Optimal Crop Selection Using Multiobjective Evolutionary Algorithms

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■ *Farm managers have to deal with many conflicting objectives when planning which crop to cultivate. Soil characteristics are extremely important when determining yield potential. Fertilization and liming are commonly used to adapt soils to the nutritional requirements of the crops to be cultivated. Planting the crop that will best fit the soil characteristics is an interesting alternative to minimize the need for soil treatment, reducing costs and potential environmental damages. In addition, farmers usually look for investments that offer the greatest potential earnings with the least possible risks. Regarding the objectives to be considered, the crop-selection problem may be difficult to solve using traditional tools. Therefore, this work proposes an approach based on multiobjective evolutionary algorithms to help in the selection of an appropriate cultivation plan considering five crop alternatives and five objectives simultaneously.*

An adequate use of land resources is an essential guarantee of sustainable development, and many authors have suggested different approaches (Chi-Mei et al. 2002; Stewart, Janssen, and van Herwijnen 2004; Matthews et al. 2000; Tsuruta, Hoshi, and Sugai 2001; Bocco, Sayago, and Tartara 2002). The optimal use of soils is the basis of all forms of sustainable land use, that is, agricultural land use that remains productive in the long term. There are many benefits of an optimal use of soils, such as a decrease of rural poverty, watershed protection, increased biodiversity, more sustainable agricultural production, and increased food security (Schroth and Sinclair 2003). Therefore, optimal soil use planning is an important problem with social, economic, and ecological implications.

Cultivation areas are usually divided in parcels, each one becoming a production unit. Every year farmers have to decide what to plant in each parcel. This requires the analysis of trade-offs between investments that have to be made, expected profits, economical risks, and environmental effects of cultivation (Schroth and Sinclair 2003). Sustainable agricultural soil use requires making the land available for farming as productive as possible while considering the environmental impact of the cultivation process. Under natural conditions, soils present chemical restrictions for crop development. Chemical soil tests are used to provide information about acidity and nutrient levels of each land parcel. According to the requirements of crops to be cultivated, it is usual to modify soil chemical characteristics, changing the quantity of nutrients and acidity through fertilizing and liming, making productive agriculture possible but affecting the quality of soils, groundwater repositories, and the overall environment (Johnson, Adams, and Perry 1991). Furthermore, economic restrictions may constrain farmers to use small quantities of mineral fertilizers or sometimes none at all,

making it necessary to use the nutrients available in the soil as efficiently as possible (Schroth and Sinclair 2003). Hence, determining the crop that best fits the chemical characteristics of each production unit is an interesting alternative to reduce the cost of soil treatment at the same time as minimizing the potential ecological damages. On the other hand, farmers want to cultivate crops with the best possible return and minimum economic risk under a set of possible scenarios. Historical yield values and crop prices can be used to simulate future economic scenarios in order to obtain expected values and measure economic risks.

Ecological and economical considerations make the selection of a crop cultivation strategy a difficult multiobjective problem. In searching for solutions to multiobjective problems, there is no single optimal solution but rather a set of solutions. These solutions are optimal in the sense that no other solutions in the search space are superior to them when all objectives are considered. They are generally known as Pareto optimal solutions (Coello Coello, van Veldhuizen, and Lamont 2007).

Multiobjective evolutionary algorithms (MOEAs) have proved to be useful tools to solve multiobjective problems in various domains (Coello Coello, van Veldhuizen, and Lamont 2007). Therefore, this work uses an MOEA-based approach that combines aspects of knowledge in agricultural science and an economic scenario generator to approximate the solution set for an optimal agricultural soil usage of various parcels considering five different crops (soybeans, wheat, corn, sunflower, and sorghum) and the optimization of five different objectives simultaneously. Objectives considered in this work are (1) to minimize the costs of fertilizing and liming, (2) to minimize the total cost of cultivation, (3) to maximize the expected return, (4) to maximize the worst-case return, and (5) to minimize the standard deviation of possible returns.

The approach presented in this work was applied using real data and run using the strength Pareto evolutionary algorithm (SPEA) (Zitzler and Thiele 1999) and the strength Pareto evolutionary algorithm 2 (SPEA2) (Zitzler, Laumanns, and Thiele 2001). These algorithms are two of the most outstanding algorithms developed to solve multiobjective problems. Also, parallel implementations of these algorithms were developed for searching for solutions in the considered crop-selection problem, different runs of parallel and sequential versions were carried out, and the obtained solutions were compared using the coverage metric (Zitzler, Deb, and Thiele 2000). Comparison shows that, for the considered problem and data, parallel implementations outperform their sequential counterparts. The obtained results are used to give insights to the decision makers concerning trade-offs that
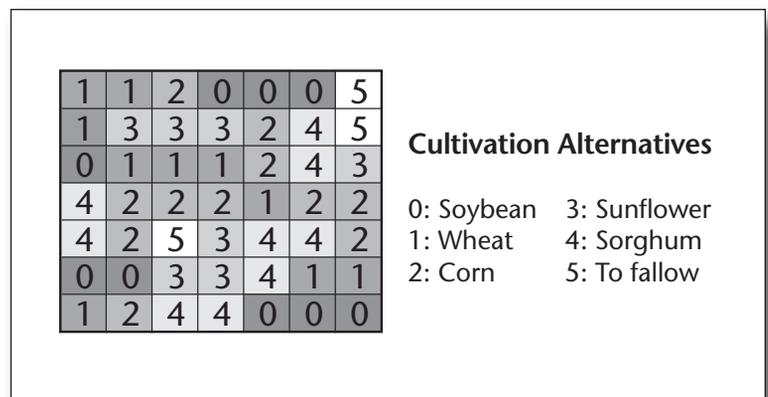

Figure 1. Representation of a Solution.

exist among the conflicting objectives and help them to implement better cultivation strategies.

