ***visibility and ceiling***, which are the subjects of this Master of Research thesis.

As defined by the International Civil Aviation Organisation, ***visibility*** is defined as the distance any black object can be seen and identified against a bright background at a ground level, or the distance at which lights 1000 candela in luminescence can be seen and recognised against an unlit background, whichever is greater (ICAO, 2004). ***Ceiling***, on the other hand, according to the International Civil Aviation Organisation's definition, is the vertical distance of the base of the lowest layer of cloud below 6000m from the surface of the earth or water and which covers more than 50% of the sky (ICAO, 2005). Accurate and reliable information obtained through measurements and models on these two atmospheric parameters are crucial in all phases of flight operations, such as the departure, arrival, and en-route phases. Figure 1 shows the visibility and ceiling requirements for aircraft flying in the Visual Flight Rule.

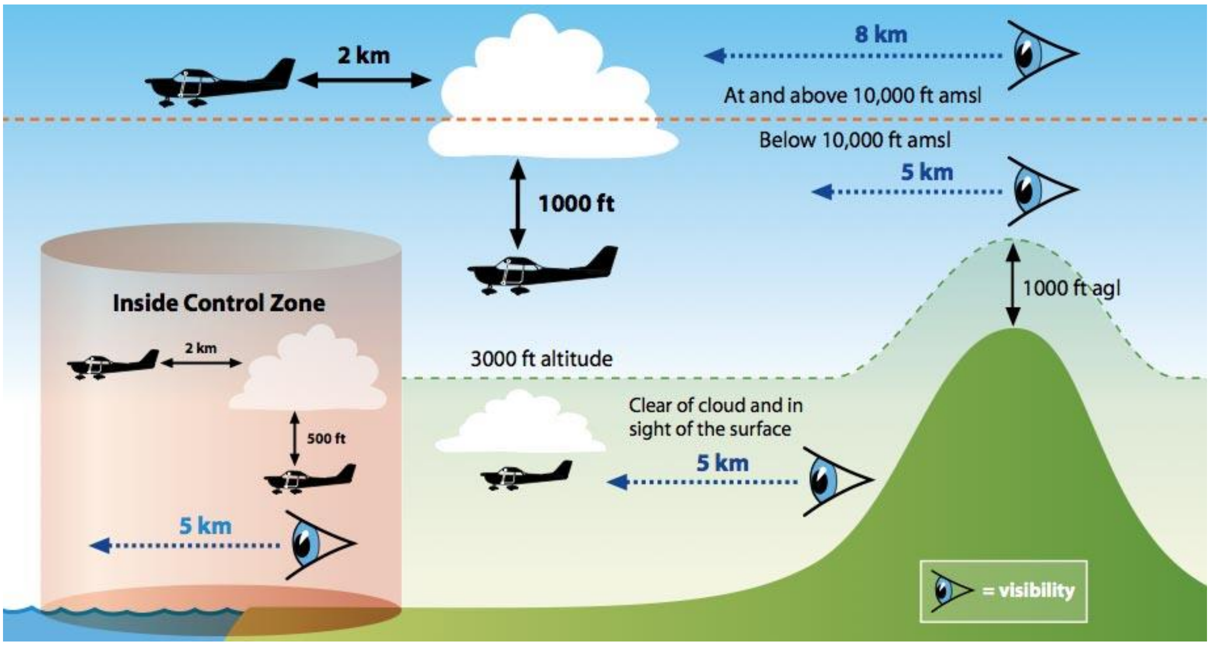

Figure 1. Visibility and ceiling requirements for aircraft flying in Visual Flight Rule (VFR). Source: (Civil Aviation Authority of New Zealand, 2024)

Meteorological forecasting methods have gradually developed over the last century along with advancements in research. This was needed to provide both pilots and air traffic controllers with improved real-time and short-term meteorological products for operational use. Early developments in forecasting were achieved by using a fully automated aviation observation system combined with statistical models (Daniel & Frost, 1982). The foundational model for the current meteorological forecast is the Numerical Weather Prediction (NWP) model, which attempts to synthesize all essential physical processes in the atmosphere over time. These models are used either on their own at each major agency, or shared between agencies, which is mostly the case (Inness & Dorling, 2013). In the United States of America, for example, an operationally implemented forecasting tool is the Localised Aviation Model Output Statistics Program (LAMP), which uses aerodrome routine meteorological reports (METAR) and buoy reports to produce station-based analysis of ceiling and visibility. The extended version is the Gridded Localised Aviation Model Output Statistics Program (LAMP), which has a higher horizontal resolution of 2.5 Km and produces an analysis every 15 minutes. Other forecasting tools include the National Ceiling and Visibility Analysis (NCVA), the Real-Time Mesoscale Analysis (RTMA) and the Real-Time Mesoscale Analysis Rapid Updates (RTMA-RU) (NOAA, 2019).

In the latter half of the twentieth century, advancements in computer technology led to studies in Machine Learning (ML) for weather forecasting. In the 1970s, Glahn & Lowry (1972) developed the Model Output Statistics (MOS) technique. In this technique, predictions are obtained using multiple linear regression models to optimize data from real-time surface observations and mesoscale NWP outputs. Though using data from both inputs, the MOS scheme adds more information from the real-time surface observation than the NWP. Therefore, it is important that the quality of the observations are good. The MOS technique was compared and combined with a purely observation-based system (OBS) in a study by Vislocky & Fritsch (1997). The OBS was constructed from a network of station observations and a persistent climatology model which used a forecast parameters time-lagged statistical relationship. This study showed that incorporating an OBS with MOS improved the quality of the forecast, while a further study by Leyton & Fritsch (2003) showed that applying a higher density of surface weather observations further improved the forecast quality for meteorological parameters associated with low visibility and ceiling. Research has continued to broaden in this area after the year 2000 to include probabilistic forecasting techniques using ensemble models, various model averaging methods, and lately, artificial neural networks (Chmielecki & Raftery, 2011).

Research which utilises Artificial Intelligence (AI) models gained significant impetus from the start of the twenty first century. This is prominently due to the increase in volume and frequency of recorded meteorological data from various observation locations stored in digital format and the increase in processing power of modern computers. AI models thrive on using large volumes of data and produce models which are more accurate, reliable and able to produce outputs in higher frequencies. Deep learning models, which are complex adaptations of neural network models, have shown their ability to handle high volumes of data and interpret patterns in stochastic system data which cannot be mathematically modelled satisfactorily (Solomatine & Ostfeld, 2008). Meteorological system data are therefore good candidates for research for forecasting using deep learning models, especially for scarcely studied meteorological parameters such as visibility and ceiling (Marzban et al., 2007).

A common practice among researchers has been forecasting visibility in classes, such as high, medium, or low visibility, or occurrence of fog or no fog. (Ortega et al., 2020; Wang et al., 2009; Zhu et al., 2017). For example, at Canberra Airport

Fabbian et al. (2007) predicted occurrences of fog using an Artificial Neural Network (ANN) at 3, 6, 12, and 18 hour horizons. The study concluded that the ANN model's classification of such events was good. A binary classification of fog study was carried out at Spain's Valladolid airport by Durán-Rosal et al. (2018). The researchers again implemented the ANN model and used multiple meteorological input variables for making predictions. A similar study classing low visibility events either as FOG, MIST or CLEAR was conducted by Guijo-Rubio et al. (2018). This study compared multiple models and proposed a hybrid window model with ordinal classification as a good predictive model for forecasting at daily time horizons. Furthermore, Fernández-González et al. (2019) used data from local weather monitors and satellite imagery to estimate cloud features and water vapour content to produce mesoscale model outputs. These outputs were then used to assess the risk of poor visibility events in the local area. Local weather station data was also used in a study done in the state of Florida, USA, where multiple ML models were used to classify visibility as low, moderate or good.

Nevertheless, there are areas in this field of research that need greater focus in research, particularly as most studies treat visibility and ceiling forecasting as a classification problem instead of a regression problem. Some research has been carried out in recent years into regression forecasting of visibility and ceiling parameters (Castillo-Botón et al., 2022; Cordeiro et al., 2021; Cornejo-Bueno et al., 2017; Ortega et al., 2023; Peláez-Rodríguez et al., 2023). The overall results show the advantages of implementing deep learning models for meteorological forecasting as a regression problem but also state that the applicability of these models will be further validated by similar studies conducted across different locations. Thus, there is a need to address this gap in knowledge in academic literature through further research.

1.2. Statement of the Problem

The Master of Research study is focussed on Fiji, an island archipelago consisting of around 322 volcanic islands and atolls in the western South Pacific region. The focus island is the main island of Viti Levu which is a volcanic island with a mountainous interior and coastal plains landscape. The islands are located in a tropical region and experience two distinct seasons annually - a warm and wet season from November to April and a cool and dry season from May to October. Localised effects and regional effects due to geographic and oceanic effects add to the variations in climate (Fiji Meteorological Service, 2006). A significant feature is the South Pacific Convergence Zone which becomes more influential during the rainy months from November to April. Additionally, the prevalent Southeast Trade Winds affect the Eastern side of the main island causing more precipitation from greater cloud formation assisted by these winds. This results in a significant difference in weather compared to the Western side of the island which has significantly less rainfall (Australian Bureau of Meteorology & CSIRO, 2011).

The two international airports are located on either side of the main island. Nadi international airport, which is the main international airport of the country, is situated on the Western side while Nausori international airport is located on the Eastern side. Therefore, each location is affected by the different weather conditions due to the previously mentioned reasons. The aviation industry relies on accurate and reliable weather reports and forecasts for safe and efficient operations, and visibility and ceiling are two of the most vital meteorological components. Most meteorological-related aviation incidents are related to poor visibility and low cloud ceiling events which have led to grave outcomes on some occasions (Herzegh et al., 2015). According to a study by Fultz & Ashley (2016), low visibility weather events most commonly overlapped with meteorological-related accidents leading to fatalities among general aviation flights. The study accounted for 70% of such accidents where low cloud ceilings, clouds and obscuration were the major factors.

Therefore, reliable and accurate meteorological forecasts of visibility and ceiling are essential tools for aviation stakeholders in planning and decision-making. Currently, studies into meteorological forecasts using deep learning algorithms are a growing field and is advancing rapidly due to higher computing capabilities and more research focus. This is especially true in visibility and ceiling forecasting as a regression problem, for which there is scarce academic literature. A recent study by

Ortega et al. (2023) recommended further research using deep learning algorithms in visibility forecasts as a regression problem because of its importance in the transportation system as well as to adding to the growing knowledge in this field of research.

1.3. Research Questions

The following research questions, answered through a research publication (see Chapter 4), are conceived to logically meet the objective of this MRES study:

1. *Which models can provide accurate hourly forecasts of meteorological visibility and ceiling using time-series data? How is this information useful for aviation applications*?
2. *How can meteorological visibility and ceiling forecasts, which are essential atmospheric parameters for aviation safety and efficiency, be improved using artificial intelligence methods*?

This research answers the aforementioned questions by employing statistical analysis of site-specific meteorological data to extract meaning trends and patterns. Following this, the data will be used with an AI-based approach including deep learning algorithms to develop a forecasting model which is reliable and useful for applications in the aviation industry.

1.4. Research Aim and Objectives

The aim of this Master of Research project is therefore to *develop an AI-based visibility and ceiling forecasting tool by combining aeronautical meteorological data with statistical and computational analysis for two different sites in Fiji*. The study aims to investigate and understand the best statistical and ML techniques to employ in order to derive the optimum predictive model for visibility and ceiling using the site-specific aeronautical meteorological data. To achieve this primary aim, the following objectives have been addressed:

1. Selecting the most appropriate features affecting the forecast of visibility and ceiling at each site from a global pool of all independent meteorological variables and their significant lags. The Iterative Input Selection (IIS) algorithm was used to obtain the optimum matrix of features to be applied to the forecasting model.

2. Proposing a hybrid IIS-LSTM (Long Short-Term Memory) integrated deep learning algorithm as an effective forecasting tool for visibility and ceiling for the aviation industry. The proposed model is compared to conventional AI models LSTM, TabNet, ANN and Random Forest to assess its practicality over these models.

The outcomes of these objectives have been reported in a journal paper in *IEEE* Access (see Chapter 4).

1.5. Thesis Layout

This thesis is comprised of five sections and is organised as follows:

Chapter 1 This chapter delivers background about this study, provides the statement of the problem, presents the research questions, and highlights the aims and objectives of this study.

Chapter 2 This chapter presents the literature review of existing research in this field in academic literature and data science techniques employed during this research.

Chapter 3 This chapter describes the study site, dataset and general methodology used in this research. Further specific details of the methodology are outlined in the following chapter.

Chapter 4 This chapter is presented as a published article in the IEEE Access journal (DOI: 10.1109/ACCESS.2024.3401091). It addresses both the objectives of this study. It shows the application of the IIS algorithm as a feature selection technique to extract the optimum and most relevant features from each independent variable in the data and their significant lags. It then proposes a hybrid IIS-LSTM integrated model and compares the benefits of the model against conventional machine learning models.

Chapter 5 The chapter summarises this research study, outlines limitations in the works and recommends avenues to further this line of research.

Chapter 2: LITERATURE REVIEW

2.1. Foreword

This chapter reviews literature relevant to the design and methodology of the proposed predictive model for visibility and ceiling forecasts. Each subsection elaborates on an important concept used in this research and highlights existing gaps in knowledge where applicable.

