

**APPLICABILITY OF NEURAL NETWORK MODELS
FOR REAL-TIME FLOOD FORECASTING IN DRY
ZONE AND WET ZONE RIVER BASINS, SRI LANKA**

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Degree of Master of Science Engineering

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University of Moratuwa- Sri Lanka

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Thesis submitted in partial fulfilment of the requirements for the degree
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Applicability of Neural Network Models for Real-Time Flood Forecasting in Dry Zone and Wet Zone River Basins, Sri Lanka

ABSTRACT

Flood forecasting is a powerful tool for flood management and early warning, where the anticipated flow values are determined by incorporating basin attributes and climatic factors. In the field, data-driven models offer beneficial solutions compared to comprehensive physical and statistical tools; neural networks have evolved to perform flood forecasting without understanding the physical mechanism. However, forecasting efficiency and reliability are insufficient due to the augmentation of predictive span and improper data handling strategies. In addition, the poor interconnectivity of spatial-temporal resolution influences the accuracy of flood forecasting in a dry zone. Thus, the present study aimed to enhance the flood forecasting ability of neural network models for a 30-day horizon by learning the daily input series of climatic and physiographic factors of the catchment region. Further, the data manipulation strategies were adapted to enhance the learning capabilities. In addition, pre-trained models were developed based on the model performance in the wet zone basin to enhance the predictive quality in the dry zone basin.

The NN models were developed for the Kelani River flood forecasting, where significant flood events have frequently destroyed the socio-economic features of the basin. Besides, pre-trained models were tested on the Maduru Basin flood events, which have encountered inundation due to prolonged flood peaks. Thus, climatic and physiographic data were gathered for both basins and improved with hydrological and data science-based data manipulation strategies. On the other hand, the Box-Cox transformation was employed to redistribute the input series into a Gaussian state to enhance the learning ability of NN models.

Consecutive windows were proposed to consider 30-day daily input to forecast the next 30-day streamflow values while sampling. Thirteen (13) NN models were compiled, fitted, and tested on the Kelani Basin. In addition, grid analysis was adapted to rank the performance of models based on statistical tools, where bidirectional models explicated excellent quality in flood forecasting. Besides, uncertainty analysis was proposed to investigate the impacts of data handling and input combination on flood forecasting. Two hybrid models significantly expounded underperformance without box-cox transformation; none of the models illustrated excellent performance without box-cox transformation. Moreover, scaling/normalization severely influenced the model performance considerably for hybrid models. Besides, sensitivity analysis was applied to verify the applicability of model architecture on model performance. Unlike the types of optimizers, other sensitivity parameters revealed inconclusive results for model performance. None of the modified models delivered more excellent performance than the core models. Further, Bidirectional Gated Recurrent Unit (Bi-GRU), Bidirectional Long- and Short-Term Model (Bi-LSTM), and Attention Based Bi-LSTM (Att-BiLSTM) expressed 0.98, 0.95, and 0.97 for the wet zone flood forecasting, respectively, which were chosen as pre-trained models delivered a similar performance for the dry basin.

In future studies, the consecutive data batches must be determined according to the guiding parameters, such as global warming and climate change. Besides, the loss function should be replaced with other statistical terms to incorporate an optimizer, and autocorrelation must be adapted to control the error propagation. In addition, the core model must be trained for extended periods to effectively perform transfer learning on other basins.

Key Words: Box-Cox; Data science; Sensitivity analysis; Sliding window; Uncertainty analysis

