# A GENETIC ALGORITHM FOR CROP ROTATION

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Abstract: In the last few years, crop rotation has gained attention due to its economic, environmental and social importance which explains why it can be highly beneficial for farmers. This paper presents a mathematical model for the Crop Rotation Problem (CRP) that was adapted from literature for this highly complex combinatorial problem. The CRP is devised to find a vegetable planting program that takes into account green fertilization restrictions, the set-aside period, planting restrictions for neighboring lots and for crop sequencing, demand constraints, while, at the same time, maximizing the profitability of the planted area. The main aim of this study is to develop a genetic algorithm and test it in a real context. The genetic algorithm involves a constructive heuristic to build the initial population and the operators of crossover, mutation, migration and elitism. The computational experiment was performed for a medium dimension real planting area with 16 lots, considering 29 crops of 10 different botanical families and a two-year planting rotation. Results showed that the algorithm determined feasible solutions in a reasonable computational time, thus proving its efficacy for dealing with this practical application.

## 1 INTRODUCTION

Brazil has an agricultural tradition, and a variety of grains and vegetables are planted on a large scale. Natural conditions, such as climate, fertile soil and relief, foster the development of this important economic sector.

(Altieri, 2002) and (Gliessman, 2000) mention that conventional agricultural production is mainly based on monoculture given the fact that its operational cost is low and can be more easily implemented. But this leads to several harmful factors, such as the extensive use of capital and toxic pesticides that are extremely damaging to the environment and facilitates the action and prevalence of pests and pathogens. Other negative economic aspects arising from this practice are the impoverishment of small farmers and the decreasing volumes of certain agricultural products.

To prevent these drawbacks, polyculture should be expanded, in a sustainable fashion, besides considering the environmental conservation of planting areas, pest control (and thus the less intensive use of chemical fertilizers) and economic gain.

In the sequel, crop rotation has been object of study within the agricultural and ecological fields. The basic idea consists in annually alternating different plant families within the same agricultural area. The selected species should have commercial and soil-recovery purposes. If crop rotation is properly adopted and conducted for a sufficiently long period, its advantages are numerous. A practice such as this improves the physical, chemical and biological characteristics of soil, helps disease and pest control, replaces organic matter, protects the soil from climactic agents and, in addition, provides a diversified production of food and other products.

Crop rotation has also been studied within the operational research domain, namely by (Lemalade et al., 2011), (Santos, 2009) and (Santos et al., 2011). In this paper we propose a new method to tackle the Crop Rotation Problem (CRP) based on a genetic algorithm (GA) which embeds a constructive heuristic.

## 2 MATHEMATICAL MODEL

In the mathematical model proposed for the CRP by (Santos et al., 2011) the objective is to maximize occupation of a specific planting area and the follo-


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wing rotation constraints are taken into account for the planning horizon:

(a) *Sowing Season:* need to respect the time of planting and the life cycle of each culture;

(b) *Continuity for Same-family Crops:* plants belonging to the same family must not be planted in adjacent parcels of land or lots;

(c) *Neighboring for Same Family Crops:* plants of the same family must not be planted consecutively on the same lot;

(d) *Green Fertilization:* in the planning horizon each lot must have a plant of the leguminosae family and be subject to the above mentioned conditions (a) and (b), also each of these must be planted only once;

(e) *Set-aside Period:* a set-aside period must be scheduled on each lot.

In this study, the objective of the CRP is to maximize profitability and a new type of restraint is imposed:

(f) *demand* - each culture has a pre-stablished market demand must be satisfied.

The planning horizon divided into $M$ periods of similar duration, a set of $N$ crops belonging to $N_f$ plant families and the planting area with $L$ lots are taken into account. Other parameters follow:

- $C$: set of trade crops;
- $A$: set of crops for green fertilization;
- $F_p$: set of plants of the p family, $p = 1..N_f$;
- $t_i$: crop planting cycle $i$, including soil preparation and harvesting;
- $l_{ij}$: profitability of crop $i$ in the period $j$ per unit of area;
- $I_i = [C_i, T_i]$: crop planting interval $i$, in which $C_i$ is the earlier period and $T_i$ is the later period.
- $p_{ij}$: production of crop $i$ in the period $j$ per unit of area;
- $D_i$: demand for crop $i$;
- $I_i^D = [C_i^D, T_i^D]$: demand interval of crop $i$, in which $C_i^D$ is the earlier period and $T_i^D$ is the later period of the demand;
- $S_k$: set of lots adjacent to lot $k$;
- $area_k$: area of lot $k$.

