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**DYNAMIC OPTIMISATION OF WATER ALLOCATION
FOR HYDROPOWER AND AGRICULTURAL
PRODUCTIVITY IN A SRI LANKAN RESERVOIR SYSTEM
UNDER FUTURE CLIMATE VARIABILITY**

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Degree of Master of Engineering in
Water Resources Engineering and Management

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University of Moratuwa
Sri Lanka

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Thesis submitted in partial fulfillment of the requirements for the degree of
Master of Engineering in Water Resources Engineering and Management

UNESCO Madanjeet Singh Centre for South
Asia Water Management (UMCSAWM)

Department of Civil Engineering
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Sri Lanka

March 2026

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Dr H. G. L. N. Gunawardhana	Date

ABSTRACT

Dynamic Optimisation of Water Allocation for Hydropower and Agricultural Productivity in a Sri Lankan Reservoir System under Future Climate Variability

At the global scale, increasing climate-driven hydrological variability is undermining the reliability of historical reservoir operating rules and intensifying competition between hydropower and irrigation, particularly in monsoon-dominated regions, as highlighted by the Inter-Governmental Panel on Climate Change (IPCC) Sixth Assessment Report. This study develops and applies a dynamic, machine learning-based framework to optimise water allocation between hydropower generation and agricultural irrigation in the Samanalawewa–Walawe reservoir system in Sri Lanka under current and near-future climate variability. The work addresses the growing conflict between energy and irrigation demands, compounded by increasingly variable monsoonal inflows, recurrent droughts, and the limitations of conventional rule-curve and programming-based reservoir operation methods in handling nonlinear, uncertain hydrological regimes. The methodology integrates three main components: (i) a daily rainfall–runoff model for the Samanalawewa sub-catchment developed in the Hydrologic Engineering Center–Hydrologic Modeling System (HEC-HMS); (ii) a machine learning module in which a Physics-Informed Neural Network (PINN) and a Long Short-Term Memory (LSTM) network are trained to simulate daily storage change based on the full reservoir water balance and are comparatively evaluated; and (iii) a Python-based dynamic water allocation model that embeds the best-performing ML architecture to generate daily irrigation and hydropower releases, subject to operational rule constraints. The HEC-HMS model reproduces historical inflows with Nash Sutcliffe Coefficient (NSE) values of 0.74 and 0.75, an acceptable Mean Ratio of Absolute Error (MRAE), and realistic flow-duration characteristics, indicating reliable representation of monsoon-driven runoff processes. Under normal hydrological conditions, both LSTM and PINN achieve high predictive skill for daily storage change ($\text{NSE} \approx 0.87\text{--}0.92$), but under hybrid datasets including extreme events, the LSTM exhibits smoothed peaks and reduced accuracy (testing $\text{NSE} \approx 0.67$), whereas the PINN maintains higher robustness (testing $\text{NSE} \approx 0.80$) and superior mass-balance consistency, as shown by lower residual variance and more physically plausible parameter sensitivities. The dynamic allocation model, driven by observed inflows and climate-conditioned inputs, yields an optimised storage trajectory that remains consistently below the historically observed storage while satisfying minimum irrigation and hydropower thresholds, revealing a persistent surplus of about 30 MCM that can be reallocated to enhance irrigated area or energy production and reduce spill and evaporation losses. Future inflow and evaporation scenarios for 2021–2040 are generated by coupling downscaled CNRM-CM6-1 precipitation and temperature projections under two Shared Socioeconomic Pathways (SSPs), SSP2-4.5 and SSP5-8.5, with the calibrated HEC-HMS and an LSTM-based evaporation model, while irrigation and hydropower demands are projected using data-driven models conditioned on climate signals. Future projections (2021–2040) reveal that, while SSP2-4.5 maintains comparatively smooth inflow and release patterns, SSP5-8.5 produces sharper inflow peaks, longer low-inflow recessions, and more episodic hydropower and irrigation releases, indicating a clear shift from seasonally regulated storage dynamics to a highly variable, event-driven operational regime.

Keywords: climate change, HEC-HMS, LARS-WG, LSTM, multipurpose reservoirs, PINN, water balance

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LIST OF ABBREVIATIONS

ABM	- Agent-Based Modelling
AI	- Artificial Intelligence
ANNs	- Artificial Neural Networks
CEB	- Ceylon Electricity Board
CMIPs	- Coupled Model Intercomparison Projects
CN	- Curve Number
CNRM-CM6	- Centre National de Recherches Météorologiques - Climate Model 06
DDDP	- Discrete Differential Dynamic Programming
DP	- Dynamic Programming
DRC	- Dynamic Rule Curves
EAs	- Evolutionary Algorithms
ECHAM5	- European Centre Hamburg Climate Model version 5
FIDP	- Fuzzy-Interval Dynamic Programming
FLP	- Fuzzy Linear Programming
GAs	- Genetic Algorithms
GCA	- Grey Correlation Analysis
GCMs	- Global Climate Models
GIS	- Geographical Information System
GNDP	- Gin–Nilwala Diversion Project
GPR	- Gaussian Process Regression
GWh	- Gigawatt hour
HEC-HMS	- Hydrologic Engineering Centre's Hydrologic Modelling System
HEC-ResPRM	- Hydrologic Engineering Centre-Prescriptive Reservoir Model
HEC-ResSim	- Hydrologic Engineering Center-Reservoir System Simulation
IAM	- Integrated Assessment Models
ID	- Irrigation Department
IM1	- First Inter-Monsoon
IM2	- Second Inter-Monsoon

IMOPSO	- Improved Multi-Objective Particle Swarm Optimisation
IWO	- Invasive Weed Optimisation
KIS	- Kalthota Irrigation Scheme
LARS-WG	- Long Ashton Research Station Weather Generator
LP	- Linear Programming
LSTM	- Long Short-Term Memory
MAE	- Mean Absolute Error
MASL	- Mahaweli Authority of Sri Lanka
MCDM	- Multi-Criteria Decision Making
MCM	- Million Cubic Meters
MIKE	- DHI MIKE Hydrological Modelling System
ML	- Machine Learning
MODSIM	- MODSIM River Basin Management Model
MOLP	- Multi-Objective Linear Programming
MPC	- Model Predictive Control
MSE	- Mean Squared Error
MW	- Megawatt
NEM	- Northeast Monsoon
NLP	- Non-Linear Programming
NSE	- Nash–Sutcliffe Efficiency
OWMP	- Open Water Management Program
PaML	- Physics-aware Machine Learning
PBIAS	- Percent Bias
PEPF	- Percentage Error in Peak Flow
PIDL	- Physics-Informed Deep Learning
PINNs	- Physics-Informed Neural Networks
PSO	- Particle Swarm Optimisation
QEPANET	- EPANET-based Water Network Optimisation Tool
QP	- Quadratic Programming
RCMs	- Regional Climate Models
RCP	- Representative Concentration Pathways

RMSE	- Root Mean Squared Error
SCS	- Soil Conservation Service
SD	- System Dynamics
SMA	- Soil Moisture Accounting
SOBEK	- Deltares SOBEK Integrated Hydraulic Modelling Suite
SSP	- Shared Socioeconomic Pathways
SVMs	- Support Vector Machines
SWAT	- Soil and Water Assessment Tool
SWM	- Southwest Monsoon
VIC	- Variable Infiltration Capacity
WEAP	- Water Evaluation and Planning System
WMO	- World Meteorological Organisation

