Multiobjective Optimization of Crop-mix Planning Using Generalized Differential Evolution Algorithm

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ABSTRACT

This paper presents a model for constrained multiobjective optimization of mixed-cropping planning. The decision challenges that are normally faced by farmers include what to plant, when to plant, where to plant and how much to plant in order to yield maximum output. Consequently, the central objective of this work is to concurrently maximize net profit, maximize crop production and minimize planting area. For this purpose, the generalized differential evolution 3 algorithm was explored to implement the mixed-cropping planning model, which was tested with data from the South African grain information service and the South African abstract of agricultural statistics. Simulation experiments were conducted using the non-dominated sorting genetic algorithm II to validate the performance of the generalized differential evolution 3 algorithm. The empirical findings of this study indicated that generalized differential evolution 3 algorithm is a feasible optimization tool for solving optimal mixed-cropping planning problems.

Keywords: Cropping Pattern, Evolution, Genetics, Optimization, Planning.

INTRODUCTION

There is no denying fact that agriculture and agricultural products play important roles in sustaining lives on the planet earth. In general, humans need animals and plants for foods, animals need plants for foods. Moreover, plants benefit from humans and animals, otherwise it would be difficult for humans, plants and animals to survive on the planet earth. The provisioning of sufficient foods to cater for the enormous populations on the planet earth requires efficient planning in agriculture. The bulk of studies on agricultural farm production planning normally focus on crop rotation or mixed-cropping techniques to keep planting areas under continuous production. The practice of mixed-cropping planning is related to many factors that may include measurable and non-measurable factors. These factors include the types of available land for cultivation, yield rates of the cultivated crops, weather conditions, rainfall, irrigation system and availability of agricultural inputs such as machinery, fertilizer, capital, labour and cost of production.

The cultivation of a sequence of crops while satisfying crop succession requirements is characterized by mixed-cropping techniques. Mixed-cropping is a cropping system involving a group of crops with more than one crop that is cultivated on a plot in the same cropping period or season. It involves the exploitation of jointly beneficial interrelationships amongst individual crops. The central objective of crop planning is to search for an optimal combination of crops amongst those considered in order to maximize the overall contributions while concurrently satisfying a set of constraints such as land availability

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and capital. The benefits of the mixed-cropping techniques include higher crop yield, better spread of crop production over the growing period, improved quality of products and reduced risk of total crop failure. The success of a mixed-cropping technique is, therefore, dependent on the integration of mathematical models to manage all the components of the production system.

This study explores the Generalized Differential Evolution 3 (GDE3), an evolutionary algorithm to solve the constrained multiobjective optimal mixed-cropping problem formulation. Evolutionary algorithms have been used in recent times to solve different classes of single and multiobjective optimization problems from the domain of operation research (Deb and Tiwari, 2005; Zhou *et al.*, 2011). There are numerous practical benefits of using evolutionary algorithms to solve real optimization problems with multiple conflicting objectives as compared with the classical optimization and artificial intelligence techniques. These benefits include their conceptual simplicity, flexibility, parallelism, potential to incorporate domain specific knowledge and ability to self-adapt the search to find global optimum solutions on the fly (Fogel, 1977; Huang, *et al.*, 2009).

The agricultural systems pose numerous challenges that can be formulated and solved as optimization problems. In dealing with numerous challenges of agricultural problems, certain authors have considered different mathematical formulations of agricultural problems and applications of diverse techniques to solve these problems. For instances, crop selection (Detlefsen and Jensen, 2007; Brunelli and von Lücken, 2009), crop planning (Sarker *et al.*, 1997; Sarker and Quaddus, 2002; Sarker and Ray, 2009; Adeyemo *et al.*, 2010; Márquez *et al.*, 2011), irrigation planning (Adeyemo and Otieno, 2009; Raju *et al.*, 2012; Chetty and Adewumi, 2014) and vegetable production (Francisco and Ali, 2006). The variety of optimization models that were previously used for crop planning ranges from single to multiobjective. These models also include linear to non-linear forms, where computational intelligence techniques such as evolutionary algorithms have been explored.

