A Fair Comparison of Representations, Operators and Algorithms for the Sugarcane Harvest Problem

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***Abstract* — This paper instantiate the sugarcane harvest problem as a multiple knapsack problem incorporating logistic data in its formulation. Different combinations of data representations, genetic operators and multi-objective (MO) evolutionary algorithms to solve the problem are evaluated. The proposed approach produced results that considered aspects such as output quality (*i.e.* relevance to decision maker), solutions spread and run-time. Tests carried out have used real data from two sugarcane mills. Finally, a MO interpretation of generated results is also suggested.**

***Keywords*—MO evolutionary algorithms, sugarcane harvest**

I. Introduction

Sugarcane is one of the most important commodities in the world, according to the Food and Agriculture Organization of the United Nations (FAO) [1]. Its end products are, mainly, sugar and ethanol (a major renewable fuel). There is no need to stress the relevance of these two products in addressing social problems such as starvation and global warming. Brazil, India, China and Thailand are the world's four biggest producers of sugarcane. As populous, developing countries, they can be considered cause of and solution for the two problems mentioned above. Thus, studies aimed at improving production of sugarcane in these areas, especially, are to be greatly welcomed and encouraged.

The sugarcane crop is very demanding of labor and management. Its production involves several steps. One in particular, the harvest, is critical to the success of the entire process. Harvesting encompasses complex decisions that directly influence the final production figures.

During one harvest cycle, the manager must provide the sequence of sugarcane lots to be harvested. This decision is linked to a number of factors, such as labor force, transportation and mill capacity. This means that several intrinsic agricultural objectives have to be maximized [2] the same time as logistics costs associated with the activity have to be minimized. These groups are usually conflicting.

It is not unusual for harvest decision-making to be carried out in an empirical or heuristic manner. In such cases the managers' expertise is heavily draw on to handle the task. Naïve considerations on production data, such as the lot's planting date and species overall agronomical behavior, are often used.

After Lima Neto's initial proposal in 1997-8 that attempted to correlate available crop data for predicting sugarcane agronomical factors using a Multilayer Perceptron (MLP) Artificial Neural Networks (ANN) [3][4], several papers have been produced outperforming the forecasting module and aggregating a search module that uses the forecast indicators in order to suggest harvest decisions [5][6][7][8].

Although, the sugarcane harvest is a multi-objective (MO) problem, only recently have Pacheco *et al.* [8] incorporated MO optimization techniques into the solution formulation. Furthermore, all these papers have considered only agronomic objectives, leaving out assumptions on logistics.

In this work, the sugarcane harvest problem (SHP) is instantiated as multi-objective, specifically, a multiple 0/1 knapsack problem (MKP) [9], which is a generalization of the simple 0/1 knapsack problem. Mumford [10] adapted from Hinterding [11] different forms of data representation and constraint handling from simple to MKP. He used a benchmark test problem proposed by Zitzler and Thiele [12] for sound comparisons. Subsequently, Colombo compared different multi-objective evolutionary algorithms (MOEA) on the same problems [13].

All this inspired us to apply the different representations, operators and MOEA to solve the specific sugarcane problem. We have also defined a mechanism to incorporate logistic data into optimization, allowing the solution to be more realistic and useful in real sugarcane harvest scenarios.

Experiments were carried out with two different data sets from Brazilian sugarcane mills. The comparisons were deemed to be fairer than in previous papers as they were performed all as multi-objective problems.

The paper is organized as follows. In section II we revised different representations of the problem, genetic operators and the MOEA algorithm. In section III the contribution is detailed, in particular (i) the instantiation of the sugarcane problem as a MKP and (ii) the incorporation of logistic data into problem formulation. In the results section of this paper some charts compare run-time analysis and 2D plots representing trade-offs between two approaches, namely Hypervolume [12] and Generational Spread [14].

