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**PERSPECTIVE REFORMULATIONS OF THE
CTA PROBLEM WITH L_2 DISTANCES**

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Abstract

Any institution that disseminates data in aggregated form has the duty to ensure that individual confidential information is not disclosed, either by not releasing data or by perturbing the released data, while maintaining data utility. Controlled tabular adjustment (CTA) is a promising technique of the second type where a protected table that is close to the original one in some chosen distance is constructed. We attempt, for the first time, to solve CTA with Euclidean distances; this gives rise to difficult Mixed Integer Quadratic Problems (MIQPs) with pairs of linked semi-continuous variables. We provide a novel analysis of Perspective Reformulations (PRs) for this special structure; in particular, we devise a *Projected* PR (P²R) which is piecewise-conic but simplifies to a (nonseparable) MIQP when the instance is symmetric. We then compare different formulations of the CTA problem, showing that the ones based on P²R most often obtain better computational results.

Key words: Mixed Integer Quadratic Programming, Perspective Reformulation, Data Privacy, Statistical Disclosure Control, Tabular Data Protection, Controlled Tabular Adjustment

1. Introduction

The most important mission of National Statistical Agencies (NSAs), and a significant mission of several other institutions, is to provide high-quality statistical data. These data are disseminated either in disaggregated (i.e., microdata or microfiles) or aggregated (i.e., tabular data) form. A microdata file is a matrix of individuals by variables, where each cell provides the information of a particular individual for some particular variable. Crossing two or more categorical variables of the microdata file produces tabular data, either a single multiway or multidimensional table, or a set of related tables. There are stringent requirements that no confidential or sensitive information of any individual can be disclosed from the released data; not only this is dictated by law, but also respondents (e.g., of a census) may be tempted to hide or change information if they suspect that their confidential information may be released. This justifies the interest in *statistical disclosure control*, i.e., the set of techniques that can be deployed to protect sensitive information. In particular, the focus of this work is on *tabular data protection*; seminal work on this field can be found in [2], and the current state-of-the-art is described in the recent surveys of [25] and [6], as well as in the monographs [27, 22].

	...	S_i	...	S_j	...		...	S_i	...	S_j	...
$\vdots$	...	...	...	...	...	$\vdots$	...	...	...	...	...
AS_k	...	450M\$	...	35M\$	...	AS_k	...	22	...	1 / 2	...
$\vdots$	...	...	...	...	...	$\vdots$	...	...	...	...	...
AS_l	...	625M\$	...	770M\$	...	AS_l	...	27	...	33	...
$\vdots$	...	...	...	...	...	$\vdots$	...	...	...	...	...

(a)
(b)

Figure 1: Example of disclosure in tabular data: (a) turnover and (b) number of companies per activity sector and state.

Although tabular data provide aggregated information, the publication of some cells may jeopardize individual information. Consider the small example of Figure 1: if there is only one company with activity sector AS_k in state S_j , then any attacker knows the turnover of this company. For two companies, any of them can deduce the other's turnover, becoming an internal attacker. Clearly, the risk in the example is due to a small number of respondents in cell (AS_k, S_j) . However, even if the number of respondents was larger, there could be a disclosure risk if some companies can obtain a tight estimator of another's turnover (for instance by subtracting its own contribution from the cell value). Unsafe or sensitive cells are a priori determined before the application of any tabular data protection method, by applying some "sensitivity rules". These rules are out of the scope of this work; e.g., see [9, 22] for details.

Disclosure limitation techniques for tabular data are classified as perturbative if one is allowed to add small perturbations or adjustments to released data, and as nonperturbative if released cell values must be exact, and therefore one is only allowed to entirely eliminate cells. Clearly, nonperturbative approaches are more rigid than perturbative ones. Furthermore, the most widely used nonperturbative approach, *cell suppression* [23, 10, 4], requires the solution of large-scale optimization problems to identify the optimal set of cells to be suppressed. It is perhaps not surprising, therefore, that perturbative approaches are being considered as emerging technologies for tabular data protection. In particular, *Controlled Tabular Adjustment* (CTA) is gaining recognition

and acceptance among NSAs [28], as testified by the recent handbook [22] and by the fact that it is currently used by Eurostat (Statistical Office of the European Communities) within a wider protection scheme for tabular data [16]. Figure 1 can be used to illustrate CTA. If cell (AS_k, S_j) of table (a) is considered sensitive, with *lower* and *upper protection levels* of 5, then the published value of this cell must be in the range $(-\infty, 30] \cup [40, \infty)$. We say that the *protection sense* is “lower” or “upper” if the published value is, respectively, in $(-\infty, 30]$ or in $[40, \infty)$. The remaining cells in the same column and row of the sensitive cell have to be accordingly adjusted to preserve the marginal values, while minimizing the distance between the original and the released values. Since each sensitive cell introduces a disjunctive constraint, which can be formulated by adding one binary variable, when the number of sensitive cells is large CTA is a difficult combinatorial optimization problem.

It is worth remarking that, while the tables of Figure 1 are two-way (two-dimensional) ones, in general the situation can be much more complex. Tables can be classified in (i) k -dimensional tables, which are obtained by crossing k categorical variables; (ii) hierarchical tables, or set of tables that share some variables with hierarchical structure (e.g., “country”, “state/province”, “city”); (iii) linked tables, the most general situation, which is a set of tables that are obtained from the same microdata. A particularly interesting case for NSAs, which will be tested in this work, are two-dimensional hierarchical tables that share one hierarchical variable (e.g., tables that show the turnover crossing “activity sector” by “country”, “activity sector” by “state/province”, and “activity sector” by “city”). These are named *one-hierarchical two-dimensional* tables (or 1H2D for short), and their relations can be represented as a tree of tables. However, table relations for any type of table are represented by linear constraints, where the sum of the inner cells is equal to the marginal cell; thus, the techniques developed in this paper are applicable to the most general case (linked tables) as well.

In all previous works on CTA, the L_1 or Manhattan norm has been used to measure the distance between the original and the protected published data [8, 3]. This has the advantage that CTA can then be formulated as a Mixed Integer Linear Problem (MILP) with a number of variables and constraints that is linear in the size of the table, and whose solution can therefore be attempted with general-purpose MILP solvers. By contrast, formulations of the cell suppression problem are much larger and typically require the application of specialized approaches such as Benders decomposition. This is not to say that CTA, even with the L_1 distance, is an easy problem: for large (1H2D) tables MILP solvers may require a long time even to provide a first feasible solution, and therefore heuristic approaches [17] are required to provide practical solutions in a reasonable time. It can be expected that CTA with L_2 (Euclidean) distance, which results in a Mixed Integer Quadratic Problem (MIQP), is even more difficult to solve; this is likely the reason why this work is, to the best of our knowledge, the first one where such a feat is attempted. Yet, protecting a table using L_2 in CTA has several benefits:

- Weighting the distance between the original and the published cell value by the inverse of the original cell value, the objective function of CTA minimizes the well-known χ^2 distance between the original and the released table, which is useful for the statistical evaluation of the results.
- The L_2 distance more evenly distributes the deviations induced by sensitive cells to other cells. This avoids concentration of deviations in few cells, which improves the overall utility of the published data, as measured, e.g., by the number of non-sensitive cells whose published value is “significantly” different from the original data.
- From a computational point of view, once the binary variables are fixed (i.e., the protection

sense is decided), the solution of the resulting continuous problem can be more efficient for L_2 than for L_1 if interior-point methods are used [3]; while this holds true already for general-purpose solvers, specialized interior-point approaches can be orders of magnitude faster than state-of-the-art general-purpose ones [5].

