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Full Length Research Paper

Differential evolution algorithm for crop planning: Single and multi-objective optimization model

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Single objective optimization for maximizing total net benefit from farming is presented in this study. Differential evolution algorithm which is a family of evolutionary algorithm for fast optimization is employed for the model. The single objective optimization is used to find a better solution using the results of multi-objective optimization of crop planning where three objectives are considered. The objectives are to maximize both total net benefit and agricultural output while minimizing the total irrigation water used. The methodology adopted in this study is used to assist in choosing a solution when many non dominated solutions are presented by a multi-objective optimization. The other two objectives are used as constraints of the problem while maximizing the total net benefit only. The ten strategies of differential evolution are tested with this model. DE/rand/1/bin generated a maximum total net benefit of ZAR 1,330,000 after 1,207 iterations from a planting area of 771,000 m^2 using 704694 m^3 of irrigation water while multi-objective differential evolution algorithm (MDEA1) generated the total net benefit of ZAR 1,304,600. It is concluded that this methodology can be used to generate better results than using a multi-objective model only. It is also suggested that each objective can be solved separately to get better solutions than the ones generated by multi-objective models using the same procedure with suitable modifications.

Key words: Single objective, multi-objective, differential evolution, crop planning, MDEA.

INTRODUCTION

Differential evolution (DE) has been applied to several engineering design problems both as single objective and multi-objective optimization techniques. In DE, all solutions have the same chance of being selected as parents without dependence on their fitness value. DE employs a greedy selection process. The better one of new solution and its parent wins the competition providing significant advantage of converging performance over genetic algorithms (GA). DE algorithm is a stochastic optimization method minimizing an objective function that can model the problem's objectives while incorporating constraints. The algorithm mainly has three advantages: Finding the true global minimum regardless of the initial parameter values, fast convergence, and using a few control parameters (Storn and Price, 1997). Being simple, fast, easy to use, very easily adaptable for integer and discrete optimization, quite effective in nonlinear constraint optimization including penalty functions and useful for optimizing multi-modal search spaces are the other important features of DE.

Differential evolution (DE) utilizes population size, NP as population of D dimensional parameter vectors for each generation (Vasan and Raju, 2007). It maintains two arrays, each of which holds a population of NP real valued vectors of dimension D. The primary array holds the current vector population while the secondary array accumulates vectors that are selected for the next generation. DE originally dealt with a single strategy (Storn and Price, 1997). Later on, 10 different strategies have been suggested by them. A set of control parameters that works out to be the best for a given problem may not work well when applied for a different problem. The best values of the control parameters to be

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Table 1. Formulation of the ten different strategies of differential evolution.

Strategy	Description	Formulation
1	DE/rand/1/bin	$v(g,i,j) = x(g,r_3,j) + F*[x(g,r_1,j) - x(g,r_2,j)]$
2	DE/best/1/bin	$v(g,i,j) = x(g,best,j) + F*[x(g,r_1,j) - x(g,r_2,j)]$
3	DE/best/2/bin	$v(g,i,j) = x(g,best,j) + F*[x(g,r_1,j)+x(g,r_2,j)-x(g,r_3,j)-x(g,r_4,j)]$
4	DE/rand/2/bin	$v(g,i,j) = x(g,r_5,j) + F*[x(g,r_1,j)+x(g,r_2,j)-x(g,r_3,j)-x(g,r_4,j)]$
5	DE/rand-to-best /1/bin	$v(g,i,j) = x(g,i,j) + F*[x(g,best,j)-x(g,i,j)] + F*[x(g,r_1,j)-x(g,r_2,j)]$
6	DE/rand/1/exp	$v(g,i,j) = x(g,r_3,j) + F*[x(g,r_1,j) - x(g,r_2,j)]$
7	DE/best/1/exp	$v(g,i,j) = x(g,best,j) + F*[x(g,r_1,j) - x(g,r_2,j)]$
8	DE/best/2/exp	$v(g,i,j) = x(g,best,j) + F*[x(g,r_1,j)+x(g,r_2,j)-x(g,r_3,j)-x(g,r_4,j)]$
9	DE/rand/2/exp	$v(g,i,j) = x(g,r_5,j) + F*[x(g,r_1,j)+x(g,r_2,j)-x(g,r_3,j)-x(g,r_4,j)]$
10	DE/rand-to-best /1/exp	$v(g,i,j) = x(g,i,j) + F*[x(g,best,j)-x(g,i,j)] + F*[x(g,r_1,j)-x(g,r_2,j)]$