II. BACKGROUND

A. Representations of the Problem

The 0/1 knapsack problem definition is very simple in spite of its resolution being of a NP-hard problem [15]. The MKP definition allows the problem data to be represented in several manners by genetic algorithms. Hinterding [11] initially defined and classified possible representations of the 0/1 MKP version by Mumford [10], as follows:

1) Binary Representation

This approach is the one most favored for MKP by researchers [10]. The individual solutions are bit strings, i.e. they are a sequence of zeros (0) and ones (1), where zero means that the represented object was not selected and one, the opposite. The bit string length represents the amount of objects that can possibly be chosen to be in the knapsacks. In this representation capacity constraints are often overloaded, thus some constraint handling mechanisms were also developed, e.g., penalty functions (PF) and decoders [11][16][17];

2) Symbolic Representation

In the symbolic representation the genes are the items themselves. Among symbolic representations, the order based representation consists in representing all items in a permutation order and using a decoder to select the ones to be kept in the knapsack [11][16][17]. This decoder ensures that only "legal" (feasible) knapsacks are produced;

3) Numeric Representation

Another kind of representation described earlier [11] is the numeric one, where the genes are numbers that map to real objects. However, previous works disencourage its use in MKP after some experiments [10][17][18]. Because of that, it has not been used in this paper.

As briefly described above, representations should be used together with their correction mechanisms. Hinterding [11] also classified these constraint handlers as: PF, preferences and heuristics (decoders). In Mumford's study [10] the use of PF and preferences was shown to be inefficient in restrictive MPK problems, so, they were not used in this paper either. Considering sound previous work [10][11][13][17][18], two heuristics were selected here to handle bit strings and order-based individuals.

The first, as the binary representation suggests, does not consider the order of the elements, but which of them were selected. The list of chosen ones is sorted by maximum *profit/weight* ratio and the objects are added to knapsack for as long as the capacity constraint is not violated. This describes the 'Best Fit Heuristic' of Hinterding [11] with the above mentioned profitable concept of Zitzler & Thiele [12].

The second heuristic is used to create valid knapsacks from order-based individuals. The 'First Fit Heuristic' [11] searches, from left to right, and adds the first object that does not exceed the established capacity. This process is repeated while a valid object can be found.

B. Approaches to MO optimization

As the problem can be represented in different manners, it is necessary to take specific operators to treat particularities of each representation. The deemed relevant algorithmic approaches paired with problem representation are described below.

1) Bit String (bit)

This approach uses binary representation with no penalty function or decoders. It purely tackles the evolution process using the one-point crossover with the bit-flip mutation. It is MOEA's "responsibility" to handle the constraints satisfaction.

2) Bit String with Best Fit Heuristic (bitD)

This approach also uses binary representation with one-point crossover and bit-flip mutation. However, it assumes the use of constraints when applying a decoder to guarantee legal knapsack production. Michalewicz and Arabas [16] tried, for single objective optimization, writing back the repaired chromosomes into the population, demonstrating no benefits. Mumford [10] did the same for MKP. Thus, none of experiments of this work consider repaired replacement.

3) Order Based + Cycle Crossover (CX)

The symbolic representation requires a decoder to produce legal knapsacks, as all items are presented in the permutation list. Thus, this approach combines the order-based, the First Fit Heuristic, the cycle crossover (CX) [19] and swap mutation operator. CX was successfully applied on MKP [10].

4) Order Based + Partially Matched Crossover (PMX)

Finally, the last approach is quite similar to the above, but it investigates how different crossover operators behave for the same problem. The partially matched crossover (PMX) [20] was chosen, as suggested in the literature [10].

C. Evolutionary Algorithms used in the simulations

1) NSGA-II

The fast and elitist multi-objective genetic algorithm (NSGA-II) was proposed by Deb *et al.* (2002) and became one of the most used MOEA. It uses dominance concepts sub-classifying all solutions in different fronts. It also applies a crowd distance operator to maintain diversity among non-dominated solutions [21].

2) SPEA2

This is an improved version of the Strength Pareto Evolutionary Algorithm (SPEA) [12]. This revision was proposed by Zitzler *et al.* (2001) with three main modifications regarding its predecessor: a fine-grained fitness assignment strategy, a density estimation technique, and an enhanced archive truncation method [22].

