Constrained GA applied to Production and Energy Management of a Pulp and Paper Mill

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Abstract

Optimization tasks issued from real industrial problems are often characterized by being multicriteria, mixed, nonconvex, large scale, ill-defined [2][9][26]. In this work such a problem is obtained from the optimization of production scheduling and energy management in industrial complexes (in the case of a kraft pulp and paper mill). Consider two criteria, one of real variables issued from the energy optimization, and another of integer (logical) variables issued from production scheduling optimization, submitted to a high number of equality and inequality constraints [19][20]. To solve this problem it is proposed a strategy based on genetic algorithms. Computational results are presented to support discussion of the several developed techniques, namely selection methods, crossover and mutation operators, and diversification techniques. Results about the industrial relevance of the method are also presented, showing that genetic algorithms can solve important industrial problems although they need yet powerful computers to get answers in an interactive way.

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1 Introduction

Continuous production industries can be described by a group of departments responsible for some specific operations and separated by intermediate buffers. The kraft pulp and paper is one example of these industries. Consider the notation of figure 1, suggested in [2], where buffer j, with level x_j $(j = 1, \ldots, m)$, receives the production from the department i, working at rate u_i $(i = 1, \ldots, n)$ units, and delivers the raw material to department $i+1$, working at rate u_{i+1} units; $b_{j,i+1} \cdot u_{i+1}$ units are consumed from buffer j for each unit of production u_{i+1}. This work is based on the case study of the flowsheet of the Centro Fabril de Viana da Portucel, represented in figure 13.

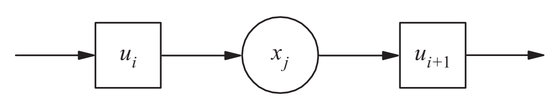

Figure 1: Flowsheet example with two departments and one buffer.

Pulp mills are rather complex systems where shutdowns and disturbances propagate and influence very easily all the mill. This will lead to mass and energy losses due to chemical incorrect dosing and consequently to production losses and quality breakdowns. A production control system must then follow the mill actual state so that the production targets are achieved.

During the last decade the optimization area has undergone a considerable growth in such a way that many of engineering problems can now be solved with the aid of non-deterministic methods. In this work a GA approach is used based on multicriteria constraint-handling techniques.

2 Mathematical Formulation

The stock equation (1) represents the overall model for the production coordination where B is the mass balance matrix, control u and state x are the departments production rates and the intermediate buffers levels, respectively. T is the discretization interval and N is the number of discretizations in the planning horizon, with $k = 0, \ldots, N-1$.

$$x(k+1) = x(k) + B \cdot T \cdot u(k) \tag{1}$$

Both control u and state x are physically constrained by equations (2) and (3).

$$0 \leq u_{\min}(k) \leq u(k) \leq u_{\max}(k) \leq U_{\max} \tag{2}$$

$$0 \leq x_{\min}(k) \leq x(k) \leq x_{\max}(k) \leq X_{\max} \tag{3}$$

The energy production and consumption in the mill can be represented by an energy balance matrix, issued from a careful study of the energetic balances in each department. The total consumption of electrical energy is expressed by the equation (4), where B_{EE} is the energy balance matrix.

$$EE_{\text{total}} = B_{\text{EE}} \cdot T \cdot u \tag{4}$$

There are some issues that should be attained in the production scheduling, as stated in [9][26]:

1. the final productions must be accomplished in the planning horizon, since delays in delivery times lead to economic losses;
2. the storage capacities should be used in order to avoid over and underflows and also to
3. avoid production rate changes, since these are responsible for additional costs due to efficiency breakdowns in almost all departments;
4. all the maintenance shut-downs should be carefully planned which will benefit the entire mill;
5. the end of a schedule plan should be seen as the beginning of the next one and therefore the final storage levels should be pre-determined;
6. some attention should be paid to the energy consumption since the pulp and paper industry is highly energy demanding.

The mathematical formulation must take into account the aspects mentioned above. From these, it is rather essential to distinguish between an objective and a constraint.

From the above statements, it is seen that in this problem two criteria are needed, given by equations (5) and (6), where $ch(k,i)$, as stated in [13], is the production rate change function (department i and instant k) defined in equation (7).

$$Obj1 = \min \sum_{k=0}^{N-1} \{B_{EE} \cdot T \cdot u(k)\} \tag{5}$$

$$Obj2 = \min \sum_{k=1}^{N-1} \sum_{i=1}^{n} ch(k,i) \tag{6}$$

$$ch(k,i) = \begin{cases} 1 \Leftarrow u_i(k) \neq u_i(k-1) \\ 0 \Leftarrow u_i(k) = u_i(k-1) \end{cases} \tag{7}$$

The formulation will be complete with a constraint set definition:

- the accomplishment of final production, during the planning time horizon, must verify equation (8), where x_{mpap} stands for the paper machine buffer level and K_{fpap} represents the desired finished paper production;

$$x_{\text{mpap}}(N-1) - x_{\text{mpap}}(0) = K_{\text{fpap}} \tag{8}$$

- the planned maintenance shutdowns and the production restrictions expressed by equation (2);
- the minimum and maximum safety limits of all storage buffers as stated in equation (3);
- the buffers final state which should be predetermined, as defined in equation (9), where x_{final} represents the intended buffers final state;

$$x(N) = x_{\text{final}} \tag{9}$$

- the contracted electrical power, which is time variant, should not be exceeded, as defined in equation (10), where $P_{\text{c}}(k)$ is the contracted power limit at instant k and $EE_{\text{EDP}}(k)$ can be computed by equation (11), where $EE_{\text{turbogenerator}}$ is the electrical energy production of the turbogenerator.

$$EE_{\text{EDP}}(k) \leq P_{\text{c}}(k) \tag{10}$$

$$EE_{\text{EDP}} = EE_{\text{total}} - EE_{\text{turbogenerator}} \tag{11}$$

The mathematical formulation of the problem is not practical to traditional optimization techniques. Other approach must be sought for.

