AN ADD/DROP PROCEDURE FOR THE CAPACITATED PLANT LOCATION PROBLEM

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Abstract

The capacitated plant location problem with linear transportation costs is considered. Exact rules and heuristics are presented for opening or closing of facilities. A heuristic algorithm based on ADD/DROP strategies is proposed. Procedures are implemented with the help of lower and upper bounds using Lagrangean relaxation. Computational results are presented and comparisons with other algorithms are made.

Keywords: capacitated plant location problem; ADD/DROP procedures; heuristic methods; Lagrangean relaxation.

Resumo

O problema de localização de facilidades capacitado com custos de transporte lineares é considerado. Testes exatos e heurísticas para abrir ou fechar facilidades são apresentados. Um algoritmo heurístico baseado em estratégias *ADD/DROP* é proposto. Os procedimentos são implementados com o auxílio de limites inferiores e superiores provenientes de relaxação lagrangeana. Resultados computacionais são apresentados e comparações realizadas com outros algoritmos.

Palavras-chave: problema de localização capacitado; procedimentos *ADD/DROP*; heurísticas; relaxação lagrangeana.

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1. Introduction

The capacitated plant location problem (CPLP) may be formulated as:

 $\begin{array}{ll} \text{minimize} & \sum_{k \in I} \sum_{j \in J} c_{kj} x_{kj} + \sum_{k \in I} f_k \, y_k \\ \text{subject to} & \sum_{j \in J} x_{kj} \leq a_k \, y_k \quad \forall k \in I \\ & \sum_{k \in I} x_{kj} = b_j \quad \forall j \in J \\ & x_{kj} \geq 0 \quad \forall k \in I, \forall j \in J \\ & y_k \in \{0,1\} \quad \forall k \in I \end{array}$

where *I* is the set of possible plant locations each with a maximum capacity a_k and fixed cost f_k , *J* is the set of demand centers each with a demand b_j , and c_{kj} is the unit transportation cost between a facility *k* and a consumer *j*. The variable x_{kj} represents the amount sent from *k* to *j*, and y_k means locating (or not) plant *k*.

The CPLP is a well known combinatorial optimization problem belonging to the class of the NP-Hard problems. For large instances there may be the need of reduction tests, problem relaxation and heuristic methods. Christofides & Beasley (1983), Beasley (1988) and Barcelo *et al.* (1991) have used problem reduction and Lagrangean relaxation to solve the CPLP. Thizy (1994) has used Lagrangean relaxation for a variant of the CPLP. Beasley (1993) has developed a framework for producing Lagrangean heuristics for the capacitated and the uncapacitated plant location problems. A good comparison of heuristic methods for the CPLP is presented by Cornuejols *et al.* (1991).

Here we present a heuristic algorithm for the CPLP based on dominance criteria between fixed and variable costs. These criteria may work in an exact way or just as a heuristic method for determining the status of facilities. Jacobsen (1983) and Mateus & Bornstein (1991) have used them within ADD or DROP heuristics. Holmberg & Ling (1995) have applied an ADD heuristic for the CPLP with staircase costs. More recently Bornstein & Azlan (1998) have used these ideas within the simulated annealing framework.

In the next section we present reduction tests and heuristics based on dominance criteria. The tests and heuristics are well known from literature. However, we combine them in a new way producing the algorithm proposed in section 3. We use lower and upper bounds for the cost increments in order to get an efficient implementation. These bounds can be obtained by Lagrangean relaxation (see Azlan, 1995).

In section 4 we present computational results. A comparison with other known algorithms is made. Finally, the last section points out to some conclusions.

2. Dominance Criteria

The dominance criteria between fixed and variable (transportation) costs are often used in reduction tests, cutting down the original size of the problem by an *a priori* opening or closing of plants. They are also useful to develop heuristics. In order to state the tests and heuristics, we consider the unified approach presented in Bornstein & Azlan (1998).

