MAXIMUM IRRIGATION BENEFIT USING MULTIOBJECTIVE DIFFERENTIAL EVOLUTION ALGORITHM (MDEA)

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Abstract**:** This study presents the application of strategies of multiobjective differential evolution algorithm (MDEA) to the maximization of irrigation benefit in the lower orange catchment of South Africa. The two strategies presented are MDEA1 and MDEA3 with binomial and exponential crossover methods respectively. The study compares the non-dominated solutions generated by the two algorithms to find the better algorithm for the irrigation model presented. From the analysis of the results, the results generated by MDEA1 with binomial crossover method are found superior to the results generated by MDEA3 with exponential crossover method. The average total irrigation water of 104 Mm^3 was generated with the corresponding averages of 32,208ha of planting areas and ZAR 1257 million total benefit using MDEA1 while the averages of total irrigation water, total area and total benefit of 128.1 Mm^3, 28,021 ha and ZAR 808 million respectively were generated by MDEA3. This study concludes that MDEA with binomial crossover method is better in terms of quantity and quality of non-dominated solutions generated. It is further shown that the maximum irrigation water of 3503 m^3 per hectare of land cultivated and ZAR 11.25 per m^3 of irrigation water used were generated using MDEA1 while MDEA3 generated the maximum irrigation water of 4570 m^3 per hectare of land cultivated and ZAR 5.92 per m^3 of irrigation water use. This shows that MDEA1 is better in achieving higher profit for farmers using lower volume of irrigation water.

Keywords**:** Irrigation planning, MDEA, Multi-objective, Optimization

I. INTRODUCTION

Over the past decade, a number of multi-objectives evolutionary algorithms (MOEAs) have been suggested [1]. The primary reason why a problem has a multi-objective formulation is because it is not possible to have a single solution which optimizes all objectives. Therefore an algorithm that gives a large number of alternative solutions lying on or near the Pareto-optimal front is of great practical value. Evolutionary algorithms (EAs) are different from conventional algorithms for non-linear optimization since they use only objective function information instead of derivatives or other auxiliary information of the problems [2]. In addition, they aim at finding the optima from a population of points in parallel rather than from a single point. These features make them attractive for addressing complex engineering problems. The procedures of EAs are initialization, mutation, crossover and selection. Populations of individuals which are potential solutions are first randomly generated. Each solution is assessed by using fitness function. A selection process is applied in each iteration to form a new population which will be better than the previous population. The selection is biased towards the solution that has better fitness function. In each iteration, the solutions undergo mutation and crossover to mimic the natural evolution technique. The iteration continues until convergence is reached.

Evolutionary algorithms (EAs) are global optimization heuristics that search for optima using a process that is analogous to Darwinian natural selection. Since their inception in the 1960s, evolutionary algorithms have been used in a tremendous array of applications. The growing popularity of evolutionary algorithms stems from their ease of implementation and robust performance for difficult engineering and science problems.

Recently, differential evolution algorithm, a family of evolutionary algorithms was extended to solve multiobjective problems [3]. The algorithm was named multiobjective differential evolution algorithm (MDEA). They suggested that the proposed MDEA can be used on any strategy, the strategy used in their study is DE/rand/1/bin which is the most widely used of all the ten strategies of DE [4]. Later on, they suggested the other three strategies of MDEA based on the existing strategies of differential evolution [5].

They named all the four strategies MDEA1, MDEA2, MDEA3 and MDEA4. The first two strategies (MDEA1 and MDEA2) use the binary crossover method while MDEA3 and MDEA4 use the exponential crossover method. In this study, the performance of two of the four strategies proposed were compared with the irrigation planning model presented by [6]. The two strategies are MDEA1 and MDEA3. These two strategies are different in the crossover method they use. MDEA1 uses binary crossover method while MDEA3 uses exponential crossover method.

Many optimization techniques have been applied to water resources management in the past. These include Linear Programming (LP); Nonlinear Programming (NLP); Dynamic Programming (DP); Stochastic Dynamic Programming (SDP); and Heuristic Programming such as Genetic Algorithms, Shuffled Complex Evolution, Fuzzy logic, and Neural Networks, Differential Evolution *etcetera*. [7] analyse multi-objective optimization problems and provide useful insights about solutions that are generated using population-based approached. Crop-planning problem as a multi-objective optimization model is formulated. Well-known multi-objective evolutionary algorithm called NSGAII and their proposed multi-objective constrained algorithm (MCA) are compared. The study by [8] unravels the complexity of water management institutions by analysing the interactive nature of actors and rules to a particular water-related problem, using a systems approach in a hamlet in the Indian Himalayas. [9] present a study to deal with the development and comparison of two models; a genetic algorithm (GA) and linear programming (LP) to be applied to real-time reservoir operation in an existing Chiller reservoir system in India. Their performance is analysed and from the results, the GA model is found to be superior to the LP model. Optimal water allocation and cropping patterns for the Jordan Valley, taking into consideration variations in expected incomes from agricultural production and rising water prices are studied by [10]. Their calculations were based on information available on water supplies, areas under irrigation and market conditions, and used linear programming models for determining solutions that maximize gross margins and minimize potential variations in these gross margins. The results indicated that optimizing cropping patterns and the allocation of irrigation water still has a substantial potential to increase the financial return from agriculture.