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Table of Content

| | |
|---|-----|
| Declaration..... | i |
| ABSTRACT..... | ii |
| Acknowledgement | iii |
| List of Figures..... | vi |
| List of Tables | ix |
| List of Abbreviations | x |
| CHAPTER 1: INTRODUCTION | 1 |
| 1.1 Background..... | 1 |
| 1.2 Problem Statement..... | 4 |
| 1.3 Main Objective and Specific Objectives | 5 |
| 1.4 Significance of the Study..... | 5 |
| 1.5 Scope of the Study..... | 6 |
| CHAPTER 2: LITERATURE REVIEW | 7 |
| 2.1 Previous Research Concepts in Forecasting using NN Models..... | 7 |
| 2.2 Neural Network Forecasting Models Available in the Literature..... | 11 |
| 2.2.1 Ordinary Artificial Neural Networks (ANN) | 11 |
| 2.2.2 Convolution Neural Network (CNN)..... | 12 |
| 2.2.3 Deep Recurrent Neural Network (RNN)..... | 12 |
| 2.2.4 Nonlinear Autoregressive with Exogenous Input Network (NARX)..... | 13 |
| 2.2.5 Hybrid Model of Discrete Wavelet Transformation – Improved Nonlinear Autoregressive with Exogeneous Input Network (DWT-iNARX) | 14 |
| 2.2.6 Stacked Bidirectional and Unidirectional LSTM Network (SBU-LSTM)..... | 14 |
| 2.2.7 Correlated Time Series – Long-term Short-term Memory (CTS-LSTM)..... | 17 |
| 2.2.8 A hybrid model of Convolutional Neural Network – Long-term Short-term Memory (CNN-LSTM)..... | 18 |
| 2.2.9 Attention-Based CNN-LSTM Neural Network Model (ALSM) | 19 |
| 2.2.10 Temporal Convolutional Network (TCN)..... | 21 |
| 2.3 Data Processing for the Development of the NN Model and Study Area | 22 |
| 2.3.1 Data Collection and Processing..... | 22 |
| 2.3.2 Physiographic Factors | 23 |
| 2.3.3 Climatic Factors | 24 |
| 2.3.4 Study Area..... | 24 |
| 2.4 Time Series Forecasting Using NN Models | 25 |
| 2.4.1 Standard Models..... | 30 |
| 2.4.2 Hybrid Models..... | 33 |
| 2.5 Identification of the Best Models | 34 |

| | |
|---|-----|
| 2.6 Uncertainty Analysis | 38 |
| 2.7 Sensitivity Analysis | 39 |
| 2.8 Transfer Learning Technique | 40 |
| CHAPTER 3: METHODOLOGY | 41 |
| 3.1 Methodology Flowchart | 41 |
| 3.2 Study Area | 42 |
| 3.3 Data and Data Checking | 44 |
| 3.3.1 Data Source and Resolution: Climatic Data | 44 |
| 3.3.2 Data Source and Resolution: Physiographic Data..... | 52 |
| 3.4 Developing Neural Network Forecasting Models | 59 |
| 3.4.1 Basic Forecasting Models | 60 |
| 3.4.2 Hybrid NN Models..... | 61 |
| 3.5 Selecting the Best NN Models..... | 66 |
| 3.6 Uncertainty Analysis | 67 |
| 3.7 Sensitivity Analysis | 67 |
| 3.8 Evaluating the NN Model Performance (Wet Zone) on Dry Zone Basin..... | 70 |
| CHAPTER 4: RESULTS AND DISCUSSION | 71 |
| 4.1 Performance of NN Models..... | 71 |
| 4.2 Selection of the Best Models | 73 |
| 4.3 Uncertainty Analysis | 81 |
| 4.4 Sensitivity Analysis | 81 |
| 4.5 Evaluating the Wet Zone Models on Dry Zone..... | 82 |
| 4.6 Comparing the Present Study Model Performance with Existing Models | 83 |
| CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS | 86 |
| 5.1 Conclusions | 86 |
| 5.2 Limitations..... | 87 |
| 5.3 Recommendations | 87 |
| REFERENCE..... | 89 |
| APPENDICES | 96 |
| Appendix A: Visual Checking of Streamflow and Rainfall of each station for Water Year (2008-2015) – Kelani River Basin..... | 96 |
| Appendix B: Visual Checking of Streamflow and Thiessen Averaged Rainfall for Water Year (2008-2015) – Kelani River Basin..... | 106 |
| Appendix C: Double Mass Curve for the Rainfall Stations – Kelani River Basin..... | 108 |
| Appendix D: Visual Checking of Streamflow and Rainfall of each station for Water Year (2008-2015) – Maduru Oya Basin..... | 109 |
| Appendix E: Visual Checking of Streamflow and Thiessen Averaged Rainfall for Water Year (2008-2015) – Maduru River Basin..... | 115 |
| Appendix F: Double Mass Curve for the Rainfall Stations – Maduru River Basin | 117 |