The class of optimization problems practically appears in many relevant application areas of human life, such as project scheduling and staffing, production planning, transportation, investment planning and many more. The improvement in solutions of optimization problems has direct consequences on costs and other important factors such as customer satisfaction. It is well known that only special classes of optimization problems like linear optimization can be efficiently solved by polynomial time algorithms. Many real world optimization problems are hard to solve because of additional requirements and the nature of such problems. Specifically, these problems may have a combinatorial structure and they may be non-linear. In order to efficiently solve such complex optimization problems, a large number of algorithmic solution approaches have been invented in recent times. These approaches can be classified into two main categories, the exact and the heuristic algorithms with each class having its assets and inherent drawbacks.

The exact optimization approaches like the branch-and-bound, dynamic programming, constraint programming and the large class of linear programming techniques like branch-and-cut, branch-and-price, branch-and-cut-and-price are guaranteed to find an optimal solution and to guarantee that the solution found is indeed optimal (Papadimitriou and Steiglitz, 1998; Hoffman and Ralphs, 2013). In general, the run-times of these algorithms often increase dramatically with increased sizes. This follows that only small or moderately sized instances can be solved within reasonable run-times. On the other hand, heuristic algorithms tradeoff optimality for run-time gain and are applicable to larger instances of hard problems.

Metaheuristics algorithms have especially proven to be highly useful in practice. This class of algorithms includes, among others, variable neighbourhood search, simulated annealing, various population-based methods like evolutionary algorithms and the estimation of distribution algorithms like ant colony optimization (Glover and Kochenberger, 2003; Hoos and Stützle, 2004; Gendreau and Potvin, 2010). The assets and drawbacks of the two classes of techniques can be seen as complementary, therefore, combining the ideas from both streams appears to be natural. The hybrid algorithms combining elements of both streams have proven to be more efficient in terms of run-time or solution quality. Such a class of hybrid algorithms is called *metheuristics*. The various models of combinations exist (Dumitrescu and Stützle, 2003; Puchinger and Raidl, 2005; Raidl, 2006) and their classification is reported (Talbi, 2002; Talbi, 2009).

The past studies on crop planning mainly differ in terms of the objective functions considered, the constraints applied and the methodologies used to solve the problems examined (Table 1). The study at hand considered both fixed cost and variable cost that are required per unit area for crops. The previous authors have extensively considered the variable costs (Sarker *et al*.

1997; Sarker and Quaddus 2002; Sarker and Ray 2009; Chetty and Adewumi 2014).

MATERIALS AND METHODS

The Optimal Mixed-cropping Planning Model

The mathematical formulation of a mixed-cropping planning problem as considered in this study is a tri-objective model. The model is designed to concurrently maximize net-profit that can be produced by maximizing total crop production and minimizing the planting area. The objective is to make an effective use of the available limited resources to determine land allocation, amongst several competing crops that are required to be planted in the year. The soil characteristics, cropping patterns, crops produced, region and cropping methods are factors that affect production cost, yield rate and earning realized by the farmer. The mixed-cropping model is designed for a large scale planning incorporated with the data collected from the South African grain information service and the South African abstract of agricultural statistics (AAS, 2012). The objective functions and constraints of the optimization model are considered as follows:

Table 1. Optimal crop planning models [↑: maximization, ↓: minimization].

Author	Methodology	Objective	Constraint
Sarker and Quaddus, 2002	Goal programming	↑Total contribution	Food demand, land, capital, contingency, area and import bond
Sarker *et al*., 1997.	Linear Programming	↑Total contribution	Food demand, land, capital, contingency, area and import bond
Sarker and Ray, 2009	Multi-objective constrained algorithm (MCA).	↑Total contribution ↓Working capital	Food demand, land, capital, contingency, area and import bond
Chetty and Adewumi, 2014	Swarm Intelligence	↑Total gross profits	Land, irrigation
Current work	Generalized Differential Evolution	↑Net profit ↑Crop production ↓Land utilization	Economic demand of crops, land resource, investment in crop production and labour cost.