3) PESA-II

The Pareto Envelope-based Selection Algorithm-II (PESA-II) is an enhanced version of PESA in which the selection is based on region; the unit of selection is a hyperbox in the objective space instead of an individual. Therefore, a hyperbox is selected and the resulting selected individual is randomly chosen within this hyperbox [23].

III. CONTRIBUTION

A. The Sugarcane Harvest viewed as a 0/1 MKP

Solving a specific problem may demand additional steps

with regard to including some problem specificities into general models. This can be seen as a bottom-up (engineering) approach. However, to be more effective in dealing with a real-world problem, identifying the problem class (*i.e.* a top-down approach), may improve results because of benefits derived from some prior knowledge.

In this way, the SHP was instantiated as a MKP, comprised of four minimizations subjected to two constraints. The main assumptions are as follows:

- Knapsacks – are represented by four objectives, three representing agronomic factors (6 – 8) and one, logistic (9). In the next subsection we explain the heuristics used to calculate the overall distance;
- Objects – are the sugarcane cultivated lots (x_i). Each lot has attributes that indicate quality, productivity and logistics. The first group (quality indicators) is given by: PCC (apparently percentage of sugar in cane juice), FIBER (calorific power in the dry residue remaining after the extraction of juice) and ATR (recoverable total sugar). The productivity indicator considered is TCH (sugarcane tonnage per hectare). And the logistic indicators are AREA (lot's surface area), DISTANCE (from lot to factory) and ID (a unique identification) [8].
- Object's profit – maximization of PCC (3), FIBER (4), ATR (5) and DISTANCE, for each knapsack respectively.
- Knapsack capacity – desired tonnage defined by the decision manager aiming at a continuous fulfillment of factory (i.e. mill) demands during harvest (1).

$$crop_{prod} = \sum_{i=1}^{n} x_i * tonnage_i \quad (1)$$

$$tonnage_i = TCH_i * AREA_i \quad (2)$$

$$prod^i_{pcc} = PCC_i * tonnage_i \quad (3)$$

$$prod^i_{fiber} = FIBER_i * tonnage_i \quad (4)$$

$$prod^i_{atr} = ATR_i * tonnage_i \quad (5)$$

$$obj_1 = -\sum_{i=1}^{n} x_i * prod^i_{pcc} \quad (6)$$

$$obj_2 = -\sum_{i=1}^{n} x_i * prod^i_{fiber} \quad (7)$$

$$obj_3 = -\sum_{i=1}^{n} x_i * prod^i_{atr} \quad (8)$$

$$obj_4 = calculateOverallDistance() \quad (9)$$

Regarding the knapsack capacity, *i.e.* desired tonnage, two constraints are considered; these are minimum and maximum acceptable values for the fulfillment of the factory demands (*i.e.* its processing capacity).

B. Incorporating Logistic Data into SHP

This paper incorporates logistic objectives in the optimization. This increases the problem complexity [8] at the same time that it makes the model more realistic.

Although it would be ideal to have the configuration of lots in the field (*i.e.* distance between them, their neighborhood etc), only distance of each lot to the factory was available (in the data set used in all simulations).

To overcome this lack of data, we have assumed a hypothetical spiral physical distribution of lots surrounding the factory. This is based on their distances (to the factory), see Fig. 1. In the figure, each square represents a lot (of different areas) and various types of neighborhoods. Black points mean the selected lot, while the grey ones are their neighbors. The concept of neighborhood of a lot is important as it directly reflects on decisions such as workforce, machinery and transport assignment. None of these logistic issues are dealt by the current model.