List of Figures

| | |
|---|----|
| Figure 1-1 Climatic Zone Maps and Selected River Basins | 6 |
| Figure 2-1 Model Structure of ANN, (de la Fuente et al., 2019)..... | 11 |
| Figure 2-2 LSTM Model Structure with Forget Gate, Input Gate, Cell State and Output Gate, (Zhang et al., 2021)..... | 13 |
| Figure 2-3 GRU Blocks with two Logic Gates, (Zhang et al., 2021) | 13 |
| Figure 2-4 NARX Model Structure, (di Nunno & Granata, 2020) | 14 |
| Figure 2-5 LSTM and LSTM-Imputation Units, (Cui et al., 2020) | 15 |
| Figure 2-6 Bidirectional LSTM, (Cui et al., 2020) | 16 |
| Figure 2-7 Structure of CTS-LSTM, (Wan et al., 2020)..... | 17 |
| Figure 2-8 The Structure of ST Cell, (Wan et al., 2020) | 17 |
| Figure 2-9 Structure of the Fusion Module, (Wan et al., 2020)..... | 18 |
| Figure 2-10 Structure of CNN, (Yan et al., 2021) | 19 |
| Figure 2-11 Input Dimension of CNN, (Yan et al., 2021) | 19 |
| Figure 2-12 The Memory Cell of LSTM, (Yan et al., 2021) | 19 |
| Figure 2-13 Input Dimension of LSTM, (Yan et al., 2021)..... | 19 |
| Figure 2-14 Structure of CNN-LSTM, (Yan et al., 2021) | 19 |
| Figure 2-15 Model Architecture of ASLM, (Qu et al., 2021)..... | 20 |
| Figure 2-16 1D CNN Extracting Features of Short-Term and Long-Term Series Pattern, (Qu et al., 2021)..... | 20 |
| Figure 2-17 The Structure of An Attention Model, (Qu et al., 2021) | 21 |
| Figure 2-18 TCN Model Structure, (Xu et al., 2021)..... | 22 |
| Figure 2-19 Anatomy of a Neural Network | 26 |
| Figure 2-20 Configuration of RNN Model | 32 |
| Figure 2-21 Configuration of Bidirectional RNN Model..... | 32 |
| Figure 2-22 Function of RNN Model: Flowchart | 32 |
| Figure 2-23 Function flowchart: LSTM..... | 32 |
| Figure 2-24 Configuration of CNN Model | 32 |
| Figure 2-25 Configuration of NARX Model | 32 |
| Figure 2-26 Configuration of CNN-LSTM Model | 35 |
| Figure 2-27 Configuration of SBU-LSTM Model | 35 |
| Figure 2-28 Configuration of DCNN Model | 36 |
| Figure 2-29 Configuration of GC-LSTM Model | 36 |
| Figure 2-30 Configuration of TCN Model..... | 36 |
| Figure 2-31 Configuration of Att- Bi LSTM Model..... | 36 |
| Figure 2-32 Flow Duration Curve and Flow Characteristics | 37 |
| Figure 2-33 Behavioral Error Estimation..... | 38 |
| Figure 2- 34 Theory of Transfer Learning..... | 40 |
| Figure 3-1 Methodology Flowchart | 42 |
| Figure 3-2 Location Map (Kelani River Basin) with DEM | 43 |
| Figure 3-3 Location Map (Maduru Oya) with DEM | 43 |
| Figure 3-4 Annual Water Balance – Kelani..... | 47 |
| Figure 3-5 Annual Rainfall and Annual Streamflow - Kelani | 47 |
| Figure 3-6 Annual Water Balance – Maduru Oya | 47 |