Safe and efficient of transportation systems, especially in air transportation are directly affected by meteorological parameters visibility and low cloud ceiling. However, due to its highly stochastic nature and complex microphysical properties, using purely numerical and statistical-based models has been challenging (Cordeiro et al., 2021). This has changed in recent decades, as visibility and ceiling forecasting quality have improved by combining surface observations with statistical postprocessing of numerical models (Marzban et al., 2007). Further improvements in forecasting quality are being achieved by advancement in computer processing power and machine learning technologies. The development of neural networks is one of these innovations, and it is highly regarded among data scientists due to its ability to: (1) learn adaptively only on data without needing a physical model or prior assumption on statistical distribution; (2) generalise fundamental non-linearity in the data having complex relationships; and (3) learn and handle temporal structures in the data (Ortega et al., 2020). For these reasons, deep learning algorithms are becoming the framework of choice when dealing with problems in forecasting meteorological parameters, or in time-series forecasting overall.

2.2. Time Series Forecasting using Deep Learning

During the ImageNet LSVRC in 2010, Krizhevsky et al. (2017) introduced an iteration of ANN's, deep learning, as a solution to an image-processing problem. Thereafter, applications for deep learning algorithms have broadened into multiple fields in science and research. The simultaneous advancements in computer technology in terms of higher processing power and greater digital data storage capabilities has added to this trend. This is certainly true in the case of time-series forecasting, which has exploited advancements in neural network architecture. Studies in the fields of finance, biology, meteorology and energy demand have featured deep learning networks to forecast using its time series data. For example, Chen et al. (2018) forecasted short-term energy load demand on power grids using end-to-end feed-forward network with residual connections. Similarly, Amarasinghe et al. (2017) employed Convolutional Neural Networks (CNN) in their research in energy load forecasting. A related work by Bianchi et al. (2017) compared different classes of recurrent neural networks (RNN) and configured them to produce optimum predictions from real world energy load demand data. Using meteorological data and climate indices, Deo & Şahin (2015) applied the Extreme Learning Machine algorithm to forecast the drought index for Eastern Australia.

Innovations and developments have brought many variants to deep learning architectures, such as Long Short-Term Memory (LSTM) (Zheng et al., 2017), gated recurrent unit (Wang et al., 2018), Neural Basis Expansion Analysis for interpretable time series forecasting (N-BEATS) (Oreshkin et al., 2019) and Attentive Interpretable Tabular Learning (Arik & Pfister, 2021). Furthermore, hybrid architectures have also been developed exploiting each algorithms advantages and these algorithms have gone on to show promising results when forecasting time series data. For example, to forecast future flood occurrence for different locations in Fiji, Moishin et al. (2021) developed a hybrid CNN and LSTM algorithm. Prasad et al. (2018) designed a hybrid algorithm consisting of the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) with ELM for their research into soil moisture forecasting. The algorithms improved overall forecasting by addressing inaccuracies arising from data non-stationarity, a typical issue found when using complex and dynamic data-driven models.

Deep learning algorithms have also been applied in visibility forecasting. For instance, in their study into air quality and lower atmospheric visibility forecasting Sharma et al. (2020) implemented a hybrid framework of an Online Sequential ELM with an Improved CEEMDAN. More recently, several ML algorithms were used in simulating visibility and ceiling base height (Cornejo-Bueno et al., 2020). The major finding from this study was stating that with accurate observational data, ML approaches can greatly improve predictions in regressive forecasts. Furthermore, Ortega et al. (2023) explored visibility distance time series forecasting using five different deep learning models - three different CNN architectures, LSTM and Multi-Layer Perceptron (MLP). After exploring their performance, they found that LSTM was the superior algorithm because of the model’s improvement in learning trends in the data of larger size and its ability to extract time-dependent patterns from the raw data.

While significant studies in forecasting meteorological visibility using deep learning algorithms have been done (Cornejo-Bueno et al., 2020; Ismail Fawaz et al., 2019; Ortega et al., 2019), this review has revealed the scarcity of studies focussing of visibility forecasting as a regression problem. The authors of one study who focussed their research in this area noted similarly the limited studies involving deep learning models forecasting visibility as a regression problem (Ortega et al., 2023). Therefore, they recommended more studies researching the applicability and practicality of forecasting visibility as a regression problem for different study sites using deep learning algorithms.

2.3. Feature Selection Techniques

Feature selection techniques are used to reduce dimensionality of the input variables while not compromising the accuracy of the outputs. By effectively employing this techniques, redundant features can be eliminated, leaving behind only the most informative and significant features of the model. The benefits of this applying this procedure in model development is the reduction in computational costs, optimized predictive performance and improved generalisation of the model (Curreri et al., 2020). Supervised methods of feature selection include filters, wrappers, embedded or hybrid.

Feature selection using filter methods order variables according to a criterion and ranks them. Usually, the principal criterion is the degree of relevancy this feature has to the output (Chandrashekar & Sahin, 2014). Two common relevancy measures are correlation and mutual information. Pearsons's correlation coefficient detects linear dependencies between the target and the independent variable (Guyon & De, 2003), while mutual information measures the amount of information one variable provides about the other variable using Shannon entropy and conditional entropy (Battiti, 1994). Filter methods are computationally light and reduces overfitting, but a drawback is that some redundant features may be selected or variables which have lower relevancy on their own but are more informative in combination with other variables can be discarded.

Wrapper methods use a model's performance to evaluate subsets of the variables. The models performance criteria could be Mean Squared Error (MSE), Akaike Information Criterion (AIC) or Mallows Coefficient statistics (Curreri et al., 2020). Different search algorithms can be used to find a subset of variables such as the Branch and Bound method (Narendra & Fukunaga, 1977), Genetic Algorithm (Goldberg, 1989) or Particle Swarm Optimization (Kennedy & Eberhart, n.d.). Wrapper methods can become computationally expensive with datasets containing more features as the search grows exponentially with each added feature.

Embedded methods incorporate feature selection algorithms as part of the model development process, such as during the training phase. For instance, since mutual information had the drawback of poor results due to only the class output being considered, Battiti (1994) proposed a “greedy” algorithm which took the MI score of the variable with the target variable as well as the already selected variables into account. Another example of the embedded method is the least absolute shrinkage and selection operator – multilayer perceptron (LASSO-MLP). In their study, Sun et al. (2017) proposed a two-step iterative approach where a least absolute shrinkage and selection operator is introduced to select the optimum input variables to be used in a multilayer perceptron algorithm. Embedded methods work best with larger datasets but tend to be slower than filter methods (Radchenko & James, 2011).

Other feature selection techniques are also used. For example, clustering is an unsupervised method which attempts to group unlabelled data into unknown natural classes (Law et al., 2004). Semi-supervised feature selection techniques use a combination of both labelled and unlabelled data to modify a hypothesis form labelled data. Finally, ensemble methods use different subsets of data through a feature selection algorithm and aggregate the results to obtain a final feature set (Chandrashekar & Sahin, 2014).

2.4. Iterative Input Selection

Iterative Input Selection (IIS) is a tree-based feature selection algorithm proposed first proposed by Galelli & Castelletti (2013). It enables data modellers to determine the optimum subset of variables from a global pool of input variables and can handle very large number of inputs by incorporating features of model-based approaches. The algorithm works by ranking variables based on a its contribution to variance reduction of the preselected output from an underlying model. It is executed in three phases: (1) Input Ranking (IR), (2) Single Input Single Output (SISO) approach and (3) Multiple Input Single Output (MISO) phase. In the IR phase, forward selection method selects the most significant inputs. The SISO phase then selects the first *p*-ranked variables and assesses it as an independent *p*-SISO model. Finally, the MISO phase assesses the effectiveness of the input matrix in forecasting by adding the most significant variables based on the coefficient of determination score. An in-depth discussion of the structure and theoretical work of the IIS is provided in the original work by Galelli & Castelletti (2013).

The algorithm was first applied in streamflow forecasting for the Ticino River in Switzerland (Galelli & Castelletti, 2013). This initial study highlighted the algorithm's ability to select the most significant and nonredundant input variables from real world large datasets. Galelli et al. (2014) further evaluated the algorithm against partial mutual information, partial correlation and Genetic Algorithm-ANN and found the IIS algorithm performed better. Streamflow forecasting was carried out in the study by Prasad et al. (2017) for the drought prone Murray Darling Basin in Australia. They integrated the IIS algorithm with a wavelet ANN model for precise forecasting of monthly streamflow and advocated the IIS's efficacy to screen model predictors.

The algorithm has since been used in studies other than streamflow forecasting, such as spatial variability patterns in surface water quality in lotic mountains carried out by Mejía & Barrios (2023). Using the IIS algorithm, the authors were able to identify three key variables which contributed the quality of water from their global pool of twenty-eight candidate variables. Finally, IIS was also used to select the optimal input features for use in the CNN model in a study to generate annual irrigation water use maps in China (Zhang et al., 2023). Still, the IIS algorithms strengths are yet to be applied in studies using meteorological data for forecasting visibility and ceiling as a regression problem.

The benefit of this algorithm is achieved from the fact that this can be applied to any sort of sample because of its reliance on ranking-based evaluation instead of statistical characteristics of the data. Another benefit is it is generally faster and more efficient than compared to computationally expensive methods such as bootstrapping. Thus, it is able to guard against data redundancy and contribute further to the robustness of the overall predictive model. However, as noted in the studies it has been used, the IIS algorithm only goes through a thorough process for selecting features from the complete set of features. It will need to be integrated with accurate predictive algorithms, such as deep learning algorithms, to output reliable forecasts and form a useful hybrid forecasting model.

2.5. Deep Learning Predictive Models

Deep Learning algorithms offer state-of-the-art predictive frameworks for time-series forecasting and has gained immense prominence due to its high performance compared to traditional models. Due to their superior capabilities in time-series forecasting, these algorithms are highly applicable for forecasting stochastic and weather parameters from large meteorological datasets. Algorithms are being innovated and hybridised constantly to meet the specific needs of each forecasting case. The subsections below elaborate further the potential for TabNet and LSTM deep learning models to address the aims of this study due to these two algorithms proven time-series forecasting capabilities and ability to handle tabular data efficiently in literature. Further characteristics of each algorithm is noted in the following subsections.

2.5.1. Attentive Interpretable Tabular Learning (TabNet)

TabNet is a deep learning algorithm which was first proposed by Arik & Pfister (2021) to address the limitations of tabular data while benefitting from a deep learning architecture. It utilises sequential attention to select the most significant features at each decision step resulting in a highly efficient learning model. This algorithm can be compared to tree-based ML models in that it can also offer explainability of each feature's importance and interpretability for tabular data. It also delivers high performance due to its deep learning design. Additionally, an encoder/decoder system is built into the algorithm which negates the need for normalizing global numerical features while also allowing for categorical features to be formatted automatically. This feature of the algorithm reduces the time and memory needed during the pre-processing phase of model development (Son et al., 2022).

Arik & Pfister (2021) first used this algorithm to test various types of real-world tabular datasets, from forest cover type, poker hand, Sarcos, Higgs boson, and Rossmann store sales. The performance of TabNet outshone popular tree-based models like Random Forest, CatBoost, LightGBM, XGBoost, and also an MLP model. Clements et al. (2020) used TabNet to design a credit risk detection technique, which showed similar performance to that of sequential models LSTM and Temporal Convolutional Network (TCN). Lv et al. (2022) similarly used TabNet to analyse the volatility of stock prices in the market. The study’s outcome showed that the TabNet model produced the best results, as it outperformed the Naïve Bayes, SVM and

XGBoost models. The comparison in this study was made using Root Mean Squared Percentage Error (MAPE) to evaluate the performance. Additionally, TabNet has been used in medical predictions such as to differentiate between comorbid functional seizures and epilepsy from pure functional seizures (Asadi-Pooya et al., 2022), diagnosis of breast cancer (Chen et al., 2021), and explainable and early-stage detection of diabetes (Joseph et al., 2022). Moreover, the TabNet model has also been utilised on meteorological data. A study used it to explore estimation of air quality and to identify the most influential chemical components affecting the quality of air using the interpretability feature of this model (Son et al., 2022).

2.5.2. Long Short-Term Memory

This deep learning architecture has been proven to perform well in time series forecasting. The reason for this is due to its architecture, being a type of Recurrent Neural Network (RNN) which learns long-term time-dependent patterns from data (Ghimire et al., 2023). However, its ability to retain historical information for long periods is due to having gate functions in the cell structure, which is different to RNN.

Visibility forecasting using LSTM has been explored in several studies. For example, Deng et al. (2019) investigated the use of LSTM to predict visibility from data obtained for an observational station in Beijing, China. Another study by Meng et al. (2020) presented a framework for visibility predictions using LSTM and data collected at observation stations at airports. The feasibility of the proposed framework was verified with a prediction accuracy of 68.9%.

Finally, the study by Zixuan et al. (2021) aimed to use LSTM with airport ground station data to forecast the visibility of the Urumqi Airport located on a plateau in Northwest China. The authors concluded that the forecasting model based on the LSTM architecture was a good fit for effectively characterizing changing visibility scenarios and being used operationally as an important reference to dispatchers when formulating flight plans.

2.6. Summary

In summary, accurate and reliable predictive models are an essential tool for forecasting meteorological parameters. The inter-related nature of most meteorological parameters and their relative historical information make data-driven models for meteorological forecasting both feasible and dependable. However, compared to statistical, physical-based models, data-driven deep learning AI models are proving more reliable and accurate. Visibility and ceiling time-series forecasting have utilised AI models frequently in studies, although most of these studies were carrying this out as a classification problem instead of a regression one. Feature selection is an important aspect of model development, enabling it to be more compact and efficient without compromising the accuracy of the model.