used for each problem are determined by trial and error. The control parameters are NP, population size, CR, cross over constant and F, weighting factor used to control the amplification of the differential variation. It has been suggested that NP should be taken to be 10 times the number of parameters to be optimized, CR and F to be from 0.5 to 1.0 (Price and Storn, 2008).

DE/rand/1/bin is the most widely used and the most successful strategy (Babu et al., 2005). The strategies are denoted by DE/x/y/z where DE represents differential evolution, x represents the individual being perturbed, y is the number of difference vectors used to perturb x and z is the crossover method used. Other strategies include DE/best/1exp, DE/rand/1/exp, DE/rand-to-best/1/exp, DE/best/2/exp, DE/rand/2/exp, DE/best/1/bin, DE/rand-to-best/1/bin, DE/best/2/bin and DE/rand/2/bin. The descriptions of these DE strategies are given in Table 1. Several studies (Angira and Babu, 2005; Babu et al., 2005; Deb et al., 2002; Madavan, 2002; Robic and Filipic, 2005; Xue et al., 2003; Adeyemo and Otieno, 2010; Adeyemo and Otieno, 2009b) have extended DE to multi-objective problems. All these algorithms produce non dominated solutions on the Pareto front. One solution will have to be chosen for system implementation. No solution is said to be better than the other on the Pareto front if all the objectives are considered. To choose a good solution from the set of non dominated solutions, more knowledge of the problem is needed. We propose to use a single objective model formulation of the problem where each objective is solved separately while the others are taken to be constraints. The bound constraints are chosen based on the results of the multi-objective formulation. By reducing the search range for the algorithm, the results of the optimization are better and the algorithm runs faster. We propose single objective differential evolution algorithm to solve the multi-objective crop planning model presented by Adeyemo and Otieno (2010). The results generated by the multi-objective crop planning are used to set the bound constraints of our model. The multi-objective optimization produced solutions that are equally good called non-dominated solutions having ranges of results for each objective presented. The bound constraints are selected within the limits of non-dominated results presented by them.

Evolutionary algorithms (EAs) as robust optimization techniques have the ability to find multiple Pareto optimal solutions in one single simulation run because of their population-approach. They are general purpose stochastic search methods simulating natural selection and biological evolution (Salman et al., 2007). They maintain a population of potential (or candidate) solutions to a problem. They are biologically-inspired optimization algorithms, imitating the process of natural evolution, and are becoming important optimization tool for several real world applications. They use a set of solutions called population to converge to the optimal solution. They are less susceptible to problem dependent characteristics, such as the shape of the Pareto front (convex, concave or even discontinuous), and the mathematical properties of the search space, whereas these issues are of concerns for mathematical programming techniques for mathematical tractability (Angira and Babu, 2005).

Several studies have used evolutionary algorithms for optimization problems with success. Angira and Babu (2005) applied differential evolution to the optimization of non-linear function. Babu and Angira (2006) used it to solve optimization of non-linear chemical processes. In the area of water resources management, Vasan and Raju (2007) demonstrate the applicability of DE to a case study of Mahi Bajaj Sagar Project in India. They employed the ten strategies of DE to asses the ability of DE for solving higher dimensional problems as an alternative methodology for irrigation planning. They compared their results with the ones generated by linear programming (LP). They suggested that DE/rand-to-best/1/bin strategy is the best strategy giving maximum benefits taking minimum CPU time. The results they got from the ten strategies of DE are comparable to those of LP. They varied the DE parameters to determine the combination of the parameters that would generate the best result. The parameters considered are population size, crossover constant and weighting factor. A similar study by Adeyemo and Otieno (2009c) found DE/rand/1/bin with values of population size, crossover constant and scaling factor of 160, 0.95 and 0.5 respectively as the strategy that obtains the best solution most efficiently.

