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Performance appraisal of evolutionary algorithms in river basin management: a review

Abstract

Evolutionary algorithms are techniques extensively used in the planning and management of water resources and systems. It is useful in finding optimal solutions to water resources problems considering the complexities involved in the analysis. River basin management is an essential area that involves the management of upstream, river inflow and outflow including downstream aspects of a reservoir. Water as a scarce resource is needed by human and the environment for survival and its management involves a lot of complexities. Management of this scarce resource is necessary for proper distribution to competing users in a river basin. This presents a lot of complexities involving many constraints and conflicting objectives. Evolutionary algorithms are very useful in solving this kind of complex problems with ease. They are easy to use, fast and robust with many other advantages. Many applications of evolutionary algorithms, which are population-based search algorithms, are discussed. Different methodologies involved in the modelling and simulation of water management problems in river basins are explained. It was found from this work that different evolutionary algorithms are suitable for different problems. Therefore, appropriate algorithms are suggested for diffe-rent methodologies and applications based on results of previous studies reviewed. It is concluded that evolutionary algorithms, with wide applications in water resources management, are viable and easy algorithms for most of the applications. The results suggested that evolutionary algorithms, applied in the right application areas, can suggest superior solutions for river basin management, especially in reservoir operations, irrigation planning and management, streamflow forecasting and real time applications. The future directions in this work are suggested. This study will assist decision makers and stakeholders on the best evolutionary algorithms to use in varied optimization issues in water resources management.

Keywords: evolutionary algorithms, multi-objective, reservoir operation, river basin management.
JEL Classification: B52, 013, Q2, Q25.

Introduction

Water is a critical and prime resource needed by human and the environment so as to survive. Hence, it is necessary to sustainably manage it. There are a lot of complexities involved about its usage such as increased population of the world utilizing the little available resource, constant oil spillage and the fear of demand being higher than future supplies. Climate change which increases drought and seasonal temperatures will challenge water resources in the near future. Therefore, a heightened need is created for water resources to be managed in a sustainable and cost effective way since water resources are vulnerable (Zheng et al., 2010). Managing a river basin is tantamount to survival in the world, even the social, economic and environmental well-being of a country is improved. Hence, greater attention must be given with regards to it. Water resources are known to be used in various ways to satisfy human and environmental needs such as industrial, hydropower, recreation, irrigation and flood control. River basins, which hold a vast amount of water available to sustain the mentioned needs, are faced with lots of problems such as shortages in the supplies of water, high demand by the society and flooding, hence, it must be managed effectively and efficiently. It, then, becomes essential that a process of continuity and sustainability be imbibed for optimum utilization of water resources [1]. A river basin consists of integrated planning and management unit, which controls, to some extent, other natural components such as wildlife and vegetation (Cai et al., 2003). As humans, we depend on water to sustain our varied needs. River basins, as a unit, usually present a high management problem ranging from different water sources to a mix of conflicting users and multiple reservoirs. Hence, river basin management is an essential approach to sustainable water use and distribution of resources amongst competing users [2]. One of the techniques for solving water resources problems in our society is to apply evolutionary algorithms. Evolutionary algorithms ascertain optimal solutions from a population rather from single point thereby placing it above other optimization techniques for solving real world issues [1].

A review on performance appraisal on application of evolutionary algorithms to river basin management is the crux of this paper. The structure of the paper is as follows: Section 1 describes river basin management, Section 2 gives a brief overview of the concept of optimization, Section 3 presents evolutionary algorithms with more emphasis on genetic algorithms and differential evolutionary algorithm which are some of the mostly used algorithms for water resources management, Section 4 discusses reservoir operations and optimization of reservoir operations using different evolutionary algorithms. A conclusion is drawn in Final section.

