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Enhancing Artificial Neural Network with Multi-Objective Evolutionary Algorithm for Optimizing Real Time Reservoir Operations: A Review

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Abstract The need for, and the process of, optimizing real time reservoir operations have attracted substantial research attention. Among these is the employment of artificial neural network (ANN), singly or with supporting algorithms, for real time multi-objective reservoir operation optimization. Using Systematic Literature Review (SLR), this paper reviews 66 studies, comprising of studies that employed ANN with or without another training algorithm(s), and those that employed evolutionary algorithm (EA) of any type for real time reservoir operations optimization. From this, it highlights the necessity of using ANN and the suitability of EA as a training algorithm. This paper, from the meta-analysis of the studies reviewed, shows that, though ANN is primarily suitable for real time forecasting, the best network architecture is the real-time recurrent learning (RTRL) neural network algorithm. And, ANN supported with supervised or unsupervised learning algorithm, has better performance potential than those singly used. Also, evolutionary algorithms are presented as viable supporting training algorithms capable of extrapolating data of deeper abstraction, complex uncertainty, with consistent predictive capacities.

Keywords: *artificial neural network, evolutionary algorithm, multi-objective framework, real time optimization, systematic literature review*

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1. Introduction

The need to manage water resources variations, especially in reservoirs, using hydrological structures is inescapable. Reservoirs, defined as formed or modified water bodies for specific purposes [1], always demand operations that are usually executed for the accomplishment of its primary purposes [2,3]. These include water supply for domestic and industrial use, power generation, agricultural irrigation, flood control, recreation, and waste disposal, in few instances [1,4]. The reservoir operations are, therefore, generally managerial and technical activities that are carried out, daily or periodically, in the handling of reservoirs, and most importantly, in achieving its purposes [3,5]. These reservoir operations differ and correspond to the design purpose(s). For instance, the details of the operational activities involved such as planning, design, implementation and monitoring, and the associated data needed for decision making in the operation of hydropower generating reservoir is different from that of irrigation-aiding. Multi-objective reservoirs are, however, reservoirs designed for more than one objective [2,4]. On another end, real time reservoir operations are operations whose variables (water discharge, sediment discharge, rainfall runoff, ground water flow, precipitation and water quality) are necessarily captured in real time for accurate decision making [6].

The need and process of optimizing real time reservoir operations have attracted substantial research attention, and numerous works have been published on both the process-driven and data-driven approaches. Process-driven optimization process, like reservoir operation rule curve [4,7,8], deals with enhancement of the regimented approach in the long-term operation guideline and policy. The data-driven, on the other hand, optimizes the reservoir operations based on the associated data variables with the aid of computational models [9,10,11]. The data-driven approach has been the most challenging due to event uncertainties, data varieties and the velocity of its changing and update [12,13]. Nonetheless, designing and implementing computational approaches to optimizing real-time reservoir operations have been largely data-driven and more advantageous over the process-driven approaches because of their abilities of strong linear mapping, uncertainty handling, and learnability [14].

Artificial Neural Network (ANN), as later shown in this work, is observed as the most prominently-used computational model in the data driven approach to optimizing reservoir operations. ANN, which has been applied in diverse fields, such as medicine, finance, management, engineering, among others [2,4], is also attracting considerable interest in reservoir operation optimization, with record of substantial studies published in this regard [8,12,15,16]. In the same vein, several studies have been conducted on the need to enhance ANN and continuously support its workability with other algorithms [17,18], which, in our case, is evolutionary algorithm (EA).

EA, consisting of different heuristics, solves optimization tasks through the emulation of certain aspects of natural evolutions. Similar to ANN, EA uses different levels of data abstraction but always works on whole population in proffering solutions to a given task [19,20]. It seamlessly learns additional problem details, and uses this for its performance improvement [21]. EA can also be applied to a wide range of domain problems, and can optimize the target function. These abilities are the considerable factors that endeared the usage of EA as supporting algorithm in computational optimization methods [20,22].

This paper, using a Systematic Literature Review (SLR) approach, presents the necessity and viability of a novel computational model of ANN, and EA as a suitable supporting algorithm in training ANN for multi-objective framework in real time reservoir operations optimization. This work, in sum, identifies the best ANN architecture for real time forecasting, and proposes that ANN can efficiently and effectively be trained with EA for optimized real time reservoir operations. The next section of this paper describes SLR, which is the research methodology employed in this study. The third section presents the findings, which serves as the answers to this study's research questions, and the fourth section presents the conclusion.