3 The Genetic Algorithm

The genetic algorithms are considered a probabilistic method with their own search techniques and though more robust than those with random character. In this section they are presented several arrangement sets for the scheduling problem presented in the previous section.

3.1 Constraint Manipulation Techniques

In order to manipulate the restriction set there are several methods which can be grouped in three major categories: (i) methods which preserve the feasibility of solutions [10], (ii) methods based in penalty functions [16][22][6][8][12][11][17] and (iii) methods based in the search of feasible solutions[21][15]. Among these the method proposed in [10] is the only one with significant results when applied to high order problems. Studies conducted in [18] showed that the other two categories are perfectly suitable only when applied either to low order problems or to spaces defined by few restrictions. If the feasible space is given by highly restrictive restrictions, like the equality ones, then the initial optimization problem results in a feasible solution search problem.

The basic idea behind Michalewicz's method lies in (i) the elimination of the equalities present in the constraint set and in the (ii) use of specific operators which guarantee that individuals are kept in the feasible space. These specialized operators, namely crossover and mutation, transform feasible solutions into other feasible solutions and so are considered closed in the feasible part of the search space.

3.2 Multicriteria Selection Techniques

The GAs have been used particularly in single objective problems but, nevertheless, most of the practical applications exhibit more than one objective. In order to properly select the next generation it is used either the Pareto ranking method or the Pareto domination tournaments method. The first technique, which makes use of the definition of Pareto optimality, was first introduced by [4] and later redefined as a slightly different scheme in [3]. As proposed by Fonseca, an individual's rank corresponds to the number of individuals in the current population by which it is dominated and, therefore, the dominated individuals are given a worse chance for reproduction. This process ends with the fitness assignment by interpolating from the best individual to the worst according to an exponential function, but possibly of other types. Here it was used the function expressed in equation (12), where P is the rank of the best individual and $0 < c < 1$ is a constant.

$$f_i = \frac{c-1}{c^P - 1} c^{P-i}; i \in \{1, \ldots, P\} \tag{12}$$

The Pareto domination tournaments [7] are inspired in the tournament selection scheme, introduced in [4][14], where the best among a random set of individuals is chosen.

The stochastic universal sampling is used in this work since it is considered the standard algorithm for sampling which exhibits null distortion and minimum spread.

3.3 Diversification Techniques

The scheme of sharing, known as fitness sharing, was introduced in [23], and later in [3], known as fitness sharing, and its main purpose is the population distribution in a set of niches of the search space. With this procedure, the existence of similar individuals are avoided which denounces the redundancy, enemy of diversity. Equation (13) represents the shared fitness function where nn_i is the niche number of individual i, $Sh\,(d)$ is the sharing function and function $d\,(i,j)$ represents the distance between individuals i e j.

$$f_i^{\text{share}} = \frac{f_i}{nn_i} \text{ , with } nn_i = \sum_{j \in P} Sh\,(d\,(i,j)) \tag{13}$$

Once the sharing scheme is applied to the population, the crossover between individuals belonging to different niches may result in descendents in any niche. The mating restriction scheme [1] involves the parameter for σ_{mate} which is quite similar to for σ_{share} [3]. The simplest mechanism using this approach is the mating radius which chooses for second progenitor the individual from the mating pool in a distance less than σ_{mate} from the first progenitor. If none is in this situation then a random individual is chosen.

3.4 Recombination Operators

During the GA reproduction stage the individuals are selected from a population and recombined resulting in descendents which will belong to the next population. The recombination is formed by the crossover and mutation techniques. The crossover techniques employed in this work were the one-point crossover [5][4], the uniform crossover [24][23], the heuristic crossover [27] and the arithmetical crossover [10].

The mutation phase is formed by a set of four strategies: uniform, boundary, non-uniform [10] and exchange mutations. The last one, the exchange mutation, two consecutives genes exchange each other. This last type can be seen as a particular case of the uniform mutation.

4 Application to the Problem

With some simplifications introduced in [20], scheduling of three out of the ten departments of the mill can be determined subsequently and, therefore, the resulting scheduling problem is formed by seven departments. A discretization interval of four hours is used in a planning horizon of fourty eight hours which leads to eighty four variables in the system.

The initial and final buffers' state are imposed to be 50% of their maximum capacity and the final state for the finished paper to be 90%. It is also imposed a shutdown in the paper mill during the third discretization interval and a reduction to 30% in the causticizing during the second discretization interval. Due to the limitations of the floating point representation a change in a production rate (equation (7)) is considered only if greater than 2% of the maximum.