The IIS algorithm showed superior ability to be applied to any sort of data and be less computationally intensive while being able to effectively select the optimal subset of features compared to the traditional feature selection method. Deep learning models offer the best advantages for data-intensive and highly stochastic time series forecasting. The TabNet model is designed to be effective in using tabular data and giving interpretable results, while LSTM is highly efficient is learning and retaining patterns of historical data for a long time.

For this study, the LSTM algorithm is chosen to be integrated with the IIS algorithm due to its proven performance in reliable time-series forecasting in multiple studies found in literature. This research will thus address the need for regressive visibility and ceiling forecasting, using feature selection techniques and deep learning algorithms to design a data driven predictive model for applications into the aviation industry.

Chapter 3: STUDY AREA, DATA AND METHODOLOGY

3.1. Foreword

This chapter presents an overview of the study area, the dataset used, and the general methodology applied in this research work. Since this is a Thesis by Publication, further details of the study area, specific methodology and implementation are presented in Chapter 4 (journal paper 1). These factors were the core contributors to developing the proposed integrated deep learning model forecasting visibility and ceiling in this Master of Research thesis. Two different sites were chosen with differing climates and geography. The data were obtained for these two sites and are described in the following subsections. Furthermore, a brief description of the methodology is provided, with specific details of model development presented in the following chapter.

3.2. Study Area

The emphasis of this research is on the Fiji Islands. It is an island archipelago consisting of 322 islands and situated between 15 to 20 degrees South latitude and 175 to 182 degrees East longitude. The islands are spread across these coordinates, with most of the population living on the two main islands of Viti Levu and Vanua Levu (Berdach, 2005). These two main islands which are of volcanic origins have rocky mountainous interior geography and flat coastal plains. The island group experiences two distinct seasons owing to it lying in the tropical region, a warm and rainy season from November to April, and a cool and dry season from May to October. Other significant factors that affect the weather for this region include the Southeast Trade Winds, the South Pacific Convergence Zone and the occurrence of tropical cyclones during the warm and rainy season.

The study locations are the two international airports located on one of the main islands of Viti Levu. Nadi International Airport, the main international airport of the country, is located on the Western side of the Island while Nausori International Airport is located on the Eastern part of the island.

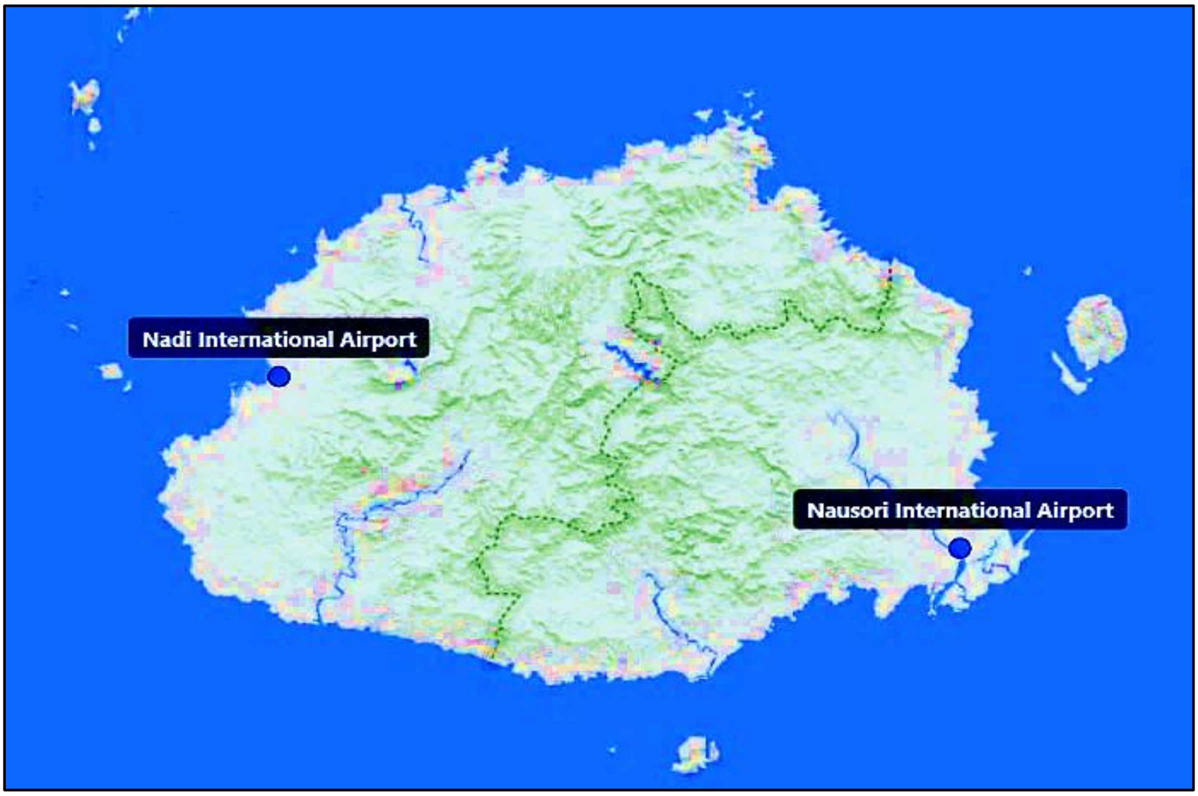

Figure 2. Map of Viti Levu indicating site locations

A brief description of the weather patterns for each study site is as follows:

- Nadi International Airport is located near the coast of the western part of Viti Levu. It has more days of sunshine and receives significantly less rainfall due to being located on the leeward side of the island. For December 2023, it was reported that the average daily temperature ranged from a maximum of 32.6 degrees Celsius to a minimum of 22.8 degrees Celsius. It had approximately 58 millimetres of rainfall from receiving rainfall on 28% of the days in the month. The average relative humidity was at 60%.
- Nausori International Airport is located on the Eastern part of Viti Levu and a few kilometres from the coastline. It has significantly more occurrences of rainfall due to being on the windward side of the main island. The Southeast Trade Winds blow moisture up the mountainous interior, causing much cloud formation and rainfall on the Eastern part of the islands. For December 2023, it was reported that Nausori Airport received approximately 181mm of rainfall from 68% of the days in the month is received rainfall. The average maximum temperature was 31.2

degrees Celsius, and the average minimum temperature was 23.3 degrees Celsius. The average relative humidity was 76% (Fiji Meteorological Service, 2024).

3.3. Dataset

The data is the routine aviation meteorological observations recorded at each station. These observations are made as per International Civil Aviation Organisation (ICAO) and World Meteorological Organisation (WMO) standards for observing and recording meteorological data for aeronautical use. Since the two international airports chosen for this study operate 24 hours a day, they are required to provide hourly weather observations which are made available to other aviation stakeholders. The organisation responsible for making these observations at our study sites is the Fiji Meteorological Services (FMS) and they record the specified meteorological parameters following international standards for aeronautical meteorological reports on an hourly basis. For our study, this data was requested and successfully obtained for a period of 10 years, beginning from January 1st, 2012, 0000 local time to December 31st, 2021, 2300 local time.

The data obtained for this research is suitable for Deep Learning (DL) model development. DL models are most suited to handle high volumes of data for model development, both in terms of higher dimensionality of the data as well as high volume of time-series inputs (Chen & Lin, 2014). This enables DL models to be effectively trained on the data and discover underlying patterns and trends that would not be fully accounted for by purely statistical models. The dataset obtained fits the characteristics for effectively developing a DL model. It had 10 years of hours of data instances totalling 87,672 and recorded 14 different meteorological attributes. Most importantly, it recorded the meteorological variables ‘Visibility’ and ‘Total Low Cloud’, the variables analogous to visibility and ceiling chosen as the target variables in the forecasting models. A summary of these and all other variables in the raw dataset obtained from FMS for the two study sites is shown in Table 1.

Table 1. Characteristics of the raw dataset for the study sites Nadi International Airport and Nausori International Airport located in Fiji.

Variable	Total Values	Data Type	Unit of Measurement	Test Site 1: Nadi			Test Site 2: Nausori		
				Missing Value Count	Missing Value (%)	Max – Min Value	Missing Value Count	Missing Value (%)	Max – Min Value

Air Temperature	87672	Continuous	Degrees Celsius (°C)	0	0	13.4 – 35	11854	13.521	14.5 – 34.5
Wet Bulb Temperature	87672	Continuous	Degrees Celsius (°C)	961	1.096	12.8 – 30.1	17695	20.183	12.95 – 29.75
Dew Point Temperature	87672	Continuous	Degrees Celsius (°C)	442	0.504	0.1 – 30.2	12850	14.657	2.4 – 28.15
Relative Humidity	87672	Continuous	Percentage (%)	945	1.078	21.5 – 100	13193	15.048	19.6 - 100
Rain	87672	Continuous	Millimetres (mm)	0	0	0 – 99	919	1.048	0 – 58.7
MSL Pressure	87672	Continuous	Hectopascals (hpa)	179	0.2	968 – 1021.3	11721	13.369	988.8 – 1022.5
Visibility	87672	Continuous	Kilometres (Km)	19	0.022	0.1 – 50	118424	13.487	0.05 – 50
Wind Speed	87672	Continuous	Metres per second (m/s)	8	0.009	0 – 30.9	1097	1.251	0 – 23.1
Wind Direction	87672	Discrete	Degrees (°)	24	0.027	0 - 360	1150	1.312	0 – 360
Present Weather*	87672	Nominal	Encoded	N/A	N/A	N/A	N/A	N/A	N/A
Past Weather*	87672	Nominal	Encoded	N/A	N/A	N/A	N/A	N/A	N/A
Total Cloud	87672	Discrete	Oktas	961	1.096	0 – 8	14687	16.752	0 – 8
Total Low Cloud (Ceiling)	87672	Discrete	Oktas	3153	3.600	0 – 8	20395	23.263	0 – 8
Total Low Cloud Height	87672	Continuous	Metre (m)	3033	3.460	0 – 2133.6	19707	22.480	0 – 3657.6

* Categorical Value – Not used for analysis in this research

Data imputation was carried out for instances of missing values in the data using two main methods. For a single instance of a missing value, a simple average of the preceding and succeeding values was taken. For consecutive instances of missing values, the calendar average method was used in combination with the simple average method. Specifically for relative humidity, which is a derived unit, the following formula was used to impute data for missing values:

$$RH = 100\mathrm{e}\left(\frac{cb(T_d - T_a)}{(c+T_a)(c+T_d)}\right) \tag{1}$$

where b = 17.625; c = 243.04; T_a = Air Temperature; and T_d= Dew Point Temperature.

There were very few instances of data which were obviously erroneous or fell outside the acceptable range of values to be recorded in the report. Those that met this criterion were adjusted according to the standards of recording meteorological observations as set out by the World Meteorological Organisation (2018).

3.4. Methodology

After obtaining the necessary data and carrying out an initial investigation on it, the data was ready to follow the steps for model preparation and development. Firstly, the data underwent a series of processes to be converted into an acceptable form for the model to be trained on it. This involved the initial cleaning and data imputation to produce a whole dataset, including removing the two variables containing categorical data. Next, statistical inferences were obtained for each variable to assist in recognising the ideal method to be used in the model development. The most important of these statistics were the Partial Auto Correlation Function (PACF) and the Cross Correlation Function (CCF). These statistics determined the number of significant lags that would be needed to effectively train the model to produce the optimum output of the predictor variable. All the independent variables and their significant lags, including the significant lags of the target variable, produced a global pool of features.

Secondly, feature selection was carried out to select the best features from the global pool. The feature selection algorithm used was the Iterative Input Selection (IIS) algorithm which was chosen due to its ability to be applied to any sort of model because it evaluates on a ranking-based approach and due to the algorithm being exhaustive in its evaluation while not being computationally expensive (Galelli & Castelletti, 2013). The algorithm was run for each target variable, visibility, and total low cloud, and for each of the two study sites. This resulted in obtaining distinct optimum features for four different models.

The deep learning model chosen for forecasting was the LSTM due to its proven excellent performance in time series forecasting as evidenced by literature search (Yu et al., 2019). The following chapter will discuss in greater detail the steps involved in the development of the model and its parameters. After the model architecture was finalised, the optimum features obtained from the IIS algorithm were supplied to the model to train it on a portion of the data and then test its forecasting performance on the remaining portion of the data. This phase constituted the development of the proposed forecasting model for this research, the hybrid IIS-LSTM integrated model. This proposed model was then compared with another benchmark model to evaluate its performance. The benchmark models chosen were the standalone LSTM algorithm, TabNet (Arik & Pfister, 2021), Artificial Neural Networks (Kim & Valdés, 2003), and Random Forest (Breiman, 2001).

Finally, several performance evaluation metrics were implemented to gauge the model's performance both independently and in comparison, with the benchmark models. These included correlation Pearson's Correlation Coefficient (r), Willmott's Index (WI), Nash-Sutcliffe Efficiency Index (E_{NS}), Root Mean Squared Error ($RMSE$), Mean Absolute Error (*MAE*), Legates-McCabe Efficiency (*LM*) and Kling Gupta Efficiency Index (*KGE*). The mathematical equations and statistical indices are depicted in the following chapter of this thesis, which is a journal paper published in *IEEE Access*.