2. Methodology: Systematic Literature Review (SLR)

The research questions posed by this study are (a) what is the best ANN's architecture for real time forecasting, and (b) is EA a supporting algorithm suitable for the training of ANN for a multi-objective framework of real time reservoir operation optimization? In answering these questions, SLR, being a structured literature review approach, is employed.

SLR is described as a structured method to identify, evaluate and interpret available information, in view of engaging a research topic, and answering research questions in a preliminary study [23,24]. It presents a systematic way of summarizing empirical evidences for meta-analysis. By defining a review protocol and specifying the topic to be researched, SLR presents a customized approach to literature review that leads to valid and reliable findings. The three main phases in SLR, which are also adapted in this study, are (a) planning the review, (b) conducting the review and (c) reporting the review [24]. Figure 1 depicts the SLR research design.

2.1. Planning the Review

The researcher outlines the necessary requirements for the collation of broad and objective information, which will be critiqued to provide insights to the research topic, or answer the research questions. In this study, Google Scholar was chosen as the indexed literature repository because it supports open access and presents vast amount of literature. The search strings used are (a) computational methods for real time reservoir operation optimization, and (b) evolutionary algorithms for real time reservoir operation optimization. These are used in identifying primary sources of information that exclusively treat the subject and suitable for meta-analysis in order to achieve an unbiased result.

From the search, a total number of 131 published articles were gathered from the order of the results presented by the Google Scholar Search Engine. The conceptual articles on (real time) reservoir operations and articles on computational methods in reservoir operations, but with no case study, modelling and simulations, were then excluded. This is to provide, most importantly, attention to articles that have implemented any computational model for reservoir operation optimization. After the sorting and filtering, a total of 66 articles were left. These articles were then categorized into two, with each article openly coded for identification and tracking. The categories are: (a) 52 articles that employed ANN, singly or supported with any other computational model, and (b) 14 articles that employed any other computational model aside ANN.

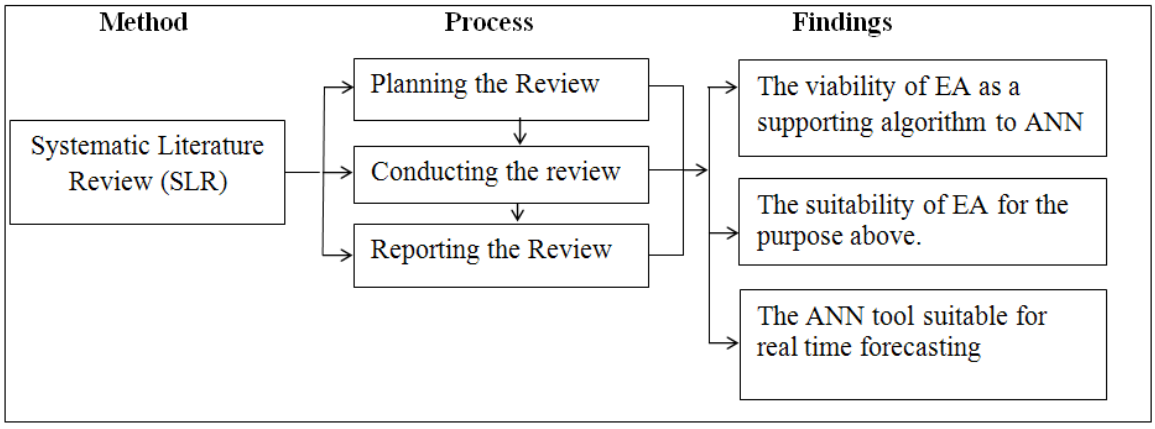

Figure 1. SLR Research Design (as adapted)

2.2. Conducting the Review

Table 1. PICOC Review Method

Population	Artificial Neural Network; Evolutionary algorithm; real time reservoir operation optimization
Intervention	Presenting the viability of EA as a supporting algorithm to ANN, and the details of ANN suitable for real time forecasting.
Comparison	Compare between: 1. Studies that employed only ANN and those that combined it with any other algorithm. 2. Studies that employed only EA and those that combined it with any other algorithm.
Outcome	(a) The prominence of ANN as a data-driven computational model for real time reservoir operation optimization, (b) The viability of EA as a supporting algorithm to ANN, and its performance improvement potential, and (c) The specific ANN tool used for real time forecasting.
Context	Understanding diverse applicability of ANN in reservoir operation optimization, and the viability and necessity of supporting it with EA in a multi-objective framework for real time reservoir operation optimization.

Ahmed and Naomie [23]'s Population-Intervention-Comparison-Outcome-Context (PICOC) format is used in conducting the review. The articles' general theme, as shown by the search strings used, is described by the population. The intervention is the converging point for each of the sub-theme as related to the research questions. The comparison is the contextual comparison of the articles, as related with their respective meta-analysis. Lastly, the outcomes are the final findings drawn from the review and the conclusions reached. The PICOC review method, as it relates with this study, is presented in Table 1.

2.3. Reporting the Review

The review is reported step-by-step to highlight results in view of answering the earlier posed research questions. These findings are presented in the next section of this paper.

2.4. Findings

The articles were reviewed on one-by-one basis by identifying the overall issue attended to, the objectives and the results. Table 2 and 3 present summaries of the articles reviewed under the 2 categories as earlier mentioned.

Table 2. Summary of the articles that employed ANN, singly or supported with any other computational model

Open Code	References	Overall Issue	Objective(s)	Results
1	Hammid, Sulaiman [25]	Hydropower production for developing countries to meet the power request and load	To predict power performance of the hydropower plant at the Himreen lake dam-Diyala using the net turbine head, flow rate of water and power production	ANN predicts the performance of the plant, using correlation coefficient of R between predicted and observed output which is higher than 0.96.
2	Mustafa, Isa [26]	Water resource engineering, with river sediment and discharge as variables in predicting sediment estimation.	To present an appropriate training model for ANN to predict sediment estimation.	ANN modelling is reported as a better method in water resources engineering, especially if compared with other conventional modelling techniques.
3	Haddad and Alimohammadi [5]	Evaluation of optimization model (ANN specifically) in reservoir hydropower operation	To evaluate ANN for the optimum operating rule of a hydropower system through (a) system performance checking and evaluation, and (b) computing performance.	The results showed that ANN and simulation model, such as stochastic dynamic programming (SDP), have close optimum releases of reservoirs.
4	Rani and Parekh [17]	Water resource management: Forecasting water level	To propose an ANN model, considering daily water inflow data in forecasting reservoir water, water level, and release.	Feed Forward Backpropagation, in ANN, appropriately predicted the real time water level.
5	Chang, Chang [27]	Intelligent modelling for reservoir operations management	To develop an intelligent control system for reservoir operation with the use of genetic algorithm (GA), a fuzzy rule base (FRB) and ANN.	The results demonstrated (1) the efficiency of GA in searching for optimal input-output patterns, (2) the ability of FRB in extracting knowledge from the operating rule curves, and (3) adaptive network-based fuzzy inference system (ANFIS) models, as a variegate of ANN, is built on different types of knowledge. Based on this, ANFIS performs better than traditional M-5 curves.
6	AbdulKadir, Salami [28]	Forecasting reservoir storage for hydropower dam operation	To present the operation of hydropower reservoirs through forecasting their future storage using Neural Network (NN) model.	The values of correlation coefficient suggested that the model fairly fit the variables and can subsequently be used for prediction of reservoir storage for operational performance.
7	Deshmukh and Ghtol [29]	Application of ANN in solving hydrological problems	To develop an ANN model for forecasting flood	The results indicated that Time lagged recurrent neural network has a satisfactory performance measured by its three hours ahead of time prediction.
8	Diamantopoulou, Georgiou [30]	Reservoir operation, scheduling, and planning: making accurate prediction of the water inflow	To forecast real time reservoir inflow.	The models have the ability to forecast peak reservoir inflows with great accuracy in developing a generalized solution to overcome the problems of outliers and noise in the data record of daily reservoir inflows.

Open Code	References	Overall Issue	Objective(s)	Results
9	Campolo, Soldati [31]	Hydrology: Flood forecasting to stem the incessant flood experience in the River Arno in Italy	To propose a forecasting model for predicting flood and water-level in the Arno Basin.	The model is suitable for flood forecasting.
10	De Farias, Santos [32]	Derivation of operating rules in Reservoir operations management.	To develop reservoir hedging rules relating end-of-period reservoir storage to initial storage and other system variables using implicit stochastic optimization (ISO) and ANN.	The ISO-ANN rules were shown to be superior to the Standard Linear Operating Policy (SLOP) and equivalent to the results derived by deterministic optimization taking the same inflows as perfect forecasts for one year ahead.
11	Joorabchi, Zhang [33]	Reservoir management, especially, flow discharge (also known as flood).	To predict a four-day ahead discharge flow of a river with the use of feed-forward neural network and error back-propagation as a learning algorithm.	The models presented an accurate prediction of flow discharge during flood events. It, however, also showed that ANN overestimates during low discharge with a mean value of 80 m^3/s.
12	Valizadeh, El-Shafie [34]	Reservoir and stream operation management: Forecasting the water level	To define the different artificial neurofuzzy interface system (ANFIS) for the prediction of the water level of the two case studies.	The best result in the ANFIS models is due to the membership functions (MFs) that have smoothness characteristics and mathematical components.
13	Khare and Gajbhiye [3]	Analysis of the limitations of traditional methods of optimizing reservoir operations in comparison with ANN.	To compare the functionality of linear regression with ANN in derivation of reservoir operating policy.	ANN can effectively approximate a nonlinear relationship between the output and input.
14	AbdulKadir, Sule [35]	Hydropower reservoir operation management	To predict water storage level of the hydropower reservoir using ANN.	The trained networks yielded good forecast of training and testing set. Correlation coefficients of 0.64 and 0.79 were obtained.
15	Ehsani, Fekete [36]	Multi-objective/Comprehensive reservoir operation.	To develop a new usage model of ANN in mapping the general input/output relationship in the actual operating rules of dams.	ANN model has the ability for a largescale hydrological modelling and simulation of reservoir operations.
16	Yadav, Naresh [18]	Stream flow forecasting in water resource operations management. Hydrological modelling generally needs forecasting future events.	To forecast daily inflow of water to prevent flood.	This study shows the ability of neural network prediction model to forecast, quite accurately, ten-day inflows of two years ahead and generate synthetic series of ten-day inflows in a multipurpose context.
17	Nohara, Sumi [37]	Reservoir sedimentation in reservoir management	To develop a real time prediction model of sediment inflow for operational efficiency of a sediment bypass tunnel.	ANN model showed better performance than Multivariable Linear Regression (MLR) model, particularly in relations to time series predictability.
18	Jain, Das [38]	Reservoir inflow prediction using ANN	To predict reservoir inflow and guide operational decision using ANN	The inter-comparison results shows that the ANN is a powerful tool for mapping input-output and can be efficiently used for reservoir inflow forecasting and operation.
19	Suryawanshi, Gedam [39]	Reservoir operation management, specifically, the water storage level to mitigate the experience of flood and drought.	To develop an inflow forecasting model	The observed and computed depths of runoff are more or less matching with peaks as well as time. Hence, it can be concluded that the design, and the training, validation and testing of the ANN network is quite satisfactory.
20	Hung, Babel [40]	Rainfall forecasting in water resource management	To present a novel methodology making use of an Artificial Neural Network technique for improving the performance of rainfall forecast.	The preliminary tests showed that the best generalization of rainfall is achieved using a generalized feed forward ANN model using hyperbolic tangent transfer function.
21	[41]	Water resource engineering: Alteration of sediment natural flow.	1) To simulate four catchments using artificial neural network (ANN) monthly average SSL (SSLm); 2) assessing the calibrated ANN (Cal-ANN) models application in three ungauged catchment representatives (UCR).	ANN generated a satisfactory results with determination coefficient (R^2) ranging from 0.81 to 0.94 in calibration stage and 0.63 to 0.87 in validation stage.
22	[17]	Reservoir water level forecasting to help in the water storage capacity management for irrigation, water supply, and hydropower.	To define ANN model through the application of different types of network tools like feed forward distributed time delay, layer recurrent and NARX on of input data sets to forecast the 10-day ahead water level for the case study.	ANN using feed forward distributed time delay is appropriate in predicting real time water level forecasting.
23	[42]	Water resource engineering: Prediction of daily river level to avert disaster by serving as early warning system	To develop and compare different models of ANN.	This method has the potential for developing early warning systems for the prevention and response to disaster in cities that are located beside the river valley in Colombia.

Open Code	References	Overall Issue	Objective(s)	Results
24	[43]	Water resource management: To surmount the challenge of obtaining accurate river flow discharge	To develop and test feed forward neural network architectures improved with two algorithms namely Levenberg-Marquardt and resilient back-propagation.	The accuracy in river flow discharge prediction can be improved by feed forward neural network optimized with Levenberg-Marquardt algorithm with sigmoid function in hidden layer and linear activation function in output layer.
25	[44]	Comparative study of ANN architectures in water distribution prediction to identify the best suit for temporal memory.	To evaluate certain ANN architectures (multilayer perceptron, mixture density network, time delay network and recurrent network) for water distribution flow time series prediction.	ANN with genetic algorithm for optimization purpose showed that the recurrent network is generally superior.
26	[45]	Flood prediction using Monte Carlo Statistical Blockade	To predict flash flood and other extreme rare events using Monte Carlo Statistical Blockade (SB).	ANN is a superior model in Beas Basin in the prediction of peak floods especially in the monsoon season, and SB method has shown its ability in offering better predictive accuracy to finding the peaks over a given threshold.
27	[46]	Early warning system for flood disaster prevention	To develop a prediction model in real time based weather radar data and/or rainguage rainfall data.	ANNs can provide a very significant speed improvement over conventional hydrodynamic simulators without excessively degrading the performance.
28	[47]	Reservoir water management: forecasting model	To demonstrate the application of ANN in development of forecasting model for changing the reservoir water level stage.	ANN model, with 4 days of time delay, produced the acceptable performance with both low error rate and high accuracy.
29	[48]	The use of ANN in river discharge prediction.	To develop a forecasting model using ANN.	A model makes use of both the seasonal expectation of the observed discharge and the rainfall index as additional inputs, shows the best performance.
30	[49]	Using ANN for controlling real time spillway gates operation of reservoir during high inflow of flood	To develop an ANN model to be used in training the hydrological data.	The control through neural network produces smoother outflow hydrographs than those gotten from actual controlled outflow.
31	[14]	Reservoir monthly inflow forecasting for operational decision making.	To develop a hybrid model for the forecasting of monthly inflow of a reservoir.	The results comparatively showed that three models have satisfactory performances in the prediction of monthly inflow, and the hybrid method (ANN, GA and Support Vector Machine (SVM)) performs better than individuals.
32	[50]	Reservior inflow forecasting in real time as part of necessary reservoir management operations.	To introduce an early stopped training approach (STA) to train multi-layer feed-forward neural networks (FNN) for real time reservoir inflow forecasting.	The real time forecast accuracy. Generally, the results show that the method proposed is effective to improve prediction accuracy. Moreover, it is an alternative in dynamic adaptive forecasting.
33	[51]	Using simulation model for valuable planning in reservoir management practices.	To present an integrated model of data-driven model (ANN), stochastic model and simulation.	The model performance showed that the ANFIS and the proposed stochastic model are useful methodology for reservoir management in the case study.
34	[52]	Managing unregulated downstream flows of the dam to attend to water sufficiency using prediction method.	To use Artificial Neural Network (ANN) model in forecasting one and two time steps ahead river flows.	In terms of R^2, both methods perform well but generally GRNN models give lower RME and MAE values showing their superiority when compared with MLP models.
35	[5]	Optimization of reservoir operations using simulation method	To use stochastic dynamic programming (SDP) as the optimum operating rule of a hydropower system.	Optimum releases of reservoir in both ANN and simulation models are very close. The combination of ANN and SDP presents a better result.
36	[53]	River forecasting using artificial neural network	To develop an indicator river flow forecasting system using ANN	L-M (Levenberg-Marcquart) algorithm is more efficient than CG (conjugate gradient) algorithm in training the ANN model.
37	[12]	Wetland management: Usage of ANN in predicting marsh land restoration in view of supporting inhabitant and aquatic life in wetland.	To present an intelligent model, based on ANN, to predict different long term (5, 10 and 15 years) restoration process.	The ANN application for marsh restoration using a network structure of 9:9:1 (input: hidden: output) devours the capacity of successfully simulating marsh restoration process with a regression coefficient of 99.8% and root mean square error of 0.88.
38	[13]	Derivation of operating rule for irrigation supply reservoir	To apply NN approach to derive the reservoir operating rule.	Neural Network with dynamic programming presents satisfactory results.
39	[11]	Hydrological engineering	To present a ANN model (Levenberg-Marquardt Back Propagation (LMBP) algorithm) developed to forecast inflow of long term reservoir using monthly inflow available data	The network could forecast the testing data set with the accuracy of MSE = 0.0283. The process of training and testing showed 0.7282 and 0.7228 as the correlation coefficient respectively.

Open Code	References	Overall Issue	Objective(s)	Results
40	[54]	Streamflow generation in reservoir management	To present a multivariate streamflow generation based on multilayer feedforward neural network	It was shown in the results that NN represents a promising modelling alternative for the purpose of simulation, with interesting potential in the water resources systems management and optimisation context.
41	[9]	Operating rules for global hydrological model	To derive fuzzy rules describing the way a reservoir is operated using the information of inflow to the reservoir and storage levels.	The release from relatively large reservoirs was significantly dependent on information concerning recent storage levels, while release from smaller reservoirs was more dependent on reservoir inflows.
42	[10]	Machine learning (of ANN) using information-rich data.	To train ANN model using the data depth function as a tool for identifying critical (information) segments in a time series.	A conceptual guide on the training of data-driven models where the training time series is not complete.
43	[22]	Intelligent models for reservoir operation management	To present a novel intelligent reservoir operation system centred on evolving artificial neural network (ANN).	The results demonstrated that the developed model (ANN and GA), being an evolving neural networks, improved the reservoir operation performance compared with its current operational strategy.
44	[55]	Reservoir operation management	A non-linear programming (NLP) model is developed and applied to certain hypothetical water resource systems.	It was shown in the result that a significant improvement in the generalized reservoir release neural network performance can be achieved using time lagged inputs of inflow and demand with ANN improved by Monte Carlo as NLP.
45	[56]	Problem of computational prohibition of incorporating simulation into optimization models.	To train a back propagation neural network to approximate the simulation model developed.	The results are further refined using the conventional simulation-optimization model.
46	[57]	Intelligent modelling for reservoir operation management	To propose the use of discrete wavelet transform (DWT) for removing the components (details) of high-frequency of an original signal, because the noises generally present in time series (for example, streamflow records).	Transformed signal is being used as input for an ANN model for forecasting inflows seven days ahead, and *RMSE* decreased by more than 50%.
47	[58]	Model-based optimization of water resource engineering processes	Model-based optimization is described and applied to solve multi-criterial decision making (MCDM) problem.	The presented method is suitable for modelling approximation in various water resources schemes optimization, with particular reference to ANN model.
48	[19]	Forecasting to aid reservoir operations management.	To propose a model that combines quantum-behaved particle swarm optimization (QPSO) with artificial neural network (ANN).	The method proposed for forecast accuracy is much better than the basic ANN model, and the QPSO algorithm (used in training ANN) is an alternative training technique for selecting ANN parameters.
49	[21]	Modelling for rainfall-runoff using meta-heuristic techniques.	Calibrating data-driven rainfall-runoff models for improving forecasting accuracies making use of meta-heuristics techniques.	The information and analyses can contribute to developing and implementing effective hydrological predictions, and thus, of appropriate precautionary measures.
50	[59]	The ANN forecast models poor performance was mainly because of the existence of the lagged prediction.	To improve the estimate of daily flow from a reservoir through an experimental process that involves three data processing techniques.	ANN-MA performed best and eradicated the lag effect.
51	[60]	Model for multipurpose reservoir real time operation.	Developing a reservoir real-time operation (RES-RT) model for determining the optimal real time release during a typhoon.	RES-RT model has produced a much better performance for all scenarios in reducing the peak flow at the downstream control point and meeting the target reservoir storage at the flood ending.
52	[61]	Real time flood control during Typhon	Developing a multi-phase intelligent real time reservoir operation model for controlling flood.	From the result of comparative operation, the RTRLNN-3P model is better than historical operations and RTRLNN-2P.

From Table 2 presented, ANN had been applied to many different aspects of reservoir operation management to execute varying tasks, but with a unifying purpose of predictive analyses. Hydropower performance [5,25,28] among others, river sediment estimation [26,37] among others, water inflow and level and flood forecasting [17,18,29,33,34,35] among others, marsh land restoration [12] and reservoir control system [27,32,36] among others are the reservoir operations identified from the review. Studies that are not task-based experimented and evaluated the performances of different ANN models [59], optimized traditional ANN model [56,57], and compared ANN models with traditional linear models [3].

Out of the 52 studies reviewed above, 27 employed ANN with supporting algorithms in training the data, while 25 solely employed ANN. The supporting

algorithms/models recorded are linear regression, Monte Carlo, particle swarm optimization (PSO), non-linear programming model (NLP), genetic algorithm, fuzzy logic, Levenberg-Marquardt, dynamic programming (DP), conjugate gradient (CG), stochastic dynamic programming (SDP), stopped training approach (STA), support vector machine (SVM), Monte Carlo statistical blockade (SB), multivariable linear regression (MLR) model, and implicit stochastic optimization (ISO). Although ANN is principally suitable for real time data-driven learning model, studies that explicitly demonstrated the capacity employed feed forward [17,50], and recurrent network [60,61] as their network architectures. Notably, studies that employed recurrent network [60,61] as their network architectures employed ANN for multi-objective framework and provided a better performance result. Table 3 presents the summary of articles that employed other computational model aside ANN.

Table 3. Summary of the articles that employed any other computational model aside ANN

Open Code	References	Overall issue	Objective(s)	Results
53	[6]	Reservoir operation management, specifically, the need to evaluate the tradeoff in managing and regulating water flow and demand, during drought and rainfall.	To present comparative review of optimization models, and suggests artificial bee colony (ABC).	ABC is preferred because it is very sensitive to the control parameters values compared to other existing stochastic algorithms including genetic algorithm (GA).
54	[62]	Concrete dam management through earlier detection of dam cracks.	To improve the cracks extraction shortcomings and deficiencies making use of a classification algorithm under crack detection system.	A new data field clustering method for classifying concrete dam cracks.
55	[63]	Optimization of water resource management	To identify near optimal designs in water treatment works using static and dynamic model and genetic algorithm	The dynamic model predicted more conservative designs than the static model.
56	[64]	Reservoir operation management	Developing a short-term (such as, daily) flow forecasting models.	A multivariable linear regression which is formulated as a function of upstream gauge stations, making use of antecedent flows, showed strong relationships (such as, having r^2 (coefficient of determination) and *RMSE* (root-mean-square deviation) of approximately 0.93 and 14 m^3/s, respectively).
57	[8]	Reservoir operation management	To propose ice flood control policy that optimizes tradeoff between hydropower generation and ice flood control requirements.	The results indicated that the rules of optimal operation are more efficient in balancing the benefits within the power generation and control of ice flood.
58	[7]	Comprehensive and generic approach to multi-purpose reservoir operations	To propose a release rules generic framework for control operation of reservoir flood during three stages.	The optimized rules satisfied objectives of operation such as dam safety, flood mitigation, smooth operation and achieving sufficient end-of-operation storage for conservation purposes.
59	[65]	Multi-reservoir system operation using particle swarm optimization algorithm	To propose an improved hybrid particle swarm optimization (IPSO) algorithm for optimizing hydroelectric power scheduling in multi-reservoir systems.	The IPSO algorithm scheduling results were found to outperform PSO and comparable with the results of the dynamic programming successive approximation (DPSA) algorithm employing PSO with GA.
60	[66]	Optimization algorithm for streamflow forecasting	To propose a procedure for real-time update for forecasting streamflow in HEC-RAS model.	An efficient improvement of the model performance for forecasting stream flow and reducing negative effects due to simulation lag errors.
61	[67]	Optimization of reservoir operations for hydropower energy production.	To propose an improved GA algorithm (with stochastic programming/operators) in solving the problem of traditional GA.	The proposed modified GA improves the quality of the solution when compared with GA adopting a penalty function or pair-wise comparison in constraint handling.
62	[68]	Optimization of reservoir operation	To present a novel model using a hybrid of genetic algorithm (as an evolution algorithm) and simulated annealing (SA) with the aid of fuzzy programming.	The results demonstrate that: (1) fuzzy programming could effectively formulate the reservoir operation scheme into degree of satisfaction among the users and constraints; (2) the hybrid GA-SA performed much better than the current M-5 operating rules.
63	[69]	Multi-objective reservoir operation management with optimization algorithms.	To propose an improved genetic algorithm-simulated annealing (IGA-SA).	GA is reported as a better algorithm to DP. And, SA has better performance than GA and the IGA-SA is more efficient than SA and GA-SA in cost effectiveness and computation time.
64	[70]	Genetic algorithm as optimization method for reservoir systems.	To evaluate several alternative formulations of a genetic algorithm for reservoir systems using the four-reservoir, deterministic, finite-horizon problem.	A genetic algorithm is satisfactorily used with stochastically generated inflows in real time operations.

Open Code	References	Overall issue	Objective(s)	Results
65	[71]	Reservoir operation optimization.	To enhance the efficiency of deterministic dynamic programming (DP) and stochastic dynamic programming (SDP) for reservoir operation with concave objective functions.	An improved DP and SDP have higher computational efficiency than conventional DP and SDP.
66	[72]	Dynamic operation for reservoir operation management.	To develop two novel algorithms (improved dynamic programming (IDP) and improved sampling stochastic DP (ISSDP)) using their monotonic relationships.	IDP and ISSDP are useful tools in controlling flood control, testing different flood scenarios, and determining the optimal decisions.

Studies on optimization of reservoir operation, as shown in Table 3, are on concrete dam crack detection [62], optimal design of water dam [63,72], daily flow and flood forecasting [64,66], hydropower performance [8,65,67], and reservoir control system [7]. The computational models used by these studies are dynamic programming (DP), improved sampling stochastic DP (ISSDP), stochastic dynamic programming (SDP), genetic algorithm-simulated annealing (IGA-SA), dynamic programming successive approximation (DPSA) algorithm, particle swarm optimization (IPSO) and artificial Bee Colony (ABC). In these cases, studies on real time and/or multi-objective optimization [65,69] employed PSO, GA and SA. From the summaries presented in Table 2 and 3, and the accompanying reviews, the research questions earlier posed by this study are therefore answered.

a) What is the best ANN's network architecture for real time forecasting?

The best ANN's network architecture for real time forecasting is the real-time recurrent learning (RTRL) neural network algorithm, which was firstly proposed by Williams and Zipser [73]. The comparative studies conducted by Hsu, Huang [61] (review presented in Table 2; Open tag 52) reported that RTRL performed better, among others, for multi-phase intelligent real-time reservoir operation model.

b) Is EA a supporting algorithm suitable for the training of ANN for a multi-objective framework of real time reservoir operation optimization?

EA is suitable as a supporting algorithm for the training of ANN as a multi-objective framework for real time reservoir operation optimization. This is so, according to the reviews presented in Table 2 and Table 3, based on the following. First, ANN is a computational model that works better with supporting algorithm for the training of its input data nodes for supervised and unsupervised learnings. From the review presented in Table 2, 27 out of the 52 studies presented employed supporting algorithm, and the findings reported comparatively showed that studies that employed supporting algorithms dealt with data of deeper abstraction, complex uncertain events, and produce consistent predictive capacities. Second, particle swarm optimization (PSO) and genetic algorithm which are leading EA algorithms, are recorded in 12 studies, either supporting ANN or another computational model for real-time optimization of reservoir operation. Third, studies that employed recurrent network [60,61], acclaimed as the best ANN architecture, used it for multi-objective framework. There is also record of studies [65,69] (in Table 3) that employed an EA algorithm for multi-objective framework.

3. Conclusion

A multi-objective optimization framework must therefore be able to attend to more than one, if not all, of the reservoir operation objectives which can be mainly classified into hydropower performance, river sediment estimation, water inflow and level and flood forecasting, marsh land restoration, and reservoir control system. In each of these objectives, the data variables and the weighing parameters to be modelled for the respective computational purpose is different, and this would inform the choice of the computational model and any of the supporting algorithms. The choice of the computational model is basically determined by the details of the reservoir operation policy intended to be modelled.

In a real time, multi-objective optimization framework for reservoir operations, ANN has been extensively employed, with or without supporting algorithm for the training of its data for supervised and unsupervised learning. It has, however, shown that, even though ANN is primarily a robust algorithm for real time multi-objective optimization, it works better with training algorithm and EA's usage in this regard has recorded consistent predictive quality for any of the objectives.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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