Given a subset $K \subseteq I$ of the potential plant locations, let

$$w(K) = \min\left\{\sum_{k \in K} \sum_{j \in J} c_{kj} x_{kj} \, \big| \, x \in X(K)\right\}$$

represent the solution value of the transportation problem T(K) associated with the CPLP, where

$$X(K) = \left\{ x = [x_{kj}] \middle| \sum_{j \in J} x_{kj} \le a_k, \forall k \in K; \sum_{k \in K} x_{kj} = b_j, \forall j \in J; x_{kj} \ge 0, \forall k \in K, \forall j \in J \right\}.$$

If $X(K) = \emptyset$, we consider $w(K) = +\infty$.

The function w() has the important property of supermodularity (Proposition 10 in Wolsey, 1983). A function w() is said to be supermodular (or equivalently -w() submodular) if $w(K) - w(K \cup i) \le w(K') - w(K' \cup i) \quad \forall K' \subseteq K$ and $\forall i \notin K$ (see Wolsey, 1983 and Nemhauser & Wolsey, 1988). Thus, supermodularity is a kind of concavity.

For $i \in I - K$ let $\delta_i(K) = w(K) - w(K \cup i) \ge 0$ evaluate the increase/decrease in transportation costs if we close/open facility *i*. Furthermore, let $\Delta_i(K) = f_i - \delta_i(K)$ evaluate the balance between fixed and variable costs with respect to facility *i*. The function $\Delta_i()$ gives rise to criteria for opening or closing plant *i*.

Let K_0 and K_1 be the sets of closed and opened plants, i.e., $K_0 = \{i \in I \mid y_i = 0\}$ and $K_1 = \{i \in I \mid y_i = 1\}$. Facilities whose status is still undefined remain in $K_2 = I - K_0 - K_1$. We can state the following rules (see Akinc & Khumawala, 1977 and Mateus & Bornstein, 1991):

Add-test: If $\Delta_i(K_1 \cup K_2 - i) \le 0$ then $y_i = 1$. **Drop-test:** If $\Delta_i(K_1) \ge 0$ then $y_i = 0$.

Starting with $K_0 = K_1 = \emptyset$ we begin using the Add-test, assigning plants to K_1 . If K_1 is big enough $(X(K_1) \neq \emptyset)$, allowing the evaluation of $\Delta_i(K_1)$, we may use the Drop-test, allocating plants to K_0 . The optimality of the decision is assured by supermodularity of w(). Increasing set K_0 decreases set $K_1 \cup K_2$ leading to non-increasing values of $\Delta_i(K_1 \cup K_2 - i)$. Similarly, increasing K_1 yields non-decreasing values of $\Delta_i(K_1)$.

The following figure illustrates how the Add- and Drop- tests work. The arrows show how $\Delta_i(K_1)$ and $\Delta_i(K_1 \cup K_2 - i)$ move while the tests are used.



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If we get $K_2 = \{i\}$ then $\Delta_i(K_1) = \Delta_i(K_1 \cup K_2 - i)$, closing the gap $[\Delta_i(K_1), \Delta_i(K_1 \cup K_2 - i)]$, meaning that the use of the Add- and Drop- tests leads to an optimal solution of the CPLP. Unfortunately this seldom happens. There is usually a situation where $\Delta_i(K_1) < 0 < \Delta_i(K_1 \cup K_2 - i) \quad \forall i \in K_2$. In order to proceed, the following heuristics may be used (see Jacobsen, 1983):

> Add-heuristic: If $\Delta_i(K_1) < 0$ then $y_i = 1$ Drop-heuristic: If $\Delta_i(K_1 \cup K_2 - i) > 0$ then $y_i = 0$

Now supermodularity does not guarantee optimality anymore. Moreover, for a plant *i* satisfying $\Delta_i(K_1) < 0 < \Delta_i(K_1 \cup K_2 - i)$ the rules above allow both $y_i = 0$ and $y_i = 1$. Trying to escape from this dilemma we look for a plant giving min $\Delta_i(K_1)$ or max $\Delta_i(K_1 \cup K_2 - i)$. The former seems to be the best one to be opened whereas the latter seems to be the most advantageous one to be closed.