4.1 Several Simulations

The simulation set presented in this section does not pretend to be an exhaustive comparison among all the operators with application to the described model. It gives a global view of genetic algorithm application to multicriteria optimization problems submitted to a constraint set.

The operators used in the GA simulations are resumed in table 1, but other several considerations are needed:

- the population is composed by fifty individuals coded as real multiparameters constructed from the concatenated codes (each gene represents a discretization of a production rhythm);
- ten thousand generations are made for each of the simulations;
- the Pareto ranking selection is used with a fitness assignment according to equation (12) where c is chosen in order that the best individual selection probability equals the double of the average selection probability;
- the Pareto domination tournaments are committed among five elements which represents 10% of the population size;
- the stochastic universal sampling is used which exhibits minimum spread and null distortion;

Sml.	Selection	Crossover	$\sigma_{\mathbf{share}}$	$\alpha_{\mathbf{share}}$	$\sigma_{\mathbf{mate}}$
$\mathbf{S}_1$	ranking $c = 0.83$	one-point $p_c = 0.7$ $att = 10$	$\frac{M_1-m_1+M_2-m_2}{49}$	1	$10{\cdot}\sigma_{\mathrm{share}}$
$\mathbf{S}_2$	ranking $c = 0.83$	uniform $p_c = 0.7$ $att = 10$	$\frac{M_1-m_1+M_2-m_2}{49}$	1	$10{\cdot}\sigma_{\mathrm{share}}$
$\mathbf{S}_3$	ranking $c = 0.83$	one-point $p_c = 0.7$ $att = 10$			
$\mathbf{S}_4$	ranking $c = 0.83$	uniform $p_c = 0.7$ $att = 10$			
$\mathbf{S}_5$	ranking $c = 0.83$	heuristic $p_c = 0.7$ $att = 10$			
$\mathbf{S}_6$	ranking $c = 0.83$	heuristic $p_c = 0.7$ $att = 10$	$\frac{M_1-m_1+M_2-m_2}{49}$	1	$10{\cdot}\sigma_{\mathrm{share}}$
$\mathbf{S}_7$	tournament $t_{dom} = 5$	one-point $p_c = 0.7$	$\frac{M_1-m_1+M_2-m_2}{49}$	1	$10{\cdot}\sigma_{\mathrm{share}}$
$\mathbf{S}_8$	tournament $t_{dom} = 5$	one-point $p_c = 0.7$ $att = 10$			
$\mathbf{S}_9$	ranking $c = 0.83$	arithmetical $p_c = 0.7$	$\frac{M_1-m_1+M_2-m_2}{49}$	1	$10{\cdot}\sigma_{\mathrm{share}}$
$\mathbf{S}_{10}$	ranking $c = 0.83$	arithmetical $p_c = 0.7$			

Table 1: Simulation set.

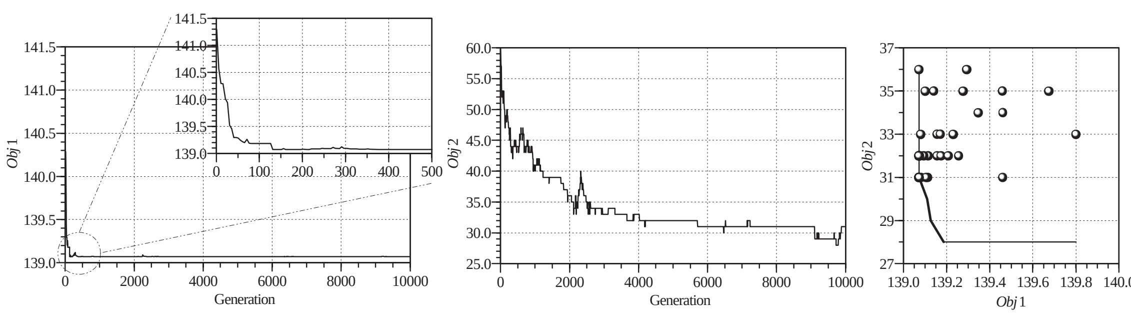

Figure 2: Objective functions and population with cumulative trade-off surface in simulation 1.

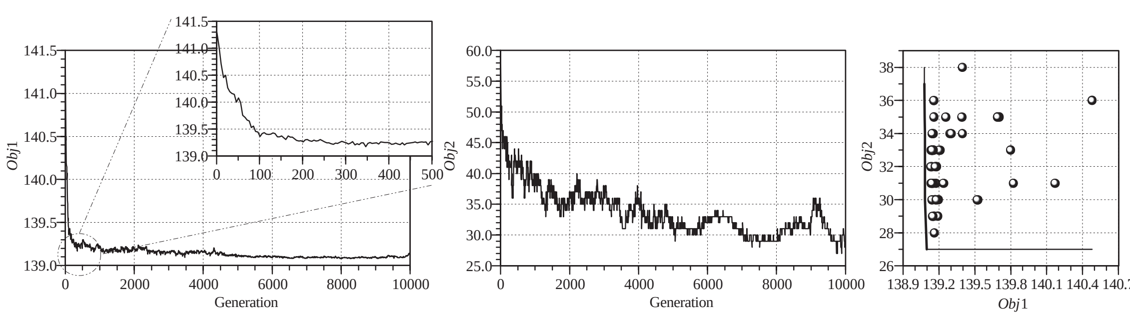

Figure 3: Objective functions and population with cumulative trade-off surface in simulation 2.