| | |
|--|----|
| Figure 3-7 Annual Rainfall and Annual Streamflow - Maduru Oya..... | 48 |
| Figure 3-8 Thiessen Polygon of Kelani River Basin | 49 |
| Figure 3-9 Thiessen Polygon of Maduru Oya Basin..... | 49 |
| Figure 3-10 Single Mass Curve – Kelani..... | 50 |
| Figure 3-11 Single Mass Curve - Maduru Oya..... | 50 |
| Figure 3-12 Double Mass Curve of Stations - Kelani..... | 51 |
| Figure 3-13 Double Mass Curve of Stations - Maduru Oya | 51 |
| Figure 3-14 Rainfall - Runoff Coefficient 2008 – 2015 (Kelani Basin) | 55 |
| Figure 3-15 Rainfall - Runoff Coefficient 2008 – 2015 (Maduru Oya Basin) | 55 |
| Figure 3-16 NDVI time series data (2008 – 2015) - Kelani..... | 57 |
| Figure 3-17 NDVI time series data (2008 – 2015) - Maduru..... | 57 |
| Figure 3-18 MNDWI time series data (2008 – 2015) - Kelani | 57 |
| Figure 3-19 MNDWI time series data (2008 – 2015) - Maduru | 57 |
| Figure 3-20 NDBI time series data (2008 – 2015) - Kelani..... | 57 |
| Figure 3-21 NDBI time series data (2008 – 2015) - Maduru..... | 57 |
| Figure 3-22 Configuration of Window Sampling | 64 |
| Figure 3-23 Configuration of Baseline Model..... | 64 |
| Figure 3-24 Configuration of Linear Model | 64 |
| Figure 3-25 Configuration of ANN Model | 64 |
| Figure 3-26 Configuration of CNN Model | 64 |
| Figure 3-27 Configuration of RNN Model | 64 |
| Figure 3-28 Configuration of Bidirectional Model..... | 64 |
| Figure 3-29 Configuration of NARX Model | 64 |
| Figure 3-30 Configuration of CNN-LSTM..... | 64 |
| Figure 3-31 Configuration of SBU-LSTM | 65 |
| Figure 3-32 Configuration of DCNN..... | 65 |
| Figure 3-33 Configuration of GC-LSTM..... | 65 |
| Figure 3-34 Configuration of TCN | 65 |
| Figure 3-35 Configuration of Att-BiLSTM | 65 |
| Figure 3-36 Skeleton of Transfer Learning..... | 70 |
| Figure 4-1 RMSE Values - NN Models..... | 71 |
| Figure 4-2 MAE Values - NN Models..... | 71 |
| Figure 4-3 R ² Values - NN Models..... | 72 |
| Figure 4-4 FDC-Q Values - NN Models..... | 73 |
| Figure 4-5 RM Values - NN Models | 74 |
| Figure 4-6 Hydrograph for Kelani (Bi-GRU) | 75 |
| Figure 4-7 FDC for Kelani (Bi-GRU)..... | 75 |
| Figure 4-8 Hydrograph for Kelani (Att-Bi-LSTM) | 75 |
| Figure 4-9 FDC for Kelani (Att-Bi-LSTM)..... | 75 |
| Figure 4-10 Hydrograph for Kelani (Bi-LSTM)..... | 75 |
| Figure 4-11 FDC for Kelani (Bi-LSTM) | 75 |
| Figure 4-12 Hydrograph for Kelani (RNN-GRU) | 76 |
| Figure 4-13 FDC for Kelani (RNN-GRU)..... | 76 |
| Figure 4-14 Hydrograph for Kelani (CNN) | 76 |

| | |
|---|----|
| Figure 4-15 FDC for Kelani (CNN)..... | 76 |
| Figure 4-16 Hydrograph for Kelani (RNN-LSTM) | 76 |
| Figure 4-17 FDC for Kelani (RNN-LSTM)..... | 76 |
| Figure 4-18 Hydrograph for Kelani (ANN)..... | 77 |
| Figure 4-19 FDC for Kelani (ANN) | 77 |
| Figure 4-20 Hydrograph for Kelani (NARX) | 77 |
| Figure 4-21 FDC for Kelani (NARX)..... | 77 |
| Figure 4-22 Hydrograph for Kelani (SBU-LSTM)..... | 77 |
| Figure 4-23 FDC for Kelani (SBU-LSTM) | 77 |
| Figure 4-24 Hydrograph for Kelani (DCNN) | 78 |
| Figure 4-25 FDC for Kelani (DCNN)..... | 78 |
| Figure 4-26 Hydrograph for Kelani (CNN-LSTM) | 78 |
| Figure 4-27 FDC for Kelani (CNN-LSTM)..... | 78 |
| Figure 4-28 Hydrograph for Kelani (TCN)..... | 78 |
| Figure 4-29 FDC for Kelani (TCN) | 78 |
| Figure 4-30 Hydrograph for Kelani (GC-LSTM)..... | 79 |
| Figure 4-31 FDC for Kelani (GC-LSTM)..... | 79 |
| Figure 4-32 Uncertainty Analysis and the Scaled Values..... | 81 |
| Figure 4-33 Sensitivity Analysis and the Scaled Values | 82 |
| Figure 4-34 Hydrograph for Att-Bi-LSTM..... | 83 |
| Figure 4-35 Hydrograph for Bi-LSTM | 83 |
| Figure 4-36 Hydrograph for Bi-GRU | 83 |
| Figure 4-37 Comparison of NN Models (Blue: Models available in the literature, Orange: Models in the study)..... | 84 |