CHAPTER 4: PAPER – Atmospheric Visibility and Cloud Ceiling Predictions with Hybrid IIS-LSTM Integrated Model: Case Studies for Fiji's Aviation Industry

4.1. Introduction

In this chapter, a copy of the paper entitled "Atmospheric Visibility and Cloud Ceiling Predictions with Hybrid IIS-LSTM Integrated Model: Case Studies for Fiji's Aviation Industry", which has been accepted for publication in the journal, *IEEE* Access, is presented in its exact form. In this paper, a hybrid IIS-LSTM integrated model was developed to forecast aviation visibility and ceiling forecasts. This predictive model used meteorological variables from hourly aeronautical meteorological observation data and their significant lags to make forecasts. The IIS component of the algorithm selected the optimum features for visibility and ceiling for each of the two study sites, which was used to train the LSTM model to make predictions. The performance of this model was evaluated using agreement and error metrics and results indicated the model to make accurate and reliable predictions. The model was further compared with benchmark models LSTM, TabNet, ANN and Random Forest, and the hybrid model developed showed superior performance against these.

Based on these results, it can be concluded that the proposed IIS-LSTM integrated model presented in this paper is an additional efficient tool for practical use in the aviation industry and which can be explored further for its implementation in a cost-effective and convenient manner for the other sites in Fiji and the Pacific region.

4.2. Published Paper

IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

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RESEARCH ARTICLE

Atmospheric Visibility and Cloud Ceiling Predictions With Hybrid IIS-LSTM Integrated Model: Case Studies for Fiji's Aviation Industry

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ABSTRACT Atmospheric visibility and cloud ceiling forecasts are essential for the safety and efficiency of flight operations and the aviation industry. Routine hourly aviation meteorological observations are recorded at every airport. However, forecasts of these two meteorological parameters using artificial intelligence techniques are limited. This research utilizes data from two study sites in Fiji, Nadi, and Nausori International Airport, and proposes a hybrid Iterative Input Selection – Long Short-Term Memory (IIS-LSTM) integrated model to forecast the consecutive hour's visibility and ceiling parameters. The IIS algorithm acts as a feature selector from the global predictor matrix of predictor variables with its significant lagged inputs and the significant lagged inputs of the target variable, while the LSTM algorithm acts as the learning model and makes forecasts. The performance of the proposed hybrid IIS-LSTM model is evaluated using seven statistical score metrics and compared with four competing benchmark models. The evaluated results illustrate the superiority of the proposed hybrid IIS-LSTM integrated model and its advanced capability to generate accurate atmospheric visibility and cloud ceiling forecasts for the next consecutive hour compared to the benchmark models. The most important features selected were the second lagged input of visibility and first lagged input of rainfall to improve visibility forecasts while the first and the fifth lagged inputs of the total low cloud cover were paramount for accurate cloud ceiling forecasts. Considering the geography of the study sites, the overall efficacy of the IIS method is strongly advocated to screen most suitable model predictors and the subsequent integration of this input selection method with the LSTM predictive algorithm to attain enhanced performance of the hybrid IIS-LSTM forecast model. This objective model is therefore proposed to be an efficient and cost-effective predictive tool for atmospheric visibility and cloud ceiling forecasts, especially its applications in the aviation industry for aeronautical purposes.

INDEX TERMS Visibility forecast, ceiling forecast, deep learning, machine learning, iterative input selection, long short-term memory.

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I. INTRODUCTION

The aviation industry heavily relies on meteorological parameters for the overall safety and efficiency of flight operations in terms of the planning, decision-making and contingency procedures. While all meteorological parameters have their relative importance to the overall aviation operations, of immediate interest are the atmospheric visibility and the low cloud ceiling parameters used at the respective airports for the monitoring of flight safety.

According to the International Civil Aviation Association [1], *visibility*, used as the first objective variable in this research study, is the distance in the lower atmosphere a black object can be seen and identified against a bright background at the ground level, or the distance at which light of 1000 candela in luminescence can be seen and recognized against an unlit background, whichever is greater. The description of *ceiling*, used as the second objective variable in this research study, is the vertical distance of the base of the lowest layer of cloud below 6000m from the surface of the earth or water and which covers more than fifty per cent of the sky [2]. These two variables play a crucial role in the operation of flights, especially in the critical phase of landing and taking-off, since most meteorological-related aircraft incidents occur during periods of poor visibility and low cloud ceiling [3]. Prior studies showed that low clouds and obscuration contributed to about 70% of fatal accidents in general aviation flights [4]. This emphasizes that a timely, reliable, and precise observation of these two meteorological parameters is essential for planning and assisting aircraft in maneuvering through hazardous situations, which is crucial for safe aviation operations.

There are currently products that are operationally implemented providing forecasts of weather elements, including visibility and ceiling, using meteorological reports. For example, in the United States of America, the Gridded Localized Aviation Model Output Statistics Program (GLMP) is implemented which has a 2.5 km horizontal resolution and produces an analysis every 15 minutes. This algorithm extends the Localized Aviation Model Output Statistics Program (LAMP), which is station-based ceiling and visibility analysis produced by the integration of METAR (aerodrome routine meteorological report) and buoy reports (NOAA, 2019). Other products include the National Ceiling and Visibility Analysis (NCVA), the Real-Time Mesoscale Analysis (RTMA) and the Real-Time Mesoscale Analysis Rapid Updates (RTMA-RU). Various types of data are used as inputs into these products including surface observations from a combination of human and automated systems (METAR), fully automated surface observation stations (ASOS), regional networks of automated meteorological observing systems (Mesonets), and satellite data from GOES-16. Despite these products developed for visibility and ceiling analysis, accurate predictive models utilizing meteorological datasets currently remain relatively limited.

The inherent abrupt and stochastic nature of the meteorological system makes mathematical modelling highly complex and resource-intensive [6]. To develop in-situ models with higher frequency and accuracy to make reliable meteorological forecasts of variables such as visibility and ceiling, Artificial intelligence (AI) models and big data approaches are necessary especially in the current era of increasing volume of datasets regarding atmospheric properties recorded at various airports. Scholars have modelled visibility as a classification problem, grading the classes as high, medium, and low or fog versus no fog instances [7], [8], [9]. For instance, a study done at Spain's Valladolid airport used hybrid prediction models such as Proportional Odds Model and Support Vector Machines (SVM) for ordinal classification of visibility events in three categories (FOG, MIST, CLEAR) [10]. Another research tried to forecast hourly short-term low visibility events at the same airport using a combination of Machine Learning (ML) techniques [11]. Similarly, an exploratory study conducted in Florida, USA used various ML algorithms to classify visibility as low, moderate, and good using local weather station data [12].

However, visibility and ceiling forecasts as a regression problem have been least explored and have recently gained some popularity. In a study conducted at Santos Dumont Airport Brazil, four machine learning models were used for both classification and regression forecasting of visibility, and regression forecasting for ceiling base height [13]. Similarly, a low visibility event forecasting study was carried out as both a classification and regression problem in Galicia, Spain using a large number of ML approaches [14]. The authors found the Artificial Neural Network (ANN) model with a simple standardization method to be the most efficient formulation after evaluating the performance of the models under a common framework. Additionally, single-step visibility forecasts using five different deep learning models were studied by [15] for weather stations in Florida. The authors recommended deep learning models for further research in visibility forecasting as a regression problem considering its importance to safety in transportation systems and a lack of similar studies. Furthermore, a study by Pelaez-Rodriguez et. al [16] concluded that a deep learning ensemble methodology gave very satisfactory results in forecasting visibility at two locations in Spain due to the ensemble containing information from all individual learners of the different deep learning architectures.

An essential aspect of model development is model parsimony, i.e., a reduction of overall model input variables whilst achieving the same level of accuracy. This is achieved by discarding irrelevant or redundant variables while selecting only the most applicable variables. The implication is that necessary information is still retained in the dataset, while variables that do not contribute to output information are excluded. The benefits of reducing the dimensionality of the data include a decrease in computational cost, improvement in generalization capability, and reduction in the probability of missing data and outliers being included in the data [17]. These input selection or dimensionality reduction methods can be classified broadly into feature extraction or feature selection techniques. Feature extraction methods transform or combine original inputs to create new features, while feature selection methods use the original input features and select the best subset of features from these.

Feature selection methods are further classified as filters, wrappers, embedded or hybrid [17], [18]. Some filter methods applied in the literature include correlation analysis [19], [20], [21], information-theoretic subset selection (ITTS) [22], minimum Redundancy Maximum Relevancy [23], [24], and the Lipschitz quotient [25] which is a backward elimination filter method. The least absolute shrinkage and selection operator – multilayer perceptron (LASSO-MLP) is an example of an embedded method [26] while studies by [26] and [27] are examples of hybrid methods of feature selection used in literature.

An alternative feature selection method called Iterative Input Selection (IIS) was proposed by [28], which can determine the optimum predictor variables from a global pool using a tree-based algorithm. The accuracy of this algorithm was demonstrated in the study for streamflow forecasting in Ticino River, Switzerland. A further study in [29] revealed that the IIS algorithm performed better than partial mutual information, partial correlation and Genetic Algorithm-ANN. Additionally, the IIS-optimized models have been found to perform better than standalone models in forecasting monthly streamflow in Australia's Murray-Darling Basin and were recommended as a suitable tool for feature selection [31]. Nonetheless, the application of the IIS algorithm in visibility and ceiling forecasting using aviation meteorological observational data is yet to be explored.

Therefore, this study aims to extend the investigative approach of utilizing deep learning architecture AI models for visibility and ceiling forecasting using hourly routine aviation meteorological observation data. The site locations chosen are two international airports in Fiji. To the best of the authors' knowledge, no such research has been undertaken to explore the capabilities of AI models for forecasting the weather elements' visibility and cloud ceiling for these two study sites, let alone deep learning models. Additionally, current literature shows a lack of research being conducted in forecasting visibility and ceiling as regression problems using aviation meteorological observational data.

This study aims to address these gaps in research by advancing the applications of deep learning AI models for visibility and ceiling forecasts, with the following objectives:

1. *Use the Iterative Input Selection (IIS) feature selection technique to find the optimum features for the model from all meteorological variables and significant lagged series.*

2. *Design and implement the proposed hybrid IIS-LSTM integrated model for a 1-hour forecast horizon and compare the outcomes with alternative AI models LSTM, TabNet, ANN and Random Forest.*

3. *Evaluate the performance of the objective model (proposed hybrid IIS-LSTM) with the alternative models using performance evaluation metrics and graphical analysis of the observed dataset with the forecasted dataset.*

4. *Briefly elaborate on the suitability of the objective model for practical visibility and ceiling forecasts, discuss any limitations and comment on any recommendation for future research.*

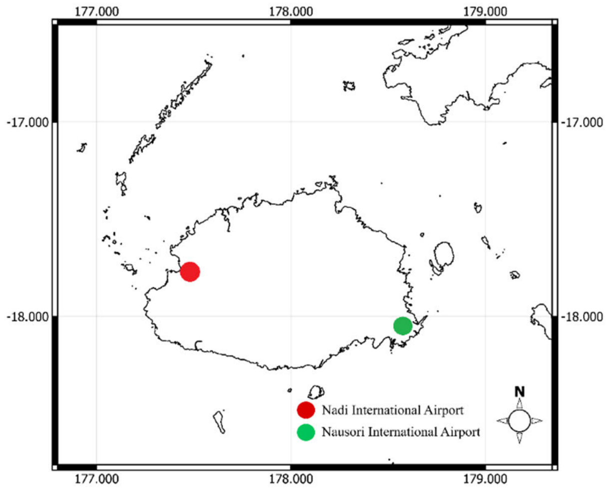

FIGURE 1. Map of Fiji showing the present study locations for which the proposed IIS-LSTM model was developed and implemented.

II. THEORETICAL OVERVIEW

A. ITERATIVE INPUT SELECTION (IIS) ALGORITHM

The study of [28] has proposed the IIS as a robust input selection tool that utilizes highly randomized trees (Extra trees). The IIS is not computationally intensive; thus, faster, and more efficient [32]. The IIS algorithm is executed in three phases. The first phase is the Input Ranking (IR), whereby the most significant predictors are selected in a forward selection method process. The variables are ranked in order or significance, but the contribution of each input information towards the output may be hidden due to the possibly redundant variable(s).

Therefore, the second phase groups the most significant p-ranked variables and assesses their significance using a Single Input Single Output (SISO) approach. The Extra-Trees model with the SISO approach is trained and compared to the observed outputs and assessed based on accuracy evaluation metrics. Based on this assessment, the best-performing inputs are added to the set p'. The third phase is the Multiple Input Single Output (MISO) phase whereby the prescribed screening model aims to rate the effectiveness of each input matrix in forecasting the output. This is done to minimize overfitting, and the procedure is repeated with the residuals from the previous iteration as the new output variable in the previous 2 phases. The operation is iterated until either the best IR variable is found in the selected p' variables, or the performance of the model does not show significant improvement based on the coefficient of determination (R^2) [33].

To further improve the feature selection process, the IIS algorithm performs K-fold cross-validation, which has the advantage of using all the data in both training and validation, which reduces the possibility of overfitting the model.

B. LONG SHORT-TERM MEMORY (LSTM)

The proposed model is a hybrid, integrating the IIS algorithm with the Long Short-Term Memory (LSTM) architecture. The deep learning LSTM Network model is a special type of Recurrent Neural Network (RNN) which can learn long-term dependencies and therefore can perform well in time-series data predictions [34]. It has memory capabilities because its gate structure is different from the RNN structure and is therefore able to retain historical information for a long time [35], [36]. The technical details of the objective model LSTM architecture are well studied and found in literature elsewhere [37], [38], [39], [40].