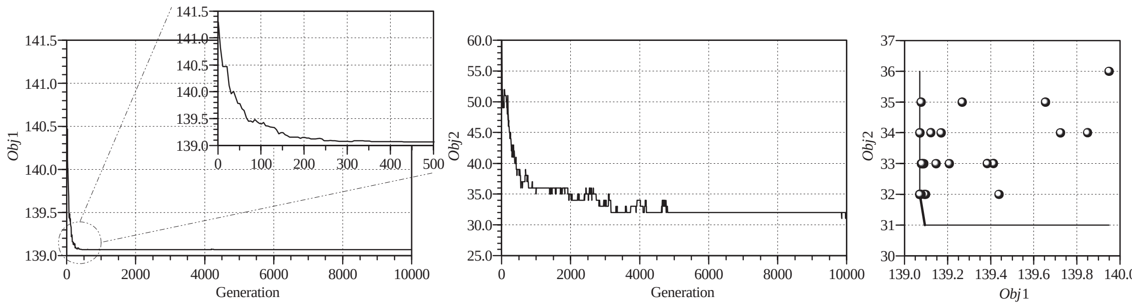

Figure 4: Objective functions and population with cumulative trade-off surface in simulation 3.

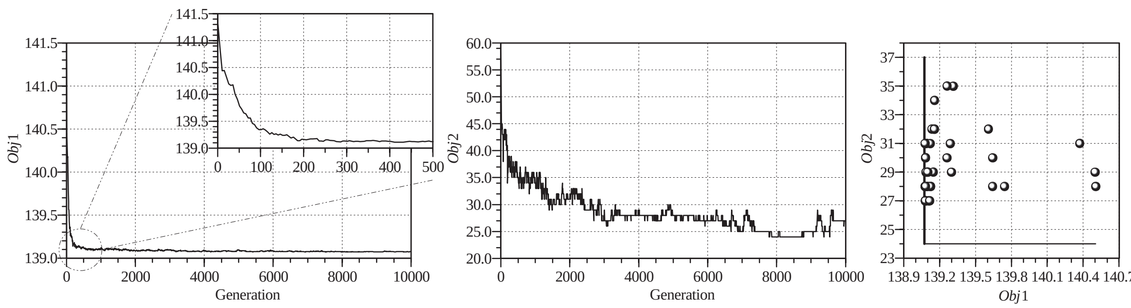

Figure 5: Objective functions and population with cumulative trade-off surface in simulation 4.

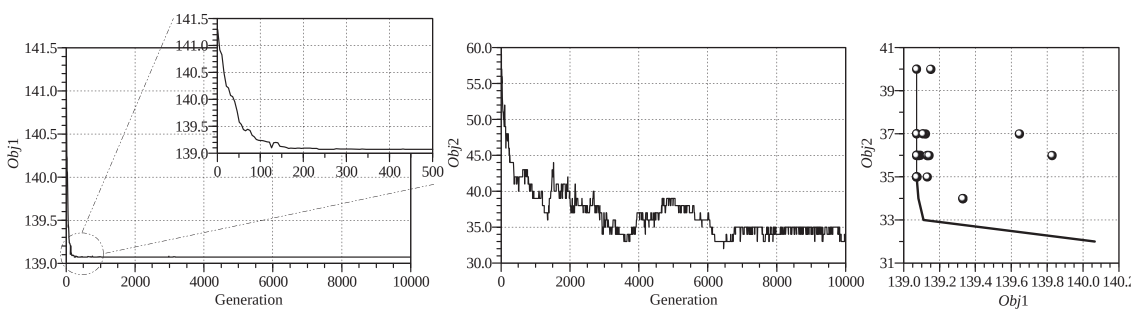

Figure 6: Objective functions and population with cumulative trade-off surface in simulation 5.

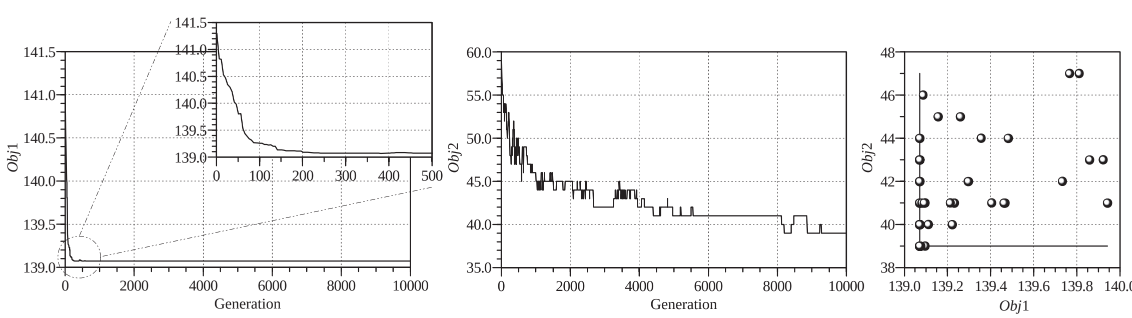

Figure 7: Objective functions and population with cumulative trade-off surface in simulation 6.