On the other hand, the protected values provided by CTA with the L_2 distance will likely be more fractional than those provided by the L_1 distance, which has been often observed in practice to provide integer values even without imposing integrality constraints. Yet, this is not a significant drawback since CTA is mainly used for “magnitude” tables which do not provide frequencies but information about a third continuous variable (salary, net profit, turnover, ...) which is most often fractional.

The main structural characteristic of MIQP formulations of CTA with the L_2 distance (from now on, simply “CTA”) is very closely related to *convex separable quadratic-cost models with semicontinuous variables*, which are naturally formulated as in the following (fragment of) MIQP

$$\min \{ wz^2 + cy : yl \leq z \leq yu, y \in \{0, 1\} \} \quad (1)$$

where $w > 0$ and $l < u$. This is useful because (1) admits the *Perspective Reformulation* (PR)

$$\min \{ wz^2/y + cy : yl \leq z \leq yu, y \in \{0, 1\} \} . \quad (2)$$

Despite the weird look and the apparent ill-definiteness at $y = 0$, the objective function in (2) is convex, and it actually is the *convex envelope* of an appropriately re-defined version of the objective function in (1), i.e., the best possible objective function to have when the integrality constraints $y \in \{0, 1\}$ are relaxed to $y \in [0, 1]$. Indeed, (2) has at least two possible further reformulations which avoid the fractional term in the objective function with the associated difficulties (nondifferentiability, possible numerical problems) at $y = 0$: one is the Mixed Integer Second-Order Cone Program (SOCP)

$$\min \left\{ v + cy : yl \leq z \leq yu, \sqrt{wz^2 + (v - y)^2/4} \leq (v + y)/2, y \in \{0, 1\} \right\} \quad (3)$$

[26, 1, 19], and another is the Semi-Infinite (SI) MILP

$$\min \left\{ v + cy : yl \leq z \leq yu, v \geq w(2\gamma z - \gamma^2 y), \gamma \in [l, u], y \in \{0, 1\} \right\} \quad (4)$$

where γ is the index of the infinitely many linear constraints (called *Perspective Cuts* in [11]) whose pointwise supremum completely describes the objective function in (2). Either (3) or any finite approximation to (4)—typically, to be iteratively refined—can be used as models of (2), whose continuous relaxation is significantly stronger than that of (1) and that therefore is a more convenient starting point to develop exact and approximate solution algorithms [11, 12, 19, 1, 15]. Somewhat surprisingly, the potentially very large and approximated (4) appears to be most often preferable to the compact and exact (3) in the context of exact or approximate enumerative solution approaches [13], likely due to the better reoptimization capabilities of simplex methods for linear programs w.r.t. those of interior point methods for conic programs.

Yet a different approach has been recently proposed in [14] that can be applied under several restrictive hypotheses, some (but not all) of which satisfied in our application. The idea is to recast the continuous relaxation of (2) as the minimization over $z \in [0, u]$ of the function

$$\phi(z) = \min_y \{ wz^2/y + cy : ly \leq z \leq uy, y \in [0, 1] \} \quad (5)$$

which effectively eliminates the y variable(s) from the model. The function ϕ is convex, and its closed form can be algebraically computed revealing a piecewise-quadratic function with at most two pieces, at most one of them actually quadratic (and the other linear). When the underlying problem has a useful structure (e.g., network flow or knapsack), the continuous relaxation of (2) obtained in this way retains that structure, which allows to use specialized algorithms to solve it and therefore to outperform both (3) and (4). Yet, direct application of that approach is only possible under rather restrictive assumptions that are not satisfied in our case.

In this paper we discuss the application of Perspective Reformulation techniques to the CTA problem. In particular, other than the standard approaches (3) and (4) we develop and test a new reformulation partly inspired by the results of [14]. However, since our problem is different and somewhat more complex, the “projected” version of the PR we obtain is substantially different and trickier to use. Thus, instead of insisting in keeping the equivalence with the original formulation we “drop the nastier pieces” and end up with an *approximated* reformulation, which is only as tight as the PR in some special cases, and looser otherwise. However, this reformulation results in a simpler (although non-separable) MIQP to be solved, and therefore it is most often preferable to the standard ones (3) and (4); furthermore, it suggests a simple modification to the latter which invariably improves their performances. Armed with these results we show on a large experimental set that CTA for randomly-generated 1H2D and real-world tables of realistic sizes can most often be solved effectively enough.

We remark that the Perspective Reformulation approach is much more widely applicable than the simple quadratic case we consider here: it not only applies to the objective function but also to constraints $f(z) \leq 0$ that are “activated” if and only if a binary variable y is 1, f can be any closed convex (possibly, SOCP-representable) function, z can be a vector whose feasible region can be any bounded polyhedron; see [7, 26, 18, 11, 21] and the recent survey [20]. Thus, some of the ideas developed here could be extendable to more complex situations.

2. Formulations of the CTA problem

Any CTA problem instance, either with one table or with any number of tables, can be represented by the following elements:

- a set of n cells a_i , $i \in \mathcal{N} = \{1, \dots, n\}$, that satisfy m linear relations $Aa = b$ ($a = [a_i]_{i \in \mathcal{N}}$); in the general case, if $\mathcal{I}_j$ is the set of *inner* cells of relation $j \in \{1, \dots, m\}$, and t_j is the index of the *total* or *marginal* cell of relation j , the constraint associated to this relation is $\sum_{i \in \mathcal{I}_j} a_i - a_{t_j} = 0$;
- the subset $\mathcal{S} \subseteq \mathcal{N}$ of indices of sensitive cells, and hence its complement $\mathcal{U} = \mathcal{N} \setminus \mathcal{S}$;
- a vector of nonnegative cell weights $w = [w_i]_{i \in \mathcal{N}}$;
- *finite* lower and upper bounds $\bar{l}^a \leq a \leq \bar{u}^a$ for each cell reasonably known by any attacker;
- nonnegative *lower and upper protection levels* for each confidential cell $i \in \mathcal{S}$, l_i and u_i respectively, such that the released values $x = [x_i]_{i \in \mathcal{N}}$ are considered to be safe if they satisfy

$$\text{either } x_i \geq a_i + u_i \text{ or } x_i \leq a_i - l_i \quad \text{for all } i \in \mathcal{S} . \quad (6)$$

Given any weighted distance $\|\cdot\|_w$, CTA can then be formulated as

$$\min \left\{ \|x - a\|_w : Ax = b , \bar{l}^a \leq x \leq \bar{u}^a , (6) \right\} \quad (7)$$

since one seeks for the released values x that are closest (in the given norm) to the true values a , compatible with the relationships that a is known to have to satisfy, and protected according to (6). Of course, the *disjunctive constraints* (6) are the difficult part of the problem, their feasible region being nonconvex. Formulating them hence requires some nonconvex element, the simplest one being a vector of binary variables $y = [y_i]_{i \in \mathcal{S}} \in \{0, 1\}^{|\mathcal{S}|}$. It is also convenient to restate the problem in terms of the *deviations* $z = x - a$ from the true cell values, which therefore have to satisfy $\bar{l}^a - a = \bar{l} \leq z \leq \bar{u} = \bar{u}^a - a$; this gives the formulation

$$\min \left\{ \|z\|_w : Az = 0, \bar{l} \leq z \leq \bar{u}, \bar{l}_i(1-y_i) + u_i y_i \leq z_i \leq \bar{u}_i y_i - \bar{l}_i(1-y_i), y_i \in \{0, 1\} \quad i \in \mathcal{S} \right\} \quad (8)$$

with “natural big- M constraints”. Indeed, when $y_i = 1$ one has $z_i \geq u_i$ and thus the *protection sense* is “upper”, while when $y_i = 0$ one rather gets $z_i \leq -\bar{l}_i$ and thus the protection sense is “lower”. While this formulation is correct, it would provide rather weak bounds when its *continuous relaxation* is formed by replacing the integrality constraints $y_i \in \{0, 1\}$ with $y_i \in [0, 1]$. The simple example with $n = 1$, “empty” A , $l_1 = u_1 = 10$ and $-\bar{l}_1 = \bar{u}_1 = 100$ shows that for $y_1 = 1/2$ the solution $z_1 = 0$ is feasible to the relaxation, whose optimal value is therefore 0 while the optimal value of the integer problem is $\|10\|_w$. Since weak bounds are very detrimental for the solution of the problem via exact or approximate approaches, we aim at constructing “better” formulations of the problem.

