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Irrigation water optimization using evolutionary algorithms

Abstract

This paper presents an overview of the use of evolutionary algorithms as a tool for effective optimization of irrigation water resources around the world. This study involves a rigorous assessment of catalogues of recent works carried out using different types of evolutionary algorithms in optimizing the scarce water resources in the semi-arid regions with particular reference to irrigation water management. The behavior and outcome of these techniques under different application types are discussed explicitly. Issues that need to be addressed with respect to the performances of these techniques during different iteration processes are also discussed. The study covers different application areas which include irrigation water allocation and scheduling, irrigation planning with special focus on crop planning and pattern; reservoir operations and irrigation water distribution network. Arid and semi-arid regions experience low annual rainfall and therefore it is imperative to optimize the available water resources for agricultural purposes via irrigation so as to promote food security. The outcome of this study will help stakeholders in the irrigation sector to determine the best evolutionary algorithm that is best suited for their optimization problems.

Keywords: irrigation, optimization techniques, evolutionary algorithms, multi-objective, genetic algorithms.
JEL Classification: C61.

Introduction

Water is the scarcest and most important natural resource on the earth. This is because the existence and survival of every life is solely dependent on it. It is equally the liveware of agricultural development in the arid regions because the availability of water is an important factor for crop production (Huang et al., 2012). However, in South Africa, water is a limited resource and irrigated agriculture is the greatest user of the available consumptive water. It accounts for about 50% of the total water in the country (Nkondo et al., 2004). The sustainable management of water resource is a necessity, particularly in the arid and semi-arid regions where crop development and food security are basically dependent on irrigation due to low annual average rainfall experienced in such regions (Belaqziz et al., 2014). Due to rising world population, changes in the climate, contamination of water supply sources, scarcity of water has been the experience in many parts of the world today. This is evident in the fact that there is an increase in water demands for irrigation, industrial, domestic and energy uses (Mishra and Singh, 2011). This scarcity of water resources is further complicated due to high temperature and drought which dries up both surface and groundwater resources (Mishra and Dehuri, 2011).

Countries and regions with little annual rainfall should be able to utilize its water resources in a more beneficial and sustainable way so as to avoid water stress in the future. To address this challenge, global optimization techniques are adopted. The objective of global optimization in irrigation planning and crop production is to achieve maximum crop yield under limited water supply within an irrigated area (Schütze et al., 2006). This involves the use of computer modelling techniques to find a near-optimal solution of the global optimization problem. According to research, the world population by year 2050 is projected to hit 9.5 billion, demand for food will also increase since food security is of vital importance to humanity but it can never be achieved without adequate provision of irrigation (Singh, 2014). The effect of this increase in population will diminish the availability of water for irrigation since water will be contested for in the areas of residential, industrial and hydropower purposes (Singh, 2012). Consequently, it is essential to optimize accessible land and water assets so as to maximize returns.

The scheduling and management of irrigation water is essential and there are several optimization techniques used in irrigated agriculture throughout the world. Some of the techniques allocate water to different crops at farm level, other studies developed mathematical models and algorithms to optimize irrigation water management for different irrigation systems (Belaqziz et al., 2014). Relevant solution methodologies are required for efficient irrigation planning that will help to provide optimum allocation of resources (Vasan and Raju, 2009). Among the optimization techniques employed for solving irrigation problems around the world are evolutionary algorithms which are the central focus of this paper. Evolutionary algorithms (EAs) go for discovery of the optima from a population of points in parallel rather than from a single point. These gimmicks make them alluring for tending to complex

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design issues (Reddy and Kumar, 2007). The paper is divided into three sections followed by list of references. Section 1 deals with evolutionary algorithms. The various applications of evolutionary algorithms in irrigation water optimization are provided in section 2. Conclusion of the study is provided in the final section.

1. Evolutionary algorithms

Evolutionary algorithms (EAs) are well renowned optimization tools suitable and useful for searching feasible decision space and solving diverse challenges that relates with planning, design and management of natural resources (Whitley, 2001). It employs the method of evolution to unravel adequate solutions that are commensurate with the challenging and complicated resource allocation problems around the world. EAs use the theory of Charles Darwin's natural selection to search for optima solutions in a given problem and they have been adopted over the years to solve diverse application problems (Adeyemo, Bux and Otieno, 2010). Another interesting feature of EAs is their ability to solve multi-objective optimization problems (MOOP) and this has actually popularised it in the last few decades (Adeyemo, Bux and Otieno, 2010). EAs go for discovery of the optima from a population of points in parallel rather than from a single point. These advantages have promoted their suitability in handling complex design issues (Reddy and Kumar, 2006).