III. MATERIALS AND METHOD

A. STUDY AREA

This study focuses on two study sites located in Fiji, an island archipelago which sits in the Southwestern Pacific Ocean. It lies approximately between 15° to 20° South latitudes and between 175° and 182° East longitude.

The main islands are Viti Levu and Vanua Levu while the remaining islands are smaller, low-lying, and widely spread across the ocean [41]. Fiji experiences a mostly tropical climate with two major seasons observed annually – a warm and wet season from November to April, and a cool and dry season from May to October. The most significant influence on the rainy season is the South Pacific Convergence Zone causing the formation of tropical low-pressure systems and cyclones as well [42]. Additionally, there are localized and regional effects which impact the weather across the islands. One cause of this is the geography of the islands, particularly the two main islands of Viti Levu and Vanua Levu, which are of volcanic origins and generally have mountainous interior terrain with flatter coastal plains [43]. Another factor which affects localized weather on the major islands is the prevailing Southeast Trade Winds which cause greater cloud formation and precipitation on the eastern parts of the main islands.

TABLE 1. The geographic description of the present study sites.

Site Name	Location		
	Longitude (°E)	Latitude (°S)	Elevation (m)
Nadi International Airport	177.43	17.75	18
Nausori International Airport	178.55	18.03	5

The two sites are Nadi International Airport and Nausori International Airport, which are located on the main island of Viti Levu (Table 1). Nadi International Airport (Nadi) is the main international airport of the country and is located on the western side of the island, while Nausori International Airport (Nausori) is the secondary international airport and is located on the eastern part of the island. As the tourism industry is one of the largest revenue earners for the country, the airport and aviation efficiency and safety are imperative. These two airports are the locations where the meteorological observations are recorded on-site. These observations are routine aviation meteorological observations and are made following the international standards for aviation weather observations [44].

Since these two airports operate 24 hours a day, they are required by the International Civil Aviation Organization (ICAO) standards to provide these routine weather observations at the airport every hour for use by aviation stakeholders such as airlines and air traffic service providers. These reports are called METAR and contain meteorological parameters which have been specified by the World Meteorological Organization (WMO) to be observed and made available at airports. Although all meteorological parameters play a role in overall flight operations, the two target variables to be forecasted, i.e. visibility and ceiling are vital for safe and efficient flight operations during the crucial phases of landing and taking off.

B. DATASET

Historical meteorological data spanning over 10 years was used for the development of the proposed forecasting model. Table 2 (a) describes the variables in the dataset that were obtained for the development of the proposed forecasting model. The data was recorded from January 1st, 2012, 0000 local time to December 31st, 2021, 2300 local time. This equated to 87672 data instances with 12 variables which were recorded in numerical values.

The visibility variable was measured in kilometers, while the Total Low Cloud variable from the dataset was used as the ceiling. Total Low Cloud is measured in oktas and is the amount of low cloud covering the sky in eight parts. Even though instrument measurements are possible, current observations for these two variables are done manually following the standards set out by the WMO [44].

While preprocessing the data, the following data imputation methods were applied to fill in the missing values. Where there was a single missing value, a simple average of the preceding and succeeding values was taken. For instances of consecutive missing values, a combination of calendar-averaged values and simple averages was applied [45]. Additionally, flawed values (falling out of the range of correct values) were replaced with the median value for better model learning [46]. In terms of the missing values for visibility (Tabel 2 (b)), there were none for Nadi but around 13.5% of missing data was recorded for Nausori. Similarly, for total low cloud cover, Nadi has significantly fewer missing data (~3.6%) compared to Nausori with 23.26%. In respect to missing data, it was noticed that significant portions of the data were missing at Nausori. This could have been due to the station being unmanned for periods of time and no observations taken as the instances of missing data coincided with the lockdown during the Covid-19 pandemic. Thus, after analyzing data by year, the years with greater than 10% missing values were excluded from model building, which left 6 consecutive years of data for study site Nausori International Airport with total data of 52632 data points.

Table 2 (b) further gives statistical aggregates of the two predictor variables - visibility and total low cloud cover - for

TABLE 2. **The characteristics of the predictor and objective variables *used to develop the proposed hybrid IIS-LSTM integrated model for 1*-hourly visibility and total low cloud cover forecasting; and (b) the descriptive statistics of Visibility (km) and Total Low Cloud cover (oktas) with details of missing data.**

(a) Variable name	Units	Mode of measurement	Variable Type in Model
Air Temperature	°C	Instrument	Predictor Variable
Wet Bulb Temperature	°C	Instrument	Predictor Variable
Dew Point Temperature	°C	Instrument/ Calculated	Predictor Variable
Relative Humidity	%	Instrument/ Calculated	Predictor Variable
Rainfall	mm	Instrument	Predictor Variable
Mean Sea Level Pressure	hPa	Instrument	Predictor Variable
Wind Speed	m/s	Instrument	Predictor Variable
Wind Direction	°	Instrument	Predictor Variable
Total Cloud	Oktas	Manual observation	Predictor Variable
Total Low Cloud Height	m	Manual observation	Predictor Variable
Visibility	km	Manual observation	Objective Variable
Total Low Cloud	Oktas	Manual observation	Objective Variable

(b) Objective Variable	Station	Missing data (%)	Maximum	Minimum	Mean	Median	Skewness	Kurtosis
Visibility (km)	Nadi International Airport	0.02	50	0.10	46.19	50	-3.10	10.54
	Nausori International Airport	13.49	50	0.05	41.14	40	-1.70	2.31
Total Low Cloud cover (oktas)	Nadi International Airport	3.60	8	0	3.45	3	0.37	-0.69
	Nausori International Airport	23.26	8	0	5.28	6	-0.49	-0.86

the 2 study sites. The visibility magnitudes ranged from a maximum value of 50 km for both study sites to a minimum of 0.1 km at Nadi and 0.05 km at Nausori. The mean visibility was 46.19 km at Nadi, higher than the value at Nausori, which was 41.14 km.

The median visibility value was also higher at Nadi at 50 km compared to Nausori at 40 km. Furthermore, the visibility data at Nadi showed high negative skewness (−3.10) and leptokurtic (10.54) tendency compared to Nausori, which exhibited a similar tendency although to a lesser degree (Skewness=−1.70, Kurtosis=2.31). This indicated that much of the data distribution is greater than the mean values with a higher probability of it being on the tail end of the data distribution [47].

Considering the statistical aggregates for total low cloud cover, it was noticed that the range was from a maximum value of 8 to a minimum value of 0 oktas for both study sites. The mean and median scores are significantly different for the 2 study sites, with Nadi having 3.45 and 3 oktas, respectively, and Nausori having 5.28 and 6 oktas, respectively. This was consistent with the physical attributes at these two study sites, where Nausori is situated in a more cloudy and rainy part of the main island compared to Nadi. The skewness and kurtosis values of total low cloud cover at both study sites indicated an almost normal distribution.

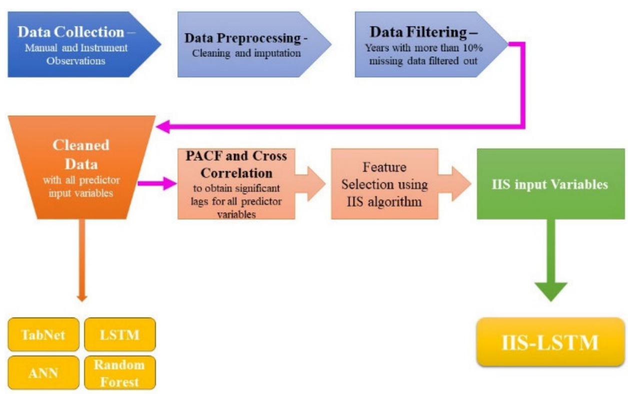

FIGURE 2. **Flowchart detailing the proposed methodology for the proposed hybrid IIS-LSTM model in the model development stage implemented forecast 1-hourly atmospheric visibility and total low cloud cover ceiling.**

C. PROPOSED MODEL DESIGN

1) DATA PRE-PROCESSING

After pre-processing the data, extraction of significant lagged inputs was carried out using cross-correlation (CCF) and partial auto-correlation function (PACF) statistical assessments. This assessment was also used to determine whether the target variables visibility and total low cloud cover have correlations both in time-space, as well as between other meteorological variables. PACF and CCF were undertaken for both visibility and total low cloud cover target variables for the two study sites. Figure 3 shows the result of the CCF statistical assessments, which indicated the correlation of the target variable visibility or total low cloud cover with the predictor variables.

Meteorological variables in the dataset are stochastic and impacts are short-lived in nature, so only up to 24 antecedent lags are considered as longer lags would be unreliable in capturing useful information for predicting the target [48]. Similarly, Figure 4 shows the results of the PACF statistical assessment, which indicates the best preceding lagged values correlating to the target variable's value in that instance. Only lags up to 12 hours were considered due to the reason mentioned earlier. For both CCF and PACF, lags were considered significant if they exceeded the 95% confidence band. This generated a global pool of 151 features each for visibility and total low cloud cover at study site Nadi, and 154 features

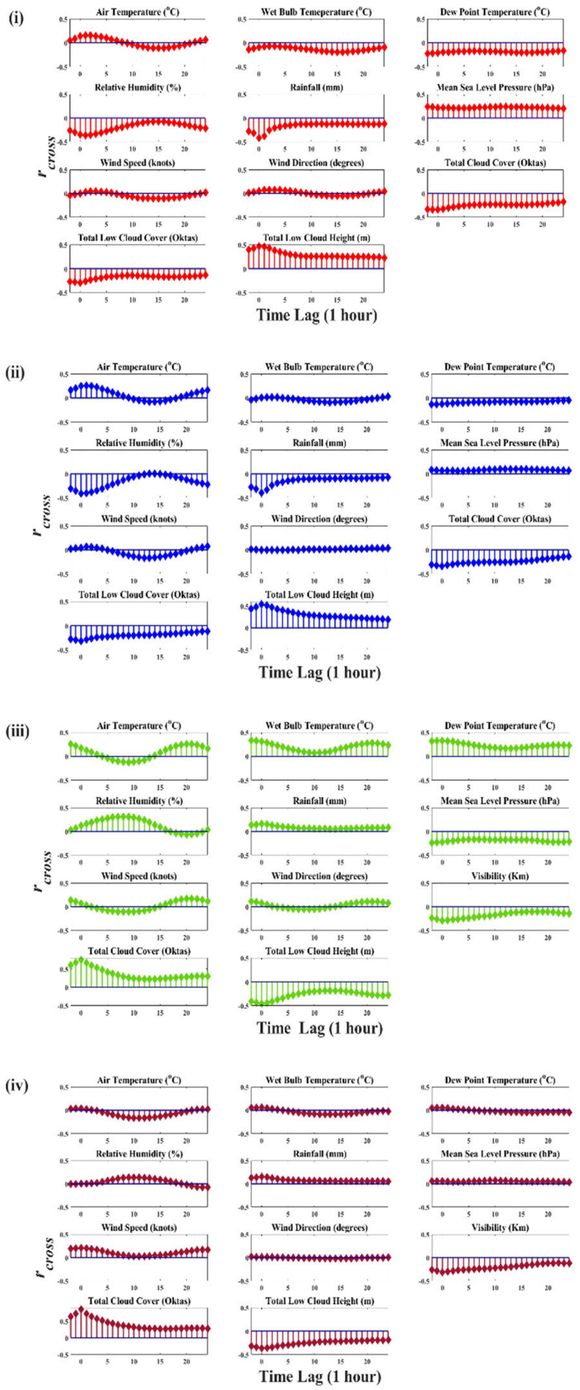

FIGURE 3. Cross-correlations coefficients (r_{cross}) showing the amount of co-variance between visibility vs. its predictor variables for the case of (i) Nadi and (ii) Nausori; and the co-variance between total low cloud *vs.* its predictor variables for the case of (iii) Nadi and (iv) Nausori.

each for study site Nausori. All predictor variables and their significant lags formed a matrix of global predictors.

2) THE IIS PROCEDURE

The global predictors were analyzed with the IIS algorithm of the proposed hybrid integrated model to extract the most

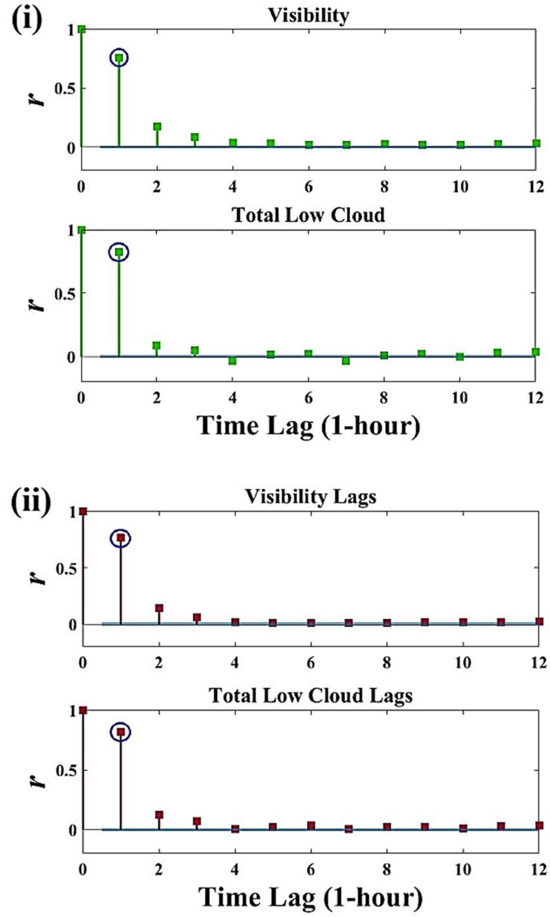

FIGURE 4. Partial Auto-Correlation Function (PACF) coefficient of the target variables for (i) Nadi and (ii) Nausori. The lag circled in blue indicates the most significant lagged inputs used in the development of the forecasting model.

useful features from this global list of features. Figure 5 illustrates the results for the two target variables at the two study sites from the IIS process. The cumulative performance of the Extra-Tree model within the IIS algorithm is R^2 denoted as the line graph in the plot while the contribution of each screened variable is ΔR^2, denoted by the bars on the plot. For Nadi's visibility target, the performance increased up to the second variable with the second hourly-lagged input of visibility being the most significant one. For target total low cloud cover, the performance of the model again increased up to the second variable with the first hourly lagged input of total low cloud being the most significant feature.