A first step in this direction is to introduce vectors of *positive and negative deviations* $z^+ \in \mathbb{R}^n$ and $z^- \in \mathbb{R}^n$, respectively, thereby redefining $z = z^+ - z^-$; this allows to reformulate the disjunctive constraints in (8) as

$$\begin{aligned} u_i y_i &\leq z_i^+ \leq \bar{u}_i y_i \\ l_i(1 - y_i) &\leq z_i^- \leq -\bar{l}_i(1 - y_i) \\ y_i &\in \{0, 1\} \end{aligned} \quad i \in \mathcal{S} \quad (9)$$

As before, when $y_i = 1$, the constraints force $u_i \leq z_i^+ \leq \bar{u}_i$ and $z_i^- = 0$, thus the protection sense is “upper”; conversely, when $y_i = 0$ we get $z_i^+ = 0$ and $l_i \leq z_i^- \leq -\bar{l}_i$, thus the protection sense is “lower”. This alone is not enough to improve on the bounds, though: in the above example we now have $z_1^+ = z_1^- = 5$ as a feasible solution for $y_1 = 1/2$, which still leads to a null bound. However the advantage of this formulation is that we now have *two semicontinuous variables*, to which we can hope to apply Perspective Reformulation techniques. This is not straightforward: the two semicontinuous variables are governed by the *same integer variable*, and unlike in standard cases—where this is possible, provided that all variables are “active” or “inactive” at the same time—one of them is “active” if and only if the other is not. Furthermore, the objective function is *nonseparable* in z^+ and z^- , and the convex envelope of multilinear functions, even if with only two variables as here, is notoriously a complex object (cf. [24] and the references therein) so that “dirty tricks” have to be used [12] in order to apply PR techniques. Thus, the next section will be devoted to the study of the convex envelope for our particular case.

3. Perspective Reformulations of the CTA problem

In the following we will most often concentrate on a single cell $i \in \mathcal{S}$; thus, to simplify the notation we will consider the index i as fixed and drop it. In order to improve the lower bound provided by the continuous relaxation, one possibility is to compute the convex envelope of the nonconvex

function

$$f(z^+, z^-, y) = \begin{cases} w(z^+ - z^-)^2 & \text{if } u \leq z^+ \leq \bar{u}, z^- = 0 \text{ and } y = 1 \\ w(z^+ - z^-)^2 & \text{if } l \leq z^- \leq -\bar{l}, z^+ = 0 \text{ and } y = 0 \\ +\infty & \text{otherwise} \end{cases} \quad (10)$$

This can be accomplished by considering two arbitrary points $u \leq \bar{z}^+ \leq \bar{u}$ and $l \leq \bar{z}^- \leq -\bar{l}$ and computing the convex combinations of the two tuples in the epigraphical space

$$(\bar{z}^+, 0, 1, w(\bar{z}^+)^2) \quad (0, \bar{z}^-, 0, w(\bar{z}^-)^2) .$$

In other words, taking any arbitrary convex combinator $\theta \in [0, 1]$ and using the shorthand $f(z) = wz^2$ (which also suggests how the approach can be generalized to general convex functions f), we have

$$\begin{aligned} \theta(\bar{z}^+, 0, 1, f(\bar{z}^+)) + (1 - \theta)(0, \bar{z}^-, 0, f(\bar{z}^-)) = \\ (\theta\bar{z}^+, (1 - \theta)\bar{z}^-, \theta, \theta f(\bar{z}^+) + (1 - \theta)f(\bar{z}^-)) \end{aligned}$$

Now, identifying $\theta \equiv y$, $z^+ \equiv \theta\bar{z}^+$ and $z^- \equiv (1 - \theta)\bar{z}^-$ we can rewrite the above as

$$\left(z^+, z^-, y, yf\left(\frac{z^+}{y}\right) + (1 - y)f\left(\frac{z^-}{1 - y}\right) \right)$$

which finally leads to

$$\overline{co}f(z^+, z^-, y) = \begin{cases} w\left(\frac{(z^+)^2}{y} + \frac{(z^-)^2}{1 - y}\right) & \text{if } \begin{matrix} uy \leq z^+ \leq \bar{u}y \\ l(1 - y) \leq z^- \leq -\bar{l}(1 - y) \end{matrix} , y \in [0, 1] \\ +\infty & \text{otherwise} \end{cases}$$

and therefore to the following PR of (8):

$$\min \sum_{i \in \mathcal{U}} w_i(z_i^+ - z_i^-)^2 + \sum_{i \in \mathcal{S}} w_i((z_i^+)^2/y_i + (z_i^-)^2/(1 - y_i)) \quad (11)$$

$$A(z^+ - z^-) = 0, \quad 0 \leq z^+ \leq \bar{u}, \quad 0 \leq z^- \leq -\bar{l}, \quad (9) \quad (12)$$

In other words, the PR can be seen as being obtained as follows:

1. substitute $(z^+ - z^-)^2$ in the objective function with $(z^+)^2 + (z^-)^2$, which is correct since $z^+z^- = 0$ holds in each *integer* solution;
2. treat z^+ and z^- as two distinct semicontinuous variables with two distinct binary variables, say y^+ and y^- , and apply the standard PR (2);
3. now exploit the fact that $y^+ + y^- = 1$ to replace $y^+ = y$ and $y^- = 1 - y$.

While this sequence of reformulation steps could have been devised independently (but, to the best of our knowledge, has never had), our analysis has suggested them, as well as proved that this is in fact the convex envelope of the fragment. Actually, the analysis suggests that one can further improve the PR even regarding the non-sensitive cells $i \in \mathcal{U}$. In fact, these can be considered as sensitive cells with $l = u = 0$, and therefore it is clear that one could have taken

$$(\text{MIQP}) \quad \min \left\{ \sum_{i \in \mathcal{N}} w_i((z_i^+)^2 + (z_i^-)^2) : (12) \right\}$$

as the *original* MIQP formulation of CTA, to which then directly apply steps 2. and 3. above, thus obtaining

$$(PR) \quad \min \left\{ \sum_{i \in \mathcal{U}} w_i ((z_i^+)^2 + (z_i^-)^2) + \sum_{i \in \mathcal{S}} w_i ((z_i^+)^2 / y_i + (z_i^-)^2 / (1 - y_i)) : (12) \right\} .$$

Note how (MIQP) have already improved the lower bound: for our example of Section 2 (with $w_1 = 1$), $z_1^+ = z_1^- = 5$ and $y_1 = 1/2$, (MIQP) gives a bound of 50 instead of 0. Yet, (PR) is even better: for the same solution it gives a bound of 100, which (as expected) is the optimal solution to the problem. One can then apply the standard SOCP and SI reformulation tricks to (PR), i.e., formulae (3) and (4), to express the objective function of (PR) in terms of one SOCP constraint/infinitely many linear constraints, respectively; we denote the two thus obtained PRs of CTA as (SOCP) and (P/C), respectively.