The general procedures of EAs as outlined by Eiben and Smith (2003) are initialization, mutation, crossover and selection. Populations of individuals which are potential solutions are first randomly generated. Each solution is assessed by using a fitness function. A selection process is applied during each iteration process to generate a new population which will be better than the previous population. The selection is biased towards the solution that has a better value of the fitness function. During each iteration process, the solutions undergo mutation and crossover to mimic the natural evolution technique. The iteration continues until convergence is reached.

Over the years in the field of operations research, EAs have found maximum usage in solving both single and multi-objective optimization problems (Sarker, 2009). In solving single objective optimization problems, EAs always go out to obtain the best global minimum or maximum as the case may be which is determined by the nature of the problem being addressed (Cheng et al., 2008). On the contrary, in multi-objective optimization problems, an EA searches for a set of solutions that are better and fulfil the boundary conditions to the remainder solutions in the search space.

The advantages of adopting EAs in solving optimization problems are so numerous and includes: (1) EAs are solid contender for issues with non-raised, irregular and multimodal functions; (2) EAs do not need to consider whether a function is convex, concave or continuous. It solves all functions without any hitch (Sarker and Ray, 2009). (3) EAs are very ideal for solving multi-objective optimization problems because it can handle the many conflicting objective functions and also bring about lots of optimal solutions in a single run (Sarker, Kamruzzaman and Newton, 2003).

The most popular of the EAs are Genetic algorithms which is a search algorithm that works based on the theory of natural genetics (Azamathulla et al., 2008). Genetic algorithm technique is robust in its capacity to search for optimal solutions and widely used in the optimization of water resources benefits (Arunkumar and Jothiprakash, 2013). It was developed in 1970 and had since been accepted as a powerful optimization method (Azamathulla et al., 2008). Examples of great research works done on multi-reservoir water optimization using Genetic algorithms include Anwar and Clarke (2001), Wardlaw and Bhaktikul (2004), Azamathulla et al. (2008), Casadesús et al. (2012), Elferchichi et al. (2009), Bieupoude, Azoumah and Neveu (2012), Chang et al. (2010).

Apart from GA, other effective and highly used evolutionary algorithms are differential evolution (DE) algorithm, Genetic Programming (GP), evolution strategies (ES), particle swarm optimization (PSO). DE technique was created and developed by Storn and Price (1995) but in solving multi-reservoir system optimization problems; genetic algorithm is mostly adopted more than differential evolution (Goldberg, 1989). DE was firstly developed for single objective optimization and due to its simplicity principle and convenience in computer programming; it has been employed for solving various application problems (Vasan and Raju, 2007). One of the most popular formats of DE is the one known as DE/rand/1/bin strategy. This format of DE mainly contains three operators: mutation, crossover and selection (Singh, 2012).

2. Application of evolutionary algorithms in irrigation water optimization

Considerable research works have been done; mathematical models have been developed for optimizing irrigation water management for different irrigation systems and reservoir systems around the world. For example, Wardlaw and Bhaktikul (2004) employed a genetic algorithm (GA) to solve the problem of irrigation scheduling and claimed better solution quality by scheduling supplies as close as possible to the Pareto front. Several other studies demonstrated the efficiency and the strength of the GA approach as an optimization tool to provide good solutions for an irrigation scheduling problem such as Reca (2001), Azamathula (2008), Fotakis (2012), Belaqziz (2013), Peralta (2014).

Raju and Kumar (2004) applied GA to irrigation planning problem in order to evolve efficient cropping pattern for maximum benefits for an irrigation project in India. This methodology was adopted to expand net profits with the imperatives, for example, progression comparison, land and water necessities, channel limit, store stockpiling confinements and trimming example contemplations. The results got from the GA model were contrasted with those got from Linear Programming model and they inferred that GA is a powerful optimization technique for irrigation water planning and can be utilized for more intricate frameworks including non-direct optimization.

Reddy and Kumar (2006) developed a Multi-objective Evolutionary Algorithm (MOEA) and applied same to problems involving a multipurpose reservoir system. The methodology was developed to find a set of well distributed optimal solutions along the Pareto front. They employed a population based search evolutionary algorithm named Multi-objective Genetic Algorithm (MOGA) to overcome the challenge faced by the classical methods for Multi-objective Optimization Problems (MOOP). The MOGA methodology was applied to a reasonable reservoir system, namely Bhadra Reservoir system, in India and the results obtained using the proposed evolutionary algorithm showed that it found a well distributed set of Pareto optimal solutions along the Pareto front and hence it shows the suitability of MOGA for solving multi-objective optimization issues.