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1. River basin management

Water demand is anticipated to double by 2035 and an estimate of two-thirds of the population of the world is expected to be faced with water scarcity for the next several decades. As such, numerous river basins around the world are to meet environmental needs associated with the increase in population and the huge demand for water (Dawadi and Ahmad, 2012). River basins are defined by river basin organizations in India, as a 'geographical unit' that encloses an area drained by channels and streams which feed into a river at some point. Precipitation that falls on these river basins will be used by living organisms and plants, or it either evaporates, sinks into a river or ground. An assumption is also made that river basins operate on a steady state and can be handled by control systems like large dam (Asia, 1999). River basins can be considered the central unit of natural runoff processes in land region (Tsujimoto et al., 2012). Therefore, it is essential to coordinate all competing demands for water through the management of river basins. This can be achieved by ensuring that this watershed retains its ability to hold water. It is also important that water usage is channelled to directions which are socially equitable, environmentally sustainable and economically productive. River basins are an enclosed catchment of water that is used to store water during a season of rainfall to serve different sectors for industrialization, population use and agricultural activities. Neither water users nor water managers have the incentives to conserve water rather it is either overused or wasted. Reservoirs are created to store away this scarce resource so as to be utilized when necessary. Reservoirs plays an essential role in water resources development [3]. Figure 1 shows a reservoir behind a constructed dam. Reservoir operations involve an intricate decision-making processes that earn maximum benefit from diverse objectives such as irrigation, supply of drinking water to municipality, control of flood and hydropower generation. They are large scale non-linear optimization problems that involve hydropower, hydrology, reliability, agriculture, environment, risk and uncertainties. Its purpose is to align the spatial water availability and the natural stream flow [4]. Nevertheless, these objectives compete and conflict with each other thereby making it a difficult decision system [5].

Fig 1. A reservoir with dam constructed [6]

2. Optimization

Bandyopadhyay and Saha [7] define optimization as the study of some kind of problems where one or more objectives which are functions of some real or integer variables are minimized or maximized. Within an allowed set, proper values of real or integer variables are chosen in a systematic way. Optimization goals are usually to find best possible solutions to problems. Civicoglu [8] suggests that optimization algorithms aim to identify the best value for a system's parameter in numerous circumstances. Olofintoye and Adeyemo [9] put it simply as an attempt to maximize a system's desired property and concurrently minimize its adverse characteristics. Optimization design is optimum when cost is lowest throughout all feasible design region. Choices of optimization design are limited to resource constraints such as material and labor. Optimization can be compared to human beings striving for perfection in all areas of life. Most objectives involve either single or multiple. Multiple objectives are conflicting in nature and comprise real world problems while single objectives comprise identifying the maximum and minimum of a single variable purpose [10]. A particular solution cannot be obtained in multi-objective optimization problem, instead, a range of good solutions recognized as Pareto optimal solutions exist. Pareto optimal set of solutions are such that movements are seen from one point to a new point in the set, and at least one objective function advances and the other deteriorates [10].

3. Evolutionary algorithms (EAs)

Inspired by various mechanisms of biological evolution, evolutionary algorithms (EAs) are the best established system theoretic class of metaheuristics that are appropriate to solving water resources problems and challenges [11]. They are motivated by diverse mechanisms of biological growth (e.g., mutation, crossover, selection and reproduction) (Nicklow, Reed, Savic, Dessalegne, Harrell, Chan-Hilton, Karamouz, Minsker, Ostfeld, Singh, Zechman, 2010). Evolutionary algorithms are also stochastic search techniques which imitate the same characteristics as natural biological evolution to examine optimal solutions in a certain problem [12]. Algorithm performances are usually defined in terms of effectiveness, efficiency, reliability and robustness.

EAs are multi-objective optimization methods that deal with discovering solutions to problems with several objectives. Optimality of many solutions known as Pareto optimal solutions are considered because none of the objectives are considered better than the other [13]. Evolutionary algorithms allow the discovery of a whole set of Pareto optimal solutions in a single run of the algorithm. Furthermore, EAs are less prone to the continuity or shape of the Pareto front (Ghosh & Dehuri, 2005). Several types of evolutionary algorithms exist, including genetic algorithm (GA), evolution strategies, learning classifier systems, evolutionary programming and genetic programming (GP). GAs have been widely accepted as the dominant optimization methods [14]. Though all the above EAs are stimulated by the same natural evolution, each of them constitutes different approach. EAs procedure includes initialization, mutation, crossover and selection [2].

Evolutionary algorithms have the characteristics of displaying an adaptive behavior. This allow (EA) to handle high dimensional non-linear problems without precise knowledge of the problem structure. EAs are very robust to time-varying behavior but can show low speed of convergence.

EAs have the benefits of conceptual simplicity, can be broadly applied, outperform classic approaches on real problems, likely to utilize knowledge, crossbreed with other methods, parallelism in search method, strong to dynamic changes, used in adapting solution to varying circumstance, proficiency for self-optimization and can solve problems with no identifiable solutions [15]. EAs also have the ability to simultaneously optimize contradictory objective functions [16]. Some disadvantages of evolutionary algorithms include high computational demand, difficult adjustment of parameters, heuristic principle [17].

