

Predicting Reservoir Water Levels using Deep Learning

Ahmed Nuzhi Meyen

168247G

MSc in Computer Science

Department of Computer Science and Engineering

**University of Moratuwa
Sri Lanka**

May 2018

DECLARATION

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Acknowledgements

My sincere appreciation goes to my family for the continuous support and motivation given to make this thesis a success. I also express my heartfelt gratitude to Dr. Amal Shehan Perera, my supervisor, for the supervision and advice given throughout to make this research a success. I also thank my parents, sister and brother-in-law for their heartfelt support. I am also thankful to Mr. Sanjaya Ratnayake for providing the required data. Last but not least I also thank my friends who supported me in this whole effort.

ABSTRACT

Currently the authorities in the field of water resource management for irrigation and hydro power electricity in Sri Lanka make use of basic forecasting methodology in order to make decisions with respect to water resource management. The results of this research would be useful to the relevant authorities as it would provide them an indication of the expected water levels allowing them to make vital decisions regarding the competing needs such as water resource management for irrigation as opposed to water resource management for hydro power electricity generation during the monsoonal as well as inter-monsoonal periods with the use of the latest predictive framework with respect to artificial intelligence technology.

Most of the current research in this area use models such as multi-linear regression, support vector machines and artificial neural networks such as adaptive neuro-fuzzy inference systems to provide predictions for hydrological models. The models are developed for varying levels of granularity with respect to time such as daily and weekly depending on the need to forecast water levels for reservoirs.

This research will focus on the novel deep learning techniques of LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) recurrent neural networks as opposed to the conventional machine learning approaches. Historical daily water levels will be used as inputs along with meteorological variables at other nearby reservoirs to do forecast future values. These methods will be benchmarked against traditional baseline machine learning techniques to validate how much of a predictive gain can be obtained by use of the deep learning techniques. Furthermore, this research will evaluate the suitability of the aforementioned techniques to make predictions regarding the water level input by the usage of various metrics such as mean square error as the cost function which can be used to validate the output of the above models.

Contents

DECLARATION	2
Acknowledgements.....	3
ABSTRACT	4
List of Figures.....	7
List of Abbreviations	10
1. Introduction.....	11
1.1 Kotmale Reservoir	12
1.2 Problem.....	17
1.3 Objectives	18
1.4 General Objectives.....	18
1.5 Specific Objectives	18
1.6 Prior Work	18
2. Literature Review	20
2.1 Introduction.....	21
2.2 Multi-Linear Regression (MLR) model.....	21
2.3 Auto Regressive (AR) model.....	22
2.4 Auto Regressive Moving Average (ARMA) model	23
2.5 Artificial Neural Networks (ANNs).....	24
2.5.1 Introduction.....	24
2.5.2 Multi-Layer Perceptron (MLP).....	24
2.5.3 Radial Basis Function (RBF) networks	26
2.5.4 Adaptive Neuro-Fuzzy Inference System (ANFIS).....	28
2.6 Support Vector Machines (SVMs).....	32
2.7 Deep Learning and Applications	32
3. Methodology	35
3.1 Proposed Methodology	36
3.2 Deep Learning.....	37
3.2.1 LSTM (Long Short-Term Memory) Recurrent Networks	38

3.2.2 Proposed LSTM Model for Water Level Prediction.....	40
3.3 Baseline Models.....	42
3.3.1 Baseline Regression Model for Water Level Prediction.....	42
3.3.2 Baseline SVM (Support Vector Machine) Model for Water Level Prediction.....	42
3.3.3 Baseline XGBoost (XGBoost) Model for Water Level Prediction.....	43
4. Solution Architecture & Implementation.....	44
4.1 Overview.....	45
4.2 Extract, Transform, Load (ETL) Process / Data Preprocessing.....	45
4.3 Knowledge Discovery.....	46
4.3.1 Data Understanding	46
4.3.2 Data Preparation	47
4.3.3 Modelling.....	47
5. Data & Analysis.....	49
5.1 Descriptive Analysis	50
5.1.1 Descriptive Analysis for Modelling.....	50
5.1.2 Evaluation and Analysis of Baseline Models	50
5.1.3 Evaluation and Analysis of LSTM Model	58
6. General Discussion & Conclusion	63
6.1 General Discussion on the Study	64
6.2 Conclusions.....	66
6.3 Further Work.....	66
References.....	68
Appendix.....	70
.....	97