A detailed comparison to prove the superiority of evolutionary methods over classical methods was done by Azamathulla et al. (2008). They conducted a detailed comparison between two models – a Genetic Algorithm (GA) and Linear Programming (LP) and they applied it to real-time reservoir operation meant for irrigation in Chiller reservoir system in Pradesh, India. The state variables considered by the real-time operation model were soil moisture status and the reservoir storage. The applied irrigation depths serve as the decision variables. In a bit to curb water wastage, the optimum crop pattern model will only allow productive irrigation and hence, the performance of both models were analyzed. GA model gives better yield than the LP model.

Paly and Zell (2009) did a comparative analysis of five Evolutionary Algorithms namely Real Valued Genetic Algorithm, Particle Swamp Optimization, Differential Evolution and two Evolution Strategy – based algorithms on the problem of irrigation optimization and their result showed that both Differential Evolution (DE) and Particle Swamp Optimization (PSO) are able to optimize irrigation schedules and achieve results that are extremely close to the theoretical optimum.

A crop planning problem was formulated as a multi-objective optimization model by Sarker and Ray (2009) and solved using three distinctive optimization approaches. The methodologies considered were; ε – constrained method, a well-known multi-objective evolutionary algorithm NSGA-II and their proposed multi-objective constrained algorithm (MCA). They critically assessed the execution of their proposed MCA with the other two methodologies and they broke down the arrangements from choice making perspective. NSGA-II failed to discover plausible solutions in 69% of the cases explained. Their proposed technique MCA did more excellently than NSGAII for both occasions of the crop planning model.

In another study carried out by Chang and Chang (2009), a multi-objective evolutionary algorithm named, non-dominated sorting genetic algorithm (NSGA-II) was applied to examine the operations of both Feitsui and Shihmen reservoir systems in Taiwan. The NSGA-II was used to minimize the shortage indices (SI) of the two reservoirs over a long term simulation period of 49 years. Their result demonstrated that NSGA-II is a compelling and vigorous multi-objective system to recognize joint operation methodologies that will address discriminating future maintainability needs in future.

GA approaches have been successfully used for the identification of optimal solutions in many hydraulic problems. Elferchichi et al. (2009) developed an optimization model based on real-coded genetic algorithms for optimising the operation of reservoirs in an on-demand irrigation system. The model was applied and tested on the Sinistra Ofanto irrigation scheme in Italy. The model analyzed the adequacy of the difference between supply and demand taking into account the storage capacity of the reservoirs. They concluded that GA is an efficient algorithm for solving problems relating to multi-reservoirs.

A comparative analysis was carried out by Vasan and Raju (2009) where they compared the application of Simulated Annealing (SA), simulated quenching (SQ) and real-coded genetic algorithm (RGA) to a case study of Mahi Bajaj Sugar project in India. The study objective was to boost the yearly net profits subjected to different irrigation system constraints for 75% trustworthy stream situation. Sensitivity investigation on different parameters utilized within the above systems showed that they yielded same solutions when compared to a set of ideal set of parameters. It was accordingly concluded that SA, SQ and RGA can be used for productive solution of any irrigation system framework with suitable constraints.

A new evolutionary optimization method was developed by Chen and Chang (2009) called evolutionary artificial neural networks (EANN) for time series forecasting. This optimization technique combined both genetic algorithm (GA) and artificial neural network (ANN) to solve optimization problems. They explained that the limitation of ANN is that it has inability to process a great number of information and deal with non-linearity but GA has the capacity to supplement the inadequacy of ANN. Ordinarily, it is very difficult to optimize the best network architecture using ANN, especially for highly non-linear data but the best way is to introduce other algorithms of global optimization (e.g. GA) that would enhance the search for near-optimal solution. The fundamental reason for their study was to propose EANN for naturally developing the ideal system construction modeling and association weights of ANN to the examined time series. They initially investigated the execution of the proposed EANN for the Mackey-Glass riotous time arrangement and the result demonstrated that EANN has effectiveness, adequacy and its robust.