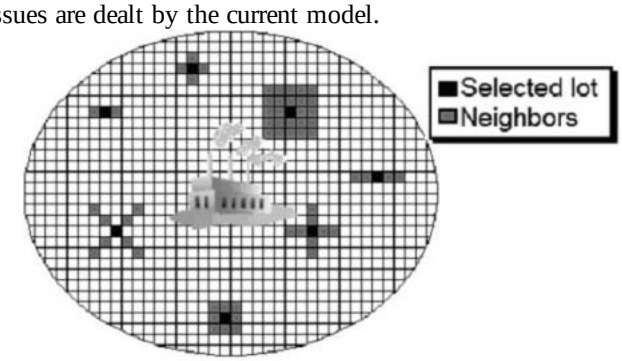

Fig. 1 Hypothetical physical distribution of lots and neighbors.

The heuristic to calculate costs was to consider the overall distance to neighborhood of lots. It is as follows:

1. Group all selected lots in neighborhoods;
2. For each group, the considered distance is the mean of all lots;
3. The overall distance is the summarization of all group distances.

IV. Experimental Method

In this section experimental results of two data sets are presented. Additionally, the metrics used for comparisons and parameters of simulations are commented upon.

A. Performance Metrics

There are several metric that have been used in EMOO comparisons and there is no general agreement on which one is the best [24]; Fonseca *et al.* suggested some unary and binary metrics to be applied [25]. We have used a combination of three metrics from previous works [10][13].

1) Hypervolume (HV) – The $\mathcal{S}$ Metric

This metric was originally proposed by Zitzler and Thiele [26]. It calculates the volume covered by members of an approximation set. For each solution in the set a hypercube is constructed with reference point (a vector of worst objective function values) and the solution as the diagonal corners of the objective [24]. In this paper we have used the modified version of Veldhuinzen (1999) that measures the *HV* ratio of the approximation set and of an ideal vector as the true Pareto front. As it approaches one, the obtained set is deemed to be near the Pareto-optimal set.

2) Generalized Spread (GS) Metric

This is an extension of the Spread metric (Deb *et al.*, 2000) to be applied to problems with more than two objectives. The distance is calculated from every point to its

nearest neighbor. As the approximation set becomes more suitably (spread out) distributed, including extreme solutions GS output values tend to zero [27].

3) Run-Time (RT) Metric

This metric measures the *RT* performance of algorithms performing exactly the same number of objective function evaluations on a given problem. Here we have measured *RT* performance on a PC Intel Core 2 Duo CPU 6400 @ 2.13GHz with 2GB of RAM, under Eclipse Platform version 3.3.0 supported by Java version 1.6.0_03.

B. Data Sets

The experiments were performed using two real data sets from sugarcane factories from Brazil. We have simulated two distinct problems, delving into the constraint processing capacity. The sets are referenced here as CLIENT1 (*CL1*) and CLIENT2 (*CL2*). They consist of 937 and 590 lots (*i.e.* objects in MKP), respectively.

C. Simulations Parameters

To be fair, we have applied the same parameter configuration to all algorithms in each data set, including population size, crossover and mutation rate, number of objective function evaluation, among others. The population size follows the sample size, as well the number of objective functions. These values were obtained experimentally. The different desired tonnages represent the knapsack restrictive condition of, approximately, 10% and 30% for *CL1* and *CL2*, respectively. Table I presents all parameter configurations for both problems designed.

TABLE I
PARAMETERS FOR BOTH DATA SETS USED IN THE EXPERIMENTS

Parameters	CLIENT 1	CLIENT 2
# of lots (*n*)	937	590
population size	400	200
Desired tonnage	50000	150000
# of evaluations	80000	25000
crossover rate	0.9	
mutation rate	1 / *n*	
Archive size[1]	400	200
bi-sections[2]	5	
selection operator	binary tournament	

D. Results

The results of 12 approaches are presented and organized by metric, data set and algorithms utilized. All approaches (*i.e.* combinations of algorithms and problem representations) were orthogonal and repeated 30 times over. They are:

- NSGA-II: (i) bit string representation – *N .bit*; (ii) bit with best fit heuristic – *N.bitD*; (iii) order-based representation with cycle crossover – *N.cx*; and, (iv) order-based representation with partially matched crossover – *N.pmx*;
- SPEA2: (i) *S.bit*; (ii) *S.bitD*; (iii) *S.cx*; and, (iv) *S.pmx*;
- PESA-II:(i) *P.bit*; (ii) *P.bitD*; (iii) *P.cx*; and, (iv) *P.pmx*.