A binary linear programming model is described below:

$$\text{maximize } z = \sum_{i\in C} \sum_{j\in I_i} \sum_{k=1}^{L} area_k\, l_{ij}\, x_{ijk} \quad (1)$$

subject to

$$\sum_{i\in F_p} \sum_{r=0}^{t_i-1} \sum_{v\in S_k} x_{i(j-r)v} \leq L\left(1 - \sum_{i\in F_p} \sum_{r=0}^{t_i-1} x_{ijk}\right),$$
$$p = 1..N_f,\, j = 1..M, k = 1..L \quad (2)$$

$$\sum_{i\in F_p} \sum_{r=0}^{t_i} x_{i(j-r)k} \leq 1, p = 1..N_f, j = 1..M, k = 1..L \quad (3)$$

$$\sum_{i=1}^{N+1} \sum_{r=0}^{t_i-1} x_{i(j-r)k} \leq 1,\ j = 1..M,\ k = 1..L \quad (4)$$

$$\sum_{i\in A} \sum_{j=1}^{M} x_{ijk} \geq 1,\ k = 1..L \quad (5)$$

$$\sum_{j=1}^{M} x_{njk} \geq 1,\ k = 1..L \quad (6)$$

$$\sum_{j\in I^D} \sum_{k=1}^{L} area_k\, p_i\, x_{ijk} \geq D_i,\ i \in C \quad (7)$$

$$x_{ijk} \in \{0,1\},\ i = 1..N+1,\ j \in I_i,\ k = 1..L. \quad (8)$$

where, for convenience of notation, the set-aside period is represented by crop $(N+1)$ and if $j - r \leq 0$ then $j - r$ is replaced by $j - r + M$. Here, the decision variable $x_{ijk}$ is equal to 1 if crop $i$ is planted in period $j$ (eventually continues in the following periods according to its cycle) in lot $k$, and 0 otherwise.

In the proposed model, the deciding variable $x_{ijk}$ will be 1 if crop $i$ is in its planting period initiated in period $j$ and if it is planted in parcel $k$, and 0 if otherwise.

The objective function (1) sets out to maximize the profitability of the rotation performed on the given area. Constraints (2) prevent the plants of the same family from being neighbors. Constraints (3) forbid the same plant family from being consecutively planted on the same lot $k$. Constraints (4) prevents two plants from occupying the same lot in the same time interval. This means that, if crop $i$ is planted on lot $k$, $t_i$ periods must elapse before a new plant occupies the same space. Constraints (5) and (6) ensure that each lot has at least one green fertilization application and a set-aside period, respectively. Notice that the neighborhood and consecutive planting restrictions do not apply to the set-aside period. Finally, constraints (7) impose satisfaction of demand for crops during the respective period.

A similar objective function (1) and the same constraints (2) to (6) and (8) are shared by this model with the one proposed by (Santos et al., 2011).

## 3 METHODOLOGY

Due to the high computational resources that are necessary to exactly solve the CRP instances arising from real applications, non-exact approaches are advisable for this problem. Genetic algorithms are specially adapted to deal with this type of combinatorial optimization problem insofar as they can easily deal with the optimization objective and the many constraints involved. Hence, a new GA was developed for the CRP.

The above model (1) to (8) uses binary variables, but it is more convenient for this algorithm to be based on integer decision variables taking values in the interval $[1, N+1]$. Otherwise, modeling with binary variables would result in bigger dimension chromosomes and enhanced difficulties in dealing with the constraints. One solution to the problem is associated with an individual identified by a single chromosome, which is encoded through an $L \times M$ integer matrix. Its element $(k, j)$ belongs to $[1, N+1]$ and identifies which crop is being planted on lot $k$ and in period $j$, for all $k = 1..L$ and $j = 1..M$.

With the purpose of exploring the set of solutions more efficiently, the initial population for the GA was determined by a new constructive heuristic. Each initial solution/individual is built lot by lot thus imposing the planting sequence constraint on the same lot, that is, rotation conditions (a) and (b).