In another study, a tolerance based fuzzy goal programming (FGP) and a FGP based genetic algorithm (GA) model for nutrient management decision-making for rice crop planning in India are presented. In the proposed model, fuzzy goals such as fertilizer cost and rice yield are included in the decision making process [11]. [12] applied one of the variants of Particle Swarm Optimization (PSO) as one of these evolutionary algorithms to two case studies: the Hanoi water distribution network and the New York City water supply tunnel system. Both cases occur frequently in the related literature and provide two standard networks for benchmarking studies. This allows them to present a detailed comparison of their new results with those previously obtained by other authors.

In the field of water resources engineering, particularly reservoir operations, genetic algorithm (GA) has been proved to be computationally superior to traditional methods like linear programming, non linear programming and dynamic programming. Two types of genetic algorithms, real-coded and binary-coded were applied to the optimization of a flood control reservoir model [13]. [14] explored the potential of alternative GA formulations in application to real time reservoir operation. They found that: (a) GA has the potentiality to large-finite horizon multireservoir system problems where objective function is complex; (b) GA needs no initial trial release policy; (c) easily applicable to nonlinear problems; and (d) GA can generate several solutions that are close to the optimum. Several other studies have shown the application of GA to water resources management [9, 11, 13-18].

In this study, the Vanderkloof Dam, along Orange River in South Africa is optimized for maximum irrigation water benefit. The objective of the study is to determine the optimum total volume of water required for maximum agricultural production downstream of the dam through the canals. The total cultivated land and total benefit in South African Rand (ZAR) are maximized while the total irrigation releases through the canals are minimized. The dam presently supplies irrigation water to an area of 34 000 ha through the canals.

II. DESCRIPTION OF THE DAM

The Vanderkloof dam is the second largest storage reservoir in South Africa with a capacity of over 3 200 million m^3. It is an important part of the Orange River Project (ORP). Water released from the Gariep Dam, which is about 130 km upstream of the dam, is either transferred through the Orange/Riet Canal to the Riet River basin or released downstream through the two hydropower generators. The combined capacity of the two installed generators is 240 MW at 120 MW each at a discharge of about 200 m^3/s and a total of 400m^3/s. The dam is currently the highest dam in South Africa with a wall height of 107 m and a crest length of 765 m. There are four gates installed in the wall and can discharge up to 8 500 m^3/s in total through the flood sluices which are positioned on the left flank of the dam. One of the main objectives of the ORP is to increase the value of the South African agricultural production to make provision for the establishment of a large number of irrigation farms. The operation of the dam for maximum irrigation benefit therefore cannot be overemphasised.

III. MATERIALS AND METHODS

A. IRRIGATION PLANNING MODEL

The irrigation planning model presented in this study was studied by [6] using only one strategy of MDEA called MDEA1. The monthly operation of the dam for irrigation release was formulated. There are sixteen crops planted on ten different areas numbered 1 to 10. The cultivated areas numbered 1 to 6 are planted with wheat and groundnut; drybean and maize; cotton and drybean; wheat and carrots; wheat and potatoes, and onions and water melon respectively with one crop after another within the year. Cultivated areas number 7 to 10 are planted with lucern, peacan, olive and citrus respectively. The irrigation system used on cultivated land numbers 1 to 7, 8 to 9 and 10 are sprinkler:centre pivot, flood:border and sprinkler:drip respectively.