1) Results for the Hypervolume (HV) – The $\mathcal{S}$ Metric

In Fig. 2, *HV* measures are shown. Even though the *HV* scales are different for both data sets (CL1 best approximantions are in the 0.91 to 1 range, and in CL2, between 0.97 to 1), a strikingly common pattern – regardless of algorithm – is revealed. NSGA-II and SPEA2 performed equivalently for all representations. Notice that *bit* and *cx* approaches were closer to the ideal Pareto, followed by *pmx* and *bitD*. PESA-II presented slightly different results when compared to the others; *bit* and *bitD* were consistently the best and worst representations, and *cx* and *pmx* swapped positions.

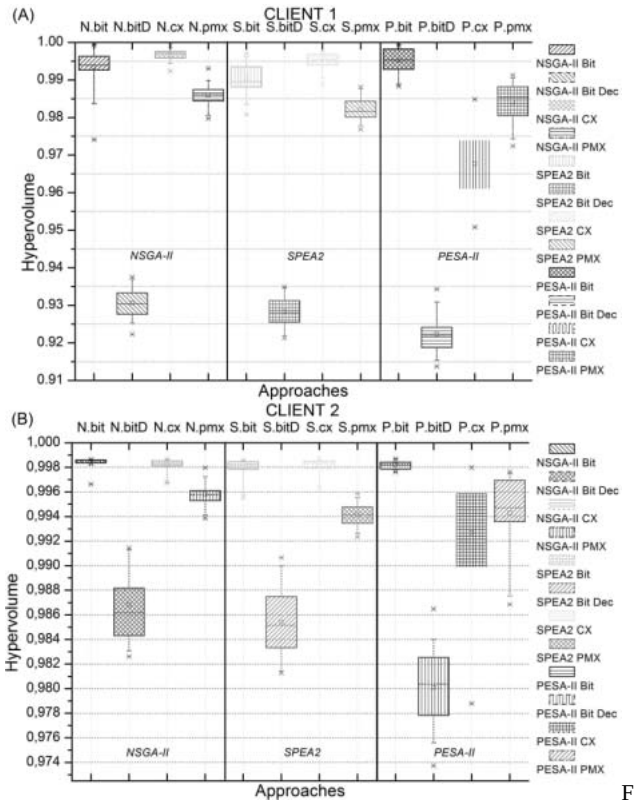

Fig. 2 HV measures for different approaches for CL1 (A) and CL2 (B).

2) Results for the Generalized Spread (GS) Metric

Fig. 3 shows results for the *GS* metric. Performance from best to worst was: *pmx*, *cx*, *bitD* and *bit*. For *CL1*, NSGA-II and PESA-II are equivalent best approaches, but *P.cx* and *P.pmx* presented high variation. In this way, *N.pmx* and *N.cx* are better options, respectively. In *CL2* the samples are more similar; therefore *N.pmx*, *N.cx*, *S.pmx* and *P.pmx* could be considered equivalent.

3) Results for the Run-Time (RT) Metric

The third metric results are shown in Fig. 4. For *CL1* the best option is *N.pmx* (about 5 min), closely followed by solutions *N.cx*, *S.pmx* and *P.pmx* (at around 7.5 min). Bit string representations (*bit* and *bitD*) took a large amount of time (near 100 min). For CL2, the majority of the approaches run in a reasonably short time (close to 4.5 min), with the exception of *bit* (at round 12 min).

[1] It is not applicable to NSGA-II.
[2] The maximum number of bi-divisions for adaptive grid (PESA-II).