Another approach used by Reddy and Kumar (2007) is called multi-objective differential evolution (MODE). They proposed MODE for the simultaneous evolution of optimal cropping pattern and operation policies for a multicrop irrigation reservoir system. They used their approach to achieve robust performance by handling interdependent relationships among the decision variables of the model. Their model results suggest that changes in the hydrologic conditions over a season have considerable impact on the cropping pattern and net benefit from the irrigation system. Chang and Chang (2009) applied NSGA-II to examine the operations of a multi-reservoir system in Taiwan. They developed a daily operational simulation model to guide the releases of reservoir system and then to calculate the shortage indices (SI) of both reservoirs over a long-term simulation period. They used NSGA-II to minimize the SI values through identification of optimal joint operating strategies. Their results indicate that NSGA-II provides a promising approach.

A combination of genetic algorithm (GA) and discrete differential dynamic programming approach called GA-DDDP was used by Tospornsampan et al. (2005) to optimize the operation of the multiple reservoir system. The model by Karamouz et al. (2009) includes a GA based optimization model linked with a reservoir water quality simulation model. The objective function of the optimization model is based on the Nash bargaining theory to maximize reliability of supplying the downstream demands with acceptable quality, maintaining a high reservoir storage level, and preventing quality degradation of the reservoir. Many other studies apply evolutionary algorithm to water resources management and find the algorithms efficient (Janga and Nagesh, 2007a; Karterakis et al., 2007; Madavan, 2002; Azamathulla et al., 2008).

METHODOLOGY

The objective of this paper is to use differential evolution algorithm to solve crop planning problem using single objective model formulation. The model was solved by Adeyemo and Otieno (2010) using multi-objective techniques. We use the results got by them to reformulate the model by maximizing one objective and using the other two objectives as constraints. The three objectives of the crop planning problem are minimization of irrigation water, maximization of total net income and maximization of total agricultural output. They used multi-objective differential evolution algorithm (MDEA) developed by Adeyemo and Otieno (2009b). They developed three other strategies of MDEA and compared the results generated by the four algorithms (MDEA1, MDEA2, MDEA3 and MDEA4). From the analysis of their results, we found that the MDEA1 generated the maximum total net income of ZAR 1,304,600 with maximum total agricultural output of 467 tons using 702,290 m^3 of water and corresponding maximum planting areas of 513,470, 551,660, 50,000 and 52,145 m^2 for maize, groundnut, Lucerne and Pecan nuts respectively and maximum total planting area of 752,210 m^2. With these results, we formulated our model within these ranges to generate more profit for the farmers. For example, we chose the search range for total agricultural output to be 98 to 467 tons, the planting areas for maize, groundnut, Lucerne and Pecan nuts to be 50,000 to 513,470, 50,000 to 551,660, 50,000 to 51,000, and 50,000 to 52,145 respectively. This reduced the search range for our results and the algorithm ran faster resulting in better results. The search ranges used by Adeyemo and Otieno (2010) are wider. The total agricultural output was set to be maximized without any maximum limit. The minimum planting areas for maize, groundnut, Lucerne and Pecan nuts are set to be 50,000 m^2 while the maximum planting areas are set to be 500,500; 255,000; 255,000 and 505,000 respectively.

The model is presented below:

Objective function: Maximization of total net income

The total net income for the farmer is maximized.

$$\text{Maximize TNI} = \sum_{i=1}^{n}(TI_i * A_i) - (A_i * CWR_i * C_w) - EXP \quad (1)$$

$$= \sum_{i=1}^{n} A_i [TI_i - (CWR_i * C_w)] - EXP \quad (2)$$

Where:

TNI - total net income for the farmer planting the 4 crops in the whole year.
TI_i - total income of ith crop in South African Rand (ZAR) per annum
EXP - total expenses on the whole farm which are the overhead costs, household expenses and fixed liabilities per annum (ZAR)
C_w - cost of water per m^3 = 8.77 cents.