One of the difficulties with the Add- and Drop- tests and heuristics is the requirement of solving a great number of transportation problems, which may be very time consuming. The use of approximations for $\Delta_i()$ is an alternative for efficient implementation. Using the dual solutions of problems $T(K_1 \cup K_2)$ and $T(K_1)$, Azlan (1995) applies Lagrangean relaxation to calculate lower bounds $w^L(K_1 \cup K_2 - i)$ and $w^L(K_1 \cup i)$. Thus, upper and lower bounds $\Delta_i^U(K_1 \cup K_2 - i)$ and $\Delta_i^L(K_1)$ are obtained (see also Bornstein & Azlan, 1998).

3. The Algorithm

The algorithm uses the dominance criteria studied in the previous section. It starts with $K_0 = K_1 = \emptyset$ and $K_2 = I$ and repeatedly applies the tests and heuristics defined above. The algorithm consists of two phases. Phase 1 defines the status of all plants, ending with $K_2 = \emptyset$. Plants are assigned to K_1 , K_0 and \overline{K}_0 , where \overline{K}_0 is the set of temporarily closed plants. Phase 2 refines the solution reexamining the plants placed in \overline{K}_0 . The number of plants assigned to \overline{K}_0 depends on a parameter ε . Smaller values of ε result in a greater number of plants to be only temporarily closed.

Phase 1 begins with the Add-test being used at step 2. Facilities still remaining in K_2 have $\Delta_i^U(K_1 \cup K_2 - i) > 0$ leading to the use of the Drop-heuristic. At step 4 facility *s* with maximum $\Delta_i^U(K_1 \cup K_2 - i)$ is chosen. For greater accuracy the exact value $\Delta_s(K_1 \cup K_2 - s)$ is calculated at step 5 and examined at step 6. If $\Delta_s(K_1 \cup K_2 - s) \leq 0$ (this is possible because now we consider the exact value) then we open facility *s*. If $0 < \Delta_s(K_1 \cup K_2 - s) \leq f_s(1 - \varepsilon)$, where $0 \leq \varepsilon < 1$, then we put *s* in $\overline{K_0}$. Finally if $f_s(1-\varepsilon) < \Delta_s(K_1 \cup K_2 - s)$ we close facility *s* definitively. Since the Drop-heuristic does not work in an optimal way, plants are definitively closed only if the gain is very evident.

PHASE 1

- **Step 0:** (* Initialization *) Set $K_2 = I$ and $K_1 = K_0 = \overline{K}_0 = \emptyset$. Choose $0 \le \varepsilon < 1$ Calculate $w(K_1 \cup K_2)$
- **Step 1:** (* Calculating approximations for K_2 *) Calculate $\delta_i^L(K_1 \cup K_2 - i) = w^L(K_1 \cup K_2 - i) - w(K_1 \cup K_2) \quad \forall i \in K_2$ $\Delta_i^U(K_1 \cup K_2 - i) = f_i - \delta_i^L(K_1 \cup K_2 - i) \quad \forall i \in K_2$
- Step 2: (* Choosing plants to be opened *) Set $A = \{i \in K_2 \mid \Delta_i^U (K_1 \cup K_2 - i) \le 0\}, K_1 = K_1 \cup A \text{ and } K_2 = K_2 - A$
- Step 3: (* Phase 2? *) If $K_2 = \emptyset$, Phase 2!
- **Step 4:** (* Choosing plant *s* *) $\Delta_s^U(K_1 \cup K_2 - s) = \max_{i \in K_2} \left\{ \Delta_i^U(K_1 \cup K_2 - i) \right\}$
- **Step 5:** (* Calculating exact values for plant *s* *) Calculate $w(K_1 \cup K_2 - s)$

$$\Delta_s(K_1 \cup K_2 - s) = f_s - w(K_1 \cup K_2 - s) + w(K_1 \cup K_2)$$

Step 6: (* Defining status of plant *s* *)

 $K_{2} = K_{2} - \{s\}$ If $\Delta_{s}(K_{1} \cup K_{2} - s) \leq 0$ then $K_{1} = K_{1} \cup \{s\}$ and go to step 3 If $\Delta_{s}(K_{1} \cup K_{2} - s) \leq f_{s}(1 - \varepsilon)$ then $\overline{K}_{0} = \overline{K}_{0} \cup \{s\}$ else $K_{0} = K_{0} \cup \{s\}$ Go to step 1

The convergence of phase 1 can be shown very easily. There are two loops. The first consists of steps 1 to 6 and the second consists of steps 3 to 6. At each iteration of phase 1 one of the two loops is executed and a facility is discarded from set K_2 at step 6. This finishes emptying set K_2 leading to phase 2.