In this study, the results of two strategies of MDEA (MDEA1 and MDEA3) are compared. The two strategies have different crossover methods. The model has three objectives of minimizing the total irrigation water and maximizing both the total area cultivated and the total benefit derived from farming. The objective functions are formulated as below:

Objective Function 1: Minimize the Total Irrigation Water

The total irrigation water released through the main canal to the farmers is minimized. This can be expressed as*:*

$$\text{Min } TIR = \sum_{i=1}^{N} IR_i \qquad (1)$$

$$IR_i = \sum_{j=1}^{M} \left(\left(CWR_{i,j} * A_j\right) \Big/ 10 \right) \qquad (2)$$

Where,

TIR = total irrigation release for the 12 months

N = number of months (12) (January to December)

IR_i = irrigation release for month i

M = number of cultivated lands (10)

$CWR_{i,j}$= crop water requirement on cultivated land j in month, i (mm)

A_j = cultivated land j (ha)

Objective Function 2: Maximize the Total Cultivated Land

The cultivated land area available for irrigation is maximized to increase employment generation in the area.

$$\text{Max } TA = \sum_{j=1}^{M} A_j \qquad (3)$$

Where TA is the total cultivated area in hectares

Objective Function 3: Maximize the Total Benefit

The total benefit in South African Rand (ZAR) in the cultivated area is maximized.

$$\text{Max } TB = \left(\sum_{i=1}^{M} \sum_{j=1}^{P} \left(TI_{i,j} * A_i \right) \right) - cw * TIR \qquad (4)$$

$$TI_{i,j} = \left(Price_{i,j} * Yield_{i,j} \right) - Exp_{i,j} \qquad (5)$$

Where,

M = number of cultivated lands

P = number of crops on each cultivated land

$TI_{i,j}$ = total income of crop j on land i

A_m = cultivated land (ha)

Cw = cost of irrigation water (8.77 cents per m^3)

$Price_{i,j}$ = selling price of crop j on land i (ZAR/ton)

$Yield_{i,j}$ = Yield of crop j on land m (tons/ha)

$Exp_{i,j}$ = expenses of crop j on land i (ZAR/ha)

The 3 objective functions above are subjected to the following constraints.

Constraint 1: Canal Capacity

The monthly irrigation release should be less than the canal capacity.

$$V_i \leq \text{canal capacity} \quad \forall\ i = 1 \text{ to } 12 \qquad (6)$$

Constraint 2: Crop Water Requirement

Monthly irrigation release must meet the crop water requirements for all the crops in the month.

$$V_i \geq (CWR_{i,j} * A_j) \quad \forall\ i = 1 \text{ to } 12 \qquad (7)$$

Constraint 3: Minimum and Maximum Cultivated Areas

The cultivated areas must not be less than 5000 ha for each of the crops. Also there is a maximum cultivated area for each crop so that the farmers may not concentrate on more profitable crops at the expense of other crops.

$$5000 \leq A_j \leq A_{jmax} \qquad (8)$$

where, A_{jmax} is the maximum area where each crop should be grown.

Using the pseudocode for MDEA1 and MDEA3 as presented by [5], the algorithm was coded in MATLAB 7.0 (The MathWorks Inc., USA) executed on a 2.0 GHz, 2 GB RAM PC and used to solve the stated objective functions and constraints and compare the results of the two algorithms. The results will be used to determine the best strategy for irrigation planning model based on the crossover method of differential evolution. The DE parameters used are population size (NP) = 100, crossover constant (Cr) = 0.95, scaling factor (F)=0.5 as suggested by [19]. The total net benefit and total cultivated area are maximized while total irrigation water is minimized.

II. PRELIMINARY RESULTS AND DISCUSSIONS

The preliminary results of the model are presented in figures 1 to 4. The other strategies of MDEA (MDEA2 and MDEA4) will be studied on the proposed model to further determine the best strategy for the model out of the four strategies. Moreover, the optimum monthly irrigation releases will be determined to suggest to the Vanderkloof dam operators based on the suggested cropping pattern.

In figure I, the Pareto optimal set using MDEA1 is presented. It is found that all the non-dominated solutions converge to the Pareto optimal front. In figure II the Pareto optimal set using MDEA3 is also presented with the non-dominated solutions converging to the Pareto optimal front. Each of the three objectives cannot be improved without sacrificing the other objectives. In a multi-objective optimization, there cannot be a solution that will satisfy all the objectives but instead, there are sets of solutions in one simulation run which correspond to non-dominated solutions [20]. It depends on a reservoir operator to choose the best solution that suits him from the set of non-dominated solutions. The solutions are optimal in the sense that no other solution in the search space is superior to them when all the objectives are considered. The goal of multi-objective problems is to find as many Pareto-optimal solutions as possible to reveal trade-off information among different objectives [20]. Once such solutions are obtained, the reservoir operator will be able to choose a final solution with further considerations like inflow to the reservoir, water availability, land area, total net benefit and other water requirements in this study.