In contrast, for Nausori's target variable visibility, the performance increased up to the fourth variable; however, only 3 features were significant with the first lagged input of hourly rainfall being the most significant. For total low cloud cover, the performance of the model decreased after the second feature, with the first and fifth hourly lagged inputs of total low cloud cover being almost equally significant. It is noteworthy that the algorithm determined the optimum number of variables up to the point where additional variables decreased performance (as was the case in Figure 5(a) targets

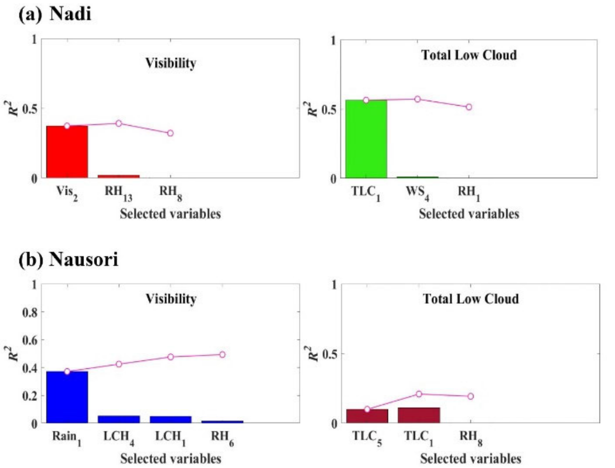

FIGURE 5. **Cross-correlations coefficients (r_{cross}) showing the amount of co-variance between visibility vs. its predictor variables for the case of (i) Nadi and (ii) Nausori; and the co-variance between total low cloud *vs.* its predictor variables for the case of (iii) Nadi and (iv) Nausori.**

visibility and total low cloud cover, and Figure 5(b) target total low cloud cover), or when an algorithm tolerance value, ε, of performance increase was not surpassed (as was the case in Figure 5(b) target visibility). Further insights into these results will be discussed in a later section.

3) THE PROPOSED IIS-LSTM MODELLING APPROACH

The IIS algorithm supplied the optimum dataset to be used in the chosen deep-learning LSTM forecasting model. This dataset was divided into a training and testing set with 20% of the training set used in validation to fine-tune the model [49]. Researchers have used different ratios of training set, such as 70% [31], [50] or 80% [51] as there are no set rules for dividing data [42]. Thus, in this study, the dataset had training (75%) and testing (25%) subsets.

The LSTM architecture was designed with one LSTM cell layer with 80 neurons, the sigmoid activation function, and a dense layer with a single output. This architecture was used to learn from the training subset data and make forecasts from the testing subset data after the data was reshaped into a format that could be acceptably processed by the model. The model was trained on different combinations of hyperparameters manually to achieve the optimum set of hyperparameters [51]. These were:

- optimizer = "adam"
- batch size = 15
- maximum epochs = 500
- Validation loss criteria = mae (Mean Absolute Error)

Furthermore, to prevent the model from overfitting or underfitting the data, early stopping [52] and ReduceLROnPlateau [53] were utilized respectively. The early stopping method was employed in 10 epochs (patience=10) when there was no further decrease in the validation loss criteria and the lowest value was saved. ReduceLROnPlateau callback method reduced the learning rate when no improvement was detected with patience of 5 [49]. The simple design of the architecture was sufficient to achieve optimal model configuration as the number of features had been greatly reduced by the preceding IIS algorithm. This negated the need for an unnecessarily large architecture which reduced the training time of the model, and the generalization of data for improved predictions [54].

4) MODEL EVALUATION PROCEDURE

The superiority of the proposed hybrid IIS-LSTM integrated model was tested by forecasting using the predictor variable from the testing subset and evaluating it with the observed data.

The performance evaluation metrics included Pearson's Correlation Coefficient (r), Willmott's Index (WI), Nash-Sutcliffe Efficiency Index (E_{NS}), Root Mean Squared Error ($RMSE$), Mean Absolute Error (MAE), Legate-McCabe Efficiency Index (LM) and Kling-Gupta Efficiency Index (KGE) [55], [56], [57], [58], [59]. These evaluation metrics are widely used in research and their mathematical equations are as follows:

Pearson's Correlation Coefficient (r)

$$r = \frac{n\left(\Sigma y\hat{y}\right) - \left(\Sigma y\right)\left(\Sigma \hat{y}\right)}{\sqrt{\left[n\Sigma y^2 - \left(\Sigma y\right)^2\right]\left[n\Sigma \hat{y}^2 - \left(\Sigma \hat{y}\right)^2\right]}} \quad (-1 \leq \mathrm{r} \leq 1) \tag{1}$$

Willmott's Index (WI)

$$WI = 1 - \frac{\Sigma_{i=1}^{N}\left[y - \hat{y}\right]^2}{\Sigma_{i=1}^{N}\left[\left|\hat{y} - \bar{y}\right| + \left|y - \bar{y}\right|\right]^2} \quad (0 \leq WI \leq 1) \tag{2}$$

Nash Sutcliffe's Coefficient (E_{NS})

$$E_{NS} = 1 - \left[\frac{\Sigma_{i=1}^{N}\left(y - \hat{y}\right)^2}{\Sigma_{i=1}^{N}\left(y - \bar{y}\right)^2}\right] \quad (-\infty \leq E_{NS} \leq 1) \tag{3}$$

Root Mean Squared Error ($RMSE$)

$$RMSE\left(y, \hat{y}\right) = \sqrt{\frac{1}{n}\sum\nolimits_{0}^{n-1}\left(y_i - \hat{y}_i\right)^2} \tag{4}$$

Mean Absolute Error (MAE)

$$MAE\left(y, \hat{y}\right) = \frac{1}{n}\sum\nolimits_{0}^{n-1}\left|y_i - \hat{y}_i\right| \tag{5}$$

Legate and McCabe's Index (LM)

$$LM = 1 - \left[\frac{\Sigma_{i=1}^{N}\left|y - \hat{y}\right|}{\Sigma_{i=1}^{N}\left|y - \bar{y}\right|}\right] \quad (-\infty \leq LM \leq 1) \tag{6}$$

Kling-Gupta Efficiency (KGE)

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\hat{y}}{y} - 1\right)^2 + \left(\frac{C\hat{V}}{CV}\right)^2} \quad (-\infty \leq KGE \leq 1) \tag{7}$$

In the equations above, the observed value for the target variable's visibility and total low cloud cover is represented as y, while the predicted value from the model is denoted $\hat{y}$ from the model. The metrics for our objective model were then compared with metrics output by the benchmark models.

The benchmark models included standalone Artificial Neural Networks (ANN) [60], Random Forest [61], the deep learning LSTM [62], and TabNet [63] models. These models were selected due to their optimal forecasting performance using atmospheric and meteorological data as shown in previous work [31], [37], [64], [65].

IV. RESULTS

This section presents the outcomes of the performance evaluation of the proposed hybrid IIS-LSTM integrated model with competition models for forecasting hourly visibility and hourly total low cloud cover using meteorological data as model inputs. The competing models included standalone TabNet, LSTM, ANN, and RF. The predictive performance of the proposed hybrid IIS-LSTM integrated model was tested against these benchmark models for the two study sites at a 1-hour forecasting horizon. The performances are summarized using the evaluation metrics as in (1) – (7) and assessed via graphical means.

Table 3 shows the outcomes of all the performance metrics for each model design for the two sites. From the results, *the* proposed hybrid IIS-LSTM integrated model produced the best outputs based on the performance evaluation metrics used.

For Nadi, the IIS-LSTM model has the highest agreement indices (r $\approx$ 0.73, WI $\approx$ 0.83, $E_{NS} \approx 0.52$) and the lowest error metrics (RMSE $\approx$ 4.81 km, MAE $\approx$ 1.9 km) for visibility forecasts. It also registered the highest agreement indices (r $\approx$ 0.84, WI $\approx$ 0.91, $E_{NS} \approx 0.71$) and least values of error (RMSE $\approx$ 0.92 oktas, MAE $\approx$ 0.67 oktas) for total low cloud forecasts.

Likewise, for Nausori, the IIS-LSTM model produced the highest agreement indices ($r \approx 0.72$, $WI \approx 0.82$, $E_{NS} \approx 0.52$) and least error (RMSE $\approx$ 8.08 km, MAE $\approx$ 5.1 km) for visibility forecast. Similarly, it has the highest agreement indices ($r \approx 0.78$, $WI \approx 0.87$, $E_{NS} \approx 0.60$) and lowest error values error ($RMSE \approx 1.23$ oktas, $MAE \approx 0.93$ oktas) for total low cloud forecasts (Table 3).

A widely used evaluation metric to measure agreement between predicted and observed values is the Nash-Sutcliffe Index (E_{NS}). This is a dimensionless value and is a scaled version of the mean squared error. However, a limitation of this index is that it can exaggerate the impact of extreme outliers. To address this, Willmott's Index (WI) is used because it considers the ratio of the mean squared error instead of the differences [66]. This testing performance is considered one of the most robust parameters to evaluate the superiority of a model against its competitors [50].

Figure 6 shows a 3D bar graph portraying the WI for each model. In Figure 6(i), for the case of visibility forecasting, the improvement in the model's performance can be seen with the proposed hybrid IIS-LSTM integrated model compared to the benchmark models. The IIS-LSTM model had

TABLE 3. The testing performance of the proposed hybrid IIS-LSTM integrated model compared with the standalone models using all variables. (a) Objective variable 1: Visibility for (i) Nadi International Airport and (ii) Nausori International Airport, and (b) Objective variable 2: Total Low Cloud for (i) Nadi International Airport and (ii) Nausori International Airport. Note: r = Pearson's Correlation coefficient, WI = Willmott's Index, E_{NS} = Nash Sutcliffe Efficiency coefficient, $RMSE$ = root mean square error, and MAE = mean absolute error. The most accurate model is boldfaced, presented in orange.

(a) Visibility	Predictive Models	r	WI	E_{NS}	$RMSE$ (km)	MAE (km)
(i) Nadi	**IIS-LSTM**	**0.7273**	**0.8282**	**0.5207**	**4.8107**	**1.8963**
	TABNet	0.0563	0.3186	-0.6312	8.9395	7.5721
	LSTM	0.0186	0.2658	-0.2461	7.7568	6.0288
	Random Forest	0.0508	0.1244	-40.311	44.9871	44.4478
	ANN	0.0203	0.1244	-40.297	44.9794	44.4397
(ii) Nausori	**IIS-LSTM**	**0.7214**	**0.8207**	**0.5199**	**8.0807**	**5.1022**
	TABNet	0.6438	0.7670	0.3122	9.7433	7.2442
	LSTM	0.5813	0.6954	0.2869	9.8477	7.7477
	Random Forest	0.6045	0.2938	-10.584	39.9857	38.2955
	ANN	0.5999	0.2942	-10.542	39.9144	38.2224

(b) Total Low Cloud	Predictive Models	r	WI	E_{NS}	$RMSE$ (km)	MAE (km)
(i) Nadi	**IIS-LSTM**	**0.8403**	**0.9071**	**0.7057**	**0.9249**	**0.6723**
	TABNet	0.8140	0.8850	0.6564	0.9915	0.7359
	LSTM	0.7875	0.8705	0.6146	1.0585	0.8248
	Random Forest	0.7902	0.5181	-1.3386	2.5869	2.1727
	ANN	0.7945	0.5122	-1.476	2.6618	2.254
(ii) Nausori	**IIS-LSTM**	**0.7785**	**0.8674**	**0.6043**	**1.2283**	**0.9297**
	TABNet	0.7288	0.8344	0.5190	1.3599	1.0733
	LSTM	0.7003	0.8086	0.4851	1.4012	1.1349
	Random Forest	0.7195	0.4457	-3.2828	4.0578	3.6609
	ANN	0.677	0.4443	-3.2448	4.0398	3.6315

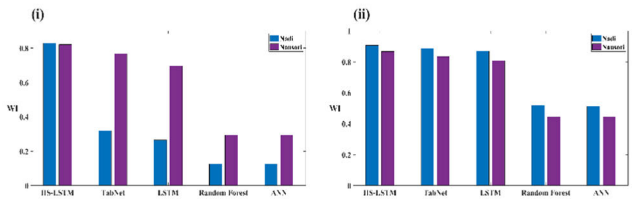

FIGURE 6. Testing performance of IIS-LSTM vs. the 4 competing models evaluated using the Willmott index of agreement (WI) for (i) visibility and (ii) total low cloud.

approximately 0.83 score for Nadi and 0.82 score for Nausori, which was an increase of almost 160% from the second-best performing model for Nadi and an increase of 7% for Nausori.