In this article we will first address the multiobjective crop-selection problem solved in this work. Then we will introduce multiobjective evolutionary algorithms in crop-acreage planning and explain the presented approach and algorithms. Later, some experimental results will be discussed. Finally, we will summarize and present an outlook on possible future developments.

Multiobjective Crop Selection

Cultivation areas are divided in parcels, which may be of different sizes. To represent the geographic position of each parcel, this work uses a grid representation, that is, a two-dimensional array of values. This is probably the simplest geographic representation (Matthews 2001). Cultivation alternatives are coded using integer indexes. Thus, for the crop-selection problem, values in the array are cultivation alternatives. Each cell in the array represents a geographic area of a fixed size—the size of cells determines the level of detail and the size of the data structure that must be manipulated (Matthews 2001). In the simplest case, each parcel is represented by a single cell, that is, adjacent parcels of the same size. Figure 1 shows an example of a cultivation area divided in 7 by 7 parcels. Each cell is used to represent a single parcel, and numbers between 0 to 4 represent soybeans, wheat, corn, sunflower, and sorghum, respectively while 5 indicates that the parcel should not be cultivated. As a matrix representation is used, a pair of indexes (i,j) identifies each parcel.

Regarding the soil characteristics, the crop-cultivation cost is considered to have a fixed and a variable cost component. Fixed costs for a crop are those that are not influenced by chemical characteristics of the parcel, for example, the cost of plowing, insecticide application, harvest picking, and harvest hauling. On the other hand, variable
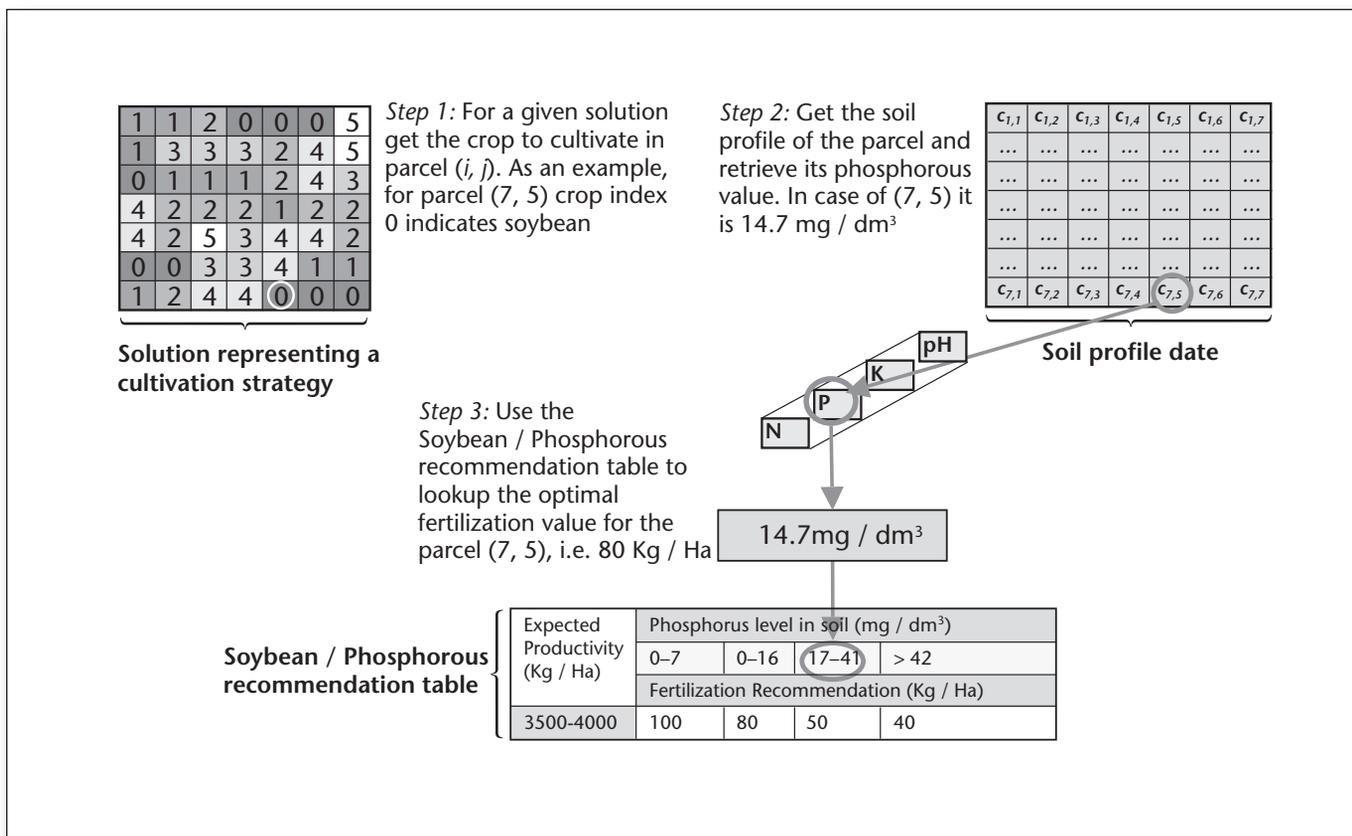
Figure 2. Outline of the Procedure Used to Estimate the Amount of Phosphorous to Be Used in a Parcel.

costs are those related to the soil treatment that needs to be made to obtain the maximum yield of a given crop and varies according to the nutrients and acidity levels of the soil.