List of Tables

| | |
|---|----|
| Table 2-1 Statistical Model for Evaluation of Performance, Jimeno-Sáez et al., 2018 | 36 |
| Table 2- 2 Uncertainty Analysis and Parameters..... | 39 |
| Table 2-3 Sensitivity Analysis and Parameters..... | 39 |
| Table 3-1 Data Type and Data Resolution..... | 44 |
| Table 3-2 Comparing the Area of Stations with WMO Standards | 45 |
| Table 3-3 Annual Runoff Coefficient and Annual Evaporation | 46 |
| Table 3-4 Thiessen Weights of Stations..... | 48 |
| Table 3-5 Comparing the quality of NASA POWER ACCESS data. | 52 |
| Table 3-6 MODIS Landcover type (MCD12Q1.006)..... | 54 |
| Table 3-7 Open Land Map soil texture class (USDA system)..... | 55 |
| Table 3-8 Landsat Band type and description..... | 56 |
| Table 3-9 Google Earth Engine Links | 58 |
| Table 3-10 Jupyter Notebook and Details..... | 63 |
| Table 3-11 Importance of Factors | 66 |
| Table 3-12 AHP Analysis and Weights | 67 |
| Table 3-13 Grid Analysis (Sample Sheet) | 68 |
| Table 3- 14 Uncertainty Parameters and Description | 69 |
| Table 3-15 Sensitivity Parameters and Description | 69 |
| Table 4-1 Grid Analysis for Uncertainty Analysis | 80 |
| Table 4-2 NN Models in the Literature..... | 84 |

List of Abbreviations

| | |
|-------------|--|
| AHP | Analytic Hierarchy Process |
| AI | Artificial Intelligence |
| ALSM | Attention Based CNN – LSTM |
| AMC | Antecedent Moisture Condition |
| ANN | Dense Artificial Neural Network |
| AMC | Antecedent Moisture Condition |
| ARIMA | Autoregressive Integrated Moving Average |
| Att Bi-LSTM | Attention -Based Bidirectional LSTM |
| BDLSTM | Bidirectional LSTM |
| Bi-GRU | Bidirectional GRU |
| Bi-LSTM | Bidirectional LSTM |
| BL | Baseline Model |
| BR | Bayesian Regularization |
| CEEMDAN | Complete Ensemble Empirical Mode Decomposition with Adaptive Noise |
| CHIRPS | Climatic Hazards Group InfraRed Precipitation |
| CNN | Convolution Neural Network |
| CNTK | Cognitive Toolkit |
| CPU | Central Processing Unit |
| CTS-LSTM | Correlated Time Series - LSTM |
| DCNN | Dilated Casual CNN |
| DEM | Digital Elevation Model |
| DL | Deep Learning |
| DWT | Discrete WT |
| DWT- | Hybrid Model of Discrete Wavelet Transformation - Improved Nonlinear |
| iNARX | Autoregressive with Exogeneous Input Network |
| FCN | Fully Connected Neural Network |
| FDC | Flow Duration Curve |
| FDC-Q | FDC Behavioral Error |
| FNN | Feedforward Neural Network |
| GC-LSTM | Graph Convolution Embedded LSTM |
| GCN | Graph Convolution Neural Network |
| GEE | Google Earth Engine |
| GPU | Graphics Processing Unit |
| GRU | Gated Recurrent Unit (RNN) |
| IDE | Integrated Development Environment |
| IGBP | International Geosphere-Biosphere Program |
| IoT | Internet of Things |
| LeM | Levenberg-Marquart |
| LS-SVM | Least Squares Support Vector Machine Regression |
| LSTM | Long Short Term Memory (RNN) |
| LSTM-I | LSTM – Imputation |
| LULC | Land Use and Land Cover |
| MAE | Mean Absolute Error |
| MANN | Memory Augmented Neural Network |
| MCS | Monte Carlo Simulation |
| MLP | Multi-Layer Perceptron |
| MLR | Multi Linear Regression |
| MNDWI | Modified Normalized Difference Water Index |
| MRTPP | Multiple Relevant and Target variables Prediction Patterns |

| | |
|------------------|---|
| N A | Not Available |
| NARX | Nonlinear Autoregressive Network with Exogenous Input |
| NDBI | Normalized Difference Built-up Index |
| NDVI | Normalized Difference Vegetation Index |
| NIR | Near Infrared |
| NN | Neural Network |
| NOAA | National Oceanic and Atmospheric Administration |
| PCA | Principal Component Analysis |
| R ² | Coefficient of Determination |
| ReLU | Rectified Linear Unit |
| R _{FDC} | FDC Behavioral Error |
| RM | Residual Max Error |
| RMSE | Root Mean Square Error |
| RNN | Recurrent Neural Network |
| S | Potential Maximum Retention |
| SAR | Synthetic Aperture Radar |
| SBU-LSTM | Stacked Bidirectional and Unidirectional LSTM |
| SCS CN | Soil Conservation Service Curve Number |
| SGD | Stochastic Gradient Descent |
| SRTM | Shuttle Radar Topography Mission |
| ST | Spatial – Temporal |
| SWIR | Shortwave Infrared |
| TCN | Temporal Convolutional Network |
| TCN-ED | TCN-Encoder Decoder |
| TOA | Top of Atmosphere |
| USDA | United States Department of Agriculture |
| WT | Wavelet Transformation |