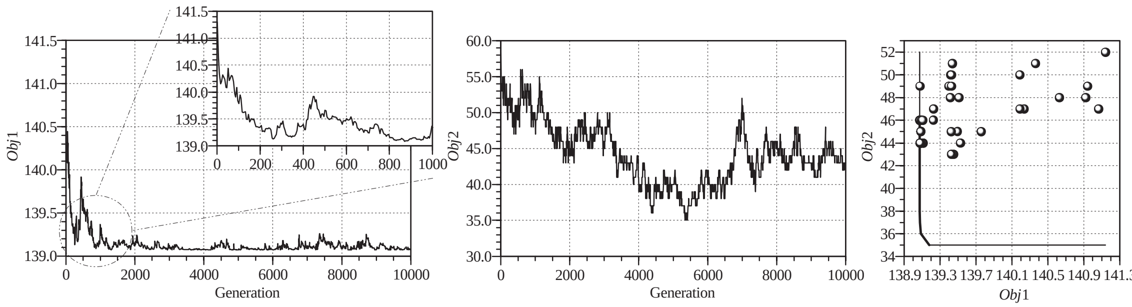

Figure 8: Objective functions and population with cumulative trade-off surface in simulation 7.

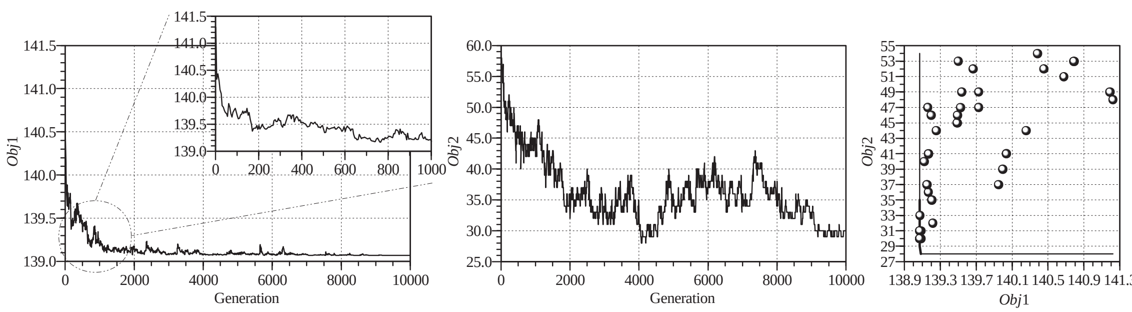

Figure 9: Objective functions and population with cumulative trade-off surface in simulation 8.

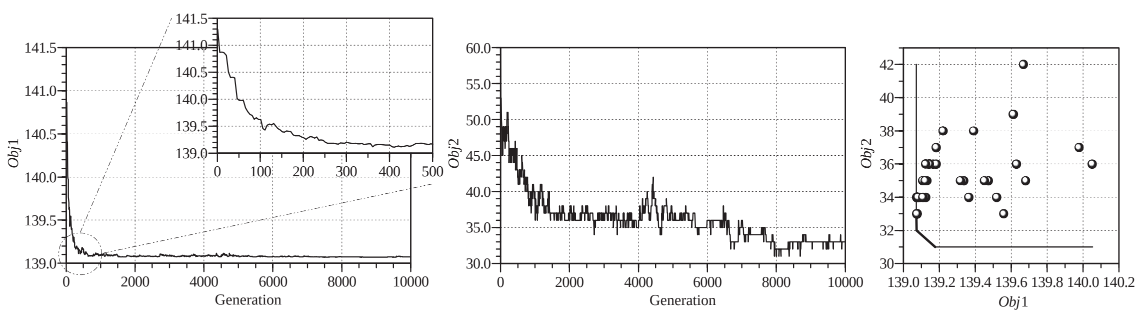

Figure 10: Objective functions and population with cumulative trade-off surface in simulation 9.

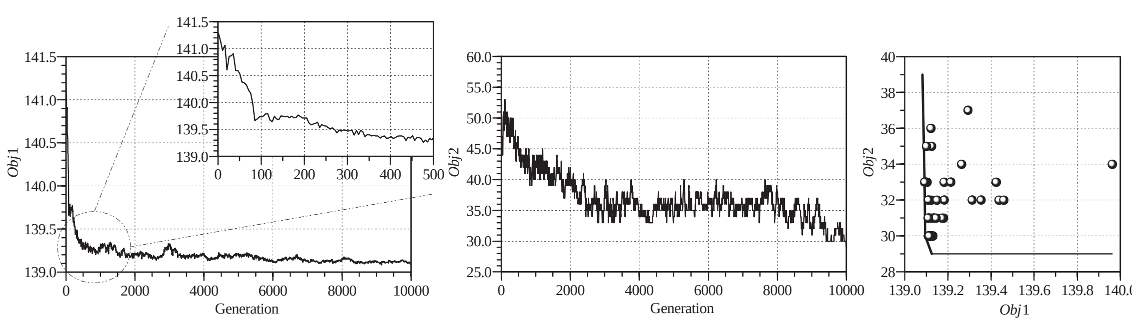

Figure 11: Objective functions and population with cumulative trade-off surface in simulation 10.