Evolutionary algorithms have been mostly studied by researchers and are, consequently, applied to river basins. For two decades, evolutionary algorithms have been used in a number of water resources studies such as hydrologic and fluvial models [18], urban drainage and sewage treatment systems [19], water supply and sewage treatment systems [20], water distribution systems [21, 22] and subterranean systems [23], as highlighted in a review by [24].

In the past, some evolutionary algorithms previously used to optimize multi-objective issues pertaining to reservoir operations included the dynamic programming (DP), genetic algorithm (GA), differential evolution (DE), linear programming (LP) and non- linear programming (NLP), stochastic dynamic programming [25], ant colony optimization (ACO), particle swarm optimization (PSO) and simulated annealing [4]. Many researchers have studied reservoir operations using single and multi-objective techniques [4, pp. 26-32]. In all these studies, reservoir problems were solved using varied optimization techniques. Particularly, genetic algorithm and differential evolution algorithm have been widely used in optimizing reservoir operations. Genetic algorithm (GA) has been demonstrated to be superior to most traditional methods like linear, non-linear and dynamic programming. For the purpose of this study, genetic algorithm (GA) and differential evolution (DE) will be discussed.

3.1. Genetic algorithm (GA). Genetic algorithm was defined by Wardlaw and Sharif [33] as exploration algorithm which is based on natural selection mechanisms and derived from natural evolution theory. GA is a strong method for probing the best possible solutions to compound problems which uses guided random choice as a tool to control the search in complex search spaces. It represents solutions with chromosomes or strings of variables which show the genetic formation of individuals using the principle of natural genetic system. GA uses some problem dependent knowledge, known as fitness function, to direct its search to favorable areas [7]. The genetic operators used are selection, mutation and crossover. Applying GAs to water resource problems may cause the chromosomes that are generated to fail in meeting the system constraints such as capacity and continuity [33]. Binary encoding of the solution parameters was the basis on which GA was developed. Application of the penalty function approach will reduce the chromosomes fitness so as to meet constraints [34].

3.2. Basic principles of genetic algorithm. Modelled on mechanism of natural genetic system, GA exploits historical data to speculate on new offspring with improved performance. A coding parameter set of the GA allows it to differ from most of the usual optimization and search procedures. GA works concurrently with multiple points and also computes search through sampling using only the payoff data. it conducts search using stochastic operators to produce new solutions. When used as an optimization technique, the search space may not be continuous so GA has minimal chance of getting stuck at a local optimum [7]. An important trait of GA adoption in water resources optimization is the 'population-by-population approach when compared to the 'point-by-point' approach employed by classical optimization techniques such as dynamic programming (DP) and linear programming (LP), where the optimal solutions are derived. To appraise the fitness or suitability of the derived solutions, GA needs only a suitable objective function that allows it to map from chromosomal to solution spaces [7]. The basic principle of GA is the natural selection or survival of the fittest disposition. GA has the disadvantages of slow repetitions to reach global optimal solution, getting stuck at a local optimum and also problem of slow convergence. Examples of improved genetic algorithm include chaos genetic algorithm (CGA), non-dominated sorting genetic algorithm (NSGA) and non-dominated sorting genetic algorithm II (NSGA-II). CGA was proposed by Cheng and Wang [35]. The characteristics show that GA mechanism did not change but the coefficient of adjustment and search space are continually reduced. CGA also has fast convergent velocity, maintains diversity of GA and has powerful search capabilities. NSGA, as suggested by Goldberg in Srinivas and Kalyanmoy [36], shows that the algorithm can sustain uniform and stable reproductive prospect across non-dominated individuals. NSGA results show that it can be used to find multiple Pareto optimal solutions but the outcome involves a lot of criticisms such as high computational complexity of non-dominated sorting, lack of exclusivity and the need for stipulating the parameter to be shared [37].

In their study, Deb and Pratap [37] suggested an advanced version of NSGA and discovered that NSGA-II was able to converge better in an obtained non-dominated fronts. It was also able to sustain an enhanced spread of solutions. NSGA-II also has the properties of parameterless approach, simple, efficient constraint-handling methods, elitist strategy and fast non-dominated sorting procedures [37].

3.3. Differential evolution algorithm. Differential evolution algorithm is an evolutionary algorithm introduced by Storn and Price in 1995 [38]. DE was proposed to achieve faster convergence and robustness in optimization problems. DE algorithm is different from other EAs at the recombination and mutation stages. Weighted difference amongst solution vectors to perturb the population is used by differential evolution but in GAs, perturbation occurs according to a random quantity. Two operators used for DEs include the mutation and crossover. The crossover operator used can either be exponential or binomial. The perturbation is usually made in any randomly chosen vector (rand) or in the best vector of the previous generation (best). The basic principle of DE algorithm is survival of the fittest [39].