Objective Function 1: Profit Maximization

The principle on which the model is based is the principle of profit maximization, wherein the farmer has to choose a production plan that is likely to maximize profit. This can be expressed in a mathematical term that represents the net profit from single crop land (k= 1), double crop land (k= 2) and triple crop land (k= 3) as follows:

$$F_1 = \sum_j \sum_{i \in M_j}^m (P_i \times U_{i,j,k=1} - V_{i,j,k=1} - F_{i,j,k=1}) \times X_{i,j,k=1}$$

$$+ \sum_j \sum_{i \in N_j}^n (P_i \times U_{i,j,k=2} - V_{i,j,k=2} - F_{i,j,k=2}) \times X_{i,j,k=2}$$

$$+ \sum_j \sum_{i \in Q_j}^q (P_i \times U_{i,j,k=3} - V_{i,j,k=3} - F_{i,j,k=3}) \times X_{i,j,k=3}$$

(1)

Objective Function 2: Crop Production Maximization

Given the choice in terms of profit maximization and challenges faced by farmers in the production process, a farmer attempts to produce a specific level of output that requires maximizing crop production, according to the objective function. (equetion2)

Objective Function 3: Planting Area Minimization

From the socioeconomic perspective, besides meeting food demand, cultivation of profitable crops is dependent on the proper land allocation. Crop production maximization will therefore require minimizing the planting area, according to the following objective function. (equetion3)

Constraints

The objective functions considered in this study are to be solved, subject to the following five essential constraints:

Economic Demands for Crops

The total crop produced in a cropping year must not be less than the economic demands of crops in the country, which can be expressed as the constraint. (equetion4)

Land Resource

The total land used for a given type of land must not be greater than the total available land of that type, which can be expressed as:

$$\sum_i \sum_j W_k \times X_{i,j,k} \leq L_k \quad \forall k \quad (5)$$

Where, $W_1 = 1$, for single-cropped land, because one crop is planted on a land, $W_2 = 1/2$, because two crops are planted on the same land, and $W_3 = 1/3$, because three crops are planted on the same land.

Labour Cost

The total time required to cultivate a crop i in a single-crop year must not be greater than the total work time at the farm which can be expressed as equetion5.

Investment in Crop Production

The total investments in crop production

$$F_2 = \sum_j^m \sum_{i \in M_j} G_{i,j,k=1} \times X_{i,j,k=1} + \sum_j^n \sum_{i \in N_j} G_{i,j,k=2} \times X_{i,j,k=2} + \sum_j^q \sum_{i \in Q_j} G_{i,j,k=3} \times X_{i,j,k=3}$$

(2)

$$F_3 = \sum_j^m \sum_{i \in M_j} X_{i,j,k=1} + \sum_j^n \sum_{i \in N_j} X_{i,j,k=2} + \sum_j^q \sum_{i \in Q_j} X_{i,j,k=3}$$

(3)

$$\sum_j^m \sum_{i \in M_j} G_{i,j,k=1} \times X_{i,j,k=1} + \sum_j^n \sum_{i \in N_j} G_{i,j,k=2} \times X_{i,j,k=2} + \sum_j^q \sum_{i \in Q_j} G_{i,j,k=3} \times X_{i,j,k=3} \geq D_i \ \forall i$$

(4)

$$\sum_{j}^{m}\sum_{i\in M_j} T_{i,j,k=1} \times X_{i,j,k=1} + \sum_{j}^{n}\sum_{i\in N_j} T_{i,j,k=2} \times X_{i,j,k=2} + \sum_{j}^{q}\sum_{i\in Q_j} T_{i,j,k=3} \times X_{i,j,k=3} \leq H_k \quad \forall k \tag{5}$$

$$\sum_{j}^{m}\sum_{i\in M_j} (F_{i,j,k=1} + V_{i,j,k=1}) \times X_{i,j,k=1} + \sum_{j}^{n}\sum_{i\in N_j} (F_{i,j,k=2} + V_{i,j,k=2}) \times X_{i,j,k=2} +$$

$$\sum_{j}^{q}\sum_{i\in Q_j} (F_{i,j,k=3} + V_{i,j,k=3}) \times X_{i,j,k=3} \leq C_a \tag{6}$$

must not be greater than the working capital, which can be expressed as the following constraint:

(equetion6)

Non-negativity of Decision Variables

The land area decision variables must not be less than zero, which can be expressed as the following constraint:

$$X_{i,j,k} \geq 0 \qquad \forall \ i, j, k \tag{7}$$

Where model variables are defined as follows:

i is a crop that can be considered for production,

j is a crop combination made up from i,

k is the land type,

$X_{i,j,k}$ is the area in hectares of land to be cultivated for a crop i of crop combination j in land type k,

