PREDICTION OF DISSOLVED OXYGEN IN HARBOURS USING ARTIFICIAL NEURAL NETWORKS: AN APPLICATION TO THE PORT OF COLOMBO

By

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DECLARATION

I hereby declare that the work included in the thesis in part or whole has not been submitted in any form for any other academic qualification of any institution.

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ABSTRACT

Maintenance of high dissolved oxygen (DO) level in harbours is highly important as it could give rise to catastrophic effects if it is depleted affecting day- to- day port functions such as dredging activities and other maintenance work. The depletion of DO results not only in toxic gases such as methane and hydrogen sulfide but also in accumulation of wastes. Frequent monitoring of DO is therefore imperative, but makes practical difficulties due to ship movements and other activities. Hence, prediction of DO with an empirical model using Artificial Neural Networks (ANNs) was done with success with an application to the Port of Colombo (PoC). This model aims to lessen the frequency of monitoring DO and to foresee the responses of the system due to environmental changes. The performances of ANNs were compared with Multiple Linear Regression (MLR). Monthly values of 14 water quality parameters at several depths for the period of four years from 1997 to year 2000 were collected. The values of weather parameters of rainfall and wind velocity for the corresponding period were also collected. The neural network possessing 7 inputs and 45 hidden neurons, performed well giving rise to correlation coefficient (R) as 0.87 and 0.67 for calibration and verification respectively. The inputs are temperature, depth and five rainfall intensities (including values on four immediate previous days). A sensitivity analysis was carried out to assess the potentials of small changes in each input on the neural network output. MLR model with 7 input variables indicated R to be 0.45 for calibration after several transformations. The temperature was the most influential variable among the ANN inputs affecting the output. In conclusion, it could be inferred that the ANN model is capable of predicting DO in PoC considerably well compared with MLR.

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TABLE OF CONTENTS

Chapter 6: Discussion

Chapter 7: Conclusions and Further recommendations

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

Symbol	Name
$\propto$	Momentum
η	Learning parameter
b_1	Change in Y for a unit change in X_2 keeping X_1 constant
b_1^*	Effect of X_1^* on Y_1^* keeping X_2^* constant.
b_2	Change in Y for a unit change in X_2 keeping X_1 constant
b_2^*	Effect of X_2^* on Y_2^* keeping X_1^* constant
N	Number of pairs.
R	Correlation coefficient
R^2	Determination coefficient
R_{YX_1}	Correlation of X_1 with Y
R_{YX_2}	Correlation of X_2 with Y
$R_{X_1X_2}$	Correlation of X_1 with X_2
$R_{X_2Y.X_1}$	Partial correlation of X_2 and Y with X_1 Controlled.
S_{LM}	The Slope between low summary point and the middle of the curve.
S_{MH}	The Slope between middle summary point and the high summary point
sd_{X_1}	Standard deviation of X_1.
sd_{X_2}	Standard deviation of X_2.
sd_Y	Standard deviation of Y data.

sd_{X_1}	Standard deviation of X_1 data.
sd_{Y^*}	Standard deviation of Y^* data.
$sd_{X_1^*}$	Standard deviation of X_1^* data.
X_1	Dependent variable.
X_2	Dependent variable.
X^*	Standardized version of X.
X_H	X coordinate of the high summary point
X_L	X coordinate of the low summary point
X_M	X coordinate of the middle summary point
$\overline{X}$	Sample mean
Y	Independent variable
Y^*	Standardized version of Y
$\overline{Y}$	Sample mean
Y_H	Y coordinate of the high summary point
Y_L	Y coordinate of the low summary point.
Y_M	Y axis value of middle summary point.

LIST OF ABBREVIATIONS

Abbreviation	Name
Ammonium-N	Ammonium Nitrogen
ANN	Artificial Neural Network
ANN-16	ANN model with 16 inputs
ANN-9	ANN model with 9 inputs
ANN-7	ANN model with 7 inputs
BPN	Backpropagation Technique
BQ	Bandaranayake Quay
CH_4	Methane
COD	Chemical Oxygen Demand
DO	Dissolved Oxygen
H_2S	Hydrogen Sulphide
JCT	Jaya Container Terminal
M	Mean
MLR	Multiple Linear Regression
MLR-16	MLR model with 16 inputs
MLR-9	MLR model with 9 inputs
MLR-7	MLR model with 7 inputs
Nitrate-N	Nitrate Nitrogen
Nitrite-N	Nitrite Nitrogen
Organic-N	Organic Nitrogen
ORP	Oxygen Reduction Potential
PoC	Port of Colombo
PVQ	Prince Vijaya Quay
QEQ	Queen Elisabeth Quay
Rain-1	Rainfall intensity on the 1^{st} day
Rain-1	Rainfall intensity on the 2^{nd} immediate previous day

Rain-1	Rainfall intensity on the 3rd immediate previous day
Rain-1	Rainfall intensity on the 4th immediate previous day
Rain-1	Rainfall intensity on the 5th immediate previous day
RMS	Root Mean Square
SLPA	Sri Lanka Ports Authority
SD	Standard Deviation
SS	Suspended Solids
Total-N	Total Nitrogen
Total-P	Total Phosphorous
WinNN	Windows Neural network