Phase 2 uses the Add-heuristic meaning the evaluation of $\Delta_i(K_1)$ or its lower bound $\Delta_i^L(K_1)$. Therefore we need K_1 big enough to guarantee $X(K_1) \neq \emptyset$. Let us show that this will always happen at the end of phase 1. One should just consider that at step 6 an element *s* will only be removed from $K_1 \cup K_2$ if $\Delta_s(K_1 \cup K_2 - s) > 0$. This means $w(K_1 \cup K_2 - s) < \infty$. Thus, we never get $X(K_1 \cup K_2) = \emptyset$. As phase 1 finishes with $K_2 = \emptyset$ we can assure that $X(K_1) \neq \emptyset$.

At phase 2 each plant in \overline{K}_0 is reexamined. It may be opened, interchanged with a plant from K_1 or closed definitively. The procedure can be divided in two main parts. Part 2.1 consists of steps 7 to 11 and uses the Add-heuristic. At step 9 we choose the best plant (plant *r*) from \overline{K}_0 to be opened. If $\Delta_r(K_1) \le 0$ it is opened at step 11 according to the Add-heuristic. Otherwise, we proceed to Part 2.2 (steps 12 to 17) which embodies an interchange heuristic. We examine whether the opening of plant *r* can still be advantageous by simultaneously closing a plant from K_1 . In case of disadvantage plant *r* is closed definitively.

PHASE 2

Step 7: (* Stop? *) If $\overline{K}_0 = \emptyset$, STOP!

Step 8: (* Calculating approximations for \overline{K}_0 *)

Calculate
$$\delta_i^U(K_1) = w(K_1) - w^L(K_1 \cup i) \quad \forall i \in \overline{K}_0$$

 $\Delta_i^L(K_1) = f_i - \delta_i^U(K_1) \quad \forall i \in \overline{K}_0$

Step 9: (* Choosing plant *r*, the most probable plant from \overline{K}_0 to be opened *)

$$\Delta_r^L(K_1) = \min_{i \in \overline{K}_0} \left\{ \Delta_i^L(K_1) \right\} \text{ and } \overline{K}_0 = \overline{K}_0 - \{r\}$$

- **Step 10:** (* Calculating exact values for plant r *) Calculate $w(K_1 \cup r)$ and $\Delta_r(K_1) = f_r - w(K_1) + w(K_1 \cup r)$
- **Step 11:** (* Is it truly better to open plant r? *) If $\Delta_r(K_1) \le 0$ then $K_1 = K_1 \cup \{r\}$ and go to step 7
- **Step 12:** (* Calculating approximations for K_1^r *)

$$\begin{aligned} K_1^r &= K_1 \\ \text{Calculate} \quad \Delta_i^U \left(K_1 \cup r - i \right) = f_i - w^L \left(K_1 \cup r - i \right) + w \left(K_1 \cup r \right) \quad \forall i \in K_1 \end{aligned}$$

Step 13: (* Choosing plant *s* the most probable plant from K_1^r to be closed *)

If $K_1^r = \emptyset$ then $K_0 = K_0 \cup \{r\}$ and go to step 7 $\Delta_s^U(K_1 \cup r - s) = \max_{i \in K_1^r} \{\Delta_i^U(K_1 \cup r - i)\}$

Step 14: (* Close plant *r* definitevely ? *)

If $\Delta_s^U(K_1 \cup r - s) \le \Delta_r(K_1)$ then $K_0 = K_0 \cup \{r\}$ and go to step 7

- **Step 15:** (* Calculating exact values for plant *s* *) Calculate $w(K_1 \cup r - s)$ and $\Delta_s(K_1 \cup r - s) = f_s - w(K_1 \cup r - s) + w(K_1 \cup r)$
- Step 16: (* Discard plant s ? *)