P_i is the price in South African Rand (ZAR) of crop i per metric ton,

$V_{i,j,k}$ is the variable cost required per unit area for crop i of crop combination j in land type k,

$F_{i,j,k}$ is the fixed cost required per unit area for crop i of crop combination j in land type k,

$U_{i,j,k}$ is the number of farming units of crop i of crop combination j in land type k,

$G_{i,j,k}$ is the yield-rate, which is the amount of production in metric tons per hectare of crop i of crop combination j in land type k,

$T_{i,j,k}$ is the work time for growing crop i of crop combination j in land type k,

H_k is the working time for land type k,

W_k is the land-type coefficient for land type k,

D_i is the expected delivery in metric tons of crop i,

L_k is the available domain of land type k,

C_a is the working capital (ZAR),

m is the number of alternative crops for single-cropped land,

n is the number of crop combinations for double-cropped land,

q is the number of crop combinations for triple-cropped land,

M_j is a crop in each j for single-cropped land, $j= 1,…,m$,

N_j is the jth crop pair of the possible crop combinations of double-cropped land, $j= 1,…,n$

Q_j is the jth crop triple of the possible crop combinations of triple-cropped land, $j= 1,…,q$

Generalized Differential Evolution Algorithm

The Generalized Differential Evolution 3 (GDE3) algorithm (Kukkonen and Lampinen, 2009) modifies the selection rule of the basic Differential Evolution (DE) (Price *et al.*, 2005). The GDE 3 also extends DE/rand/1/bin strategy (Qin *et al.*, 2009) to multiobjective and multi-constraint problems. The selection rule is that old

vector is replaced by the selected trial vector in the next generation, if it weakly constraint-dominated old vector (Kukkonen and Lampinen, 2005). In the case of comparing feasible, incomparable and non-dominating solutions, both offspring and parent vectors are saved for the population of the next generation. This reduces the computational cost of the metaheuristic.

The population size may increase at the end of a generation, thereby making the population size higher than the original value. The population is then reduced back to the original size based on a similar selection method used in NSGA-II algorithm. The sorting of members of the population is based on the goal for a posteriori optimization. The worst members of the population are removed according to non-dominance and crowding to reduce the population size to the original size. GDE3 is similar to earlier developed differential evolution approaches such as Pareto-frontier Differential Evolution (PDE) (Abbass *et al.*, 2001), and DE for Multiobjective Optimization (DEMO) (Robič and Filipič, 2005). In constrast, DEMO does not contain constraint handling and does not recede to basic DE in single objective optimization. This is because DEMO modifies the basic DE and it does not consider weak dominance in the selection. GDE3 improves the ability to handle multiobjective optimization problems by giving a better distributed set of solutions and less sensitive to the selection of control parameter values compared to the earlier GDE versions.(Luo *et al.*, 2008).

Solving the Mixed-cropping Planning Model

There are more than 207 different crops cultivated in South Africa. Consequently, a full-scale model, considering all these crops would consist of more than 789 constraints and 550 decision variables. This is a very complex problem, but decision makers are interested only in the major crops and aggregate information of other crops (Sarker *et al.*, 1997). As a result, all the crops are divided into 8 major groups, such as Deciduous Fruit and Viticulture, Field Crops, Vegetables, Citrus Fruit, Subtropical fruits, Flowers, Nuts and Other horticultural products.

The crop groups are shown in Appendix I. The number of crop combinations identified for single, double and triple-cropped lands is 8, 14, and 3 respectively, according to the current cropping patterns in Appendix II. Any of the crop groups can be planted in a year, depending on the land type. In this study, as discussed earlier, the three objective functions considered are net profit maximization, crop production maximization and planting area minimization. The multiobjective evolutionary algorithm can generate a good number of alternative solutions in a single run to build the Pareto frontier, irrespective of the properties of the objective functions and the solution space.

Experimental Design

The GDE3 and Non-Dominated Sorted Genetic Algorithm II (NSGA-II) techniques were implemented using NETBEAN version 7.3, on an HP PC with Pentium dual core processor having 2.30 GHz clock speed and 4 GB of RAM.