To calculate the total income (ZAR/m^2) from each crop, the selling price (ZAR/ton) and yield (ton/ha) of crop are multiplied and divided by 10 000. The selling price and yield of the crops are taken from Agriculture (2008).

$$TI_i\,(ZAR/m^2) = [Price_i\,(ZAR/ton) * Yield_i\,(ton/ha)]\,/10\,000 \quad (3)$$

Constraint 1: Total planting area

In maximizing both the total net income and total agricultural output, the farm size can not exceed the total farm area of 771 000 m^2. Therefore, the sum of all the planting areas for the 4 crops should be less than or equal to the total planting area.

$$TPA = \sum_{i=1}^{n} A_i \le 771000 \quad (4)$$

Where TPA is the total planting area in m^2.

Constraint 2: Total irrigation water

The total irrigation water used on the farm in the whole year can not exceed the allocation of 704,694 m^3 per annum in the area.

$$TIW \le 704694 \quad (5)$$

Constraint 3: Monthly irrigation water

The monthly irrigation water use on the farm can not exceed the total monthly water release to the farm. The water is supplied to the farm for 5½ days a week. The water supply for one hour is 150 m^2. Therefore, the total monthly release is:

(150 m^3/h * 24 h * 5.5 days * 52 weeks)/12 months = 85,800 m^3/month

Therefore, the total crop water requirements for the 4 crops in any month of the year should not exceed 85 800 m^3/month.

$$IRD_t \le 85800 \;;\; (t = 1, 2, --- 12) \quad (6)$$

Where, IRD_t is the irrigation demand in month t.

Constraint 4: Minimum and maximum planting areas

Based on the minimum and maximum planting areas generated by Adeyemo and Otieno (2010), minimum and maximum planting areas are chosen to reduce the search range for the algorithm. This will enable the algorithm to generate more quality results in a short time.

$$50000 \le A_1 \le 513470 \quad (7)$$

$$50000 \le A_2 \le 551660 \quad (8)$$

$$50000 \le A_3 \le 51000 \quad (9)$$

$$50000 \le A_4 \le 52145 \quad (10)$$

Where A_1, A_2, A_3 and A_4 are the planting areas for maize, groundnut, Lucerne and Pecan nuts respectively.

Constraint 5: Maximum total output

From the results of Adeyemo and Otieno (2010), the maximum total agricultural output is 467 tons. We want our search to be limited to a maximum of 467 tons.

$$TAP \le 467 \quad (11)$$

RESULTS AND DISCUSSION

The results in this study are generated by single objective formulation after multi-objective non dominated results of Adeyemo and Otieno (2010) to the maximizations of both the total agricultural output and total net benefit while minimizing the total irrigation water. The objective of this paper is to help a farmer who desires to maximize his total net benefit while satisfying other objectives and constraints. The other objectives are treated as constraints. A farmer is faced with the problem of choosing a desired solution from many non-dominated solutions presented to him even if his main objective is just one of the three objectives. In practice, the decision maker ultimately has to select one solution from this set for system implementation (Deb, 2001). The use of single objective after multi-objective to find the ultimate solution can improve our results and help a decision maker in finally selecting the best solution.

The ten strategies of differential evolution are tested with this model. The results generated by the ten strategies are comparable and better than the ones by Adeyemo and Otieno (2010). In Table 2, DE/rand/1/bin generated the highest total net benefit of ZAR 1,330,000 of all the ten strategies. The total net benefit generated by MDEA1 (multi-objective) is ZAR 1,304,600 which is less than the one generated by DE/rand/1/bin (single objective). This shows that single objective model formulation can be used to find a better solution after

Table 2. The total net benefit, total planting areas, total irrigation water, total agricultural outputs and the corresponding planting areas for the four crops for the ten strategies of differential evolution