A fixed-cost table is used to store fixed-cost estimations for each crop. Thus, given a cultivation plan, the fixed cultivation cost for each parcel, represented by a matrix position, is obtained by using the crop index in that position to look for its corresponding value in the fixed cost table.

Nutritional requirements are unique for each crop. Optimal fertilization and liming values depend on crop requirements and soil test results (Baker, Ball, and Flynn 2002). This means that for an optimal yield, each crop-soil combination may have a different soil treatment cost. The soil analysis considered in this work provides a profile of each land parcel in terms of nitrogen, phosphorus, potassium, and pH level. The two components of soil treatment cost considered in this work are mineral fertilization cost and the pH corrective application cost.

In order to approximate fertilization and corrective application costs to cultivate a given crop in a parcel it is necessary to make some estimates about the total amount of fertilizers and correctives to be used for an optimal yield. Agricultural science pro-

vides information about the crop requirements for each soil component. Then there are recommendation tables for effective fertilization for each crop-nutrient combination. In this work, these tables are used to estimate the amount of fertilizers to be applied in parcels. Thus, the amount of chemical components to be added in a parcel is estimated by using the soil test results of the parcel and the particular recommendation table for the component according to the crop that is supposed to be cultivated. As an example, figure 2 outlines the procedure used to calculate the amount of phosphorous by hectare to be applied in parcel ($7,5$) for a given cultivation strategy. The crop index indicates that it is supposed to cultivate soybeans in the considered parcel. Soil test results can be stored in a bidimensional array C with each element containing values of a given parcel. In this case we are interested in $C_{7,5}$, which indicates that the amount of phosphorous in parcel ($7,5$) is 14.7 milligrams per decameter. Then the information about the phosphorous level is used to look up the optimal fertilization value of phosphorous by hectare for soybeans in the corresponding fertilization table. This way, the optimal quantity of phosphorous for parcel ($7,5$) for soybean cultivation is obtained. The cost is estimated by multi-

plying the obtained quantity by phosphorous price and parcel size. A similar procedure is applied to calculate fertilization cost of each other chemical component. Adding up these costs, an estimate of the total fertilization cost of a parcel is obtained. Finally the total fertilization cost of a given cultivation strategy is the summation of the expected cost of every parcel. Mathematical formulation is presented in von Lücken and Brunelli (2008).

The other variable cost considered in this work is related to the soil acidity or pH correction. Soil acidity can be modified by adding a basic element, usually agricultural limestone or aglime. There is an optimal pH value for each crop and there is an optimal amount of aglime to be used. Tables can be used to store recommendations for aglime application according to the actual pH level and crop. Aglime recommendation tables and explanations about how to obtain them can be found in Kelling et al. (1998) and the related bibliography. Using aglime application tables, the cost to correct the acidity of a production unit for a given crop can be obtained by retrieving the recommended aglime application per hectare for the crop-soil combination and multiplying this value by the parcel size and by the cost of aglime application. Thus, considering a given cultivation plan, the total variable cost is obtained by adding the total cost of fertilizers and aglime application for all parcels.

Soil treatment cost is directly related to the amount of fertilizers and correctives that need to be used. Therefore, minimization of this cost implies a reduction of the amount of fertilizers and correctives to be applied, which in turn reduces the environmental impact of the cultivation process. The total investment cost of a given cultivation strategy is obtained by adding all the costs related to the acreage allocation of crops.

The future earnings of a given crop in a parcel are uncertain as well as the final yield and selling price. One way of modeling uncertainty is through a set of feasible scenarios. Each scenario represents a hypothetical realization of all uncertain parameters in the model. In this work, the uncertain values are the production market prices of the crops at the time of selling the production. These scenarios may be provided by an analyst or be obtained by means of a scenario generator (Yu, Ji, and Wang 2003). Then, after determining a solution that indicates which crop to cultivate in each parcel, farmers use scenarios to calculate the different objectives.

Multiobjective Soil Planning Using MOEAs

Real-world crop-selection problems involve simultaneous optimization of several objective func-tions. Some of these functions, such as maximize the expected return and minimize the risk, are often conflicting objective functions. Usually multiobjective optimization problems with conflicting objectives do not have a single optimal solution when all objectives are considered simultaneously but rather a set of optimal compromise solutions. Compromise solutions are called Pareto optimal or nondominated regarding a given subset if no element in the subset can be considered better than any other when all objectives are taken into account. A true Pareto optimal solution is nondominated considering the whole search space. True Pareto optimal solutions form the so-called true Pareto optimal set, and its image in the objective space is called the true Pareto optimal front (Coello Coello, van Veldhuizen, and Lamont 2007). Ideally, decision makers must choose a solution from the true Pareto optimal set. Then the essence of multiobjective optimization is to find the Pareto front. If the true Pareto optimal set is not known and exact methods cannot be applied, a good approximation may be useful to aid decision makers in selecting the best compromise solution according to their preferences.

Traditional optimization methods applied to multiobjective problems usually work by means of an aggregated weight sum of all the objectives. Then they really work with only one objective obtained by a scalar combination. These methods are not well suited to finding multiple solutions for a multiobjective problem in a single run. In fact, classical search methods identify one solution at a time, requiring multiple executions to identify a set of different solutions (Coello Coello, van Veldhuizen, and Lamont 2007). Meanwhile, MOEAs have been demonstrated to be efficient and effective in exploring huge and complex search spaces, finding good approximations of the entire true Pareto optimal set for many difficult multiobjective problems in a single run.