Parameter Settings

As discussed in the earlier section, GDE3 requires very few parameter settings in comparison to other evolutionary algorithms. Only three parameters i.e. population size, crossover rate (CR) and scaling parameter (F) are needed for GDE3. The problem was solved with GDE3 having a population size of 100 and the number of generations was 50. An experiment was performed to determine the best values of F and CR for better performance in GDE3 algorithm. For this purpose, both CR and F vary from 0.1 to 1 with an increment of 0.1. The simulations were conducted for each value of F with respect to all values of CR. Hence, 100 such simulations were conducted. It was found from the results that a better Pareto optimal front is obtained by GDE3 with $F= 0.5$ and $CR= 0.9$. The NSGA-II control parameters are crossover probability $P_c= 0.9$ and mutation probability $P_m=1/D$. The parameter D is the number of decision variable, which in this work is 336. The distribution index of crossover operator $\eta_c= 20$ and distribution index of mutation

Appendix I. Various crops in South Africa and their groups.

1. Deciduous fruit and viticulture
    Apples, peaches, pears, plums, table grapes, wine grapes, other deciduous fruit and viticulture
	2. Field crops
	    Summer cereals (maize for grain, grain sorghum and other summer cereals), winter cereals (wheat, barley and other winter cereals), oilseeds (sunflower seeds, groundnuts, soya beans and other oil seeds), legumes (dry beans and other legumes), fodder crops (lucerne, maize for silage, teff and other fodder crops), other field crops (sugar cane, cotton, tobacco, seeds and other field crops)

3. Vegetables
    Potatoes, pumpkins, tomatoes, cabbage, cauliflower, green beans, onions, sweet potatoes, peas, beetroot, carrots and other vegetables
	4. Citrus fruit
	    Oranges, lemons, naartjie and other citrus fruit

5. Subtropical fruits
    Pineapples, bananas and other subtropical fruit
	6. Flower
	    Cultivated, wild and pot plants

7. Nuts
    Pecan, macadamia and other nuts
	8. Other horticultural products
	    Rooibos tea, herbs, seeds and seedlings and other products

Appendix II. Crop combinations.

Single cropped land: Any one of the following crop (/group) can be selected for this type of land

Combination No	Crop (/Crop group)
1	Deciduous fruit and viticulture
2	Field crops
3	Vegetables
4	Citrus fruit
5	Subtropical fruits
6	Flowers
7	Nuts
8	Other horticultural products

Double cropped land: Any combination of the following crops (/groups) can be selected for this type of land

Combination no	Members of the combination	
	Crop 1	Crop 2
1	Deciduous fruit and viticulture	Subtropical Fruits
2	Deciduous fruit and viticulture	Citrus fruit
3	Field crops	Vegetables
4	Field crops	Flowers
5	Field crops	Nuts
6	Field crops	Citrus fruit
7	Vegetables	Nuts
8	Vegetables	Citrus fruit
9	Citrus fruit	Subtropical fruits
10	Subtropical fruits	Field crops
11	Flowers	Vegetables
12	Nuts	Other horticultural products
13	Other horticultural products	Vegetables
14	Other horticultural products	Field crops

Triple cropped land: Any combination of the following crops (/groups) can be selected for this type for land

Combination No	Members of the combination		
	Crop 1	Crop 2	Crop 3
1	Deciduous fruit and viticulture	Subtropical fruits	Field crops
2	Nuts	Citrus fruit	Vegetables
3	Other horticultural products	Vegetables	Citrus fruit

operator η_m= 20. The number of the needed function evaluations for GDE3 was set to be 10,000.

RESULTS AND DISCUSSION

The mixed-cropping planning model of this study was solved using GDE3. The result obtained using GDE3 was compared with the NSGA-II algorithm, which is a representative of the state-of-the-art evolutionary multiobjective optimization algorithms. The optimization is formulated with three objectives of concurrently maximizing net profit, maximizing total crop production and minimizing total planting area. Figures 1(a-b) show the contour lines that display the patterns of net profit, total crop production and total planting area for the data produced by GDE3 and NSGA-II, respectively. In plotting the contour lines, the raw outputs computed by the GDE3 and NSGA-II algorithms were standardized in order to increase the effects of a variable whose variance is small and to reduce the effects of a variable with large variance. The minimax standardization procedure, which is one of the useful ways to standardize inputs was adhered to in this study. Given the data distribution $x = (x_1, x_2, x_3, \ldots, x_n)$, the minmax standardization procedure computes

a standardized value $f(x_i)$ in terms of the minimum value x_{min} and maximum value x_{max} of x for each ith data point x_i ($i = 1, 2, \ldots, n$) and is given by a simple formula:

$$f(x_i) = 100 * (\frac{x_i - x_{min}}{x_{max} - x_{min}})$$

(8)