According to Reddy and Kumar [14], DE technique has proven to be numerical, robust and faster for numerical optimization problems. It is able to optimize all discrete and continuous variables, integers and can handle all nonlinear objective functions with nontrivial solutions [14]. DE has the advantages of handling difficult problems with interdependencies amongst input parameters, devoid of computational cost and operation complexities. DE also retains correlated self-adaptive mutation step sizes so as to make quick progress in optimization. An example of an improved version of DE is multi-objective differential evolution (MODE), proposed by Reddy and Kumar [14] which was compared with NSGA-II so as to validate the standard performance measures and was tested with some benchmark problems. Results showed that MODE technique can be a substitute to generate optimal adjustments in multi-objective optimization of water resources structures.

DE ignores the use of some probability functions to present variations to the population but uses alteration between randomly selected individuals as the basis of random variations for a third vector known as the target vector. This is the reason why the trial solutions that will contest among the parent solutions are produced by adding the weighted difference vectors to the target vector [10].

Differential evolution algorithm (DE) varies from genetic algorithm (GA) in certain ways:

1. A new offspring in DE can only replace a randomly selected vector from the population if its fitness level is higher but in GA, offspring replaces the parents with some degree of probability irrespective of their fitness.

2. Real number representation is used by DE while GA uses binary strings, although some GA uses real number representation or integer occasionally.
3. In DE, the crossover strategies involve selection of three parents while the child is a perturbation of one of them but in GA, selection for crossover involves two parents while the child is a recombination of the parents [10].

4. Reservoir operations

Reservoirs are facilities used to stored away water for future use. Other reservoir purposes include recreation, flood control, irrigation, domestic and industrial water supplies. Reservoirs are created, most importantly, to provide flood protection for downstream areas and also for low flow regulation, especially during dry seasons. Reservoirs which are composed of varied physical components such as pipelines, irrigation area and hydropower plants have a heightened need for information on the reservoir guideline process. A reservoir guideline process is critical for ideal use of water from the system thereby allowing adequate management of water resources (Rani and Moreira, 2010). To determine the reservoir size before a dam construction, an optimization modelling is needed before the plan takes place. Irregular inflow of water must be catered for through reservoir erections so that the stored water can be utilized in period of low rainfall [40].

4.1. Optimization of reservoir operations using different evolutionary algorithms. The functions of any reservoir are multipurposed in nature such as monitoring stream flow and impounding water for future use. Inflows, discharge, return flows, storages, domestic and industrial water supply demand and diversions are many intricate problem variables that make it difficult to manage reservoir operations. Popularity has been gained tremendously since 1990s when evolutionary algorithms (EAs) were used for optimizing reservoir operations. Globally, researchers have used optimization techniques for reservoir systems operation control [26, pp. 41-44].

Several studies have reported the use of evolutionary algorithms in reservoir operations in river basins. Regulwar and Choudhari [3] applied differential evolution (DE) for the best operation of multipurpose of reservoir with the interest of exploiting the hydropower production. The algorithm application was undertaken through Jayakwadi project stage-1, Maharashtra state, India. The outcomes of GA and ten DE strategies show that both results can be compared. Chang and Chang [29] applied a multi-objective evolutionary algorithm, the non-dominated sorting genetic algorithm (NSGA-II), to observe a Taiwan multi-reservoir system operation. The study was applied to the Feitsui and Shihmen reservoirs in Northern Taiwan. Realization of optimal joint operating strategies by NSGA-II was the objective of the model. This was to minimize the shortage indices (SI) value. A day to day operational simulation model to reduce the shortage indices (SI) values of both reservoirs for a long term simulation period was developed. The results showed that a promising approach is provided by NSGA-II by providing enhanced operational strategies which would lessen the SI for both reservoirs using a 49-year data set.