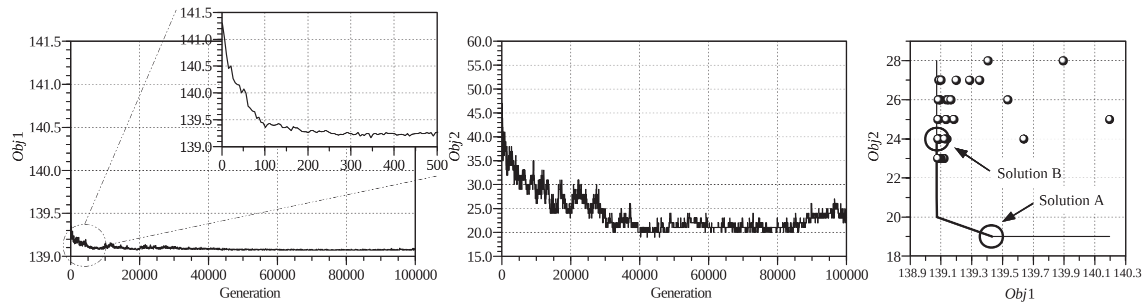

Figure 12: Simulation 2 along 100000 generations; objective functions and population with cumulative trade-off surface.

- some of the crossover operators need an extra parameter (*att*) which represents the number of attempts to generate feasible solutions;
- the mutation operator is composed simultaneously by four strategies: uniform, boundary, non-uniform and exchange mutations, each with a mutation probability of one gene in 30% of the population (this gives a mutation probability of $\frac{0.3}{84}$);
- the elected reinsertion mechanism was the generational reproduction [25] where all the population is replaced in each generation.
- the scheme of sharing uses two parameters: σ_{share} which is estimated in each generation and proportional to the range of both objective functions and α_{share} which equals one;
- the mating restriction scheme involves the parameter σ_{mate} which is made ten times σ_{share}; this comes from the fact that function $Obj2$ gets only integer values and, so, all the members of small niches have the same value for this objective function.

Figures 2 to 11 represent the evolution of the objective functions $Obj1$ and $Obj2$ in the ten simulations and also the situation of the population in generation ten thousand with the cumulative trade-off surface.

4.2 Analysis of Simulation Results

The analyses of results is, in a certain manner, related with the guidelines responsible for the choice of this simulation set. There are three major points: (i) the confrontation of the main multicriteria selection schemes, (ii) the comparison among the main crossover operators and (iii) the inclusion of sharing and mating restriction schemes in order to diversify the trade-off surface.

Objective function $Obj2$ presents a oscillatory character in all the simulations due to its own definition which does not represent the variations degree but only the presence or the absence of them. Objective function $Obj1$, in the other way, reaches its optimum, in almost all simulations, more or less in an hundred generations which reveals a great ease with the total energy cost minimization.

Simulations three and eight reveal a higher convergence time for the Pareto ranking either with $Obj2$ or $Obj1$. This situation was expected since the tournaments are accomplished only in a local set of individuals then the selection probability of a worse individual is considerable and its permanence degrades the convergence. Bigger tournaments, in the other way, should lead to elitism with inevitable premature convergence.

Among crossover operators used in this work (simulations three, four, five, eight and ten) the only one which is inherently closed is the arithmetical. A number of attempts too low results in an overall crossover probability also too low and, consequently, in a slow convergence time and in a high number of generations. However the uniform crossover is the one with the best results on both objective functions, manly in $Obj2$. The diversity in the optimum Pareto set is considered poor in heuristic crossover since about 80% of population converged prematurely to solutions out of trade-off surface in generation ten thousand. With arithmetical crossover objective function $Obj1$ has a rather weak behavior; in ten thousand generations this crossover did not achieve the value the others did in two hundred generations.

Two of the diversification techniques used were the sharing and the mating restriction. Globally, the intended variety in the trade-off surface is achieved but with a longer convergence time. With the one-point crossover (simulations one and three) the results were identical since this operator has, by itself, a diversified feature. The other operators had distinct behaviors: in heuristic operator (simulation six) the niche formation was present in final generation but $Obj2$ produced a worse evolution with only one solution in the Pareto set. This can be justified by the limited ability of the heuristic crossover to produce feasible solutions since this, by definition, has a tendency to get out of the convex space. The low diversifier character of the arithmetical crossover is improved with inclusion of these diversification techniques (simulation nine) and, so, a better investigation of feasible space not yet sampled. The uniform crossover showed a regular response with a lower convergence time but with more alternative solutions.

The inclusion of the two diversification methods in the Pareto domination tournament selection proved to be perfectly disastrous (simulation seven). The time convergence got worse in both objective functions and no improvements were found in the population diversification.

A genetic algorithm capable of a convenient convergence time on both objective functions and composed by a population of non-dominated solutions in a problem of this dimension is rather hard to find. However, from the analyses made above, the best genetic algorithm to this