As we discussed in the previous section, when planning the crops to cultivate in a set of land parcels, farm managers have to deal with issues such as crop options and their nutritional requirements, production costs, chemical characteristics of each parcel and the potential economic scenarios. Considering these issues simultaneously makes the crop-selection problem difficult to analyze with common tools. Therefore, this work presents an optimization framework based on multiobjective evolutionary algorithms to aid decision making in difficult crop-selection problems with conflicting objectives.

Figure 3 shows the general architecture of the proposed approach. Main elements of the model are an optimization core, an agricultural science knowledge base, a scenario generator, and a solution viewer. The agricultural science knowledge
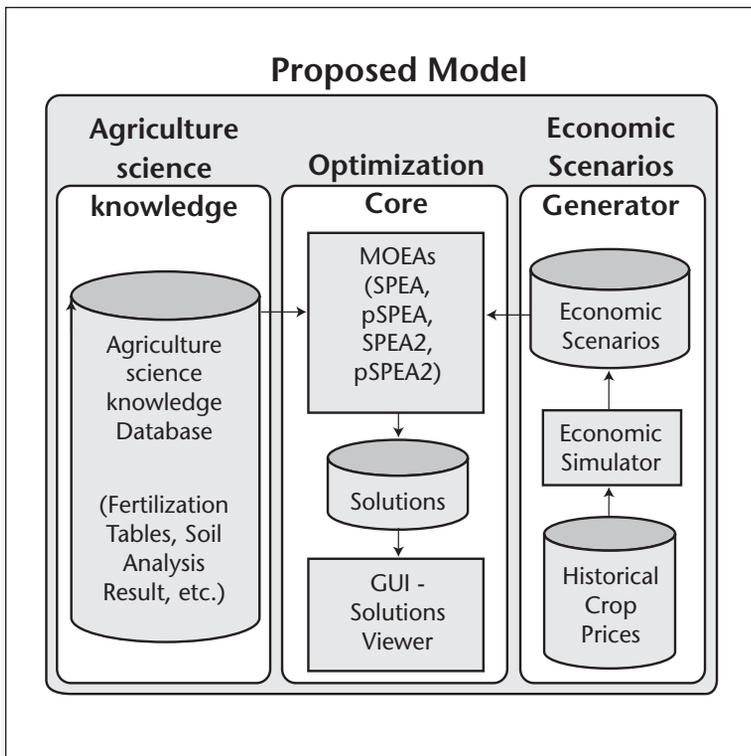
Proposed Model

Agriculture science knowledge

Optimization Core

Economic Scenarios Generator

Agriculture science knowledge Database

(Fertilization Tables, Soil Analysis Result, etc.)

MOEAs (SPEA, pSPEA, SPEA2, pSPEA2)

Solutions

GUI - Solutions Viewer

Economic Scenarios

Economic Simulator

Historical Crop Prices

Figure 3. Basic Architecture of the System.

base contains information regarding soil test results and optimal application values of fertilizers and aglime. The economic scenario generator module implements the model to generate a database of future feasible scenarios from historical crop prices and yields of the different considered crops. In this work, information about the mean and variance of the productivity and market values of each crop is used to produce scenarios by generating normally distributed random variables. Experts using the system may want to analyze some specific scenarios. Thus, the system allows introduction of scenario sets in the database. Both the science knowledge base and the scenario database feed the optimization core composed of an MOEA that receives as inputs soil test results and dimensions of each parcel, nutritional requirements of considered crops, a set of feasible scenarios, and specific algorithm parameters. The MOEA evaluates candidate solutions, searching for optimal ones to obtain a Pareto set of crop-cultivation strategies. Finally, solutions are saved in a database and passed on to the solution viewer.

MOEAs mimic the mechanisms of natural evolution, where a biological population evolves over generations to adapt to an environment by selection according to fitness, recombination, and mutation of genes. The first step to solve a multiobjective problem using the Pareto-based multiobjective evolutionary algorithm is to determine the

function to be optimized and the solution representation or chromosome. The previous section presents the representation used in this work. After representation setting, it is necessary to integrate it to a specific MOEA algorithmic search process. This search process typically begins with the random generation of a so-called genetic population, that is, a set of possible solutions of the problem or individuals. Then, the algorithm assigns a fitness value to each solution in the population according to its relative quality. The selection probabilities of individuals are calculated based on their fitness values. Then individuals are selected based on their selection probabilities. Selected individuals, called *parents,* interchange information by means of a crossover procedure. Also, in order to preserve the diversity, a mutation operator that randomly modifies some solutions is introduced. The overall sequence of fitness assignment, selection, crossover, and mutation is repeated until some criteria are met, or the maximum number of generations is reached. It is expected that populations improve from one generation to the next one. A general background on various multiobjective evolutionary algorithms is provided in the paper by Coello Coello, van Veldhuizen, and Lamont (2007).

Using the framework presented in figure 3, sequential and parallel versions of SPEA (Zitzler and Thiele 1999) and SPEA2 (Zitzler, Laumanns, and Thiele 2001) were implemented to solve the crop-selection problem. Figures 4 and 5 present the flowchart diagram of SPEA and SPEA2, respectively. In spite of the vast literature on the implemented algorithms, it is important to point out the most outstanding characteristics of them. First, they work simultaneously with a set of solutions known as the *evolutionary population.* Second, each algorithm processes its population iteratively using random-based genetic operators (such as selection, mutation, and crossover). Third, SPEA and SPEA2 are Pareto-based fitness assignment MOEAs, that is, they explicitly use Pareto dominance in order to determine the reproduction probability of each individual. In this way, a good approximation to the Pareto set may be obtained from the final set of solutions. Fourth, both use an elitism mechanism to avoid losing good solutions once they are found.