Reddy and Kumar [26] present a multi-objective evolutionary algorithm (MOEA) to develop a set of optimal operation plans for a multipurpose reservoir system. A population-based search evolutionary algorithm named multi-objective genetic algorithm (MOGA) to create a Pareto optimal set was applied to Bhadra reservoir system in India. The outcomes specified that the evolutionary algorithm proposed was able to suggest many alternate plans for the reservoir operator thereby allowing flexibility in choosing the best, hence, proving that MOGA was capable of solving multi-objective optimization issues. Li and Wei [45] developed a parallel dynamic programming algorithm to optimize a multi-reservoir system joint operation. The parallelization is based on the message passing interface (MPI) protocol and the distributed memory architecture. The results show that the good performance in parallel efficiency was exhibited by the parallel DP algorithm and was also applied to five-reservoir system in China. In another study, Zhang and Jiang [46] presented the improved adaptive particle swarm optimization (IAPSO) to resolve the problem of reservoir operation optimization (ROO) that involves a lot of conflicting objectives and constraints. The results of this method show that IAPSO gives better operational results with much robustness and effectiveness when compared with other methods.

In his study, Chang [47] recommends a reservoir flood control optimization model with linguistic description of existing and required procedures for coherent operating decisions. A genetic algorithm (GA) was used to represent a search instrument and formulated reservoir flood process as an optimization issue. GA was used to examine a global optimum of a combination of mathematical and non-mathematical inventions. The recommended methodology was applied to the Shihmen reservoir in North Taiwan. Hence, it was discovered that a penalty-type genetic algorithm can conveniently offer balanced hydrographs, especially, when some constraints are violated due to its huge number and the proposed model can help in guiding the GA search process.

Chang and Chang [30] proposed a procedure which includes the constrained genetic algorithm (CGA) whereby the natural base flow necessities are taken into consideration as limitations to reservoir operation water flow when optimizing the 10-day reservoir storage. A lot of penalty functions aimed for diverse types of limitations were integrated into the operational goals of the Shih-Men Reservoir to form the fitness function. The Shih-Men Reservoir and its downstream were used as a case study. Hence, it was concluded that to optimize reservoir operations for numerous users and enhance the effectiveness and efficiency of water supply ability to natural base flow requirements and human needs, CGA approach is the best option to use.

Karamouz and Ahmadi [48] focused on presenting a method to improve operating tactics that can be used for releasing water from a reservoir with adequate quantity and quality. The model that they proposed comprises a genetic algorithm (GA)-based optimization model associated with a reservoir water quality simulation model. A support vector machine (SVM) model is required to create the functional guidelines for the discerning extraction from the real time process of the reservoir. The method proposed was applied to the Satarkhan Reservoir in the north-western part of Iran. It was concluded that the planned model might be used as operative tools in reservoir operation.

Genetic algorithm (GA) and linear programming (LA) approaches are compared and utilized in real-time reservoir process of a current Chiller Reservoir system in Madhya Pradesh, India by Azamathulla and Wu [49]. The performance of the two models was analyzed and it was found that the GA model is superior to the LP model. An ideal reservoir operating strategy that combines field level resolutions was obtained and also agrees on time and quantity of water to release from reservoir.

In another study, Wang and Chang [28] proposed a multi-tier interactive genetic algorithm (MIGA) that disintegrates a complex structure into numerous trivial scale sub-systems with GA used on each sub-system while the multi-tier evidence interacts equally among single sub-systems to discover a prime outcome of long-term reservoir process. The Shih-men Reservoir in Taiwan was used as their case study. The results were compared to a three long term process of an individual GA search and a simulation based on the reservoir rule curves and it showed that MIGA was far more resourceful than the individual GA and can intensify the chance of attaining an optimal solution.

Karamouz and Ahmadi [48] presented a procedure to improve operating plans for a reservoir release with satisfactory quality and quantity. A model that takes account of a genetic algorithm (GA) optimization model associated with a reservoir quality simulation model was recommended. To reduce the run time of the GA-based optimization model, the key optimization model was divided into a stochastic and deterministic one. The independent role of the optimization model was based on the Nash bargaining theory so as to take full advantage of the reliability of attaining to the demands of the downstream chain with suitable water quality, prevention of the reservoir degradation and maintaining a steady balance of reservoir storage level. The proposed method was applied to the Satarkhan Reservoir in the north-western part of Iran. The results showed that the recommended model can be utilized in reservoir operation as an operational tool. Modelling and analysis method for assessing water supply abilities of reservoir/river structures that may be used on river basins worldwide using the water rights analysis package (WRAP) was studied by Wurbs [50].

Another optimization technique called bayesian network (BN) was presented by Malekmohammadi and Kerachian [51] for making monthly functional rules of a cascade system of reservoir for irrigation and flood control. The inputs of the BN include water demand from downstream, monthly flows and reservoir storage at the start of a month. The extended period optimization model in monthly gauge was adopted to reduce excessively the agricultural water shortage costs and the expected flood. A link was created between a flood damage estimation model and a short period optimization model that offers the optimal hourly releases for the duration of flood.