Conversely, applying the projection approach of [14] following the same guidelines is not possible. The reason is that the main condition required for that to work is that *the binary variable corresponding to one semicontinuous variable only appears in the corresponding constraints (9) and nowhere else*, or, in other words, that there are no constraints directly linking the binary variables to one another. This is clearly *not* the case here, as the constraint $y^+ + y^- = 1$ is crucial. In order to extend the projection approach of [14] to CTA we then have to explicitly carry out the analysis for our case. This is done by considering the function

$$g(z^+, z^-) = \min_y \left\{ \overline{cof}(z^+, z^-, y) : y \in [0, 1] \right\} \quad (13)$$

(clearly convex, being the partial minimization of a convex function) and carrying out a case-by-case analysis of its shape. This is significantly more complex and rather tedious, so the details are best relegated to the Appendix. These can be summarized by the following Theorem.

Theorem 3.1. *The function $g(z^+, z^-)$ is piecewise-conic-quadratic with at most three pieces. If cell i is reasonably balanced, i.e., $\max\{l_i, u_i\} < \min\{\bar{u}_i, -\bar{l}_i\}$, then $g(z^+, z^-)$ has exactly three pieces, the “central” one of which is*

$$w_i(z_i^+ + z_i^-)^2 \quad (14)$$

that is also the lower approximation to $g(z^+, z^-)$ corresponding to the relaxation of the bounds constraints. If, furthermore, cell i is totally symmetric, i.e., $\bar{u}_i = -\bar{l}_i$ and $l_i = u_i$, then (14) actually coincides with $g(z^+, z^-)$.

It would be then possible to derive a projected model analogous to those of [14] for CTA, but the prospects of doing so are not particularly encouraging. First of all, the corresponding model would be a SOCP with up to three SOCP constraints for each sensitive cell; the standard formulation (SOCP), which already has only two of them, is typically not competitive with (P/C) [13], a fact that we directly verified to be true for CTA also. Furthermore, the rationale of [14] is to exploit structural properties in the original problem, which are absent here for general tabular data since the matrix A lacks exploitable characteristics.

Yet, the analysis readily suggests a workable alternative: use the model

$$(MIQP+) \quad \min \left\{ \sum_{i \in \mathcal{N}} w_i (z_i^+ + z_i^-)^2 : (12) \right\}$$

instead of (MIQP), (SOCP) or (P/C). This is possible since (14) is a lower approximation to (13); furthermore, the two objective function obviously coincide on integer solutions. The model

is clearly stronger than (MIQP); on sensitive cells its objective function is weaker than that of (SOCP) or (P/C), unless in the *totally symmetric* case, in which they are equivalent. However, on non-sensitive cells its objective function is stronger than that of (SOCP) or (P/C). Note that the objective functions of (MIQP) and (MIQP+), on non-sensitive cells, could seem to actually be equivalent on the constraints (12), since these can all be written in terms of $z = z^+ - z^-$. In other words, the coefficient of z^- in every constraint is always the opposite to that of z^+ . Hence, one could always assume that $z^+z^- = 0$ in the optimal solution of each continuous relaxation, since if this were not the case then one could reduce both variables at the same rate, keeping feasibility and improving the objective function value. However, this line of reasoning fails when *valid inequalities* are added to the formulation. These, typically, do not obey to the condition that the coefficients of z^+ and z^- are opposite, and therefore $z^+z^- > 0$ can (and indeed does) happen. So, in terms of strength of the continuous relaxation (and after introduction of valid inequalities) the models (MIQP+) and (PR) are not comparable. The (MIQP+) model is somewhat simpler than (SOCP), not requiring SOCP constraints; however, it has a nonseparable (albeit only slightly so) objective function. It is also more compact than (P/C), which however is a separable quadratic model.

Note that, as in the previous case, there is no need to distinguish between sensitive and non-sensitive cells: the reformulation of the objective function can be applied to either, and this actually has—as it can be expected—positive results. Indeed, *since non-sensitive cells are equivalent to totally symmetric sensitive ones*, as previously seen the analysis suggests to rather consider

$$(PR+) \quad \min \left\{ \sum_{i \in \mathcal{U}} w_i (z_i^+ + z_i^-)^2 + \sum_{i \in \mathcal{S}} w_i \left((z_i^+)^2 / y_i + (z_i^-)^2 / (1 - y_i) \right) : (12) \right\}$$

as the “starting” Perspective Relaxation. Thus, other than (MIQP), (SOCP), (P/C) and (MIQP+), there are two further possible models: (SOCP+) and (P/C+), obtained from (PR+) exactly as (SOCP) and (P/C) are obtained from (MIQP), respectively. Compared to (SOCP) and (P/C), these new models have (slightly) nonseparable objective function but may provide better results. The relative strengths and weaknesses of these six models can only be gauged computationally, which is done in the next section.

4. Computational Tests

We performed a large computational experience to compare the six models (MIQP), (P/C), (SOCP), (MIQP+), (P/C+), and (SOCP+). All models have been solved with **Cplex** 12.2 in single-threaded mode on a computer with 2.2 GHz AMD Opteron 6174 CPUs and 32 GB of RAM, under a GNU/Linux operating system (Ubuntu 10.10). In addition, models (MIQP), (SOCP), (MIQP+), and (SOCP+) have been solved, for some real-world difficult instances, with **Cplex** 12.1 in multi-threaded mode (up to 24 parallel threads) on a computer with 3.33GHz Intel Xeon X5680 CPUs and 144 GB of RAM, under a GNU/Linux operating system (Suse 11.4). A few details are noteworthy:

- (SOCP) and (SOCP+) have been tested but were regularly worse than (P/C) and (P/C+), respectively, for single-threaded executions, confirming the results of [13]; therefore, the corresponding results have not been reported.
- (P/C) and (P/C+) could not be considered for the multi-threaded executions, since the addition of perspective cuts deactivates the parallel capabilities of **Cplex**. (SOCP) and (SOCP+), which are inefficient for single-threaded executions, allow **Cplex** to exploit its parallel features, and then are recovered for the multi-threaded executions.

- The large values of $\bar{l}_i$ and $\bar{u}_i$ in the instances created substantial numerical problems, whereby a variable (say z_i^-) that should have been zero (say because $y_i = 1$) actually had a “substantial” nonzero value (say because $1 - y_i \approx 1\text{e-}6$, and therefore $-\bar{l}_i(1 - y_i)$ was still “large”), leading to some of the cells in the table not actually being protected. This has been solved by setting the Cplex parameter `CPX_PARAM_NUMERICAL EMPHASIS` to 1.
- The runs were performed with a time limit of 10000 seconds (wall-clock time) and requiring a global accuracy of 0.01%.