DE strategies	No of Iterations	Total net benefit (ZAR)	Total planting areas	Total irrigation water	Total Agricultural output	Planting areas			
						Maize	Groundnut	Lucerne	Peacan nut
MDEA1		1304600	725123	702000	316.26	73463	551660	50000	50000
DE/rand/1/exp	768	1179700	747870	703190	379.87	229410	417980	50086	50394
DE/best/1/exp	2656	1224600	699580	704160	308.49	97060	478290	50000	74226
DE/best/2/exp	1657	935730	674870	702790	363.13	309940	199110	50000	115820
DE/rand/2/exp	1375	1168600	681020	704400	301.25	91661	449780	61756	77828
DE/rand-to-best/1/exp	1907	900040	676250	703030	373.15	309940	199110	69996	97202
DE/rand/1/bin	1207	1330000	724640	704694	307.85	50000	574640	50000	50000
DE/best/1/bin	3400	1224600	699580	704160	308.49	97060	478290	50000	74226
DE/best/2/bin	2980	935130	711610	703506	258.49	67500	478290	50000	115820
DE/rand/2/bin	4328	936130	582629	702136	313.13	50000	376504	61756	94369
DE/rand-to-best/1/bin	3651	870060	675448	702360	303.15	309740	198910	69796	97002

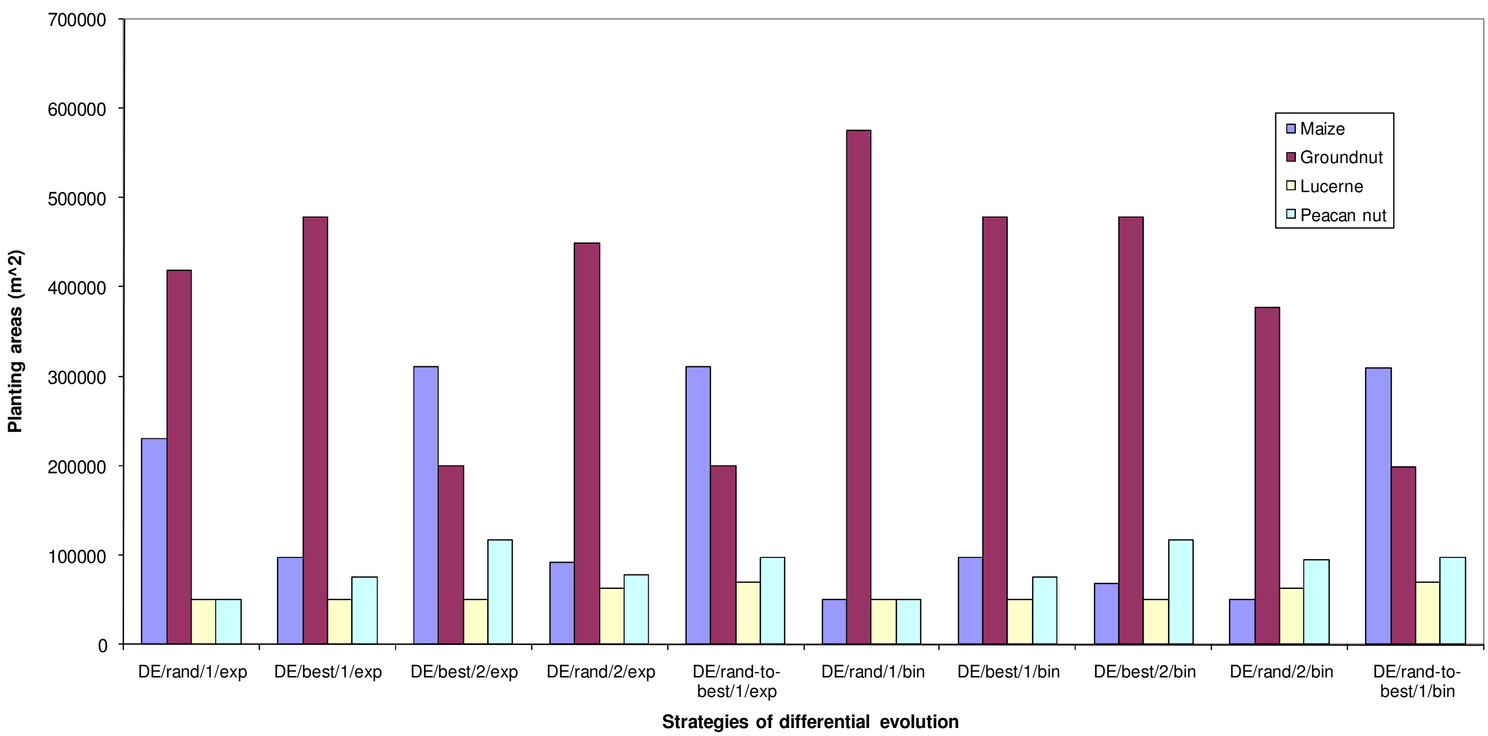

Figure 1. Different planting areas for the four generated by the ten ten strategies of different evolution.