List of Figures

Figure 1.1: Water Distribution Diagram of the Accelerated Mahaweli Program	13
Figure 1.2: The three physiographic regions of the catchment above the Kotmale Reservoir	14
Figure 1.3: Mahaweli Ganga, Kotmale Oya and the location of some major reservoirs	14
Figure 1.4: Storage of the Kotmale Reservoir at various water levels	16
Figure 1.5: Surface area (ha) of the Kotmale Reservoir at various water levels	17
Figure 2.1- McCulloch and Pitt's mathematical model of a neuron. The inputs x_i are multiplied by the weights w_i , and the neurons sum their values. If their sum is greater than the threshold θ then the neuron fires, otherwise it does not.	24
Figure 2.2: The Perceptron network, consisting of a set of input nodes (left) connected to McCulloch and Pitts neurons using weighted connections.	25
Figure 2.3: The Multi-Layer Perceptron (MLP) Network, consisting of multiple layers of connected neurons	25
Figure 2.4: The Radial Basis Function network consists of input nodes connected by weight to a set of RBF neurons, which fire proportionally to the distance between the input and the neuron in weight space.	27
Figure 2.5: Fuzzy Inference System	29
Figure 2.6: Architecture of Adaptive Neuro-Fuzzy Inference System	29
Figure 3.1: Architecture of proposed solution.....	37
Figure 3.2: An unrolled recurrent neural network	38
Figure 3.3 :The repeating module in a standard RNN	39
Figure 3.4: The repeating module in an LSTM consisting of four interacting layers	40
Figure 5.1 -Predicted Vs Actual Values Over Time using Linear Regression.....	52
Figure 5.2- Predicted Vs Actual Values Scatterplot for Training Data using Linear Regression	53
Figure 5.3-- Predicted Vs Standardized Residual Values Scatterplot for Training Data using Linear Regression.....	53
Figure 5.4 -Predicted Vs Actual Values Scatterplot for Test Data using Linear Regression...	54
Figure 5.5 - Predicted Vs Standardized Residual Values Scatterplot for Test Data using Linear Regression.....	54
Figure 5.6 - Predicted Vs Actual Values Over Time using XGBoost	56
Figure 5.7 -Predicted Vs Actual Values Scatterplot for Training Data using XGBoost	57
Figure 5.8: Predicted Vs Actual Values Scatterplot for Test Data using XGBoost	57
Figure 5.9- Variation of error in the train and test set for GRU RNN with 100 neurons in first layer	58
Figure 5.10- Variation of error in the train and test set for GRU RNN with 150 neurons in first layer	59
Figure 5.11- Variation of error in the train and test set for GRU RNN with 200 neurons in first layer	59