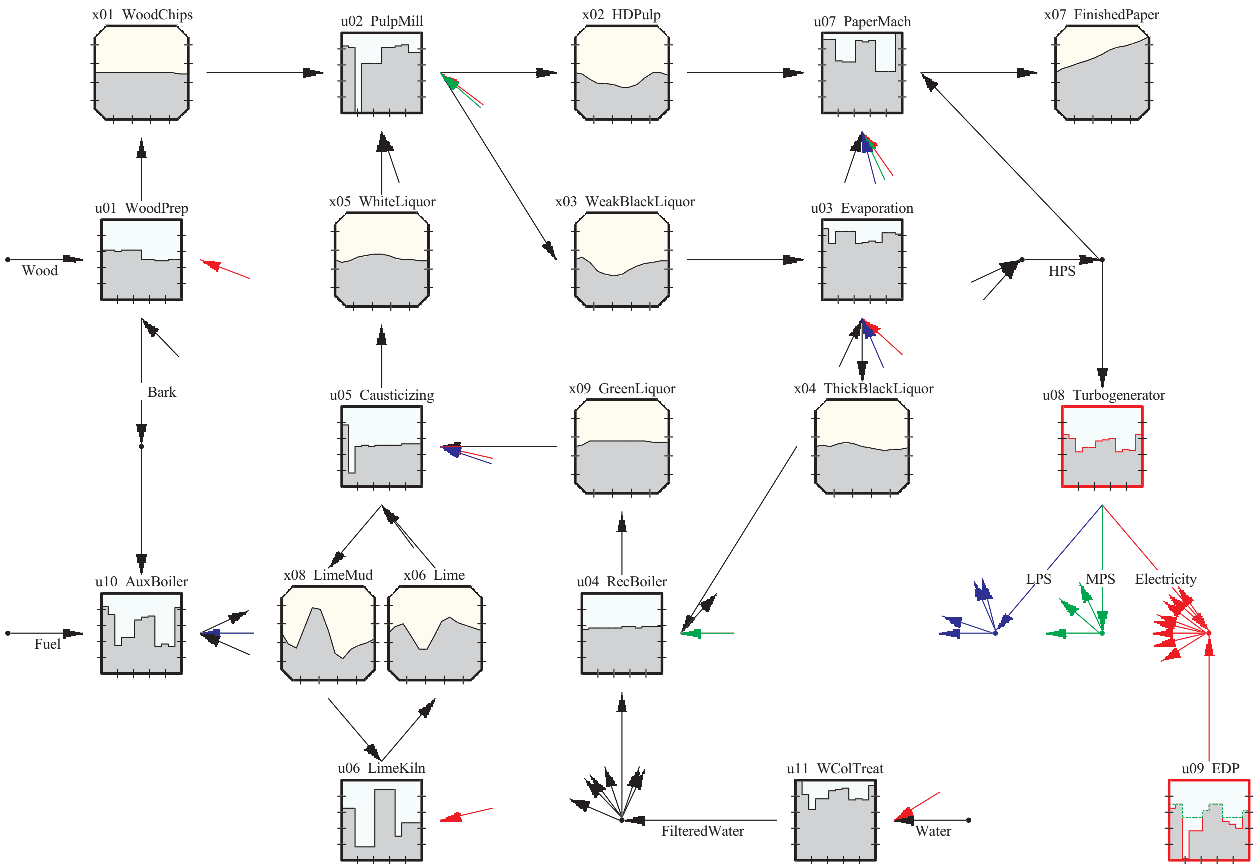

Figure 13: Solution B from the trade-off surface in generation 100000 (figure 12).

propose is the one of the second simulation. Therefore this simulation was extended to generation one hundred thousand, represented in figure 12. Figure 13 represents the solution marked in figure 12 as solution B, being one of the possible solutions from the non-dominated set.

5 Conclusions

This work analyzed the ability of several operators and schemes in a genetic algorithm approach for the resolution of a large scale optimization problem. The obstacles inherent to the problem nature were, namely, its order, constrained space and multiple criteria. In order to handle the constraint set this work used a method which guarantees the generation of feasible solutions with the aid of closed recombination operators. The presence of multiple objectives was treated by two selection schemes involving the Pareto definition, the Pareto ranking and the Pareto domination tournaments. Diversification techniques were obviously needed bearing in mind the intended trade-off surface. The best results were found to be with the fitness sharing and mating restriction.

Although GA is a iterative technique, the literature shows several functional examples with reasonable computational times implemented in sequential architectures. However if this purpose is not attained it is always possible to go over parallel technologies, not necessarily with multiprocessors. Further work could use existent resources, as personal computers and data networks, with the aid of protocols like PVM (Parallel Virtual Machine) or MPI (Message Passing Interface).

References

[1] Deb, K., and Goldberg, D. An investigation of niche and species formation in genetic function optimization. In *Proceedings of the 3rd International Conference on Genetic Algorithms* (George Mason University, June 1989), J. D. Schaffer, Ed., Morgan Kaufmann, pp. 42–50.

[2] Dourado, A., and Santos, A. (optimal) rule-based system for production and energy management. In *Proceedings of IEEE International Conference on Systems, Man and Cybernetics* (1993), vol. 4, pp. 731–736.

[3] Fonseca, C., and Fleming, P. Genetic algorithms for multiobjective optimization: Formulation, discussion and generalization. In *Proceedings of the 5th International Conference on Genetic Algorithms* (San Mateo, California, 1993), S. Forrest, Ed., Morgan Kaufmann Publishers, pp. 416–423.

[4] Goldberg, D. *Genetic Algorithms in Search, Optimization and Machine Learning.* Reading. Addison-Wesley, Massachusetts, 1989.

[5] Holland, J. *Adaptation in natural artificial systems*. University of Michigan Press, Ann Arbor, 1975.

[6] Homaifar, A., Qi, C., and Lai, S. Constrained optimization via genetic algorithms. *Simulation 62*, 4 (Apr. 1994), 242–253.