using a multi-objective model formulation. The results of DE/rand/1/bin are better than those of MDEA1. The total planting area is 724,640 m^2 which is less than 725,123 m^2 generated by MDEA1. This shows that a higher total net benefit can be generated using less total planting areas with DE/rand/1/bin. Also, 307.85 tons was generated by DE/rand/1/bin against 316.26 tons generated by MDEA1. The planting areas for Lucerne and Peacan nut are the same for the two algorithms. The planting areas for groundnut are 574,640 m^2 for DE/rand/1/bin and 551,660 m^2 for MDEA1. The planting areas for maize are 73,463 m^2 for MDEA1 and 50,000 m^2 for DE/rand/1/bin. Therefore, the planting area generated for maize by MDEA1 is more than that generated by DE/rand/1/bin but less than that of groundnut.

In Figure 1, different planting areas for the four crops generated by the ten strategies of differential evolution are presented. In seven out of ten strategies, the planting

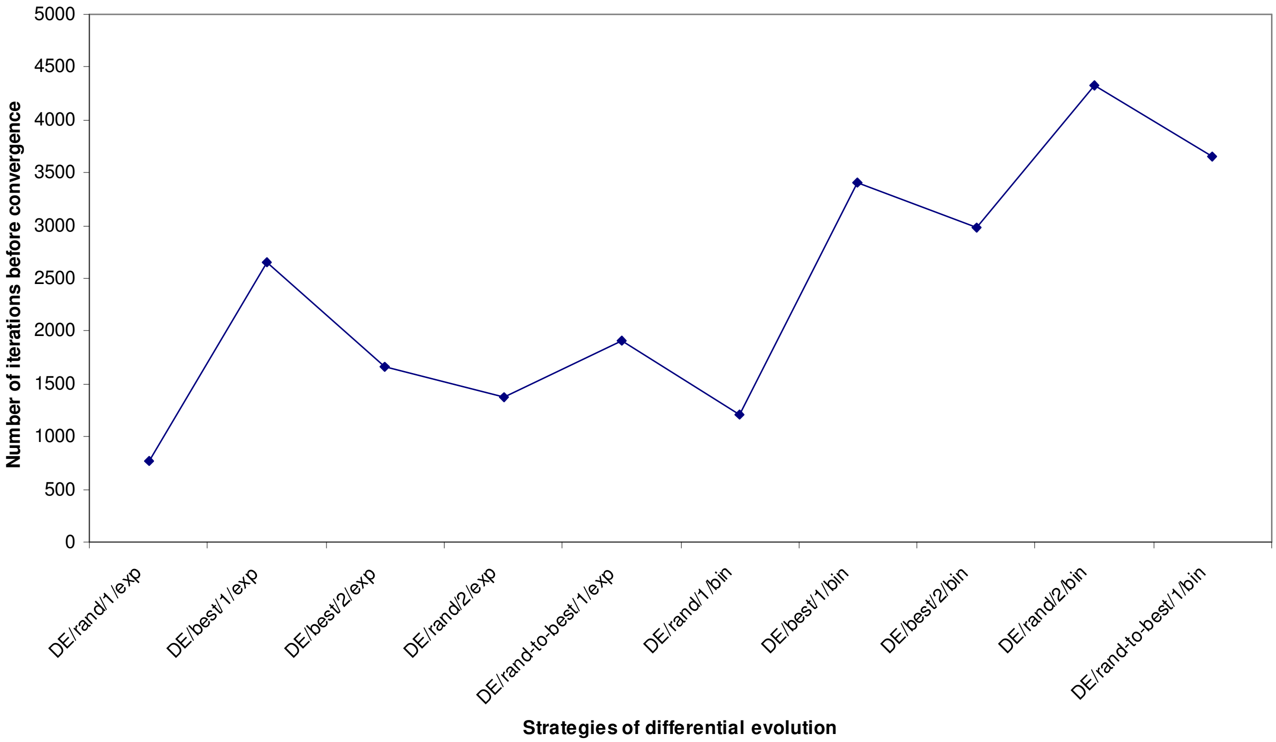

Figure 2. Number iterations before convergence for the ten strategies of differential evolution.

areas for groundnut are more than the other crops. Maize has the highest planting areas in three out of the ten strategies. Maize follows groundnut in the planting areas in five out the ten strategies. The results are in agreement with those of Adeyemo and Otieno (2010).