If $\Delta_s(K_1 \cup r - s) \le \Delta_r(K_1)$ then $K_1^r = K_1^r - \{s\}$ and go to step 13

- **Step 17:** (* Interchange plants *r* and *s* *)
 - $K_1 = K_1 \{s\} \cup \{r\}, K_0 = K_0 \cup \{s\}$ and go to step 7

Let us examine the interchange heuristic with a little more detail. Plants that will be further examined in order to be closed are placed in K_1^r . Initially, at step 12, we make $K_1^r = K_1$. At step 13 we choose plant $s \in K_1^r$ with the largest upper bound $\Delta_i^U (K_1 \cup r - i)$. The next steps compare the cost increase $\Delta_r(K_1)$ with the cost reduction $\Delta_s(K_1 \cup r - s)$.

At step 14 if $\Delta_s^U(K_1 \cup r - s) \leq \Delta_r(K_1)$ then an interchange between *r* and *s* will not lead to an improvement. Neither will an interchange between *r* and any other plant from K_1 , because *s* has a maximum upper bound. Thus, $\Delta_i(K_1 \cup r - i) \leq \Delta_r(K_1) \quad \forall i \in K_1$ and plant *r* can be definitively closed.

Otherwise $\Delta_r(K_1) < \Delta_s^U(K_1 \cup r - s)$ and a refinement is necessary. We calculate the exact value $\Delta_s(K_1 \cup r - s)$ at step 15. If we still have $\Delta_r(K_1) < \Delta_s(K_1 \cup r - s)$ the interchange is accomplished at step 17, opening plant *r* and closing plant *s*.

Finally, $\Delta_s(K_1 \cup r - s) \leq \Delta_r(K_1) < \Delta_s^U(K_1 \cup r - s)$ means that although an interchange with *s* does not improve the solution, another plant in K_1^r could do it. Plant *s* is discarded from K_1^r and a new attempt is made. The result is the loop between steps 13 and 16.

With respect to the convergence of phase 2 let us first consider the innermost loop which runs from step 13 to step 16. Each time this loop is executed one element is discarded from K_1^r . In the worst case we get $K_1^r = \emptyset$, exiting the loop at step 13. The other loops all include step 9 where one facility *r* is discarded from set \overline{K}_0 . We finish by getting $\overline{K}_0 = \emptyset$ bringing phase 2 to an end.

At this point a general comment relating to upper and lower bounds $\Delta_i^U()$ and $\Delta_i^L()$ should be made. They are only used where a great number of transportation problems would have to be solved otherwise. Where plants are opened or closed, even temporarily closed, exact values are calculated.

4. Computational Results

The algorithm was implemented in FORTRAN 77 using a transportation procedure based on Ahrens & Finke (1980). When solving a transportation problem we generally start from the solution of the problem solved previously. One should not forget that most problems differ from the previous one in a single closed or opened plant.

With respect to upper and lower bounds, $\Delta_i^U(K_1 \cup K_2 - i)$ is evaluated following Bornstein & Azlan (1998) and $\Delta_i^L(K_1)$ is calculated according to Ω_i^D in Mateus & Bornstein (1991). The value of ε was fixed in 0.05.

The computational results mainly compare the algorithm proposed in the previous section with the algorithms presented by Bornstein & Azlan (1998), Van Roy (1986) and Beasley (1993). The first one also builds on dominance criteria, but uses these ideas within a framework of simulated annealing. The cross decomposition algorithm proposed by Van Roy (1986) is quite effective for small problems (see Beasley, 1988). Finally, we compare the

proposed algorithm with Lagrangean heuristics which have proved to work quite well even with large problems. The comparison is made with an algorithm due to Beasley (1993).

The proposed algorithm (PA) and the SAE-best algorithm considered by Bornstein & Azlan (1998) were run on a PC 486, 100 MHz. Results of the cross decomposition algorithm were extracted from Table I in Van Roy (1986). They were generated on a IBM 3033U. The Lagrangean heuristic in Beasley (1993) was run on a Cray X-MP/28 using CFT compiler with maximum optimization.