Also, a study presented by Chaves and Kojiri [52] shows application of stochastic fuzzy neutral network (SFNN) accomplished by a GA based model for developing reservoir operational approaches taking into consideration the water quantity and quality aims. A quasi optimal solution was produced. The SFNN was applied well to the optimization of the monthly working plans while allowing for maximum water utilization and water quality improvement.

In their study, Regulwar and Kamodkar [32] designed a fuzzy linear programming reservoir process technique and applied this approach to Jayakwadi reservoir stage-II, Maharashtra state, India with the aim of maximizing the hydropower and irrigation releases using three different models. The primary model involves fuzzy resources, second model considers fuzzy technological factors and third model reflects both the first and the second models. The outcomes revealed that the recommended method provides a useful instrument for reservoir operation.

Zheng et al. (2014) designed the water distribution network (WDN), a novel multiobjective optimization system, to advance the efficacy of a typically difficult water resource problem using decomposition techniques. A propagation method was proposed to evolve Pareto fronts of different subnetworks towards the full network Pareto front. The results from the proposed approach showed that it is able to find better fronts than conventional complete search algorithms with better efficiency.

The optimal design of water distribution systems (WDSs) as an example to show how efficient the genetic algorithms (GAs) can be improved through the use of heuristic domain knowledge in the sampling of the initial population was studied by Bi and Dandy [54]. A new heuristic procedure called the prescreened heuristic sampling method (PHSM) was proposed and tested on seven WDS cases of varied sizes. The resulting performance was compared with another heuristic sampling method and two non-heuristic sampling methods. It was concluded that the PHSM performs better both in computational effectiveness and capability to discover near-optimal solutions.

Elferchichi and Gharsallah [55] presented a stochastic methodology that depends on real coded genetic algorithms for enhancing the process of reservoirs in an on-demand irrigation system. It was shown that the procedure analyzes the appropriateness of the difference between supply and demand accounting for the storage volume of the reservoirs. A weighted objective function, containing damages of the permissible reservoir water levels, was also proposed. The study was tested on the Sinistra Ofanto irrigation scheme (Foggia, Italy). The results showed that the model was robust and efficient.

In a similar study, Chen and Mcphee [56] developed and applied a novel multi-objective optimization known as macro-evolutionary multi-objective genetic algorithm (MMGA) to a reservoir operation. MMGA was applied to rule-curve optimization of a multipurpose reservoir scheme. This issue involves a nonlinear problem with mixed integer variables and a non-convex Pareto frontier. Decisions can be made by the operators with respect to hydropower generation and water supply release from the operating rule curves by defining long term targets release and storage level. Implementing the algorithm is easy and it yielded enhanced range of solutions than NSGA-II. Their results showed that MMGA discovered an adequate solution spread on the Pareto front with a low diversity metric.

Genetic algorithm (GA) has been proven scientifically to be superior in computation than traditional methods such as linear programming, particularly in reservoir operations, a subset of river basin and a field of water resources engineering [2].

Conclusion

For almost two decades, evolutionary algorithms have been applied and studied vastly in many research fields. Numerous approaches have been developed by the researchers worldwide so as to solve optimization problems as shown in the literature review. Evolutionary algorithms, with vast applications in water resources management, are worthwhile and easy algorithms utilized in most of the applications. EA have also exhibited many prospects from its applications to optimization problems. Evolutionary algorithms have been applied to different facets of river basins such as irrigation planning, crop planning and reservoir operations which are all variables that emanated from river basins concept. River basin management is similar to conflict management when compared to human beings and their environment. Shortage of water will ultimately place a huge pressure on economic growth, social and technological demands of any country in the world. Reservoir operation models are mostly identified in single and multi-objectives. Reservoir operations are usually formulated with multidimensional, nonlinear objective functions with lots of constraints. The research gap identified in this review of previous studies is such that appropriate algorithms are not identified specifically for different methodologies and applications. The review also notes another research gap that it is imperative to streamline or have a specific identifier for each algorithm in relation to a particular aspect of water resources multi-objectives aligning them to advantages and drawbacks of each. It is recommended that evolutionary algorithms, used in the precise application areas, can suggest superior solutions for river basin management, particularly in reservoir operations, irrigation planning and management, streamflow forecasting and real time applications. Therefore, future researches should concentrate on determining the best, among all proposed evolutionary algorithms, that can conveniently and sufficiently reach an optimal solution when applied to a river basin to enhance its management.

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