As reported by Grove (2006), peacan nut can not be planted in the highest planting areas because of water shortage. Peacan nut could have increased the expected net value if planted in more areas but it requires more irrigation water. Peacan nut is planted in more areas than Lucerne in eight strategies and has the same planting area with Lucern in the remaining two strategies.

In Figure 2, DE/rand/1/exp converged after 768 iterations which is the lowest of all the strategies. It is the strategy that converged faster than the others. DE/rand/1/bin converged after 1,207 iterations and generated the highest total net benefit. Strategies with binomial crossover method converge slower than strategies with exponential crossover as reported by Adeyemo and Otieno (2009c). DE/rand/2/bin which converged after 4,328 iterations is the strategy with the highest number of iterations. In Figure 2 and Table 2, we can conclude that the number of iterations before convergence has no correlation with the quality of results generated by the DE strategies. This confirms the study of Otieno and Adeyemo (2009b).

The increase in the total net benefit generated has no correlation with total area, total volume and total output as shown in Figure 3. DE/rand/1/bin with the highest total net benefit of ZAR 1,330,000 has the corresponding total area, total volume and total output of 724,640 m^2, 704,694 m^3 and 307.85 tons respectively. Conversely, DE/ran-to-best/1/exp with the total net benefit of ZAR 900,040 has the corresponding total area, total volume and total output of 676,250 m^2, 703,030 m^2 and 373.15 tons respectively.

The best results from all the strategies considering a single objective of maximizing total net benefit from farming within the limit of land and water availabilities was generated by DE/rand/1/bin. The solution was generated after considering the limit of solutions generated by the multi-objective model formulation solved by MDEA1 by Adeyemo and Otieno (2010). The solution by DE/rand/1/bin cannot utilize all the available land because of shortage of water as previously reported by Grove (2006) and Adeyemo and Otieno (2010). We recommend that other water sources should be made available to farmers in the study area. From the results generated, strategies with binomial crossover have more quality results than strategies with exponential crossover method as reported in the literatures (Adeyemo and Otieno, 2010, 2009c, d, a; Raju and Vasan, 2004; Reddy and Kumar, 2007). Some of the strategies with exponential crossover method have premature convergence hence their inability to generate quality results.