[7] Horn, J., and Nafpliotis, N. Multiobjective optimization using the niched pareto genetic algorithm. Tech. Rep. IlliGAL Report No. 93005, University of Illinois, Urbana-Champaign, 1993.

[8] Joins, J., and Houck, C. On the use of nonstationary penalty functions to solve nonlinear constrained optimization problems with GAs. In *Proceedings of the 1st IEEE International Conference on Evolutionary Computation* (Piscataway, NJ, 1994), H.-P. S. D. F. Z. Michalewicz, D. Schaffer and H. Kitano, Eds., vol. 2, IEEE Service Center, pp. 579–584.

[9] Leiviskä, K. Short term production scheduling of the pulp mill. *Acta Polytechnica Scandinavica, Math. Comp. Science 36* (1982), 1–80.

[10] Michalewicz, Z. *Genetic Algorithms + Data Structures = Evolution Programs*, 2 ed. Springer, Berlin, 1994.

[11] Michalewicz, Z. A survey of constraint handling techniques in evolutionary computation methods. In *Proceedings of the 4th Annual Conference on Evolutionary Programming* (Cambridge, MA, 1995), MIT Press.

[12] Michalewicz, Z., and Schoenauer, M. Evolutionary algorithms for constrained parameter optimization problems. *Evolutionary Computation Journal* (1996). To appear in.

[13] Monteiro, P. Short-term production scheduling: A new and more efficient algorithm and its application to the pulp and paper industry. *Information and decision technologies 18* (1992), 241–263.

[14] Mühlenbein, H. Parallel genetic algorithms, population genetic and combinatorial optimization. In *Proceedings of the 3rd International Conference on Genetic Algorithms* (San Mateo, CA, 1989), J. Schaffer, Ed., Morgan Kaufmann Publishers, pp. 416–421.

[15] Powell, D., and Skolnick, M. Using genetic algorithms in engineering design optimization with non-linear constraints. In *Proceedings of the 5th International Conference on Genetic Algorithms* (San Mateo, CA, USA, July 1993), S. Forrest, Ed., Morgan Kaufmann, pp. 424–431.

[16] Richardson, J., Palmer, M., Liepins, G., and Hilliard, M. Some guidelines for genetic algorithms with penalty functions. In *Proceedings of the 3rd International Conference on Genetic Algorithms* (San Mateo, CA, 1989), J. Schaffer, Ed., Morgan Kaufman Publishers.

[17] Riche, R. L., Knopf-Lenoir, C., and Haftka, R. A segregated genetic algorithm for constrained structural optimization. In *Proceedings of the 6th International Conference on Genetic Algorithms* (San Francisco, July15–19 1995), L. J. Eshelman, Ed., Morgan kaufmann Publishers, pp. 558–565.

[18] Santos, A. Production and energy optimization in an industrial complex: A genetic algorithm approach (in portuguese). Master's thesis, Dep. de Engenharia Informática da Universidade de Coimbra, 1996.

[19] Santos, A., and Dourado, A. Global optimization of energy and production in basic industries: A genetic algorithm application. In *Proceedings of IFAC/IFIP Conference on Management and Control of Production and Logistics* (1997), pp. 139–144.

[20] Santos, A., and Dourado, A. Production and energy optimization in a industrial complex: A genetic algorithm approach. In *Proceedings of 15th IMACS World Congress on Scientific Computation, Modelling and Applied Mathematics* (1997).

[21] Schoenauer, M., and Xanthakis, S. Constrained GA optimization. In *Proceedings of the 5th International Conference on Genetic Algorithms* (San Mateo, CA, USA, July 1993), S. Forrest, Ed., Morgan Kaufmann, pp. 573–580.

[22] Siedlecki, W., and Sklansky, J. Constrained genetic optimization via dynamic reward-penalty balancing and its use in pattern recognition. In *Proceedings of the 3rd International Conference on Genetic Algorithms* (George Mason University, June 1989), J. D. Schaffer, Ed., Morgan Kaufmann, pp. 141–150.

[23] Spears, W., and De Jong, K. On the virtues of parameterized uniform crossover. In *Proceedings of the 4th International Conference on Genetic Algorithms* (San Mateo, CA, 1991), R. Belew and L. Booker, Eds., Morgan Kaufman, pp. 230–236.

[24] Syswerda, G. Uniform crossover in genetic algorithms. In *Proceedings of the 3rd International Conference on Genetic Algorithms* (George Mason University, June 1989), J. D. Schaffer, Ed., Morgan Kaufmann, pp. 2–9.

[25] Syswerda, G. A study of reproduction in generational and steady state genetic algorithms. In *Proceedings of the 1st Workshop on Foundations of Genetic Algorithms* (San Mateo, July 15– 18 1991), G. J. E. Rawlins, Ed., Morgan Kaufmann, pp. 94–101.

[26] Uronen, P. Production planning systems for integrated paper mills: Tasks and methodology. *Pulp & Paper Canada 82*, 3 (1981), 90–94.

[27] Wright, A. Genetic algorithms for real parameter optimization. In *Proceedings of the 1st Workshop on Foundations of Genetic Algorithms* (San Mateo, July 15– 18 1991), G. J. E. Rawlins, Ed., Morgan Kaufmann, pp. 205–220.