Figure I: Pareto optimal set using MDEA1

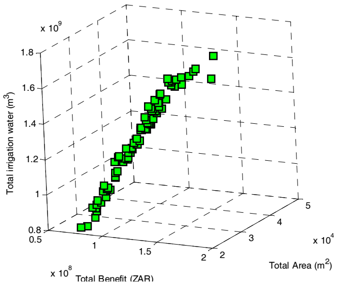

Figure II: Pareto optimal set using MDEA3

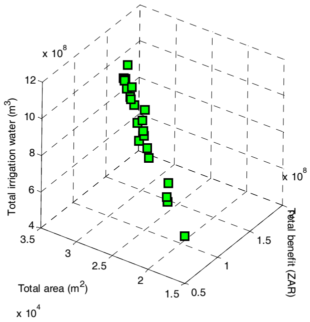

Figure III presents the total benefit, total area and total volume for the non-dominated solutions using MDEA1. The average total irrigation water of 104 Mm^3 was generated with the corresponding averages of 32,208 ha of planting areas and ZAR 1257 million total benefit. When minimum total irrigation water is calculated, a value of 74.69 Mm^3 of water is used on an area of 23,971 ha and generating a total benefit of ZAR 827.53 million. With the maximum total irrigation water of 144.77 Mm^3, a total area of 41,319 ha is cultivated with a total benefit of ZAR 1257.16 million.

Figure III:

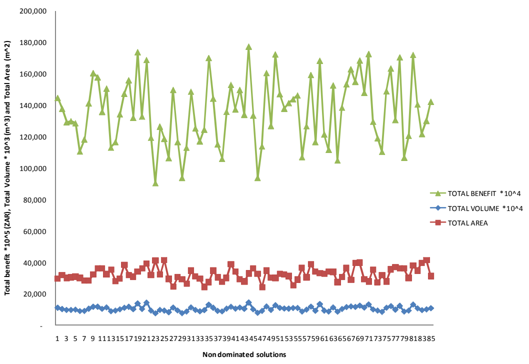

Figure 3: Total benefit, total area and total volume for the non-dominated solutions using MDEA1

Analysis of the results in figure IV shows the averages of total irrigation water, total area and total benefit of 128.1 Mm^3, 28,021 ha and ZAR 808 million respectively. The minimum values for total irrigation water, total area and total benefit are 77.76 Mm^3, 17,000 ha and ZAR 490.61 million respectively. The maximum values for total irrigation water, total area and total benefit are 173.5 Mm^3, 36,800 ha and ZAR 1027.5 million respectively.

FIGURE IV:

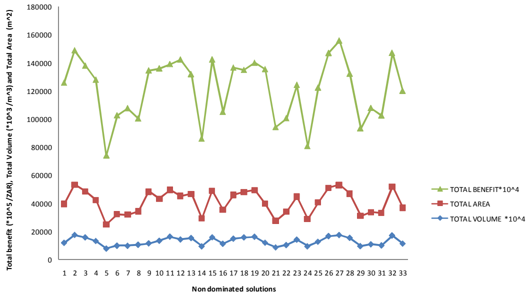

Figure 4: Total benefit, total area and total volume for the non-dominated solutions using MDEA3

MDEA3 generates maximum irrigation water of 4570 m^3 per hectare of land cultivated and ZAR 5.92 per m^3 of irrigation water used. When using MDEA1, the maximum irrigation water of 3503 m^3 per hectare of land cultivated and ZAR 11.25 per m^3 of irrigation water used was generated. This shows that MDEA1 is better in achieving higher profit for farmers using lower volume of irrigation water. Moreover, the number of non-dominated solutions generated by MDEA1 and MDEA3 are 85 and 33 respectively from feasible solutions of 100 and population size of 100. MDEA1 has the ability to generate more non-dominated solutions than MDEA3. It can be concluded in this study that MDEA1 with binomial crossover performs better than MDEA3 with exponential crossover using the proposed irrigation planning model. This confirms the previous studies on DE which suggests that MDEAs with binomial crossover method are better for solving multiobjective water resources problems than MDEAs with exponential crossover method [5].

V. CONCLUSIONS

The irrigation planning model presented in this study shows that multi-objective differential evolution algorithm (MDEA) is capable of solving multi-objective water resources problems. The two strategies of MDEA found in the literatures are presented. From the results, 85 non-dominated solutions were found from 100 feasible solutions and 100 population size using MDEA1 with binomial crossover method. Also, 33 non-dominated solutions were found from the 100 feasible solutions and 100 population size using MDEA2 with exponential crossover. Also MDEA1 produced higher profit for farmers with lower irrigation water use than MDEA3. This shows that MDEA1 performs better in terms quantity and quality of non-dominated solutions than MDEA3. Therefore, binary crossover method is preferred to exponential crossover method in solving this type of multi-objective water resources problems.

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