Similarly, Figure 6(ii) depicts the WI performance for total low cloud cover forecasts. Again, the IIS-LSTM models have the best score at site Nadi with approximately 0.91 and Nausori with 0.87 which is an approximate increase of 2.5% and 4 % respectively. The proposed hybrid IIS-LSTM integrated model produces the best agreement between the observed and predicted outputs compared to the benchmark models in our dataset.

Comparatively, Figure 7 shows the error metrics used to evaluate the model performances, where Root Mean Squared Error ($RMSE$) is used. For visibility forecasts (Figure 7(i)) the proposed hybrid IIS-LSTM integrated model produces the lowest error for Nadi with 4.81 km and 8.08 km for Nausori. When comparing the error for total low cloud forecasts (Figure 7(ii)) the IIS-LSTM model again has the lowest value of $RMSE$ at approximately 0.92 oktas for Nadi and 1.23 oktas for Nausori. Based on these results, the proposed hybrid IIS-LSTM integrated model has been shown to minimize the $RMSE$ for the forecast at both study sites with this dataset.

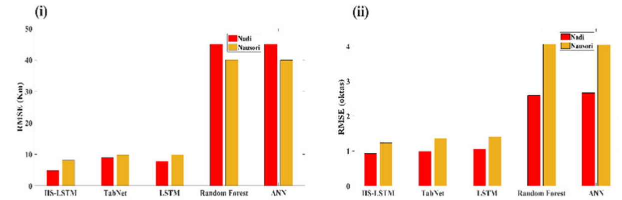

FIGURE 7. 3D Bar graph of root mean square error in the testing phase of the IIS-LSTM vs. the 4 competing models for (i) visibility *(RMSE, km)* and for (ii) total low cloud *(RMSE, oktas)*.

TABLE 4. Evaluating the Testing performance of the proposed hybrid IIS-LSTM integrated model for one-hourly forecasts for (a) Objective variable 1: Visibility for (i) Nadi International Airport and (ii) Nausori International Airport, and (b) Objective variable 2: Total Low Cloud for (i) Nadi International Airport and (ii) Nausori International Airport; using *LM* = Legate's and McCabe's Index, and *KGE* = Kling-Gupta efficiency. The best model is boldfaced and presented in orange.

(a) Visibility	Predictive Models	*LM*	*KGE*
(i) Nadi	**IIS-LSTM**	**0.3972**	**0.6447**
	TABNet	-1.3406	-0.1883
	LSTM	-0.9165	-0.3868
	Random Forest	-12.739	-0.6532
	ANN	-12.737	-0.6758
(ii) Nausori	**IIS-LSTM**	**0.4046**	**0.5954**
	TABNet	0.1558	0.5844
	LSTM	0.0959	0.4141
	Random Forest	-3.4627	-0.389
	ANN	-3.4542	-0.3886

(b) Total Low Cloud	Predictive Models	*LM*	*KGE*
(i) Nadi	**IIS-LSTM**	**0.5382**	**0.7621**
	TABNet	0.4876	0.7131
	LSTM	0.4335	0.6959
	Random Forest	-0.5127	-0.0178
	ANN	-0.5693	-0.0339
(ii) Nausori	**IIS-LSTM**	**0.4404**	**0.6833**
	TABNet	0.3587	0.6407
	LSTM	0.3169	0.5772
	Random Forest	-1.1872	-0.1226
	ANN	-1.1697	-0.1363

The Legates and McCabe's Index *(LM)* is an improved measure from the *WI* which further eliminates the amplification from outliers by removing the squaring effect [56].

Compatibly, the *KGE* avoids the limitations of the E_{NS} by computing the Euclidian distance of the correlation, bias, and variability measure instead of it being scaled by the standard deviation of the observed values [67]. Table 4 shows these alternative metrics used to evaluate the model's performance, *LM* and *KGE*. For visibility forecasts, the proposed hybrid IIS-LSTM integrated model has the highest value of *LM* with 0.397 and 0.405 for Nadi and Nausori respectively.

Likewise, for total low cloud cover forecasts, the IIS-LSTM model scores were 0.538 and 0.440 for Nadi and Nausori respectively. Negative values for some benchmark models can be *attributed to* the lower bound of this coefficient being negative infinity, indicating poor performance of these models [68].

When the *KGE* metrics are considered, the proposed hybrid IIS-LSTM integrated model performed the best according to this criterion as well. When considering visibility forecasts, the Nadi and Nausori international airport site scores of 0.645 and 0.595 were registered by the IIS-LSTM model respectively. Similarly, for total low cloud cover forecasts, the IIS-LSTM model had the highest scores of 0.762 and 0.683 for Nadi and Nausori airports, respectively.

V. DISCUSSION

In this section, the results of this study are expounded on in terms of its highlights as well as its limitations of the present study. The proposed hybrid IIS-LSTM integrated model has shown its superiority in performance compared to the benchmark models in forecasting visibility and total low cloud cover at two study sites. This was shown from the results of various performance evaluation metrics depicted in the previous section.

The results emphasized the suitability of the IIS algorithm in selecting useful features for the model. This is consistent with the outcomes of similar studies, such as [30], where the results from the performance metrics (*WI*, E_{NS}, *RMSE* and *MAE*) determined the suitability of the IIS-optimized model compared to the standalone models. As previously deduced by [28], IIS was a useful tool for selecting non-redundant inputs in different test conditions (e.g., different sites, different target variables, presence of several redundant features). Removal of redundant features was shown to be an important aspect affecting the forecasting accuracy of data-driven models. Fewer input variables imply low dimensionality of the sources of uncertainty and lower propagation of error from input variables [33].

Additionally, the LSTM model's efficiency in 'learning' and making predictions from this time-series data is also pivotal in this study. Reference [13] concluded from their results that ML methods can improve the visibility and ceiling forecasts up to an hour ahead forecast horizon when accurate observations are used for analysis.

Similarly, [15] recommended the development of deep learning models, particularly LSTM models, from their study due to LSTM's ability to extract time-dependent features from the raw data auto automatically and its increase in efficiency when the size of the training set increases.

Referring to the results of the features selected by the IIS algorithm as shown in Figure 5, some assumptions can be made regarding the correlation between the objective variable and the optimal feature selected variables. For visibility forecasting, the most significant feature at Nadi International Airport was the second lagged value of visibility, while for Nausori international airport it was the first lagged value of the Rainfall variable. The difference in the selected feature can be explained by the geography of the sites, as Nausori International Airport is located in the region which receives significantly more rainfall, while Nadi International Airport is located in the drier region of the country.

The study of [64] reported that for December 2023, Nadi airport received 57.7 mm of rainfall while Nausori airport received 181 mm of rainfall. The total days of rainfall were

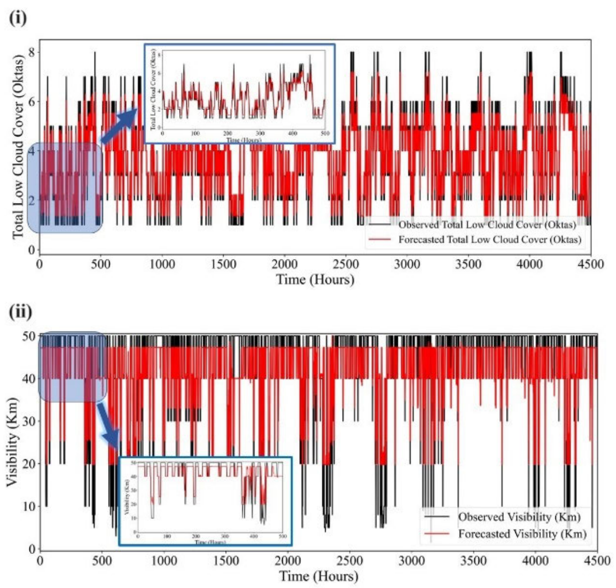

FIGURE 8. **3D Comparison of observed (actual) and forecasted (predicted) values for the IIS-LSTM model in the testing phase for (i) Visibility – Nausori, and (ii) Total Low Cloud – Nadi.**

11 for Nadi airport and 21 for Nausori airport, which is 28% and 68% of the month respectively and represents a difference of 40% rain days a month between the two sites. Rainfall is naturally known to be a significant physical factor in the reduction of visibility [70], [71].

Consequently, variation in rainfall data was the most important factor in determining the variation in visibility at Nausori International Airport than it was for Nadi International Airport. On the other hand, when the optimal variable for total low cloud cover is considered at both study sites, the most significant feature variable is the 1st hourly lagged data series of total low cloud cover, with Nausori also having the 5th hourly lagged data series as equally significant.

Clouds have been difficult to forecast due to their 3D nature, various physical properties such as coverage, thickness, top height and base height, and the different types of clouds. Additionally, mechanisms driving cloud formation vary from region to region and current models offer mesoscale resolution in cloud forecasts and extrapolation for higher resolution forecasts [72], [73]. Therefore, it is reasonable that the IIS algorithm identified the lagged values of only total low cloud cover as the optimal and reliable features for future total low cloud cover predictions.

Generalization of the model was an important factor for consideration with the design of the proposed hybrid IIS-LSTM integrated model, ensuring that the model's applicability is not limited to the study locations used for this research. This was achieved firstly by training the model on a large dataset which accounted for variations caused by daily and seasonal changes. Secondly, the IIS component ensured that the model learned patterns of data from only the relevant features affecting the predictand. It also reduced dimensionality and complexity of the model, preventing overfitting on the data used for this study. Additionally, early stopping technique and an overall simple architecture of the LSTM algorithm contributed to the prevention of overfitting.

Figure 8 takes a closer look at the comparison between the observed data and the forecasted output. When Figure 8(i) is examined visually, the visibility graph of the forecasted output follows the pattern of the graph of the observed outputs for Nadi. However, the values at the lower extremities are not fairly forecasted. A possible reason for this could be a limitation in the dataset.

As noted in Table 2 (b) earlier, the visibility data for Nadi has a mean of 46.19 km, a median of 50 km, and notably, a high kurtosis of −3.10. This indicated that many of the data points in the higher extremity and the lower values are not proportionately represented in the dataset. This would have been a factor when the model was trained as the extreme magnitudes might not have been properly captured.

Added to this fact is the consistency and accuracy of the observational data. For instance, visibility data is collected through manual observations according to international aviation meteorological observation standards at both study sites. The data intervals vary, ranging from 50m intervals when visibility is less than 800m; 100m intervals until 5 km; 1 km intervals until 10 km; and 10 km intervals until 50 km [44]. Thus, manual observations could readily be affected by irregularities from different observers and would not have been as consistent as instrument measurements adding another layer of complexity.

VI. CONCLUSION

In this study, a hybrid deep learning IIS-LSTM integrated model is proposed for forecasting visibility and total low cloud cover for two study sites in Fiji, Nadi International Airport and Nausori International Airport. The proposed model was tested against four benchmark models using performance evaluation metrics for a 1-hourly forecast horizon.

The following are the main contributions and key findings of this research:

1. The analysis focusing on hourly aviation meteorological observation data for Nadi International Airport and Nausori International Airport found key statistical metrics of target variables visibility and total low cloud cover to develop models.

2. A hybrid IIS-LSTM integrated model was presented which combined the effectiveness of the IIS algorithm to select the optimum features from the range of predictor variables and their significant lags, with the deep learning LSTM model with the superior capability for time-series forecasting.

3. The robustness of the proposed hybrid IIS-LSTM integrated model to forecast visibility and total low cloud cover was illustrated when the performance of the IIS-LSTM model was evaluated against the benchmark models (TabNet, LSTM, ANN, RF). The objective model had the highest agreement metrics (r, WI, ENS) while also having the least error (RMSE, MAE) compared to the benchmark models.

4. This research study makes a significant contribution to knowledge in the scope of visibility forecasts as a regression problem using deep learning models, and a first of any kind of AI-based forecasting study of visibility and total low cloud cover predictions for the chosen study sites.

5. The development of this objective model using only hourly aviation meteorological observation data indicates the capacity of this method to be extended to any station with similar data for further investigative research into practical usage in the aviation industry.

The approach undertaken for this study can be enhanced with the scope of further research. Firstly, model hyperparameters for this study were optimized with an inexhaustive grid search method. This can be improved with state-of-the-art techniques such as Hyperband [74] and Bayesian Optimization [75], [76], which can further assist in fine-tuning the model to attain the optimum architecture of the model and its forecast. Additionally, the potential for data inconsistency which could have arisen from manual measurements of the visibility and low cloud cover variables in the data can be mitigated through the use of instrument measures. Moreover, recording and using shorter and near-real-time data would be beneficial bearing in mind the highly dynamic nature of visibility and cloud base, since current industry and ICAO standards have meteorological data being collected at hourly intervals.

Further independent study can be undertaken to evaluate forecasts at higher timesteps, such as 3-hour, 6-hour, 12-hour or 24-hour horizons as necessary for practical operational use. The approach undertaken in this study can be extended to other aviation meteorological data collection sites in Fiji and elsewhere. This will verify the applicability of this approach beyond the study sites, as well as the possibilities of connecting multiple sites in a network for higher resolution forecasts for a region.