In a study carried out by Adeyemo and Otieno (2010), the ability of multi-objective differential evolutionary algorithm (MDEA) as an evolutionary algorithm for solving multi- objective optimization problems is demonstrated. They presented an evolutionary algorithm methodology for solving a multi-objective crop planning problem. The objectives of the problem include; minimization of total irrigation water, maximization of both the total net income from farming and the total agricultural output. They applied the proposed MDEA to Vaalharts irrigation scheme (VIS) in South Africa and from the study, it was concluded that MDEA is a good algorithm for solving crop planning problems. It is also an effective and concise technique for solving multi-objective problems in water resources systems.

A new and innovative evolutionary algorithm developed specifically for solving spatial optimization problems was developed by Fotakis and Sidiropoulos (2012) and it is used for solving both land use planning and resource allocation problems. The optimization methodology is multi-objective, based on non-domination criteria and it is called multi-objective self-organizing algorithm (MOSOA). It was applied to solve a complex, non-linear, combined land use and water allocation problem. The objectives of the problem solved includes; (a) The minimization of soil and groundwater pollution and (b) the maximization of economic profit. The studied area was divided into land blocks and it included a number of wells in fixed positions. The results obtained by MOSOA were compared to a standard multi-objective genetic algorithm (NSGA-II) and the former yielded better and satisfactory outcomes as it generates a set of optimal solutions along the Pareto front and it also satisfies the compaction criteria.

Another application of evolutionary algorithms is demonstrated in the study carried out by Belaqziz et al. (2013) where they proposed a new methodology for irrigation scheduling optimization based on the stochastic search algorithm called Covariance Matrix Adaptation Evolution Strategy (CMA-ES). It is one of the most powerful techniques for the optimization of single-objective problems. It is an iterative stochastic optimization algorithm where at each iteration process, a population of candidate solutions are sampled. They applied CMA-ES to an irrigated sector located at Tensift plain in Morocco. Their objective was to offer the irrigation managers a complete scheduling tool for irrigation rounds including data dates and times of opening and closing the canals to irrigate plots and the amount of water needed. They concluded that the proposed approach is very promising for managing and optimizing irrigation schedules in the gravity irrigation systems.

Peralta, Forghani and Fayad (2014) applied Multi-objective Genetic Algorithm (MOGA) to a hydraulically and economically nonlinear system in which all significant flows, including stream – aquifer – reservoir – diversion – return flow interactions, are simulated and optimized simultaneously for multiple periods. Three considered conflicting objectives are: maximizing water provided from surface and groundwater resources, maximizing hydropower production and minimizing operation costs of moving water from resources to destinations. The MOGA optimizer satisfactorily generated diverse and well distributed solutions to show decision makers a true picture of trade-offs between conflicting objectives.

Conclusion

From this study, it can be observed that many researchers around the globe have developed, initiated and applied various evolutionary algorithms to solve irrigation water problems. Also, the ability of evolutionary algorithms to evaluate multi-objective optimization problems and find near Pareto optimal solutions was also demonstrated in this paper. Up till now, there are few (if any) alternatives to EA-based multi-objective optimization. The numerous applications and the rapidly growing interest in the area of multi-objective evolutionary algorithms (MOEAs) take this fact into account. Furthermore, genetic algorithm (GA), as an evolutionary algorithm, has been utilized to solve complex non-linear and non-arched optimization issues. It is appropriate in achieving worldwide ideal solutions of different optimization problems as well as yielding much better results when contrasted with other evolutionary algorithms. The primary preference of utilizing GA is that it is chiefly suitable for remotely connecting the numerical display inside the optimization model. One of the few research gaps observed from these review is that there are no enough studies providing performance comparisons and investigation of different aspects of the several evolutionary approaches. The few comparative studies that have been published remain mostly qualitative and are often restricted to a few algorithms. There is a need to answer the following questions and observations as regards the scope of this paper:

- Which EA implementations are suited to which sort of problem?
- What are the specific advantages and drawbacks, respectively, of different techniques?
- Are there sufficient and commonly accepted definitions of quantitative performance metrics for multiobjective optimizers?
- The various MOEAs incorporate different concepts, e.g. elitism and niching, which are in principle independent of the fitness assignment method used. What are the benefits of these concepts? Can elitism improve multi-objective search in general?

Therefore, from the review above, there are research gaps that have been identified as regards the operation of evolutionary algorithms in solving most irrigation water problems which is a multi-objective optimization problem. The above discussion is advantageous in providing a focus for possible applications of evolutionary algorithms in water resources management around the world.

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