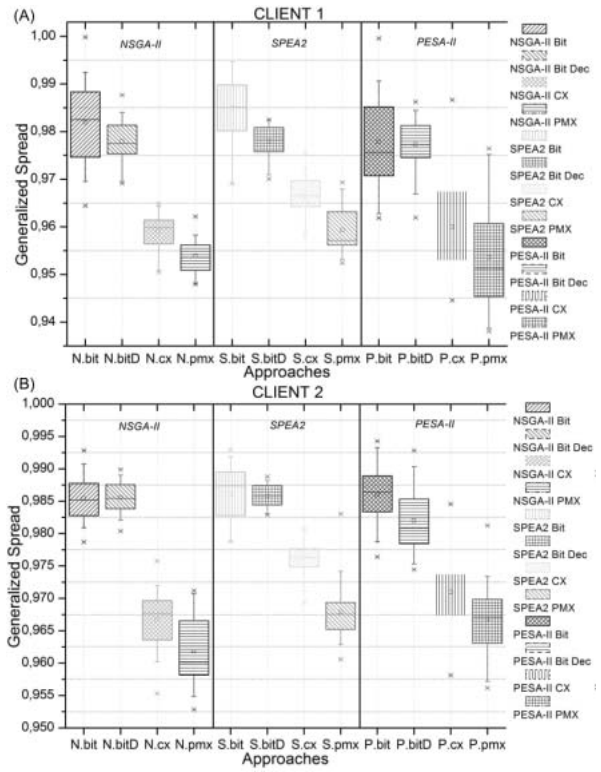

Fig. 3 *GS* measures for different approaches for *CL1* (A) and *CL2* (B).

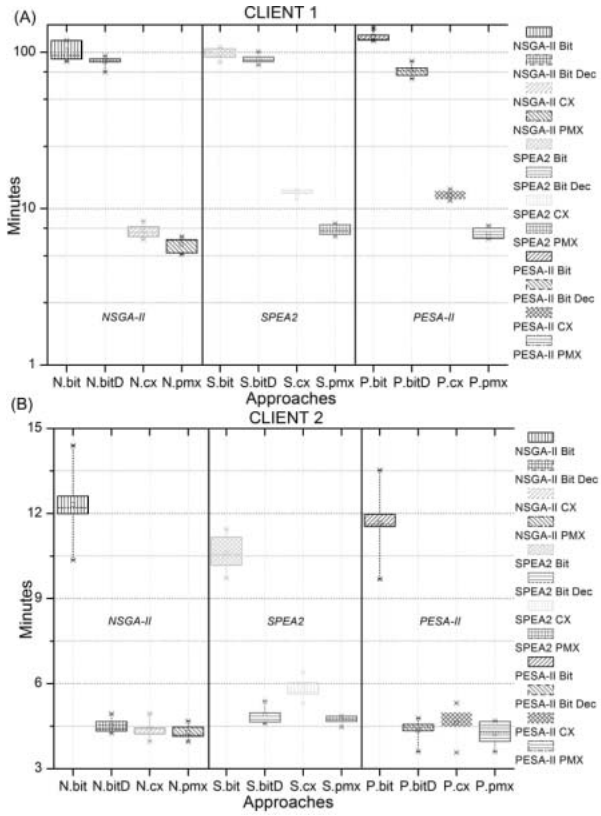

Fig. 4 *RT* measures for different approaches for *CL1* (A) and *CL2* (B).

To treat the comparison more fairly, Fig. 5-A and Fig. 6-A illustrate how candidate solutions are positioned in the objective space, and how close they are to the *Pareto*. In part B of the figures, the spaces present run-time contours.