In 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 that correspond to non-dominated solutions (Deb, 2001). In Figures 1(a-b), solutions with values of 70–90 are examples of such solutions. In Figure (1-a), solutions with values of 10 to 50 produced a lower value of land used compared to the respective solution in Figure (1-b), indicating that GDE3 produced a better performance compared to NSGAII. In practice, the decision-maker ultimately has to select one solution from the solutions with net profit values of 10 to 50.

Evaluating the quality of results for a single-objective optimization problem is relatively straightforward and significantly less challenging than for a multiobjective optimization problem. In a single objective optimization problem, researchers validate whether the quality of a specific solution
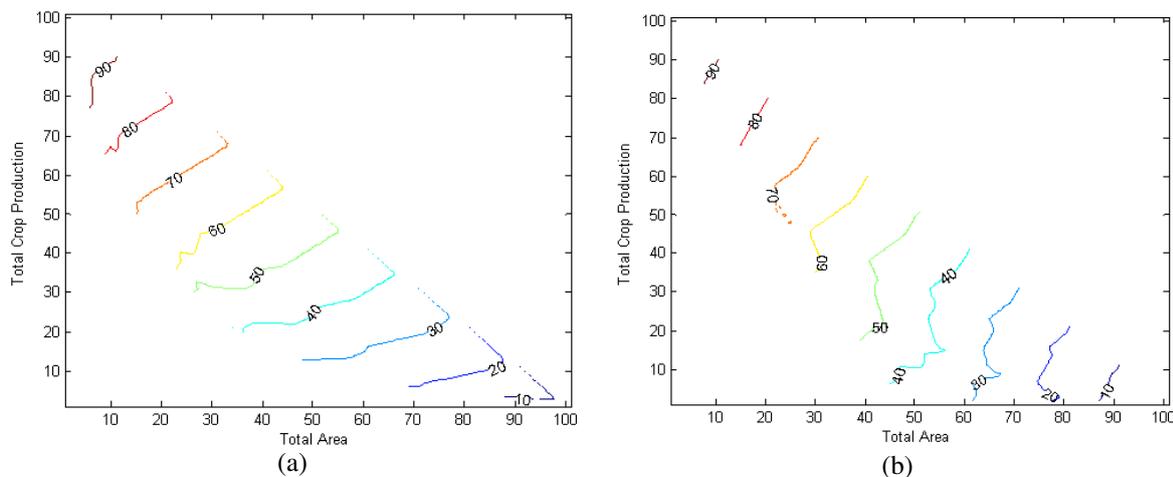

(a)   (b)

Figure 1. Contour lines for data produced (a) by GDE3. and (b) by NSGA-II.

was realized, how much computational feat was required, and how often such quality was realized (Khare *et al.*, 2003; Mohan and Mehrotra, 2011). The difference between obtaining solutions can clearly be measured and this measure can be used as a performance metric (Einstein, 2012). In contrast, the evaluation of the quality of results obtained for a multiobjective optimization problem is rendered challenging by the absence of a supreme, simple, and generally accepted performance metric (Deb and Tiwari, 2005).

A set of Pareto-optimal solutions form a Pareto optimal front and an approximation of the Pareto optimal front is called a set of non-dominated solutions (Manzano-Agugliaro *et. al.,* 2013). The goals of multiobjective optimization, therefore, are to find a set of solutions close as possible to the Pareto-optimal front and to find a set of solutions as diverse as possible to reveal trade-off information among different objectives. It has been argued that no single metric can be effective for measuring the performance of an algorithm (Deb and Jain, 2002), as a result, four commonly used metrics were used to measure the performances of the two algorithms explored in this study. The metrics for this study were selected based on predominant knowledge about their suitability to measure certain characteristics. The convergence of the obtained set of solutions was measured by generational distance (GD) and error ratio (ER) metric, while the diversity of the obtained set of solutions was measured with spacing (S), and maximum spread metrics (MS) (Knowles and Corne 2002; Zitzler *et al.* 2003).