Table 1 presents the computational results for Kuehn & Hamburger (1963) test problems. The data was obtained from Beasley's (1990) OR-Library. Problems IV-VI are 16×50 , problems VIII and IX are 25×50 and problems XI and XII are 50×50 . The first number relates to potential plant locations and the second to the number of demand centers. Van Roy (1986) uses a different numbering.

The second column of Table 1 shows that the relative difference between the solution value obtained by PA and the optimal value was always under 0.4%. For 22 out of 25 problems, i.e. 88%, the optimal solution was found. Times were always under 0.55 seconds.

		x					0	
	Prop. Algorithm (PA)		Bornstein-Azlan (98)		Van Roy (1986)		Beasley (1993)	
Prob.	Err (%)	Sec.	Err (%)	Sec.	Gap (%)	Sec.	Err (%)	Sec.
IV-1	0.00	0.02	0.00	11.2	0.00	0.06	0.00	0.97
IV-2	0.00	0.04	0.00	12.6	0.01	0.28	0.00	0.57
IV-3	0.00	0.04	0.00	13.5	0.01	0.25	0.00	0.58
IV-4	0.00	0.05	0.00	13.7	0.01	0.22	0.00	0.59
V-3	0.00	0.05	0.00	50.3	0.04	0.25	0.00	0.80
VI-1	0.00	0.02	0.00	16.1	0.00	0.05	0.00	0.46
VI-2	0.00	0.06	0.00	27.9	0.00	0.05	0.00	0.44
VI-3	0.00	0.06	0.00	101.7	0.13	0.20	0.00	0.71
VI-4	0.00	0.06	0.00	51.2	0.00	0.21	0.00	0.36
VIII-1	0.00	0.11	0.00	129.9	0.18	0.16	0.00	2.27
VIII-2	0.00	0.12	0.00	135.3	0.04	0.60	0.00	1.74
VIII-3	0.00	0.12	0.00	151.7	0.25	1.21	0.00	1.90
VIII-4	0.38	0.15	0.00	142.8	0.18	3.08	0.00	2.86
IX-1	0.00	0.09	0.00	97.5	0.00	0.06	0.00	1.23
IX-2	0.00	0.12	0.00	331.4	0.09	0.17	0.00	1.11
IX-3	0.00	0.14	0.00	428.6	0.20	0.29	0.00	1.17
IX-4	0.00	0.14	0.00	250.5	0.47	0.55	0.06	1.25
XI-1	0.00	0.54	0.00	1205.0			0.00	2.74
XI-2	0.38	0.46	0.06	1367.4			0.00	3.11
XI-3	0.22	0.48	0.22	1565.8			0.00	2.71
XI-4	0.00	0.46	0.44	1582.9			0.44	4.22
XII-1	0.00	0.38	0.00	1731.3			0.00	2.37
XII-2	0.00	0.41	0.00	2533.3			0.00	1.72
XII-3	0.00	0.38	0.06	1649.5			0.00	1.47
XII-4	0.00	0.39	0.00	2081.1			0.17	1.91
Aver.	0.04	0.20	0.03	627.3	0.09	0.45	0.03	1.57

Table 1 – Computational results based on Kuehn and Hamburger data.

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Although numbers from Table 1 give an idea about the efficiency of each algorithm, comparisons have to be made very carefully. To measure the quality of the solution, PA, Bornstein & Azlan (1998) and Beasley (1993) use the relative difference (ERR%) between the solution value obtained by the algorithm and the optimal value. However, for Bornstein-Azlan, ERR% is calculated taking the best solution of a 5-run of each problem. Considering an average value instead of the best value for the 5-run, shifts the average ERR% for the 25 problems from 0.03% to 0.13% ! On the other hand, Van Roy (1986) evaluates his solutions using the relative duality gap (GAP%) which only provides an upper bound for ERR%. The fact that Van Roy does not give the value of the generated solutions unfortunately makes it impossible to calculate ERR% for his results at Table 1.

With respect to times only the first two algorithms can effectively be compared, since similar machines were used. The SAE-best algorithm presented by Bornstein & Azlan (1998) expends much more time than PA. Also Beasley (1993) and Van Roy (1986) are computationally more expensive than PA. Although times of the first two algorithms are almost equivalent to times spent by PA, one has to consider that they were run on more powerful machines. One should also take into account that both Beasley (1993) and Van Roy (1986) provide upper and lower bounds for the optimal solution.