The fitness of an individual is initially set equal to the sum of the profitabilities on all lots. Then an exponential penalization process is used to punish the infeasible solutions due to violation of the remaining rotation conditions. Hence, penalizations of the neighborhood, set-aside period, green fertilization and demand violations are added. Considering that their sum is $p$, the fitness of the individual is multiplied by $e^{-p/K}$, where $K$ is a positive constant equal to 10.

The GA was applied with 120 generations, 451 individuals (solutions) in the population of all the generations and using selection, crossover, mutation, migration and elitism operators.

The selection method used was a biased roulette wheel.

As to crossover the option favored a uniform crossover with a rate of 80%. The chromosome break points for this genetic operator were horizontally and randomly selected (to keep feasibility in the line).

Mutation consists of randomly selecting lots of the individuals and replacing the respective cultures with crops constructively assigned.

The migration operator was devised to avoid premature convergence of the algorithm and, at the same time, it explores the feasible region more efficiently. In this context, 50% of the population in the generations 120γ is replaced by randomly generated individuals (with γ, a control parameter taking the value 0.80).

Migration as well as mutation rates both equal to 5%.

The elitism consists of saving the best solution before the action of the operators in each generation and inserting it in the population for the next generation.

## 4 COMPUTATIONAL RESULTS

The computational experiment was performed with the algorithms coded using Matlab software, version 7.4.0 R2007a, on Core 2 Quad microcomputers with 2GB memory and 250 GB hard-disk memory.

The computational experiment took into account a real instance of CRP with a planting area that presents 16 non-parallel lots, as shown is Figure 1, and other real data for crops coming from a medium size planting area at São Paulo state, in Brazil.

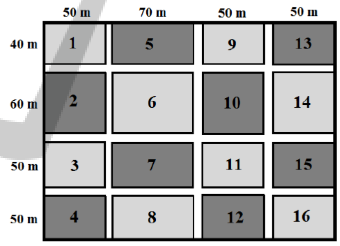


Figure 1: Plantation area.

A two-year planting program was considered and each period fixed at one month. Crops 23 to 29 were selected for green fertilization and crop 30 for the set-aside period. The plants represented by 1 to 25 correspond to marketing purposes.

The above GA ran 100 times for this real life problem.

To access the performance of the GA in this context, we measured the average CPU time per GA run ($t$ in seconds), the number of times the algorithm provided a feasible best solution out of 100 (α), the average profitability of the best solution found per run ($\overline{z}$ in R$), the average penalizations for the fitness of the best solution at the initial population per run ($\overline{p}_{inicial}$) and the same for the best solution at the final population per run ($\overline{p}_{final}$). Lastly, the value $\overline{\Delta z}$ represents the average relative deviation between the profitability of the best first and best final solutions found at each run of the GA. These last three figures are determined with the purpose of accessing the improvement achieved with the algorithm from its beginning