SPEA (Zitzler and Thiele 1999) stores nondominated solutions in an external set representing the known front among all solutions considered so far. Figure 4 outlines the SPEA computational flow. The algorithm starts generating a random initial genetic population P_0 and an empty external set A_0. Nondominated solutions are copied from the genetic population to the external set. If the number of elements in the external set exceeds a given limit, a clustering technique is used to get a set of

centroids of the individuals in the external set; otherwise, the evolutionary procedure goes on. The SPEA clustering procedure is based on creating clusters according to the value of solutions in the objective space and the select centroids. This way, the procedure loses boundary solutions. The evolutionary process is executed until the stop condition is reached, in this case a maximum number of generations. A fitness value is assigned to individuals in both the external and genetic populations. The procedure that SPEA uses to set the fitness value for individuals ensures that the search is directed to nondominated solutions while, at the same time, both dominated and nondominated solutions are maintained. It starts with the so-called strength assignment procedure that assigns a real value in [0, 1] called *strength* for each element in the Pareto optimal set proportional to the number of individuals covered by the solution. In this case, the strength of a Pareto solution is at the same time its fitness. Then the fitness of each individual in the population is the sum of the strengths of all external Pareto solutions by which it is covered, adding one to the resulting value. This fitness value is used in the selection process that operates using individuals in the genetic and external sets. Evolutionary operators are in charge to create a new offspring in the genetic population. Then from this new population nondominated solutions are copied in the external population. When the algorithm reaches the stop criterion, the solutions are in the external set.

As figure 5 shows, SPEA2 (Zitzler, Laumanns, and Thiele 2001) also uses two populations, but only members of the archive participate in the selection process. The main differences between SPEA and SPEA2 are the method to calculate the scalar fitness and the external set truncation operator. The SPEA2 fitness assignment procedure incorporates density information to discriminate between individuals having identical fitness values. This information is related to the number of solutions that are near in objective space. After fitness evaluation, all nondominated solutions from both the current genetic population and the external population are passed to a next population A_{t+1}. If the number of solutions in this population is less than a defined size, it is filled with the "best" dominated individuals from both populations considering its fitness value. In case of having a greater number of solutions SPEA2 uses an enhanced archive truncation method based on a nearest neighbor criterion that guarantees the preservation of boundary solutions as described in the reference paper. At the end the external set contains the optimal solutions obtained so far.

Many factors affect the quality of final solutions obtained by MOEAs, such as population size, the number of generations, and the number of evalu-
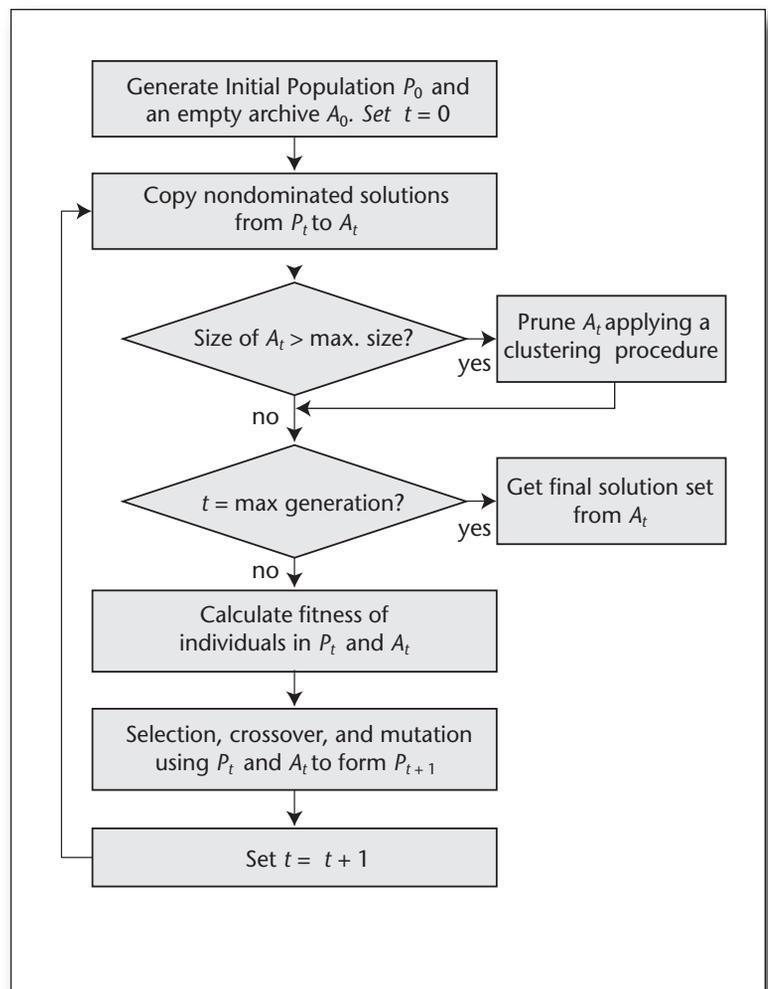

Figure 4. SPEA Flowchart.

ated scenarios. To improve the final solutions, parallel MOEAs (pMOEAs) based on the island model are used (van Veldhuizen, Zydallis, and Lamont 2003). In island evolutionary algorithms, one population is divided into subpopulations called *islands,* or regions. The evolution of solutions proceeds in each island independently. In addition to the basic operators of evolutionary algorithms, a migration operator is introduced to control the exchange of individuals between islands. By dividing the population into regions and by specifying migration criteria, the island model adapts well to various parallel architectures.

The parallel model used in this work is composed of a collector and several pMOEAs (Barán, von Lücken, and Sotelo 2004). The collector spawns all pMOEA processes and receives calculated solutions from them. In addition, it maintains an archive of the nondominated solutions interchanged between islands and provides the final Pareto approximation set. This process does not utilize any evolutionary operator and does not
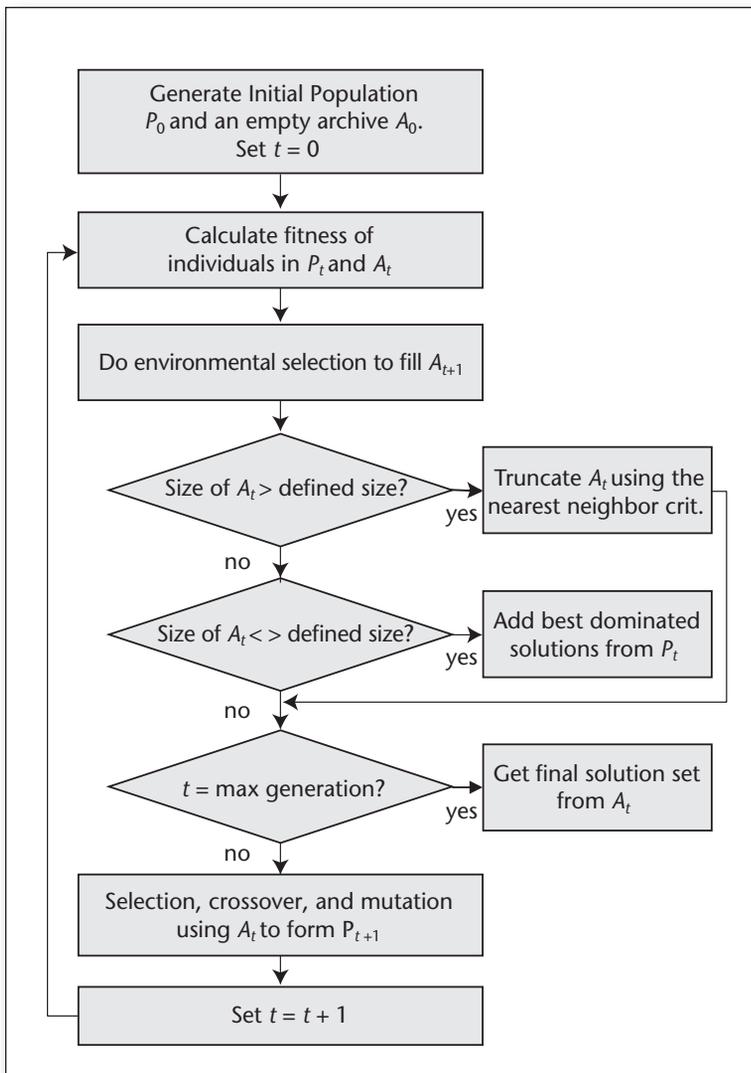
Figure 5. SPEA2 Flowchart.

interfere with the evolutionary process. Meanwhile, pMOEAs perform the real computation.

pMOEAs are based on sequential multiobjective evolutionary algorithms that were modified to incorporate a migration operator. Figure 6 shows a general pMOEA. Initially, parallel MOEAs receive evolutionary parameter values and a set of feasible scenarios. Then a randomly generated genetic population and an empty archive are created. Before a new generation starts, if solutions arrive from other islands, individuals in the genetic population are replaced by received ones. To preserve diversity between islands only a random selected percentage of received individuals are chosen for replacement. Then the evolutionary process continues by generating a new population as defined by the MOEA specification. After each generation, the migration condition is tested. If the migration condition is true, migrants are selected. In this

work, the migration condition is based on a probability test. Since there is not a unique best solution to migrate, some criterion must be applied. Thus, elements to migrate are considered only among nondominated solutions in the current archive. A parameter controlling the maximum number of migrants is provided. Therefore, migration of individuals is controlled by two parameters, one for the frequency of communications and another for the number of migrants. Migrating elements may represent a fraction of the nondominated set of individuals that currently are in an MOEA's population. Then, as long as a stop criterion is not reached, the evolutionary process continues. If the stop criterion is reached, pMOEAs send nondominated solutions in the external archive to the collector. Once the collector receives the solutions obtained in each island, nondominated solutions are saved and passed on to the solution viewer for presentation to the decision maker who is in charge of selecting one of the proposed solutions to be implemented. An extended review of pMOEA approaches is presented in the papers by van Veldhuizen, Zydallis, and Lamont (2003) and Coello Coello, van Veldhuizen, and Lamont (2007).

Experimental Results

Sequential and parallel implementations of SPEA (Zitzler and Thiele 1999) and SPEA2 (Zitzler, Laumanns, and Thiele 2001) with real data of a cultivable area in Alto Parana, Republic of Paraguay, were implemented to test the practicality of the approach presented in figure 3. The scenario generator used in these runs is based on normal distribution of historical values.

The implemented algorithms produce solution sets having many different cultivation schedules. These result sets were compared in order to determine the best multiobjective approach for system implementation and extensions. Using the same problem parameters and population size, 10 different runs of sequential and parallel versions of SPEA and SPEA2 using two, four, and eight processors were carried out. Results obtained by each implementation were combined and the Pareto front extracted. As the true Pareto front is unknown, the coverage metric (Zitzler, Deb, and Thiele 2000) was used for a direct comparison of the solution sets. The coverage metric compares two result sets and indicates the number of points in one set that dominate or are equal to points in the other set. According to comparison results, parallel versions outperform sequential ones, and in all cases SPEA2 obtains better solutions than SPEA. According, with such metric, SPEA2 with eight processors obtains the best solution set.

Members from the Soil Department of the Agri-

culture School of the National University of Asunción and users from the private sector helped us in the design and development of the application, providing experimental data and information about the problem and evaluating the obtained results.

As a pest-control measure some sustainable production models consider that crops of the same kind (or family) do not have be planted in consecutive periods or adjacent parcels. This collides with the practical desire that adjacent parcels are likely to be used for the same kind of crop in order to make best use of agricultural machinery and farm equipment. The system presented in this work does not consider these criteria in the search of solutions; thus, decision makers must analyze solutions considering these issues before selecting a solution for application. Because the search for solutions does not consider decision-maker preferences from cause to effect, the system is allowed to obtain solutions that may not be considered if the search space is pruned before execution. However, these questions will be considered in future extensions of the system in order to set decision-maker preferences iteratively as the search process goes on. This will simplify the work that must be done after the solution set is provided.

It is very important to extend the system to consider crop rotations. It will give a schedule of crops to be planted in consecutive periods. As was indicated it is very important for some agricultural models to alternate different crop types in the same or adjacent parcels in consecutive periods but also to take into account the uses of other resources. Issues to consider in rotation include restrictions about crops to be planted in successive seasons and the use of cover crops between main crops. Besides, it is very important to take into account nitrogen management since insect damage can be reduced by avoiding excess nitrogen levels.

It was shown to be useful to present a large number of solutions to give insights of the different alternatives that exist. However, as the number of proposed solutions is around 200, it is very difficult to examine and compare each proposed solution to determine the solution to be applied. Also, the number of considered objectives makes it difficult to process solutions. A graphic interface to filter solutions serves to select a subset of alternative solutions in order to analyze them more carefully before selecting one for implementation. This module offers the capacity to export solutions to spreadsheet formats, a very useful function because users usually want to use the tools they usually work with.

The results obtained by the system vary considering different cultivation areas, fixed and variable cost structures, and economic scenarios. Thus, it is
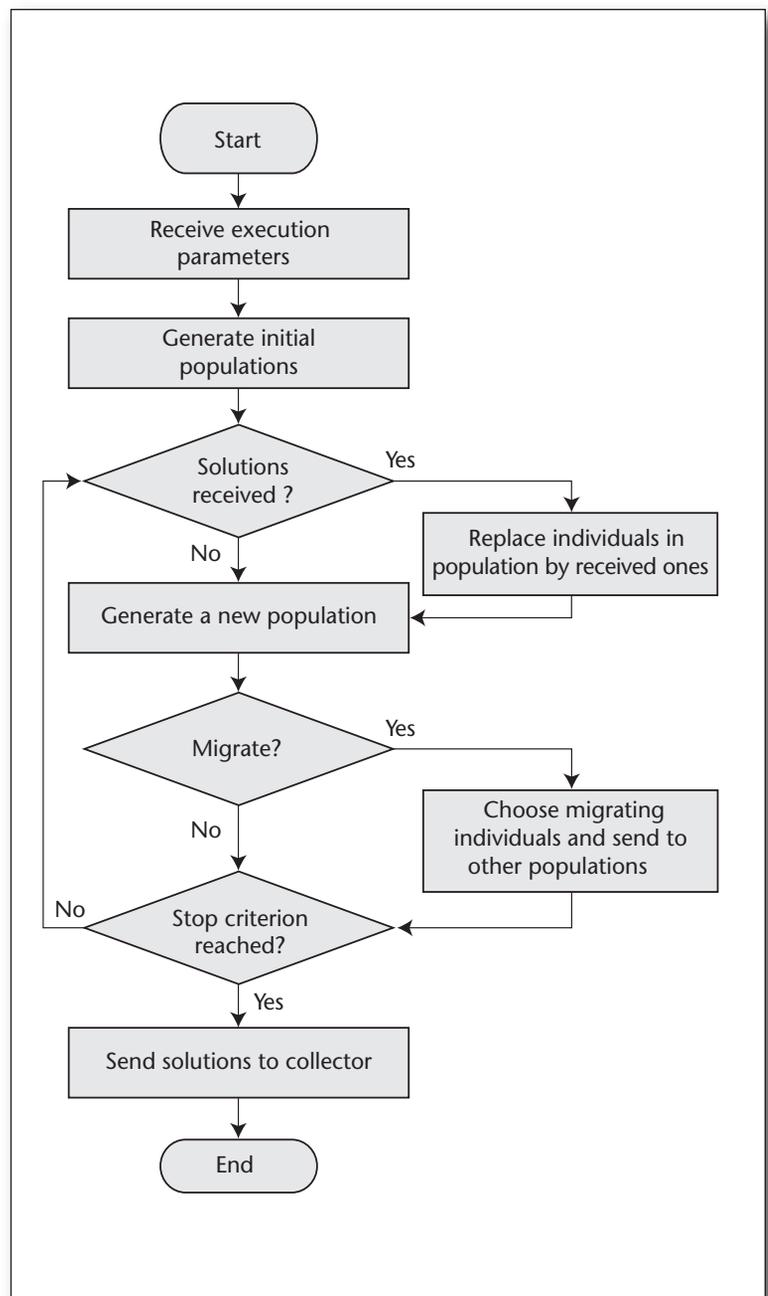

Figure 6. Computational Flow of a General Parallel MOEA.

not possible to determine an optimal strategy for all cases. However, as an example of the kind of results we have, in figure 7 the obtained values in the objective space are shown, using SPEA2 with eight processors and the particular soil analysis result, scenario set, and parameter values used in the runs we carried out. Figure 7 also includes the values obtained considering the option of using all the available land for only one kind of crop. Axis X represents the minimum net gain, axis Y the expected total cost, while the bubble size represents the standard deviation of returns. As shown,
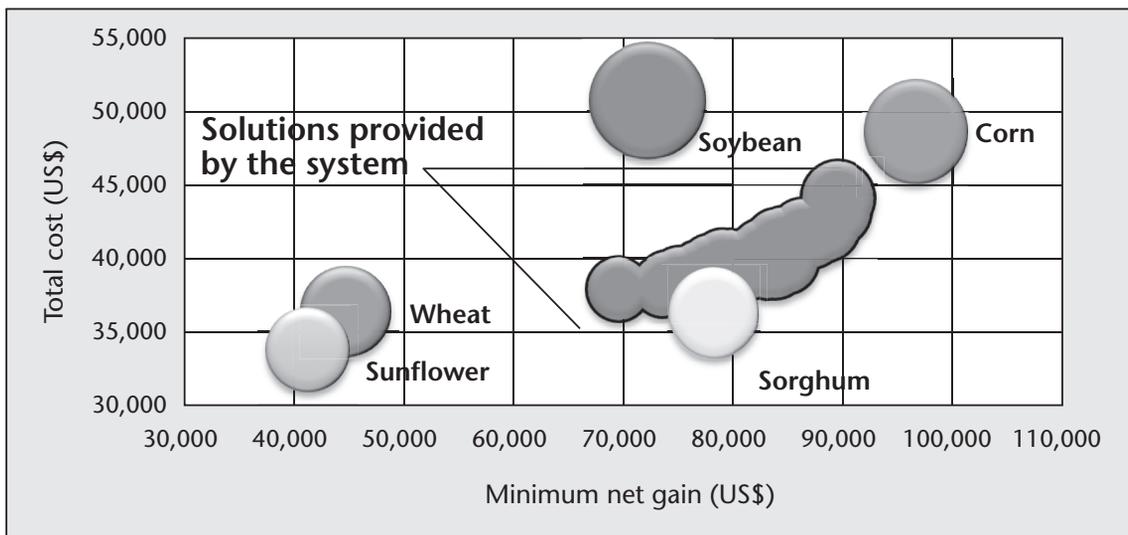
Figure 7. Objective Values of Solutions Proposed by the System and Using Monocultivation Strategies.

considering these three objectives, solutions proposed by the system dominate the cultivation option of having all soybeans or all corn, that is, they have a lesser total cost, obtain a greater minimum net gain, and have a better standard deviation value. In all cases the diversification strategy proposed by the system obtains minimum values for standard deviation. As can be seen, there are many proposed solutions from which the decision maker may choose.

Summary

This work proposes an approach based on multiobjective evolutionary algorithms to solve multiobjective crop-selection problems considering different objectives and crops simultaneously. Using the proposed model, both sequential and parallel implementations of two MOEAs were implemented as optimizers. A comparison between the different implementations was carried out using the coverage metric. For the implemented test problem, pSPEA2 with eight processors appears to be the best suited optimizer for the problem at hand.

The obtained solutions were passed on to a solution viewer that presents solutions to decision makers for them to select one for further analysis and implementation. The visualization module shows the various obtained solutions and objectives, helping decision makers to gain insight about the problem at hand.

Multiobjective evolutionary algorithms applied to crop selection have significant potential for assisting decision makers in determining better cultivation strategies considering various objectives at a time. According to the expert's preference, the implemented tool may be used to aid the selection of a solution that will improve soil usage, reduce cultivation costs, minimize economic risks, maximize the economic return, adjust fertilization use to a given budget, and minimize the environmental impact of the cultivation process. Also, tools such as those proposed in this work may allow farmers to become better informed about the different alternatives and interactions between the different objectives analyzed.

Future work includes testing the proposed framework using other multiobjective metaheuristics as optimizers and a planning scope that contemplate crop rotations. It is also proposed to extend the solution model to include the related resource allocation issues and to include the decision makers' preferences in an interactive way while the search procedure goes on. It is important as well to improve the tools to show multiobjective solutions.

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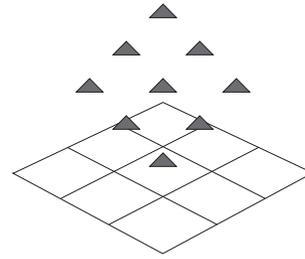
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AAAI 2010 Spring Symposium Series

The 2010 Spring Symposium Series will be held March 22–24, 2010 at Stanford University. The call for participation will be available in August on the AAAI web site (www.aaai.org /Symposia/Spring/sss10.php). Submissions will be due to the organizers on October 2, 2009. For more information, please contact the symposium chair, Marjorie Skubic, at skubicm@ missouri.edu or AAAI at sss09@aaai. org. A preliminary list of symposia will be available at the SSS-10 website in July.

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