4.1. Test instances

For our tests we have considered both synthetic hierarchical instances and real-world ones. Hierarchical instances were obtained with a generator of 1H2D synthetic tables [4] that was retrieved from http://www-eio.upc.es/~jcastro/generators_csp.html. This is a relevant class of instances, since a significant fraction of the tables released by NSAs are 1H2D. The generator produces a set of two-dimensional subtables with hierarchical structure according to the setting of several parameters, among which the mean number of rows per subtable, the number of columns per subtable, the depth of the hierarchical tree, the percentage of sensitive cells, the minimum and maximum number of rows with hierarchies per subtable, and the random seed. We fixed all these parameters, but three: the mean number of rows per subtable (“ r ” $\in \{10, 20\}$), the number of columns per subtable (“ c ” $\in \{20, 30\}$), and the percentage of sensitive cells (“ s ” $\in \{3, 5, 10\}$). In addition, we generated both symmetric and asymmetric instances. The former have the property that $u_i = l_i$; note that in general this does *not* imply $\bar{u}_i = -\bar{l}_i$, since in many cases one have to ensure non-negativity of the perturbed values, which usually leads to $\bar{u}_i > -\bar{l}_i$. Asymmetric instances were instead obtained by considering $u_i = a \cdot l_i$, “ a ” $\in \{2, 5, 10\}$ being the *asymmetry parameter*. Instances are thus named by the particular combination of parameters used for its generation, i.e., “ r - c - s ” for symmetric instances and “ r - c - s - a ” for asymmetric ones. For each combination of parameters we generated 5 instances varying the random generator seed, and all the reported results are averaged on these five instances.

We also dealt with a set of real-world instances. These are a subset of public instances that have been previously used in the literature [3, 10], and some confidential ones provided by Eurostat and the Australian NSA. Of the available real-world instances, we selected those that are neither too easy, i.e., solved by every model in a few seconds, nor too difficult, i.e., very large (up to millions of cells) and such that one cannot even find the first feasible solution—and often even solve the continuous relaxation at the root node—within the allotted timeframe. Unlike the synthetic 1H2D instances, the real-world ones have symmetric protection levels (i.e., $u_i = l_i$); as we shall see, this turns out to be a questionable modeling choice from the computational viewpoint.

Tables 1, 2 and 3 report the characteristics of, respectively, the 1H2D symmetric, 1H2D asymmetric, and real-world instances: the number of cells $|\mathcal{N}|$, the number of sensitive cells $|\mathcal{S}|$, the number of table relations m , the number of variables and constraints in the resulting (MIQP) or (MIQP+) models, and the percentage of pure binary variables (that are in one-to-one correspondence with sensitive cells). As already mentioned, these data is averaged over the 5 instances of the same type for synthetic tables. Note that (P/C), (P/C+), (SOCP), and (SOCP+) models have more variables and constraints than these due to the reformulation tricks (3) and (4); in particular, (P/C) and (P/C+) formulations in theory have infinitely many constraints, but only finitely many ones are dynamically generated in order to approximate the objective function value of (PR) or (PR+), respectively, with the same global accuracy required to the solution of the problem.

Table 1: Size and properties of symmetric instances.

instance	$ \mathcal{N} $	$ \mathcal{S} $	m	vars.	cons.	%bin
10-20-3	2877	81	452	5835	777	1.39
10-20-5	3163	150	466	6475	1064	2.31
10-20-10	2772	262	447	5806	1495	4.51
10-30-3	4569	131	612	9270	1137	1.42
10-30-5	4185	201	600	8571	1403	2.34
10-30-10	4706	452	617	9864	2426	4.59
20-20-3	6607	188	630	13401	1381	1.40
20-20-5	6426	305	621	13157	1841	2.32
20-20-10	6212	590	611	13013	2969	4.53
20-30-3	9145	264	760	18554	1816	1.42
20-30-5	8947	431	754	18324	2478	2.35
20-30-10	9164	884	761	19211	4296	4.60

4.2. Computational Results

The computational results obtained with models (MIQP+), (P/C+), (MIQP) and (P/C) in single-threaded executions are reported in Tables 4 and 5 for the symmetric and asymmetric 1H2D instances, respectively. In the tables, the column “gap” reports the gap between the value of the best feasible solution (UB) and the lower bound provided (LB) by the algorithm at termination (i.e., $\text{gap} = (\text{UB} - \text{LB}) / \text{LB}$); this is the optimality gap “perceived” by the algorithm. The column “pgap” reports the analogous measure, only using the *best known lower bound* ever computed in our tests (on the same architecture) in place of LB; this is our best measure of the actual optimality gap of the feasible solution produced by the algorithm, and the difference between “gap” and “pgap” gives a sense of how much weaker the lower bound attained at termination is w.r.t. the best among the four models. The columns “time” and “nodes” report, respectively, the total CPU time and the number of Branch&Cut nodes expended by the algorithm.

The results show that, as it could be expected, (MIQP) attains by far the worst results. Similarly to what has been reported several times [11, 12, 19, 1, 15, 21], the use of “standard” PR techniques, i.e. (P/C) (and (SOCP), which is always worse) significantly improve on (MIQP) by delivering much better lower bounds, which in turn dramatically reduce the number of required B&C nodes. Note that typically (P/C) enumerates fewer nodes than (MIQP) in the same time, which is reasonable since adding valid inequalities requires repeated solutions of the continuous relaxation. This is true consistently both for symmetric and asymmetric instances.

In many cases (P/C+) is even more efficient than (P/C), showing that the trade-off between the (slightly) non-separable objective function and the higher bound is often favorable. This is true for all symmetric instances, and for roughly half of the asymmetric ones, in particular the smallest ones. Furthermore, most often (MIQP+) performs better than (P/C+). This is true for all symmetric instances, and for most of the asymmetric instances except some of those with large asymmetry parameter, e.g., 10_30_10_5, 10_30_10_10, 20_30_10_5, and 20_30_10_10. This is consistent with our theoretical results: (MIQP+) and (P/C+) should provide the same lower bound on fully symmetric instances, and although this is not really the case even for our symmetric instances (cf. §4.1), it appears that the bounds are close enough to be roughly equivalent within the B&C approach. Indeed, the same phenomenon observed for (MIQP) and (P/C) shows off once again here: (P/C+)

Table 2: Size and properties of asymmetric instances.

instance	$ \mathcal{N} $	$ \mathcal{S} $	m	vars.	cons.	%bin
10-20-3-2	2877	81	452	5835	777	1.39
10-20-3-5	3163	89	466	6414	822	1.39
10-20-3-10	2919	82	454	5920	784	1.39
10-20-5-2	3095	146	462	6337	1048	2.31
10-20-5-5	2835	134	450	5804	986	2.31
10-20-5-10	3188	151	467	6526	1070	2.31
10-20-10-2	3230	306	469	6765	1691	4.52
10-20-10-5	3146	298	465	6589	1655	4.52
10-20-10-10	3024	286	459	6334	1603	4.52
10-30-3-2	4476	129	609	9081	1124	1.42
10-30-3-5	4383	126	606	8893	1110	1.41
10-30-3-10	4452	128	609	9031	1121	1.42
10-30-5-2	4439	213	608	9091	1460	2.34
10-30-5-5	4427	212	608	9066	1457	2.34
10-30-5-10	3999	192	594	8190	1360	2.34
10-30-10-2	4334	416	605	9084	2270	4.58
10-30-10-5	4204	404	601	8811	2216	4.58
10-30-10-10	4545	437	612	9526	2359	4.59
20-20-3-2	5985	170	600	12140	1280	1.40
20-20-3-5	6556	186	627	13299	1372	1.40
20-20-3-10	6737	192	636	13665	1402	1.40
20-20-5-2	5905	280	596	12091	1717	2.32
20-20-5-5	6573	312	628	13458	1876	2.32
20-20-5-10	6409	304	620	13123	1837	2.32
20-20-10-2	6082	577	605	12740	2913	4.53
20-20-10-5	6094	578	605	12767	2919	4.53
20-20-10-10	6577	624	628	13779	3126	4.53
20-30-3-2	8804	254	749	17862	1767	1.42
20-30-3-5	9219	266	762	18705	1828	1.42
20-30-3-10	9176	265	761	18617	1822	1.42
20-30-5-2	9126	440	759	18693	2519	2.35
20-30-5-5	8661	417	744	17740	2414	2.35
20-30-5-10	8996	434	755	18426	2490	2.35
20-30-10-2	9170	884	761	19224	4298	4.60
20-30-10-5	9151	883	760	19185	4291	4.60
20-30-10-10	9033	871	756	18938	4241	4.60

Table 3: Size and properties of real-world instances.

instance	$ \mathcal{N} $	$ \mathcal{S} $	m	vars.	cons.	%bin
australia_ABS	24420	918	274	49758	3946	1.84
cbs	11163	2467	244	24793	10112	9.95
hier13	2020	112	3313	4152	3761	2.70
hier13x13x13a	2197	108	3549	4502	3981	2.40
hier13x13x13b	2197	108	3549	4502	3981	2.40
hier13x13x13c	2197	108	3549	4502	3981	2.40
hier13x13x13d	2197	108	3549	4502	3981	2.40
hier13x13x13e	2197	112	3549	4506	3997	2.49
hier13x13x7d	1183	75	1443	2441	1743	3.07
hier13x7x7d	637	50	525	1324	725	3.78
osorio	10201	7	202	20409	230	0.03
sbs2008_C	4212	1135	2580	9559	7120	11.87
sbs2008_E	1430	382	991	3242	2519	11.78
table7	624	17	230	1265	298	1.34
table8	1271	3	72	2545	84	0.12
targus	162	13	63	337	115	3.86

Table 4: Results for symmetric instances.

instance	MIQP+				P/C+				MIQP				P/C			
	gap	pgap	time	nodes	gap	pgap	time	nodes	gap	pgap	time	nodes	gap	pgap	time	nodes
10-20-3	0.01	0.00	442	474	0.00	0.00	486	357	6.49	0.01	9686	10365	0.00	0.00	1331	1973
10-20-5	0.01	0.00	765	690	0.01	0.00	1016	611	67.62	0.05	10000	2649	0.16	0.00	6695	8675
10-20-10	0.01	0.01	3852	10507	2.21	0.07	7660	2676	72.75	0.14	10000	5536	12.39	0.14	10000	3230
10-30-3	0.01	0.00	1470	760	0.01	0.00	1749	457	127.03	0.02	10000	778	0.98	0.01	9070	3022
10-30-5	0.01	0.01	4850	4003	0.07	0.01	7102	4769	118.53	0.12	10000	1422	15.80	0.03	10000	1853
10-30-10	2.44	2.44	10000	3512	8.26	2.53	10000	889	128.67	2.62	10000	1619	35.30	2.54	10000	643
20-20-3	0.00	0.00	1710	260	0.00	0.00	1874	291	158.64	0.01	10000	636	17.84	0.04	8559	596
20-20-5	0.01	0.01	3543	1507	1.27	0.01	7237	1185	138.59	0.12	10000	625	12.33	0.01	8808	481
20-20-10	7.10	7.10	10000	1968	24.51	7.21	10000	504	142.82	7.60	10000	777	38.22	7.39	10000	262
20-30-3	0.40	0.40	6113	738	3.60	0.41	6800	458	138.85	0.47	10000	726	27.17	0.45	10000	379
20-30-5	7.39	7.39	8791	751	15.19	7.46	8885	379	156.73	9.37	10000	801	32.83	8.02	10000	406
20-30-10	19.92	19.92	10000	674	32.04	21.13	10000	102	153.79	23.08	10000	496	44.06	21.20	10000	56

Table 5: Results for asymmetric instances.

instance	MIQP+				P/C+				MIQP				P/C			
	gap	pgap	time	nodes	gap	pgap	time	nodes	gap	pgap	time	nodes	gap	pgap	time	nodes
10-20-3-2	0.00	0.00	23	9	0.00	0.00	58	1	0.01	0.00	1218	7823	0.00	0.00	106	17
10-20-3-5	0.01	0.00	19	1	0.00	0.00	82	1	0.01	0.00	322	197	0.00	0.00	111	1
10-20-3-10	0.00	0.00	15	7	0.00	0.00	55	1	0.01	0.00	270	124	0.00	0.00	78	1
10-20-5-2	0.01	0.00	58	30	0.00	0.00	119	9	0.04	0.00	10000	113601	0.00	0.00	152	32
10-20-5-5	0.01	0.00	21	15	0.00	0.00	79	1	0.01	0.00	1293	2332	0.00	0.00	81	1
10-20-5-10	0.00	0.00	20	2	0.00	0.00	106	1	0.01	0.00	1483	660	0.00	0.00	111	1
10-20-10-2	0.01	0.00	438	556	0.00	0.00	637	181	0.04	0.00	10000	67541	1.49	0.00	2904	370
10-20-10-5	0.01	0.00	4315	31344	0.00	0.00	142	1	0.08	0.00	10000	102641	0.00	0.00	142	1
10-20-10-10	0.01	0.00	416	2135	0.00	0.00	120	1	0.04	0.00	5044	26508	0.00	0.00	109	1
10-30-3-2	0.00	0.00	115	28	0.00	0.00	271	5	0.02	0.00	10000	55266	0.00	0.00	391	35
10-30-3-5	0.00	0.00	40	4	0.00	0.00	220	1	0.01	0.00	2447	1333	0.00	0.00	237	1
10-30-3-10	0.00	0.00	31	1	0.00	0.00	232	1	0.01	0.00	1468	565	0.00	0.00	258	1
10-30-5-2	0.00	0.00	193	103	0.00	0.00	377	19	0.05	0.00	10000	28721	0.00	0.00	455	72
10-30-5-5	0.01	0.00	119	39	0.00	0.00	333	1	0.01	0.00	4055	24181	0.00	0.00	258	1
10-30-5-10	0.01	0.00	63	46	0.00	0.00	207	1	0.01	0.00	1855	1104	0.00	0.00	216	1
10-30-10-2	0.01	0.00	1158	1035	0.00	0.00	1905	230	7.03	0.00	10000	27461	0.82	0.00	3066	986
10-30-10-5	0.01	0.00	6489	38818	0.00	0.00	401	1	8.53	0.00	10000	60347	0.00	0.00	311	1
10-30-10-10	0.01	0.00	4806	22519	0.00	0.00	522	1	0.09	0.00	10000	52141	0.00	0.00	372	1
20-20-3-2	0.00	0.00	136	25	0.00	0.00	393	1	0.03	0.00	10000	13721	0.00	0.00	502	9
20-20-3-5	0.01	0.00	72	1	0.00	0.00	625	1	0.01	0.00	4074	1207	0.00	0.00	691	1
20-20-3-10	0.00	0.00	76	1	0.00	0.00	574	1	2.18	0.00	5356	465	0.00	0.00	644	1
20-20-5-2	0.00	0.00	257	47	0.00	0.00	601	4	1.40	0.00	10000	14362	0.00	0.00	598	24
20-20-5-5	0.01	0.00	117	10	0.00	0.00	690	1	1.19	0.00	10000	15635	0.00	0.00	638	1
20-20-5-10	0.01	0.00	128	54	0.00	0.00	736	1	0.52	0.00	6434	2076	0.00	0.00	623	1
20-20-10-2	0.01	0.00	1448	212	0.00	0.00	2802	138	63.41	0.04	10000	1006	0.00	0.00	2525	228
20-20-10-5	0.02	0.00	9203	22462	0.00	0.00	943	1	3.40	0.00	10000	9950	0.00	0.00	634	1
20-20-10-10	0.03	0.00	7910	19421	0.00	0.00	1327	1	7.33	0.00	10000	9801	0.00	0.00	801	1
20-30-3-2	0.01	0.00	439	28	0.00	0.00	1477	1	13.94	0.00	10000	1203	0.00	0.00	1649	16
20-30-3-5	0.01	0.00	140	1	0.00	0.00	1597	1	5.39	0.00	8400	1767	0.00	0.00	1510	1
20-30-3-10	0.00	0.00	157	8	0.00	0.00	1601	1	8.34	0.00	9321	691	0.00	0.00	1547	1
20-30-5-2	0.00	0.00	777	65	0.00	0.00	2160	17	48.34	0.01	10000	612	0.00	0.00	2111	34
20-30-5-5	0.01	0.00	618	462	0.00	0.00	1800	1	19.74	0.01	10000	1692	0.00	0.00	1622	1
20-30-5-10	0.01	0.00	622	243	0.00	0.00	1988	1	2.14	0.00	9815	2623	0.00	0.00	1625	1
20-30-10-2	1.23	1.23	7575	1454	3.67	1.24	8407	297	79.80	1.39	10000	422	4.16	1.23	7705	262
20-30-10-5	0.52	0.00	10000	12890	0.00	0.00	2784	1	36.91	0.03	10000	718	0.00	0.00	1915	1
20-30-10-10	0.04	0.00	10000	17526	0.00	0.00	2619	1	27.08	0.03	10000	1441	0.00	0.00	1817	1

Table 6: Single-threaded results for real instances.

instance	MIQP+				P/C+				MIQP				P/C			
	gap	pgap	time	nodes	gap	pgap	time	nodes	gap	pgap	time	nodes	gap	pgap	time	nodes
australia_ABS	2.29	2.29	10000	2401	8.08	3.15	10000	401	113.69	2.60	10000	1501	9.45	2.87	10000	763
cbs	1.24	0.61	10000	32281	0.77	0.77	10000	1801	96.38	1.22	10000	16400	0.77	0.74	10000	1801
hier13	24.77	24.77	10000	145	129.83	118.55	10000	15	111.65	27.21	10000	126	74.02	28.40	10000	73
hier13x13x13a	30.52	29.87	10000	123	29.87	29.87	10000	119	114.41	29.74	10000	200	55.41	29.74	10000	171
hier13x13x13b	30.54	29.88	10000	114	29.88	29.88	10000	99	114.41	29.74	10000	200	55.41	29.74	10000	171
hier13x13x13c	32.30	29.90	10000	100	29.90	29.90	10000	90	114.41	29.77	10000	197	55.41	29.77	10000	171
hier13x13x13d	0.00	0.00	3357	89	0.00	0.00	3479	78	0.00	0.00	9135	162	0.00	0.00	4960	100
hier13x13x13e	0.00	0.00	3293	149	0.00	0.00	3830	90	0.00	0.00	9887	185	0.00	0.00	5489	111
hier13x13x7d	0.01	0.01	1458	805	0.00	0.00	3052	1033	0.00	0.00	4995	4310	0.00	0.00	2928	2595
osorio	0.00	0.00	3754	255	0.00	0.00	6493	252	27.42	0.00	10000	83	0.72	0.00	10000	145
sbs2008_C	4.97	4.97	10000	33839	219.57	26.69	10000	389	49.66	5.24	10000	11332	12047.9	2594.78	10000	110
sbs2008_E	50.15	50.15	10000	401380	68.49	47.97	10000	11988	55.82	48.16	10000	507901	31.75	17.30	10000	7937
table7	0.01	0.01	0.55	1	0.00	0.00	5.74	1	0.00	0.00	76.61	12	0.00	0.00	3.86	1
table8	0.00	0.00	1.84	15	0.00	0.00	2.85	15	0.00	0.00	1.22	9	0.00	0.00	3.01	15
targus	0.01	0.00	0.16	3	0.00	0.00	0.28	13	0.01	0.00	0.21	16	0.01	0.00	0.32	3

most often enumerates less nodes than (MIQP+), which means that the (P/C+) bound is usually somewhat stronger. However, most often (MIQP+) is faster on the instances that are solved within 10000 seconds, and it provides better gaps on the ones that stop at the time limit. This is due to the fact that, by not requiring constraint generation to compute the (approximated) PR bound, its time-per-node is lower.

The results show that, as it could be expected, the main driver of the difficulty of an instance is the percentage of sensitive cells: while instances with up to 5% of sensitive cells are routinely solved within the time limit, instances with 10% of sensitive cells are typically more difficult. However, this is only true for symmetric instances: as the asymmetry parameter “ $\mathbf{a}$ ” grows, the instances become easier. Indeed, almost all asymmetric instances are solved within 10000 seconds by (P/C) and (P/C+), and values $\mathbf{a} > 2$ are associated to the easiest ones. This is not unreasonable, as a high degree of symmetry (albeit in a technically different sense) is well-known to be detrimental for combinatorial problems. Remarkably, a trade-off shows off for (MIQP+). While that model is almost invariably the best for $\mathbf{a} = 2$, it is typically worse than (P/C+) and (P/C), often by a relevant margin, when $\mathbf{a} > 2$. Also, these are the cases where most often (P/C) bests (P/C+). This seems to indicate that the approximation (14) of the objective function only makes sense, both for sensitive and non-sensitive cells, only when a reasonable degree of symmetry is present (which is, however, the most difficult case).

It should be remarked that protection levels, and therefore their (a)symmetry, are a choice of the modeler. Indeed, in practice NSAs derive the upper protection levels u_i from the sensitivity rules [22], and, as a rule of thumb, this value is assigned to the lower protection level l_i , too. Since asymmetric instances are more efficiently solved than symmetric ones, however, such a practice should be discouraged in favor of choosing decidedly asymmetric values with any appropriate heuristic. This will likely keep the same confidentiality protection and data usability in the disclosed tables while making their computation more efficient.

Tables 6 and 7 show the results on the real-world instances for, respectively, single- and multi-threaded executions. Note that the column “pgap” in each table is computed considering only the lower bounds of the four algorithms of the table, since the others were solved on a different computer and by a different Cplex release. As it is customary, column “time” in Table 7 reports wall-clock time.