Figure 5.12- Variation of error in the train and test set for LSTM RNN with 100 neurons in first layer	60
Figure 5.13- Variation of error in the train and test set for LSTM RNN with 150 neurons in first layer	60
Figure 5.14- Variation of error in the train and test set for LSTM RNN with 200 neurons in first layer	61
Figure 5.15- Predicted Vs Actual Values Over Time using Optimal LSTM model	61
Figure 5.16- Predicted Vs Actual Values Scatterplot for Training Data using Optimal LSTM Model.....	62
Figure 5.17- Predicted Vs Actual Values Scatterplot for Test Data using Optimal LSTM Model	62
Figure A.1- Variation of Meteorological Variables with time (Broadlands Reservoir)	71
Figure A.2- Variation of Meteorological Variables with time (Laxapana Reservoir)	72
Figure A.3- Variation of Meteorological Variables with time (Norton Reservoir)	73
Figure A.4- Variation of Meteorological Variables with time (Upper Kotmale Reservoir)	74
Figure A.5 - Variation of Meteorological Variables with time (Castlereigh Reservoir).....	75
Figure A.6 - Variation of Meteorological Variables with time (Canyon Reservoir).....	76
Figure A.7 - Variation of Meteorological Variables with time (Maskeliya Reservoir)	77
Figure A.8 - Variation of Meteorological Variables with time (Nilambe Reservoir)	78
Figure A.9 - Variation of Meteorological Variables with time (Polgolla Reservoir).....	79
Figure A.10 - Variation of Meteorological Variables with time (Victoria Reservoir)	80
Figure A.11 - Histograms of Meteorological Variables (Broadlands Reservoir)	81
Figure A.12 - Histograms of Meteorological Variables (Laxapana Reservoir)	82
Figure A.13 - Histograms of Meteorological Variables (Norton Reservoir).....	83
Figure A.14 - Histograms of Meteorological Variables (Upper Kotmale Reservoir)	84
Figure A.15 - Histograms of Meteorological Variables (Castlereigh Reservoir)	85
Figure A.16 - Histograms of Meteorological Variables (Canyon Reservoir)	86
Figure A.17 - Histograms of Meteorological Variables (Maskeliya Reservoir)	87
Figure A.18- Histograms of Meteorological Variables (Nilambe Reservoir).....	88
Figure A.19- Histograms of Meteorological Variables (Polgolla Reservoir).....	89
Figure A.20- Histograms of Meteorological Variables (Victoria Reservoir).....	90
Figure A.21 - Correlation plot of Meteorological Variables (Broadlands Reservoir)	91
Figure A.22- Correlation plot of Meteorological Variables (Laxapana Reservoir).....	91
Figure A.23- Correlation plot of Meteorological Variables (Norton Reservoir).....	92
Figure A.24- Correlation plot of Meteorological Variables (Upper Kotmale Reservoir).....	92
Figure A.25- Correlation plot of Meteorological Variables (Castlereigh Reservoir)	93
Figure A.26- Correlation plot of Meteorological Variables (Canyon Reservoir)	93
Figure A.27- Correlation plot of Meteorological Variables (Maskeliya Reservoir)	94
Figure A.28- Correlation plot of Meteorological Variables (Nilambe Reservoir).....	94
Figure A.29- Correlation plot of Meteorological Variables (Polgolla Reservoir)	95
Figure A.30- Correlation plot of Meteorological Variables (Victoria Reservoir).....	95
Figure A.31 - Predicted Vs Actual Values Over Time using Epsilon SVR (Linear Kernel).....	96
Figure A.32- Predicted Vs Actual Values Scatterplot for Training Data using Epsilon SVR (Linear Kernel).....	96

Figure A.33- Predicted Vs Actual Values Scatterplot for Test Data using Epsilon SVR (Linear Kernel).....	97
Figure A.34- Predicted Vs Actual Values Over Time using Epsilon SVR (Polynomial Kernel)	97
Figure A.35- Predicted Vs Actual Values Scatterplot for Training Data using Epsilon SVR (Polynomial Kernel).....	98
Figure A.36- Predicted Vs Actual Values Scatterplot for Test Data using Epsilon SVR (Polynomial Kernel).....	98
Figure A.37- Predicted Vs Actual Values Over Time using Epsilon SVR (Sigmoid Kernel)	98
Figure A.38- Predicted Vs Actual Values Scatterplot for Training Data using Epsilon SVR (Sigmoid Kernel).....	98
Figure A.39- Predicted Vs Actual Values Scatterplot for Test Data using Epsilon SVR (Sigmoid Kernel).....	98
Figure A.40- Predicted Vs Actual Values Over Time using Nu SVR (Linear Kernel)	98
Figure A.41- Predicted Vs Actual Values Scatterplot for Training Data using Nu SVR (Linear Kernel).....	98
Figure A.42- Predicted Vs Actual Values Scatterplot for Test Data using Nu SVR (Linear Kernel).....	98
Figure A.43- Predicted Vs Actual Values Over Time using Nu SVR (Polynomial Kernel)	98
Figure A.44- Predicted Vs Actual Values Scatterplot for Training Data using Nu SVR (Polynomial Kernel).....	98
Figure A.45- Predicted Vs Actual Values Scatterplot for Test Data using Nu SVR (Polynomial Kernel).....	98
Figure A.46- Predicted Vs Actual Values Over Time using Nu SVR (Sigmoid Kernel)	98
Figure A.47- Predicted Vs Actual Values Scatterplot for Training Data using Nu SVR (Sigmoid Kernel).....	98
Figure A.48- Predicted Vs Actual Values Scatterplot for Test Data using Nu SVR (Sigmoid Kernel).....	98

List of Abbreviations

Abbreviation	Description
ARMA	Auto Regressive Moving Average
MLR	Multi Linear Regression
ANN	Artificial Neural Network
AR	Auto Regressive
MLP	Multi-Layer Perceptron
MA	Moving Average
MSE	Mean Square Error
MAE	Mean Absolute Error
RBF	Radial Basis Function
ANFIS	Adaptive Neuro-Fuzzy Inference System
SVM	Support Vector Machine
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory