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The Need for Recurrent Learning Neural Network and Combine Pareto Differential Algorithm for Multi-Objective Optimization of Real Time Reservoir Operations

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ABSTRACT

Reservoir operations need computational models that can attend to both its real time data analytics and multi-objective optimization. This is now increasingly necessary due to the growing complexities of reservoir's hydrological structures, ever-increasing its operational data, and conflicting conditions in optimizing the its operations. Past related studies have mostly attended to either real time data analytics, or multi-objective optimization of reservoir operations. This review study, based on systematic literature analysis, presents the suitability of Recurrent Learning Neural Network (RLNN) and Combine Pareto Multi-objective Differential Evolution (CPMDE) algorithms for real time data analytics and multi-objective optimization of reservoir operations, respectively. It also presents the need for a hybrid RLNN-CPMDE, with the use of CPMDE in the development of RLNN learning data, for reservoir operation optimization in a multi-objective and real time environment. This review is necessary as a reference for researchers in multi-objective optimization and reservoir real time operations. The gaps in research reported in this review would be areas of further studies in real time multi-objective studies in reservoir operation.

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1. Introduction

Reservoirs, being formed or modified water bodies, are of great economic importance, and largely instrumental to environmental (human and aquatic) safety [1,2]. To this end, reservoir purposes, which include power generation, water supply for industrial and domestic uses, flood control, recreation, agricultural irrigation, and also disposal of wastes on few occasions [3], must be duly optimized for effective performance. Many related studies have been conducted in view of optimizing reservoir operations. A three-stage generic framework of release rule for reservoir [4,5], dynamic rule curves multipurpose reservoir involving flood control [6,7], water flows network modeling system [8,9] real time flood control [9,10] and evolutionary algorithms for reservoir operations optimization [11,12] among others, are some of these studies. These studies made remarkable contributions, such as the storage at the end of operation which is useful for conservation and reservoir operations [5], secured downstream reservoir operation [6], synthetic stream flow and reservoir regulation (SSARR) models for irrigation return flows [8]. Many of these studies [13–15] are for singular objectives, with few on multi-objective optimization of real-time reservoir operations [10,16], using different algorithms, including but not limited to recurrent learning neural network (RLNN).

RLNN is an ANN type of architecture with a self-feedback loop and hidden neurons. Single-layer feedforward and multilayer feedforward networks (also known as multilayer perceptron) are other types of ANN architecture [17,18]. Fundamentally, ANN, modelled after the information processing mechanism of human brain and neurons, is a parallel and massively simple processing units from distributed processor. In mimicry of human brain, the knowledge of the environment is acquired by a learning process and stores the acquired knowledge using interneuron connection strength which is known widely as synaptic weight [17,19]. It is mainly partitioned into three layers; namely, input, hidden and output layers as found in Figure 1.

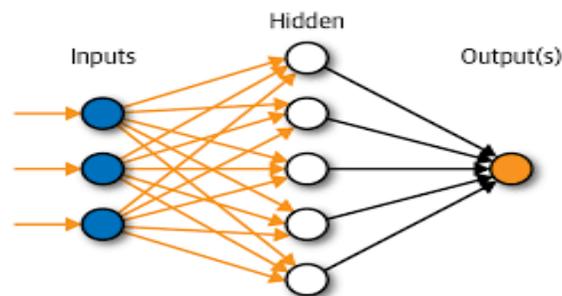


Fig. 1. Structure of ANNs [17].

ANN, unlike stochastic models which are process-driven, is a data-driven model, and thus capable of dealing with uncertainties in events, varieties of data, and the frequency and the velocity of data update [20]. It also has strong linear and non-linear mapping, environmental adaptability and learnability [21]. Different criteria used to design tuned mass damper in high-rise building were compared [22]. The study considers the soil-structure interaction effects. In another study, shear contribution of fiber reinforced polymer was predicted in reinforced

concrete beams that are strengthened [23]. The modeling used multigene genetic programming. The study produced competitive results showing the efficacy of the algorithm to beam design. A fuzzy inference system was successfully used to evaluate building designing process [24]. Other examples of applications of optimization to real life situations are provided [25] with an application of NSGA-II and DANN model having successful applications [26]. The study by [18] presents the use of ANN to predict the mortar compressive strength. Adaptive neuro-fuzzy was implemented to adjust the behavior of training data in a new study [27].

RLNN has been applied in diverse fields and its extensive application in reservoir operation optimization has received considerable attention [28]. Combine Pareto Multi-objective Differential Evolution (CPMDE), on the other hand, is an evolutionary algorithm, and of different metaheuristics. Evolutionary algorithms (EAs), generally, are computational methods modelled after natural theory of evolution. The algorithms comprises of a two way steps where selection follows random variation [29,30]. CPMDE works with specified Pareto methods for multi-objective optimization [31].

This study, as a preliminary contribution to real time multi-objective optimization solutions for dam operations, reviews the suitability of a hybrid algorithm of Recurrent Learning Neural Network (RLNN), as suitable ANN architecture, and CPMDE, as a Differential Evolution algorithm which can be further developed for real time operations. The next sections of this paper review past related studies, specifically the architectures of the neural network used in the reservoir operation optimization's studies. The third section further describes RLNN, as the identified most suitable type of ANN architecture, for optimizing real time reservoir operations. The fourth section describes CPMDE algorithm for optimizing multi-objective reservoir operations. The fifth section, as a conclusion, summarizes the need for the hybridization of RLNN and CPMDE algorithm for a multi-objective real time optimization of reservoir operations.

2. Review of past related studies

2.1. Neural network architecture for reservoir operation optimization

Studies in computational modelling of reservoir operations, in terms of time-based or discrete event system engineering, can be categorized into real and non-real time operations. ANN techniques of different architectures have been employed for varying objectives in solving the optimization problems of reservoir operations. Multilayer feedforward [4,20,32–39], backpropagation [38], recurrent learning neural networks [9,10] and single layer feedforward [19,40] are noticeable ANN architectures in this regard. The architecture of these ANN varies and invariably determine their suitability and performance for individual use cases.

Feedforward ANN, which are differentiated by the number of processing layers – single and multi, allows information movement in only one direction, without touching the node twice. Feedforward neural networks do not have memory; consider only the current input, and do not act with the order of time. Therefore, it is generally bad at predicting the next event.

Backpropagation architecture, on the other hand, describes a backward movement through the neural network in order to find some partial derivatives of the weights' errors in view of subtracting them from the weight. These derivatives are used by gradient descent which iteratively minimizes the error function. Thus, continuously train the data to identify the best fitness.

Recurrent learning neural network are suitable for sequential data, such as time-series data, video, speech and text in natural language processing. It is an ANN architecture with internal memory and thus can remember the important things about the inputs received. It has the ability of forming better context of understanding sequence compared to other algorithms because it can map input to output in a many-to-many. Recurrent neural network tweaks its weight through gradient descent and backpropagation through time (BPTT). Table 1 presents a review articles – systematically sought, sorted and collated – on optimization of reservoir operations for different tasks, using ANN. The review categorizes the studies into real-time and non-real-time optimization to highlight the type of ANN architecture employed, the reservoir operation designed for, and any supporting algorithm where applicable.

It is shown, from Table 1, that there are limited available studies on real time framework for reservoir operation optimization, when compared with non-real time studies. Bridging this scholarly gap is essential. More importantly, considering the evolving technologies for capturing reservoir data in real time, such as satellite altimeter and water level sensor, there is ease of decision making when such data is readily available for analysis and process optimization. Even though multilayer feed-forward network is mostly used in these studies, recurrent neural network is the network architecture fundamentally meant for real time optimization and performed better than multilayer feedforward network for real time optimization of reservoir operation [10].

3. Recurrent learning neural network for optimizing real time reservoir operations

RRLNN is an ANN algorithm built on the recurrent network architecture. Its synaptic weights are adjusted in real time, that is, as the network processes its signal. It has input-feedback layer with another processing layer comprising of computation nodes. The synaptic connections are feedforward and feedback structures. The description of its state-space is given in equations 1 and 2.

$$\mathbf{X}(n + 1) = \varphi(\mathbf{W}a\mathbf{X}(n) + \mathbf{W}b\mathbf{U}(n)) \quad (1)$$

$$\mathbf{Y}(n) = \mathbf{C}\mathbf{X}(n) \quad (2)$$

$\mathbf{W}a$ is a q -by- q matrix; $\mathbf{W}b$ is a q -by- $(m + 1)$ matrix; \mathbf{C} is a p -by- q matrix; and φ is the activation function, defined as amplitude limiting object of the output. Equation 1 and 2 are the process and measurement equations of the RRLNN model. In these, $\mathbf{X}(n)$ is the vector state of a nonlinear discrete-time system, $\mathbf{U}(n)$ is the input applied to the system, and $\mathbf{Y}(n)$ is the output of the system.

Table 1

Review of ANN-based Studies on Real-Time Reservoir and Non-Real-Time Operation Optimization.

	Reservoir operation	Network Architecture	Supporting algorithm (if applicable)	Reference
Real time	Forecasting water level	Multilayer feedforward	Feed Forward Backpropagation	[39]
	“Intelligent control system for reservoir operation”	Not indicated	“Genetic algorithm (GA) and a fuzzy rule base (FRB) programming”	[28]
		Multilayer feedforward	Genetic algorithm	[33]
	Prediction model for sediment inflow	Multilayer feedforward network	Multivariable Linear Regression	[41]
	Forecasting flood	“Real-time recurrent network”	Fuzzy rules applied in “Adaptive Network-based Fuzzy Inference System (ANFIS)”	[10]
		“Real-time recurrent network”	Genetic algorithm and Fuzzy rule	[9]
	Rainfall forecasting	Multilayer feedforward network	“Feedforward algorithm using hyperbolic tangent transfer function”	[32]
Hydropower energy	Single step evolving ANN	Particle Swarm Optimization	[42]	
Non-real time	Hydropower performance prediction	Single-layer perceptron	None	[19]
	Predicting sediment estimation	Multi-layer perceptron	Radial basis function in dynamic programming	[38]
	Forecasting reservoir storage for Hydropower dam operation	Multilayer feedforward network	None	[31]
		Multilayer feedforward network	Quantum-behaved particle swarm optimization (QPSO)	[21]
	Developing reservoir hedging/operating rules	Multilayer feedforward	Implicit stochastic optimization	[34]
		Multilayer feedforward	Dynamic programming	[20]
		Multilayer feedforward	Fuzzy rule	[4]
	Forecasting the daily flow discharge	Multilayer feedforward	“Feed-forward neural network and error Back-propagation learning algorithm”.	[43]
		Multilayer neural network	Linear and non-linear regression formulated through dynamic programming.	[44]
		Multilayer neural network	Genetic algorithm and Support Vector Machine	[21]
		Multi-Layer Perceptron	None	[45]
	Forecasting reservoir water level	Multilayer neural network	Fuzzy rule	[35]
		Multilayer feed-forward networks	None	[31]
	Reservoir inflow	Levenberg-Marquardt Back Propagation (LMBP) algorithm	None	[42]
	Simulating hydrological performance & activities	Not indicated	None	[46]
		Single layer feed-forward network	“Dynamic stochastic model with Thomas-Fiering model, and Hidden Markov Model (HMM)”	[46]
		Multilayer feed-forward networks	Backpropagation algorithm in a Hooke and Jeeves nonlinear programming model.	[36]
Water distribution prediction	Multilayer feed-forward networks	Discrete wavelet transform (DWT) for noise cleansing	[37]	

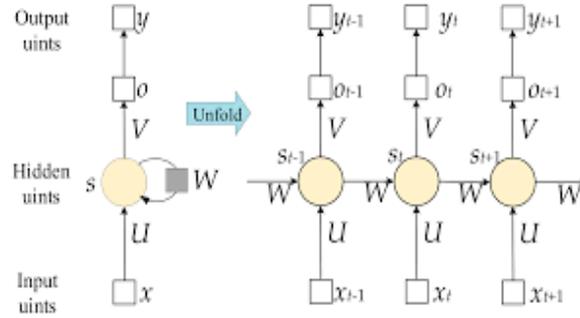


Fig. 2. Real time Recurrent Learning Neural Network [47].

In summary, the parameters for the real time recurrent learning algorithm are dimensionality of input space (m), dimensionality of state space (q), dimensionality of output space (p), and synaptic weight vector of neuron (nodes) (\mathbf{W}_j), where $j = 1, 2, \dots, q$. RRLNN is initialized by (i) setting the synaptic weights of the algorithm to selected small values from a uniformly-distributed range, (ii) setting the initial value of the state vector $\mathbf{X}(0) = 0$, and (iii) setting $\Lambda_j(0) = 0$, ($\Lambda_j(n)$ is defined as a partial derivative of the state vector $\mathbf{X}(n)$ when the weight vector is \mathbf{W}_j), for $j = 1, 2, \dots, q$.

The computation is for $n = 0, 1, 2, \dots$, where:

$$\Lambda_j(n) = \frac{\partial \mathbf{X}(n)}{\partial \mathbf{w}_j} \quad (3)$$

And, $\mathbf{U}_j(n)$ is a q -by- $(q + m + 1)$ matrix whose rows are all zeros, except the j th row, and $\Phi(n)$ is a q -by- q diagonal matrix, with k th diagonal element being a partial derivative of the activation function (φ).

Therefore, the computation to initialize $\Lambda_j(0)$ is:

$$\Lambda_j(n + 1) = \Phi(n)[\mathbf{W}a(n)\Lambda_j(n) + \mathbf{U}_j(n)] \quad (4)$$

$$\mathbf{e}(n) = \mathbf{d}(n) - \mathbf{C}\mathbf{X}(n) \quad (5)$$

$$\Delta \mathbf{W}_j(n) = \eta \mathbf{C} \Lambda_j(n) \mathbf{e}(n) \quad (6)$$

The core strength of RRLNN in its optimization of real time operations is the use of instantaneous gradient (denoted as $\Delta \mathbf{W}_j \xi(n)$) of the synaptic weight vector $\Delta \mathbf{W}_j$ (see eqn. 6), as against true gradient ($\Delta \mathbf{W}_j \xi_{total}$) used in non-real time optimization.

$\xi(n)$, the instantaneous sum of squared errors at time n , is defined in terms of $\mathbf{e}(n)$ (see equation 5):

$$\xi(n) = \frac{1}{2} \mathbf{e}^T(n) \mathbf{e}(n) \quad (7)$$

On another hand, for system stability during real time operation optimization, the learning parameter, η (see equation 6), could be made small enough that it makes time scale of the weight changes to be smaller than the time scale needed for the network operation. RRLNN, though being a computational model capable and sufficient for real time operation optimization, would

necessarily be supported by an evolutionary algorithm for a multi-objective operational framework.

4. Combine pareto differential evolution algorithm for optimizing multi-objective reservoir operations

CPMDE can be mathematically represented thus (see eqn.8).

$$x[t + 1] = s(v(x[t])) \quad (8)$$

The population at time t is denoted as $x[t]$, and operated on by random variation v . With the selection s , a new population $x[t + 1]$ is produced.

EAs conceptually simulate evolution of individual structures through selection, mutation and crossover processes. They maintain rule-based evolving population structures, with cross over and mutations as genetic operators [29]. EAs' application are recorded in a range of domain problems, and the target function is optimized [48,49]. Implementation simplicity, flexibility and robustness, and its no-need-for-derivative-information are the factors considered that informed the EA usage in some computational optimizations [33,50]. Most importantly, the strength of EAs when using it to solve some multi-objective optimization problems is responsible for its wide range of domain applicability.

In solving real world engineering problems, there are always several conflicting criteria and goals, and this characterizes multi-objective optimization. EAs are, however, meant to proffer adequate solutions for such conflicting multi-objective paradigms through optimization of the several conflicting criteria by searching for an optimal vector, and this is not used as a single value. The Pareto front is optimal solutions set; a non-dominated and non-inferior set of solutions that present as solutions to multi-objective optimization problems [31]. The multi-objective optimization problem, according to [50] in its general is presented in Figure 3:

1	Minimize/Maximize $f_m(x)$,	$m = 1, 2, \dots, M;$
	subject to	
2	$g_j(x) \geq 0,$	$j = 1, 2, \dots, J;$
3	$h_k(x) = 0,$	$k = 1, 2, \dots, K;$
4	$x_i^{(L)} \leq x_i \leq x_i^{(U)},$	$i = 1, 2, \dots, n;$

Fig. 3. Multi-objective Optimization Problem [50].

The solution is a variable vector with a corresponding objective vector. It is $\mathbf{x} \in \mathbf{R}n$ of n decision variables, where $\mathbf{x} = (x_1, x_2, \dots, x_n)^T$. The values $x_i^{(L)}$ and $x_i^{(U)}$ are corresponding lower and upper bounds for the variable x_i , respectively. Therefore, the solutions to satisfy the constraints (2) – (4), as shown above, is a possible decision variable space $\mathbf{S} \subset \mathbf{R}n$. The objective functions (1) constitute a dimensional space M , also called objective space $\mathbf{Z} \subset \mathbf{R}M$. There is a point $\mathbf{z} \in \mathbf{R}M$ in the objective space for each solution \mathbf{x} in the decision variable space. This is denoted by $\mathbf{f}(\mathbf{x}) = \mathbf{z} = (z_1, z_2, \dots, z_M)^T$. Multiple Pareto-optimal solutions, in solving multi-objective optimization, are therefore meant to discover values close to the Pareto

front as much as possible. It also needs to be as diverse as it can be in the non-dominated front obtained [50,51].

On another hand, in solving multi-objective optimization problems, DE is a simple but strong EA, which has been widely employed. Though DE was initially employed for single-objective optimization problems, it has now been successfully applied to multi-objective optimization problems [51–55]. The commonality in these DE approaches, however, is that new candidate solutions are created by combining the parent individual with other individuals within the same population. The new candidate only replaces the parent if it has better fitness, otherwise, it is discarded. It is an ambitious selection scheme that outperforms traditional EAs.