Summing up, a good trade-off seems to exist for PA between the quality of the solution and the computational time. This is what should be expected from a heuristic.

To test the performance of PA for larger instances, we considered 100×1000 randomly generated problems available at Beasley's (1990) OR-Library. Table 2 compares PA only with Beasley (1993) because for the other algorithms data was not available for problems of this dimension. The relative error of PA was always less than 0.75%, but for only 4 out of 12 problems the optimal solution was obtained. Times were less than one minute. Again, PA obtains solutions with quality similar to those obtained by Beasley (1993). Times, however, are much smaller.

Problem	Proposed Alg	gorithm (PA)	Beasley (1993)		
Tioblein	Err (%)	Sec.	Err (%)	Sec.	
A-1	0.11	53.31	0.24	73.65	
A-2	0.09	51.29	0.45	65.49	
A-3	0.34	49.75	0.00	29.87	
A-4	0.00	45.48	0.00	16.58	
B-1	0.00	54.88	0.40	131.84	
B-2	0.38	64.82	0.14	111.78	
B-3	0.72	56.06	0.91	96.14	
B-4	0.11	58.63	0.00	48.92	
C-1	0.00	54.68	0.00	105.74	
C-2	0.00	52.55	0.00	83.42	
C-3	0.18	54.25	0.44	86.89	
C-4	0.26	50.02	0.00	59.11	
Average	0.18	53.81	0.22	75.79	

Table 2 – Computational results based on Beasley data.

5. Conclusions

A central dilemma of the CPLP is the conflict between the minimization of fixed and variable costs each driving the solution in a different direction. The minimization of variable/transportation costs in the extreme case forces the solution towards putting a plant near each demand center i.e. represents a tendency towards decentralization. On the other hand, due to economies of scale, fixed costs are generally minimized by placing a central unit which supplies all demand centers. Of course, the joint minimization of fixed and variable costs means that there needs to be a compromise between the centralization and decentralization tendencies.

The algorithm presented in this paper moves around this dilemma, detecting dominances among the two types of costs and locating plants according to these dominances. The computational results show that it is able to tackle large scale problems finding almost always near optimal solutions at very low cost.

However not everything is as positive as it may seem. The Achilles' heel is the shortsightedness of the algorithm, i.e. the tendency to act only locally, determining whether each plant should be opened or not sequentially. One should not forget that the dilemma mentioned above is a global question where all the complex interrelations between the various plants and demand centers play an important role. To counterbalance this tendency the algorithm has at phase 2 an interchange heuristic which tries to detect relations between plants.

Detecting dominances locally may lead to distortions with respect to determining a global optimal solution. These distortions may heavily rely on data. This is the reason for introducing parameters which may correct these distortions. In the sense of greater transparency only one parameter was introduced in the algorithm. Greater values of ε make it easier to close plants at phase 1. Closed plants are not further examined at phase 2. On the other hand smaller values of ε result in putting plants in \overline{K}_0 instead of K_0 . Plants in \overline{K}_0 will be examined again at phase 2 and are object of the interchange heuristic. As a general principle one should have in mind that decreasing ε generally leads to better solutions at a higher computational cost. For the set of tested problems, using ε equal to 0.05 seems to lead to the best value solution, i.e. leads to the best possible solution within a reasonable computational cost. Decreasing ε further down may only lead to a very slight improvement of the solution at a much higher computational cost.

Among the results of the PA, Bornstein-Azlan, Van Roy and Beasley's algorithms, only the first two can be compared effectively due to the fact that similar machines were used. Van Roy and Beasley's algorithms were run on more powerful machines. Results for Bornstein-Azlan were similar to those obtained by PA at a much more expensive computational cost. Although average percentage errors presented at Table 1 for Bornstein-Azlan are slightly better than those of PA, one should not forget that the former considers the best solution of a 5-run for each problem. When considering an average value for the 5-run, the performance of PA is much better than the performance of Bornstein-Azlan. For the larger instances of Table 2, PA presents similar results to those obtained by Beasley's algorithm. However PA results in a lower computational cost.

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