The main factor in implementing the proposed forecasting model effectively is data availability and data quality. In order to have high quality data for aviation purposes, the main prerequisite is that the data needs to be recorded under the ICAO standards. The recording station needs to be certified by both the International Civil Aviation Organization (ICAO) and the World Meteorological Organization (WMO). The data for this study was obtained from the Fiji Meteorological Service which abide by WMO and ICAO standards for aviation meteorological reports. The observations are made according to international requirements, which ensures that data is consistent, accurate, reliable, and reported in standardized units. Such weather reports, which are readily available for specific locations, would be reliable for use in the proposed model. Additional factors would need to be addressed to have the proposed model's practical implementation for operational use. Firstly, the model would need to be modified accordingly to accept real-time data and produce real-time analysis. Secondly, comparisons to assess the accuracy and reliability of this proposed hybrid model with existing forecasting tools in a live environment will have to be undertaken. Thirdly, the appropriate computational resources will need to be allocated based on whether a cloud based, or in-situ model is implemented. For example, an online cloud-based system would not be suitable for remote and maritime locations with poor or no internet connectivity. Hence, in-situ models would need to be parsimonious (as shown by the removal of the redundant features using IIS) and lightweight requiring least computational resources. Other considerations include assessing the practicality of use for the proposed model as a forecasting tool at a particular location considering the availability of other such tools.

Looking further towards the adoption and acceptance of the proposed model as a predictive tool used within the aviation industry, important considerations must be taken into account. The aviation industry is a highly regulated industry, especially for aviation stakeholders operating under the International Civil Aviation Organization body, and any change to standard operating procedures are assessed subject to very standards before being adopted for widespread use. However, such predictive tools still have a niche such as in general aviation, private or recreational flights. It could be used by pilots flying to destinations with a limited flight information service provision but having weather reports available at or in the vicinity of the airport. Additionally, it could be a cost-effective but efficient tool for flight information service providers at airports where there is a lack of infrastructure for accurate on-site forecasts, such as at remote or private airports. Therefore, this study paves the path for further applications of AI in aviation industry, particularly forecasting of important parameters such as visibility and cloud base.

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4.3. Links and Implications

A newly constructed hybrid IIS-LSTM model demonstrates its superior performance in forecasting aeronautical visibility and ceiling meteorological parameters for the consecutive hour. Against the benchmark AI models, the proposed model shows its outstanding performance by achieving the highest agreement metrics as well as the lowest error metrics when forecasting either visibility or ceiling for each of the study sites of Nadi and Nausori international airports in Fiji. The integration of the IIS algorithm into the proposed model not only selects the most optimum features for the forecasting model but also ranks the features according to their degree of relevancy (in terms of coefficient of determination, R2). The most important feature for visibility forecasting was found to be the lagged input of visibility for Nadi and rainfall variable for Nausori, with relative humidity and total low cloud have minor importance. For ceiling forecasting, the antecedent memory of total low cloud has the most influence for its predictions. The results are consistent with the geography and climate of the study sites together with physical mechanisms driving cloud formation and are further validated by the remarkable performance of the forecasting model when using the optimal features.

This proposed hybrid IIS-LSTM integrated model constructed using aviation meteorological observational data can be implemented as an additional tool for visibility and ceiling forecasts in the aviation industry. It can be applied to other sites in the region as the model is trained on site-specific data and will be able to interpret the most applicable variables affecting visibility and ceiling for that location. Because it relies on data which is collected at most airfields and all manned airports, this tool can support aviation stakeholders in routine aviation operations where information on visibility and ceiling is required. In particular, remote locations or unmanned airports where data is available coupled with automatic weather observation stations can benefit from the implementation of this forecasting model to deliver accurate and reliable forecasts of visibility and ceiling.

CHAPTER 5: CONCLUSION, STUDY LIMITATIONS, AND FUTURE RESEARCH DIRECTIONS

5.1. Summary of Research and Findings

This study has focussed on advancing the development of artificial intelligence models to predict atmospheric visibility and cloud cover (ceiling) as important properties for the aviation industry. The primary areas of the study are the two international airports located on Fiji's main island of Viti Levu, where the meteorological observations were made and the data were obtained. Given the high volume and dimensionality of the data, a hybrid model was proposed to select optimum features as well as effectively forecasting the time-series data, which was attained through the IIS-LSTM integrated model. The hybrid model demonstrated its ability to uniquely select the optimum features for each target variable at each distinct study location and effectively make accurate and reliable forecasts.

This research made key findings from the meteorological data and forecasting model development. Firstly, it verified the quality and the availability of aviation meteorological data that could be used to develop data-driven AI models effectively. Ten years' worth of hourly data were retrieved successfully, with minor data imputations made to recover missing data, and each individual meteorological variable was analysed individually and in relation to the predictor variables visibility and ceiling. The data for each variable indicated that the overall weather pattern for both of the study sites were considered tropical based on the temperature range, humidity and rainfall pattern. However, the significant difference between the two locations were the frequency and amount of rainfall and cloud cover were greater for Nausori than for Nadi.

Secondly, it was able to identify the variables and the significant lags which influenced the target variable's visibility and ceiling at each of the study sites. This global pool of variables was then narrowed down using the IIS algorithm to identify the optimum subset of variables that would efficiently be able to train the forecasting model. As mentioned in the journal paper presented in Chapter 4, the most significant features for predicting visibility were noted to be the second lagged input of visibility for Nadi, and the rainfall variable for the Nausori site. This was deemed to be consistent with the physical observations, where increased rainfall was a major factor in reduction of visibility (Bernardin et al., 2014). Considering the difference in geography and climate between the two sites, this factor was more profound for Nausori than for Nadi and was rightly indicated as such through the selection of the different optimum feature for visibility between Nadi and Nausori. Additionally, in predicting low cloud cover, the most significant feature both study sites were identified as the lagged inputs of low cloud cover. Cloud formation and development is a highly stochastic process, and descriptions using mathematical and physical models require the consideration of numerous variables interacting in a highly complex manner (Ye & Chen, 2013). Additionally, these would necessarily need accurate upper atmospheric variables and is not included in this study's dataset, which is limited to mostly atmospheric variables observed at ground level. Therefore, it is logical that the most optimum feature for cloud cover forecasts from this dataset are its lagged variables, and this consistently shown in the analysis result for both Nadi and Nausori.

The next step in developing the model was training the LSTM algorithm on the data and testing its forecasts. The performance evaluation metrics of the model emphasised the model's suitability to make reliable and accurate forecasts. The agreement metrics which indicated this was the Willmott's Index (WI). This index produced a score of 0.83 and 0.82 in predicting visibility for Nadi and Nausori respectively. When predicting total low cloud cover, the WI similarly produced a high score of 0.91 for Nadi and 0.87 for Nausori. The proposed model also minimised the error metrics. When the Root Mean Squared Error (RMSE) in visibility forecasting is considered, the values are 4.8km and 8.1km for Nadi and Nausori respectively, and when forecasting total low cloud cover, it is 0.9 oktas and 1.2 oktas for Nadi and Nausori respectively. These results also have an overall better performance in terms of having higher agreement metrics and minimising error compared to other benchmark models. The benchmark models were the standalone LSTM, TabNet, ANN and Random Forest models, which have proven their ability in time series forecasting in numerous previous studies. Therefore, fact that this proposed integrated model not only performed on par with, but bettered the performance of the benchmark models confirms the reliability of this model. These results also validated that the outputs produced from previous component of this model (IIS algorithm) are optimum for the forecasting algorithm to be accurately and efficiently trained and for it to produce superior results.

This study has made a significant unique contribution in advancing the knowledge in this field of research. Firstly, key statistical metrics for visibility and ceiling were found for Nadi and Nausori international airports in Fiji after analysing hourly aviation meteorological observation data and these were vital in developing a suitable forecasting model. Secondly, a novel hybrid IIS-LSTM integrated model is presented which combines the IIS algorithm's feature selection ability with the LSTMS model's superior time-series forecasting capability. The robustness of the model was verified by comparing the model with benchmark ML and DL models using various statistical performance evaluation metrics for both agreement and error. Thirdly, this research work has made further contributions to knowledge in the scope of forecasting visibility and ceiling as a regression problem by applying deep learning algorithms. Additionally, meteorological forecasting of visibility and ceilings using AI-based models are a first of its kind for these study sites in Fiji. Finally, the development of this data driven model demonstrates the capacity of this methodology to be extended to any study location with similar availability of data for both investigative research and practical usage in the aviation industry.

5.2. Contributions and Novelty

This study has various distinctive aspects which justifies it as a novel research work. Firstly, this study has used aviation meteorological data from Fiji, and this dataset has not been used in any previous research in academic literature to the best of the author's knowledge. Furthermore, the meteorological variable chosen to be forecast, visibility and total low cloud, have limited studies carried out in terms of have AI-based deep learning models developed for forecasting it as noted in the literature review. Certainly, these two variables have not been used in any previous research work for the chosen study sites. Additionally, this study proposes a new hybrid IIS-LSTM integrated model which is one of a kind. Though the LSTM standalone model has been recommended as an effective and reliable forecasting algorithm for visibility and ceiling, the IIS algorithm has mostly been used in streamflow forecasting studies. Therefore, this study has successfully employed the IIS algorithm in using meteorological dataset to form the feature selection component of the overall visibility and total low cloud cover forecasting model. Thus, the overall forecast of the two meteorological target variables using this methodology with applications to the aviation industry makes this work original and unique.

This research work encompasses a multidisciplinary approach by applying artificial intelligence methods on meteorological data specific for use in the aviation industry. The inferences drawn from the results are applied practically for the aviation industry. Although this work is original and unique, the core artificial intelligence techniques utilised are an extension of previous studied and established work in this field. Considering the core objectives of this study focused on forecasting meteorological visibility and ceiling parameter as a regression problem using aviation meteorological data from the two study sites in Fiji, this study made the following contributions in this field of research:

- It analysed hourly aviation meteorological observation data for Nadi International Airport and Nausori International Airports and found key statistics of the dataset. In particular, the statistics for the target variables visibility and total low cloud cover were used to design a novel forecasting model using artificial intelligence methods.
- This study designed a hybrid IIS-LSTM integrated model which was made up of two major components, the IIS algorithm which is an effective algorithm to select the optimum features from the range of predictor variables and their significant lags, and the deep learning LSTM algorithm, which has proven to have superior capability for time-series forecasting.
- The study also tested the robustness of the proposed hybrid IIS-LSTM integrated model to forecast visibility and total low cloud cover. This was demonstrated when the performance of the IIS-LSTM model was evaluated using performance evaluation statistics of agreement and error. The proposed model was further compared to four benchmark models (TabNet, LSTM, ANN, RF). The results showed that objective model had the highest agreement metrics (r, WI, ENS) while also having the least error (RMSE, MAE) compared to the benchmark models and thus proved its superiority over them.
- When the results are analysed, this research study makes a significant contribution to knowledge in the scope of visibility forecasts as a regression problem using deep learning models, and a first of any kind of AI-based forecasting study of visibility and total low cloud cover predictions for the chosen study sites. It has described the key features that are significant in affecting visibility and ceiling forecasts for each study site and has provided a benchmark on the accuracy of a deep learning models for visibility and ceiling forecasts at these two study sites for any future research work.

- The development of this objective model using only hourly aviation meteorological observation data indicates the capacity of this method to be extended beyond the scope of this study region to any station with similar data. This study has therefore provided a foundation for implementing this proposed model for further investigative research as well as for its practical usage as an additional tool in the aviation industry.

5.3. Limitations of the Study and Recommendations for Future Work

Although the objectives of this research were met, there remain some limitations that could be the subject of future studies. The specific limitations linked with addressing the objectives are discussed in the journal paper presented in Chapter 5. Further, only the general limitations associated with this overall research work are discussed here. Firstly, only two different sites were used to compare and contrast the data-driven models built in this study. This constraint was due to the scope of this research being limited to the international airports operating 24 hours a day. The other sites not located within the vicinity of, or away from the airport were not considered due to not meeting this criterion or not having data recorded 24 hours at these stations. Therefore, this study was limited in its ability to rigorously compare the model for the 2 study sites with multiple other sites in Fiji. This could be a potential for future research work when the scope is expanded or when the required data becomes available.

The study also considered creating a hybrid model using one feature selection technique (IIS) and one DL model (LSTM). This model was then compared to standalone benchmark DL and ML models only. It is recommended that in future, other feature selection techniques be explored, many of which have been outlined and discussed thoroughly by Pudjihartono et al. (2022). Additionally, more efficient architectures for deep learning models are being designed, as have been done with the introduction of convolutional layers and then attention layers in the recent past. It is thus beneficial to consider the rapid innovations being made to deep learning architectures to make significant improvements and apply efficiency techniques for further research and experimental gains (Menghani, 2023). Furthermore, model optimization techniques such as Hyperband and Bayesian Optimization, which have shown good performance in recent studies (Joseph et al., 2022; Wang et al., 2018), could be explored further to improve the efficiency in model development.

It is further recommended that in-depth investigative research should be done to discuss the process of taking this proposed model and similar ones in future from the realms of research to full practical implementation into the aviation industry. The main challenge would no doubt be the hurdles in airline, air traffic service operator, state and international regulatory standards, which would need to be met before is accepted for use. There could also be niches in the aviation sector that may not be governed under as stringent standards where this tool may be examined, such private operators of airport and airlines or remote location with implementation in situ due to online connectively challenges. Furthermore, this the application of implementing the proposed model in road and marine transportation applications is also recommended to be explored.

Finally, this research project has shown that by using from the two study sites in Fiji, a novel hybrid deep learning forecasting model has been developed which can be used practically in the aviation industry. This was done without any prior research having explored this data in research work for forecasting models which limited the literature this study could refer to while designing methodologies and comparing the results of this research. However, this research study has laid the foundation for future research in data-driven meteorological forecasting models for Fiji, particularly for visibility and ceiling forecasting using aeronautical meteorological data.

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