Table 2 shows the mean and standard deviations of the metric values for the final approximation set over 50 independent executions. It can be observed from the result shown in Table 2 that GDE3 performed either similar to or better than NSGA-II. The superior performance of GDE3 over NSGA-II for the problem considered can be traced to the convergence and divergence improvement of the algorithm. The values produced by GDE3 and NSGA-II, with respect to the GD-metric, are very close. However, the value produced by GDE3 is much closer to zero, indicating that most of the generated solutions by the algorithm are on the true Pareto front. The value produced by GDE3, with respect to the ER-metric, is small when compared to the value produced by NSGA-II, indicating that GDE3 produced a better non-dominated set of solutions, which formed the Pareto optimal set of the problem. The value produced by GDE3, with respect to S-metric, is closer to zero

Table 2. Mean and standard deviation of metric values for algorithm performance across 50 independent executions.

	GD-metric (10^{-3})		ER-metric (10^{-3})		S-metric (10^{-3})		MS-metric	
	Mean (Std.Dev.)	Rank	Mean (Std. Dev.)	Rank	Mean (Std. Dev.)	Rank	Mean (Std. Dev.)	Rank
GDE3	0.5208 (0.4872)	1	0.1157 (0.0957)	1	0.3648 (0.4152)	1	0.4732 (0.3841)	1
NSGA-II	0.6283 (0.7397)	2	0.1181 (0.1021)	2	0.4015 (0.6534)	2	0.5149 (0.4256)	2

than the value produced by NSGA-II. This gives an indication that most of the non-dominated solutions produced by GDE3 are all the non-dominated solutions that are evenly spaced. The GDE3 produced a value much closer to zero than NSGA-II, with respect to MS-metric, meaning the solutions are ideally distributed and are perfectly spread out across the Pareto front. Overall, both algorithms had a good performance, but GDE3 produced a better performance than NSGA-II.

CONCLUSIONS

This work suggests that Generalized Differential Evolution 3 (GDE3) algorithm is a useful multiobjective optimization tool for optimal crop planning decision making. It has been shown that GDE3 can be successfully employed to search the feasible solutions space for a complex mixed-cropping planning problem that involves multiple objectives and multiple constraints. The GDE3 algorithm also uses a very simple mechanism to deal with constrained functions and results generated by the algorithm indicate that such mechanism, despite its simplicity, is effective in practice. From this study, it can be concluded that GDE3 is practically effective for optimal crop planning decision making. Given the features of GDE3, an extension of the paradigm for multiobjective optimization can be particularly useful to deal with dynamic functions. As part of future work, other optimization methods can be compared to GDE3 to establish its superiority for crop planning. The performance comparison of these optimization algorithms is valuable for a decision maker to consider tradeoffs in method accuracy versus method complexity. Finally, future work will extend GDE3 for crop planning decision under uncertainty. This will produce a novel approach to deal with practical situations for which profit coefficients of agriculture are uncertain.

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بهینه سازی چند منظوره کشت مخلوط با استفاده از الگوریتم عمومی تکامل تفریقی

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چکیده

این مقاله مدلی برای بهینه سازی محدود و چند منظوره برنامه کشت مخلوط ارایه می کند. چالش هایی که معمولا کشاورزان در تصمیم گیری برای دستیابی به حداکثر بازده (عملکرد)با آن رو به رو هستند عبارتند از تعیین نوع کشت، زمان کشت، مکان کشت، و سطح کشت. در نتیجه، هدف اصلی این پژوهش بیشینه سازی همزمان سود خالص وعملکرد و کمینه کردن سطح کشت بود. به این منظور،الگوریتم عمومی تکاملی تفریقی ۳ (generalized differential evolution 3 algorithm) برای اجرای مدل برنامه ریزی کشت مخلوط استفاده شد که با داده های اداره خدمات اطلاعاتی تولید غله و چکیده آمار نامه کشاورزی آفریقای جنوبی آزمون شده بود. آزمون های مشابه سازی با راستی آزمایی الگوریتم تکاملی تفریقی ۳ به وسیله الگوریتم ژنتیکی II با دسته بندی غیر-چیره انجام شد. یافته های عملی این پژوهش چنین اشاره داشت که الگوریتم عمومی تکامل تفریقی ۳ برای حل مسایل برنامه ریزی بهینه کشت مخلوط ابزار بهینه سازی قابل اجرایی است.