Conclusion

The use of single objective optimization model to choose

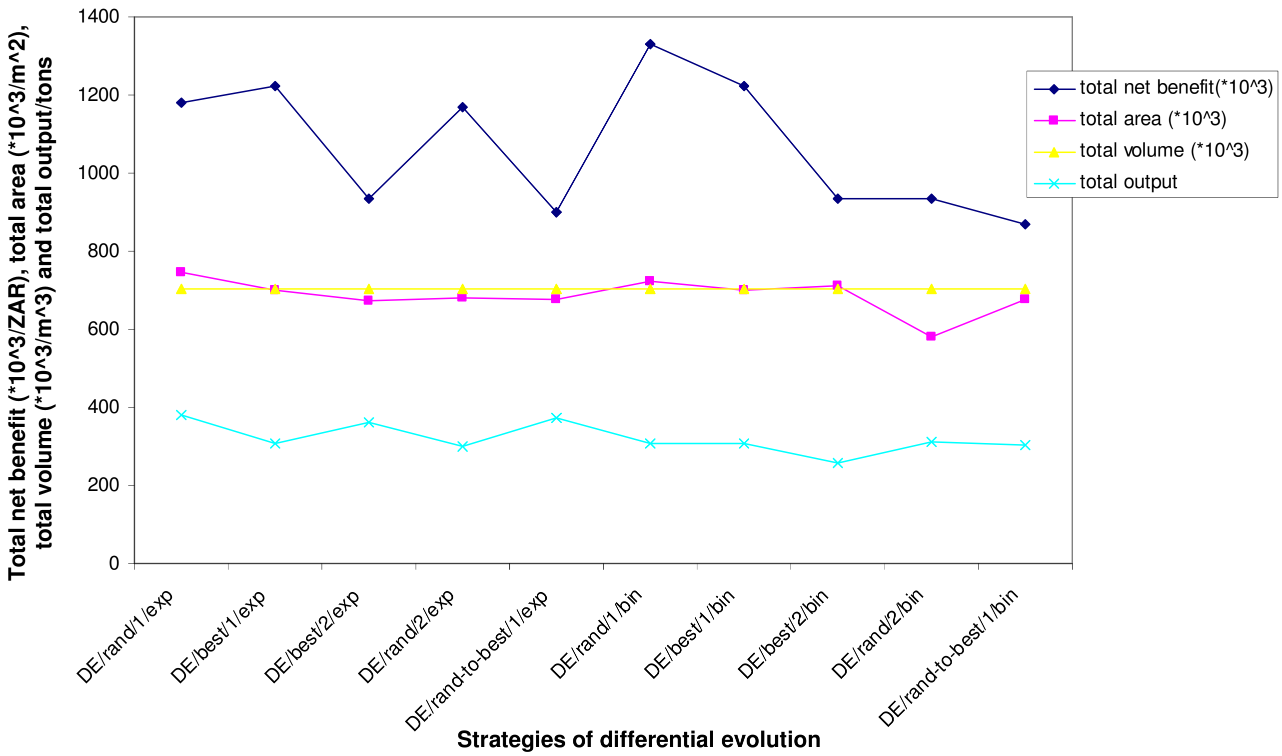

Figure 3. Total net benefit , total volume generated by the ten strategies of differential evolution.

a viable and the best solution from a set of non dominated solutions generated by multi-objective optimization model is demonstrated in this study considering one of the objectives and using the others as constraints. The single objective optimization model was solved using novel differential evolution algorithm which a family of evolutionary algorithms. The multi-objective differential evolution algorithm (MDEA) developed by Adeyemo and Otieno (2009b) based on differential evolution algorithm was used as a multi-objective algorithm in this study. The crop planning problem presented in this study was studied by Adeyemo and Otieno (2010) using multi-objective model. This study maximizes the total net benefit while considering the other two objectives of minimizing irrigation water and maximizing total output as constraints. The other constraints used were taken from previous studies. The bound constraints were chosen from the limits of the results presented by Adeyemo and Otieno (2010). From the results generated in this study, groundnut is the most profitable of the four crops planted. The total net benefit of ZAR 1,330,000 was generated by DE/rand/1/bin which is higher than ZAR 1,304,600 generated by MDEA1. Land is also efficiently utilized with DE/rand/1/bin using 724,640 m^2 while MDEA1 uses 725,123 m^2. The total net benefit generated by the ten strategies of DE ranges from ZAR 870,060 by DE/rand-to-best/1/bin to ZAR1,330,000 by DE/rand/1/bin. The total area ranges from 582,629 m^2 generated by DE/ran/2/bin to 747,870 m^2 generated by DE/rand/1/exp. The total volume of irrigation water ranges from 702,136 m^3 (DE/rand/2/bin) to 704,694 (DE/rand/1/bin). Finally, the total agricultural output ranges from 258.49 tons (DE/best/2/bin) to 379.87 tons (DE/rand/1/exp).

The planting areas for maize, groundnut, Lucerne and peacan nuts range from 50,000 to 309,940 m^2, 198,910 to 574,640 m^2, 50000 to 69,996 m^2 and 50,000 to 115,820 m^2 respectively. We conclude that single objective differential evolution algorithm can be used to complement multi-objective differential evolution algorithm to generate better results in crop planning and water resources management problem generally. It can also be used to choose one solution out of many non dominated solutions generated by a multi-objective algorithm using the results of multi-objective algorithm to set the bound constraints. This will reduce the search range resulting in less number of iterations with more quality results.

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