| | Year 1 | | | | | | | | | | | | Year 2 | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| 1 | 28 | 28 | 23 | 23 | 23 | 23 | 30 | 1 | 1 | 26 | 26 | 26 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 12 | 12 | 12 | 28 | 28 |
| 2 | 13 | 13 | 13 | 13 | 13 | 13 | 30 | 9 | 9 | 9 | 9 | 1 | 1 | 23 | 23 | 23 | 23 | 2 | 2 | 2 | 2 | 20 | 20 | 20 |
| 3 | 10 | 19 | 19 | 19 | 19 | 19 | 30 | 2 | 2 | 2 | 2 | 27 | 27 | 27 | 13 | 13 | 13 | 13 | 13 | 13 | 10 | 10 | 10 | 10 |
| 4 | 15 | 15 | 15 | 15 | 15 | 15 | 30 | 9 | 9 | 9 | 9 | 25 | 25 | 25 | 22 | 22 | 22 | 22 | 22 | 22 | 16 | 16 | 16 | 15 |
| 5 | 13 | 13 | 13 | 13 | 13 | 13 | 30 | 23 | 23 | 23 | 23 | 18 | 18 | 18 | 18 | 18 | 30 | 21 | 21 | 21 | 21 | 20 | 20 | 20 |
| 6 | 23 | 1 | 1 | 16 | 16 | 16 | 30 | 2 | 2 | 2 | 2 | 28 | 28 | 28 | 28 | 8 | 8 | 6 | 6 | 6 | 6 | 23 | 23 | 23 |
| 7 | 27 | 27 | 7 | 7 | 3 | 3 | 3 | 23 | 23 | 23 | 23 | 2 | 2 | 2 | 2 | 19 | 19 | 19 | 19 | 19 | 30 | 1 | 1 | 27 |
| 8 | 28 | 28 | 28 | 2 | 2 | 2 | 2 | 1 | 1 | 18 | 18 | 18 | 18 | 18 | 16 | 16 | 16 | 7 | 7 | 12 | 12 | 12 | 30 | 28 |
| 9 | 22 | 22 | 22 | 22 | 22 | 22 | 30 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 27 | 27 | 27 |
| 10 | 15 | 15 | 15 | 24 | 24 | 24 | 30 | 9 | 9 | 9 | 9 | 1 | 1 | 11 | 11 | 11 | 11 | 11 | 8 | 8 | 15 | 15 | 15 | 15 |
| 11 | 19 | 19 | 19 | 19 | 19 | 8 | 8 | 2 | 2 | 2 | 2 | 25 | 25 | 25 | 5 | 5 | 5 | 5 | 11 | 11 | 11 | 11 | 11 | 30 |
| 12 | 16 | 16 | 16 | 5 | 5 | 5 | 5 | 30 | 12 | 12 | 12 | 2 | 2 | 2 | 2 | 23 | 23 | 23 | 23 | 1 | 1 | 25 | 25 | 25 |
| 13 | 23 | 23 | 23 | 14 | 14 | 14 | 14 | 25 | 25 | 25 | 20 | 20 | 20 | 22 | 22 | 22 | 22 | 22 | 22 | 16 | 16 | 16 | 30 | 23 |
| 14 | 28 | 28 | 21 | 21 | 21 | 21 | 30 | 30 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 5 | 5 | 5 | 5 | 12 | 12 | 12 | 28 | 28 |
| 15 | 26 | 2 | 2 | 2 | 2 | 30 | 30 | 12 | 12 | 12 | 27 | 27 | 27 | 1 | 1 | 8 | 8 | 19 | 19 | 19 | 19 | 19 | 26 | 26 |
| 16 | 28 | 28 | 28 | 8 | 8 | 1 | 1 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 3 | 3 | 3 | 30 | 11 | 11 | 11 | 11 | 11 | 28 |

Figure 2: The best rotation for the real instance with 16 lots.

to the end. These values are displayed in Table 1.

Table 1: Mean of computational results.

| $t$ | $\overline{z}$ | $\alpha$ | $\overline{p}_{inicial}$ | $\overline{p}_{final}$ | $\overline{\Delta z}$ |
|---|---|---|---|---|---|
| 1,017 | $1.53 \times 10^6$ | 72 | 44.0 | 0.43 | 0.23 |

From the results in Table 1 one may observe that the 100 runs of the GA consumed 1017 seconds of CPU time. However, for 72 of the 100 GA runs the best solution attained was feasible. The average penalizations for the fitness of the first generation best solution are high ($\overline{p}_{inicial} = 44.0$) at the end the best solution fitness is penalized on average with $\overline{p}_{final} = 0.43$. It means that the best solution from most of the 100 GA runs is non-penalized, that is, it is feasible, thus satisfying all the CRP constraints.

The figure $\overline{\Delta z} = 0.23$ represents an average increase of 23% on the total profitability of the best solution in the population from the beginning to the end of the algorithm.

The best feasible solution determined by the GA following the 100 runs, a rotation for the planting area studied, is given in Figure 2.

## 5 SOME CONCLUSIONS

In this study, a new GA was deve loped, along with a simple constructive heuristic, for the Crop Rotation Problem.

The method provided good quality feasible solutions in short computing time, thus proving to be a viable, simple and efficient approach to tackling a real instance of this problem of a highly complex combinatorial nature.

Moreover, the model presented for the CRP possesses perfect real applicability insofar as it takes into account both technical as well as economic considerations.

Therefore, the methodology is a promising tool to help farmers in decision-making processes.

The authors intend to continue this study by testing the methodology with more real cases besides working with instances randomly built to simulate the real contexts addressed.

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