

**NEURAL NETWORK BASED INFLOW FORECASTING
FOR OPTIMUM POND OPERATION OF A RUN-OF-
RIVER TYPE HYDRO PLANT**

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Degree of Master of Science

Department of Electrical Engineering

University of Moratuwa

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Thesis submitted in partial fulfilment of the requirements for the degree of Master of
Science in Electrical Engineering

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DECLARATION

I declare that this is my own work and this thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidate has carried out research for the Masters Thesis under my supervision.

Signature of the supervisor:

(Dr. Lidula N. Widanagama Arachchige)

The above candidate has carried out research for the Masters Thesis under my supervision.

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(Eng. W.J. L. Shavindranath Fernando)

ABSTRACT

The current practise of pond operation of Upper Kotmale Hydropower Station is studied, where management of the pond is by subjective judgements of the operator. Accurate and reliable inflow forecast makes up an important basis for optimum pond operation connected with effective spillway gate operation. This research proposes a novel technique to forecast inflow to the pond and utilise these forecasts to optimise the operation of the pond.

In the first phase of the research, an artificial neural network based Nonlinear Autoregressive eXogenous model, which is a dynamic neural network meant for time series forecasting, is used to develop the real time inflow forecasting system. Cross correlation analysis is used as feature selection for effective selection of the inputs to the Nonlinear Autoregressive eXogenous network. In the second phase, real time inflow forecast for next six hours is used to optimise the pond operation focusing on goals of shorter-term nature, such as maximising power generation, maximising pond storage and minimising spillway discharge. Multi-objective global optimisation using MATLAB “fmincon” algorithm and weighted approach of solving multi-objective problem are utilised to solve the optimisation problem. Trading-off conflicting objectives by this approach proves very effective. This optimisation approach enhances the flexibility of the operator in the decision making process resulting in achievement of efficiency in pond operation.

The results show that the Nonlinear Autoregressive eXogenous modelling is an efficient tool for inflow forecasting and MATLAB “fmincon” algorithm can be used effectively to carry out the multi-objective optimisation of run-of-river pond. Simulation studies for the past years show that there exists an opportunity for optimising run-of river ponds for generation using inflow forecast and with the use of the proposed methodology, it enhances the hydropower generation with gains of over 5% which is significant in a plant of this type.

Keywords : Artificial neural network, cross correlation, dynamic neural network, feature selection, inflow forecast, multi-objective global optimisation, Nonlinear Autoregressive Exogenous (NARX); pond operation, run-of-river, time series forecasting, ,

DEDICATION

To my wife Anusha Priyadarshani and my children Laksandi, Sithuli and Senuk Wimalaratne throughout my study. Without their patience dedication this thesis would not have been completed in this short period of time. To my parents Nita and Rohana Wimalaratne , who nurtured me and educated me and showed me the right path and introduced me to the Library in a tender age.

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LIST OF ABBREVIATIONS

ANN	: Artificial Neural Network
AOF	: Aggregated Objective Function
AW_RF	: Ambewela Rainfall
CD_RF	: Calidonia Rainfall
CD_WL	: Calidonia Water Level
CEB	: Ceylon Electricity Board
FF&WS	: Flood Forecasting & Warning System
IEEE	: Institute of Electrical and Electronic Engineers
IFM	: Inflow Forecasting Model
MAD	: Mean Absolute Deviation
MSE	: Mean Square Error
NARX	: Nonlinear Autoregressive eXogenous
NE_RF	: Nuwara Eliya Rainfall
NO_WL	: Nanuoya Water Level
PACF	: Partial Auto Correlation Function
POM	: Pond Optimisation Model
PS	: Power Station
R	: Correlation Coefficient
RMSE	: Root Mean Square Error
SCC	: System Control Centre
SH_RF	: Sandringham Rainfall
TK_RF	: Talawakelle Rainfall
TK_WL	: Talawakelle Water Level
UKPS	: Upper Kotmale Power Station