1	“Evaluate the initial population P of random individuals”.
2	“While stopping criterion not met, do”:
2.1	“For each individual $P_i (i = 1, \dots, popSize)$ from P repeat”:
(a)	“Create candidate C from P_i ”.
(b)	“Evaluate the candidate”.
(c)	“If the candidate is better than the parent, the candidate replaces the parent. Otherwise, the candidate is discarded”.
2.2	“Randomly enumerate the individuals in P ”.

Fig. 4. Outline of Differential Evolution Procedure [51].

CPMDE is a differential evolutionary algorithm and it works according to the generic procedural format of DE (as presented in Figure 4), to solve multi-objective optimization problem (as presented in Figure 2). It potentially outperforms traditional EAs, as typical of DE. Its novel workability in creation of candidate (see 2.1(a) in Figure 4), or new selection from each population generation, is by combining methods of Pareto ranking and Pareto dominance. These methods –Pareto ranking and Pareto dominance– are mostly singly used by past related studies. In Pareto ranking, ranks are assigned to every solution in both the trial and target population based on their non-domination levels. In doing this, solutions are selected with the best ranked for propagation to the next generation. In Pareto dominance, however, ranks are not assigned, but a winning solution at the dominance space moves to the next generation. CPMDE has been found to perfectly handle optimization constraints, provide diverse solution sets, and robust enough on tuneable problems [31]. The algorithm procedure of CPMDE is presented in Figure 5.

1	“Input the DE parameters required”.
2	“Randomly initialize all solution vectors within the limits of the variable bounds”.
3	“Set the generation counter, $g = 0$.”
4	“Generate a trial population using DE’s mutation and crossover operations”.
5	“Domination check is performed on the combined trial and target population. All non-dominated solutions as ‘non-dominated’ while marking others as ‘dominated’”.
6	“Play domination tournaments at each population index”.
7	“Increase the generation counter, g , by 1, that is, $g = g + 1$ ”.
8	“If $g < gMax$, then go to step (4) above. Else, go to step (9)”.
9	“Remove the dominated solutions in the last generation”.
10	“Output the non-dominated solutions”

Fig. 5. Combine Pareto Differential Evolution (CPMDE) Algorithm Procedure [31].

5. Conclusion

Reservoir operations include, but not limited to, hydropower generation, marsh land restoration, river sediment estimation, flood and water inflow level forecasting, reservoir control system and recreation and conservation, environmental conservation, flood mitigation, and rural-urban water supply. These operations differ in mechanism and therefore in the design of their underlying hydrological and computational models. Reservoirs designed for many objectives is called multi-objective reservoir. It can also be designed for many operations. Therefore, it logically demands more complex design models and larger operational data to handle.

Also, real time reservoir operations are operations whose variables are captured and processed in real time using technology for accurate and timely decision making. Instead of the technological, but periodic, inspection of reservoirs to capture needed information for decision-making and operational optimization, information and communication technologies (ICT), such as Piezometers, are permanently located at the reservoirs' locations. These ICT tools capture, transfer and process the needed reservoirs' operational data for process optimization. Therefore, real time reservoir operations' data are captured, transferred, and processed in real time for optimization and decision making.

The need for RRLNN and CPMDE for multi-objective real time reservoir operation optimization can be summarily classified into four. First, with the preponderance of real time data capturing technologies, such as Piezometers, satellite altimeter and water level sensor, more data are generated real time and needed to be deployed into analytics system, also in real time. This is a practical implication of such computational models for domain experts' decision-making process. Second, for specificity, RRLNN and CPMDE are combinable algorithms with prospect to attend to the real time and multi-objective functions and constraints of reservoir operations. RRLNN, being an extension of recurrent network –an ANN network architecture suitable for real time functionality, while CPMDE is a novel DE algorithm suitable for multi-objective optimization.

Training the RRLNN operational data with CPMDE, with its learning parameter, η , will present a computational model that adequately handles the reservoir operational data in real time within a multi-objective framework. Third, aside the practical problems in optimizing real time reservoir operations within a multi-objective framework that the hybridization of RRLNN and CPMDE would solve, the model presents a new frontier in computational modelling. It presents a hybridization process whereby the non-dominated vectors from the CPMDE serves the data population or the training of the RRLNN. This includes training the RRLNN's nodes and abstracting its data hidden layers. Fourth, the hybrid of RRLNN and CPMDE would be the basis for the design and development of an intelligent system that handles multi-objective decision making of reservoir operations in real time.

Conflict of interest

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

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