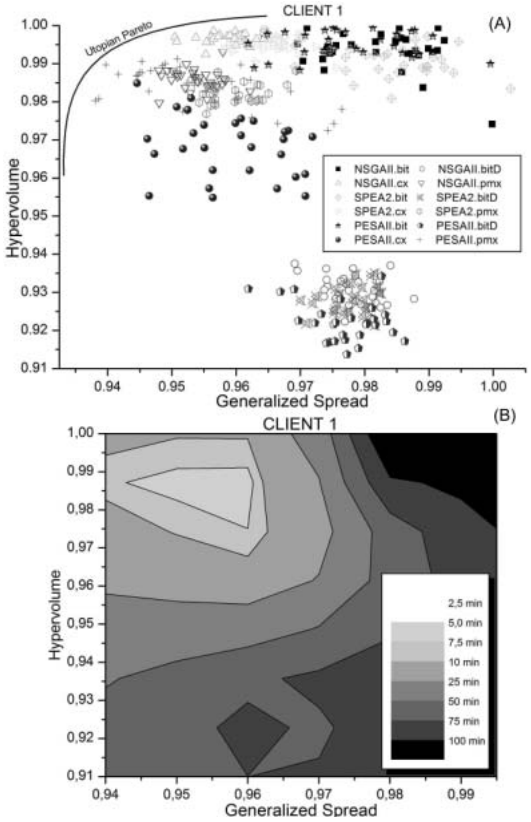

Fig. 5 Candidate solutions(A) and *RT*contour-plot(B); *CL1* objective space.

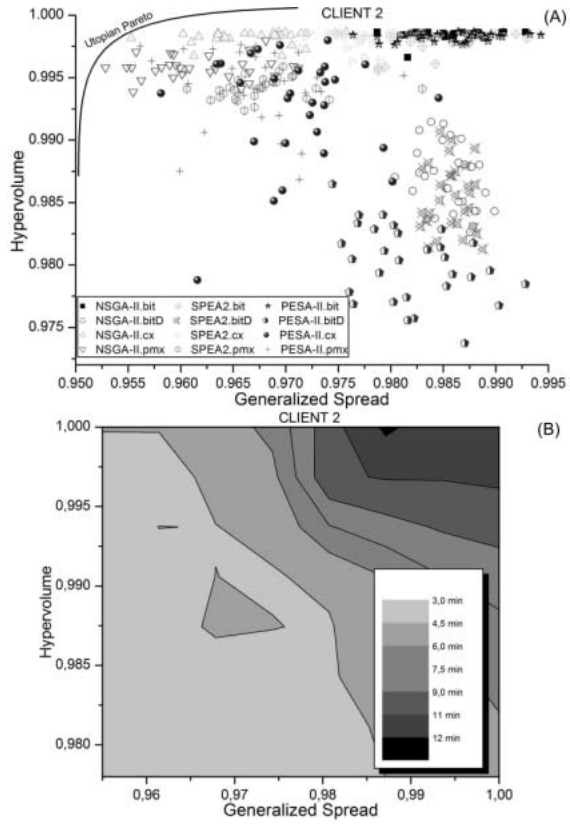

Fig. 6 Candidate solutions(A) and *RT*contour-plot(B); *CL2* objective space

V. CONCLUSION AND FUTURE WORKS

This paper instantiates the sugarcane harvest problem (SHP) as a multiple 0/1 knapsack problem (MKP). It then incorporates logistic data into the problem resolution by

affording more realism to simulations. By equating the SHP to the MPK we explore wide forms of representation, different operators and state-of-the-art MOEA algorithms. For testing, we used two distinct sugarcane harvest problems with data from two factories in Brazil. The problems were posed here in order to explore many features such as:

- Multi-objective SHP: 4 objectives and 2 constraints;
- Real scale: large number of lots (knapsack items) considered; 937 and 590, respectively;

Restrictiveness – desired tonnage (knapsack capacity) greatly restrictive; 10% and 30%, for CL1 and CL2. Comparisons considered quality (hypervolume), distribution on Pareto front (generalized spread) and performance (run-time) of all approximation sets.

Results suggest that order-based representations with *CX* or *PMX* are recommended for NSGA-II and SPEA2 while for PESA-II, *PMX* perform is best. The *bit* representation was good for the hypervolume metric; however its performance is low with respect to spreading and run-time. As the problem complexity was high, the use of a decoder without reinsertion was not effective.

As for future works, further investigations should be performed aimed, especially, at fine-tuning the algorithms' parameters. As a real world problem, the articulation of preferences is encouraged, allowing interactions between optimizer and decision maker; further investigations are to be welcomed to improve such a dialogue. Finally, the multiobjective interpretation of results associated with financial factors, might indicate higher hypervolume solutions

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