Table 7: Multi-threaded results for real instances.

instance	MIQP+				SOCP+				MIQP				SOCP			
	gap	pgap	time	nodes	gap	pgap	time	nodes	gap	pgap	time	nodes	gap	pgap	time	nodes
australia_ABS	1.41	1.41	10000	30870	13.77	3.25	10000	1780	137.12	12.98	10001	9010	14.45	3.79	10001	221
cbs	1.12	0.59	10000	737465	71.70	39.80	10001	4828	94.98	1.09	10000	198867	1.00	1.00	10000	5990
hier13	0.00	0.00	4290	3185	143.47	2.99	10003	829	0.00	0.00	9403	6256	174.56	5.39	10000	0
hier13x13x13a	0.00	0.00	7038	5092	169.62	3.67	10000	0	12.15	0.00	10001	4609	169.08	1.79	10001	5308
hier13x13x13b	0.00	0.00	7018	5122	169.62	3.67	10000	0	0.00	0.00	9015	6750	167.00	0.83	10001	5866
hier13x13x13c	0.00	0.00	7165	5591	63.44	32.99	10000	0	0.00	0.00	7771	6425	172.30	3.04	10001	5910
hier13x13x13d	0.00	0.00	154	139	62.73	0.01	10000	0	0.00	0.00	409	261	109.16	0.02	10000	0
hier13x13x13e	0.00	0.00	148	169	62.73	0.01	10000	0	0.00	0.00	429	251	89.86	0.02	10000	0
hier13x13x7d	0.00	0.00	160	1704	120.07	9.71	10000	0	0.00	0.00	1258	11812	113.26	3.42	10000	0
hier13x7x7d	0.00	0.00	34.08	2029	56.28	3.99	10000	0	0.00	0.00	91.52	3801	56.74	2.33	10000	4
osorio	0.00	0.0	363	255	0.00	0.00	250	505	0.00	0.0	2439	255	0.00	0.00	224	509
sbs2008_C	2.39	2.39	10000	726715	17.37	2.82	10001	4979	4.82	2.21	10000	292576	8.09	3.20	10001	5131
sbs2008_E	39.34	0.82	10000	12640158	0.01	0.01	6097	20602	43.08	0.00	10000	13122442	184.90	2.49	10000	184041
table7	0.01	0.00	0.26	0	0.00	0.00	64.23	1283	0.00	0.00	28.31	9	0.00	0.00	73.89	1280
table8	0.00	0.00	1.52	15	0.00	0.00	10.40	15	0.00	0.00	0.96	9	0.00	0.00	9.85	15
targus	0.01	0.00	0.46	3	0.00	0.00	11.82	316	0.00	0.00	0.32	25	0.00	0.00	6.17	177

The single-threaded results in Table 6 basically confirm these on the synthetic instances: (MIQP) is the worst model, (P/C) is significantly better, (P/C+) is usually (but not always) better yet, (MIQP+) is (at least on our test set) invariably the best. Yet, in several cases the obtained results can hardly be deemed satisfactory, with several gaps larger than 20%, and one as high as 50%. It thus makes sense to investigate if the problems can be solved with reasonable precision when more computational power is available.

The 24-threads results of Table 7 show mixed success for (SOCP) and (SOCP+); sometimes they are better than (MIQP), sometimes worse. In general (MIQP+) is by far the best option, as in previous tables, although it is very occasionally bested by (SOCP+) (cf. sbs2008_E, one of the most difficult confidential instances). What is perhaps more relevant is that, coupled with a relatively powerful—but by no means “super”—24-threads machine, (MIQP+) is capable of providing solutions with pretty reasonable accuracy for all the real-world instances in our test bed.

The good results obtained with (MIQP+) for all the types of instances show that appropriate modeling techniques combined with state-of-the-art, general-purpose (parallel) MIQP solvers can provide accurate solutions to real-life (and realistic) instances within a reasonable timeframe.

5. Conclusions

This paper studies the CTA problem with L_2 distance. The peculiar structure of the problem are *pairs of alternative semicontinuous variables*, that is, such that exactly one of them is nonzero in any feasible solution. Exploiting ideas from the Perspective Reformulation approach we developed and analyzed several MIQP, SOCP, and Semi-Infinite LP strong formulations for the problem, which provide different degrees of approximation to the objective function of the classical PR. We show that one particularly simple MIQP model is often preferable, from the computational viewpoint, at least on instances that are not “too much asymmetric”. Yet, other models are better on highly asymmetric instances, which are usually easier to solve; this also provides a practical indication to practitioners about setting the protection levels to the cells in order to make the instances more easily solvable. The right choice of the model allows to solve real-life instances in reasonable time with off-the-shelf, general-purpose MIQP solvers, at least on relatively powerful multi-core computers.

Since CTA is a difficult problem, instances with a large number of sensitive cells and/or a high degree of symmetry remain difficult to solve with high accuracy; further research will then be required to improve the effectiveness of the solution methods for these cases. Also, the specific structure of CTA may show up, perhaps with non-quadratic functions, in other applications: the techniques developed in this paper could be adaptable to these cases.

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Appendix. Proof of Theorem 3.1.

As in Section 3 we will concentrate on a fixed cell $i \in \mathcal{S}$ and therefore drop the index i . Also, in the development we assume w.l.o.g. $w = 1$, because it is a multiplicative factor which just goes untouched through the derivation. It is easy to see that the constraint

$$\min\{l, u\} \leq z^+ + z^- \leq \max\{\bar{u}, -\bar{l}\} \quad (15)$$

is implied by (9): in all integral solutions one has either $z^+ \leq \bar{u}$ and $z^- = 0$, or $z^- \leq -\bar{l}$ and $z^+ = 0$, and, analogously, either $z^+ \geq u$ and $z^- = 0$ or $z^- \geq l$ and $z^+ = 0$. Therefore, we can consider (15) as explicitly added to the formulation if we need it. Furthermore, the constraints $0 \leq z^+ \leq \bar{u}$ and $0 \leq z^- \leq -\bar{l}$ are always valid.

From (9) we immediately obtain

$$\begin{aligned} 0 \leq z^+/\bar{u} &\leq y \leq z^+/u \\ (l - z^-)/l &\leq y \leq (z^- + \bar{l})/\bar{l} \leq 1 \end{aligned}$$

which yields

$$\delta(z^+, z^-) = \max\left\{\frac{z^+}{\bar{u}}, 1 - \frac{z^-}{l}\right\} \leq y \leq \min\left\{\frac{z^+}{u}, 1 + \frac{z^-}{\bar{l}}\right\} = \Delta(z^+, z^-) . \quad (16)$$

We now want to develop a closed-form formula for the optimal solution $y(z^+, z^-)$ of (13). We therefore need to find the value of y such that

$$\frac{\partial h(z^+, z^-, y)}{\partial y} = -\frac{(z^+)^2}{y^2} + \frac{(z^-)^2}{(1-y)^2} = 0$$

which leads to

$$\begin{aligned} (1-y)^2(z^+)^2 &= y^2(z^-)^2 &\Leftrightarrow (1-2y+y^2)(z^+)^2 &= y^2(z^-)^2 \\ y^2((z^+)^2 - (z^-)^2) - 2y(z^+)^2 + (z^+)^2 &= 0 &\Leftrightarrow y &= z^+/(z^+ + z^-) = \tilde{y} \end{aligned}$$

as $0 \leq y \leq 1$, $z^+ \geq 0$ and $z^- \geq 0$. In fact, the other root of the quadratic equation, $z^+/(z^+ - z^-)$, coincides with $\tilde{y}$ when $z^- = 0$, is > 1 when $z^+ > z^- > 0$, is indefinite when $z^+ = z^-$ and is < 0 when $z^- > z^+$, and therefore is never relevant. Moreover, the second derivative

$$\frac{\partial^2 h(z^+, z^-, y)}{\partial y^2} = 2\frac{(z^+)^2}{y^3} + 2\frac{(z^-)^2}{(1-y)^3}$$

is greater than zero in $y = \tilde{y}$ when $0 < \tilde{y} < 1$. We must now distinguish three cases:

- 1) $\tilde{y} \leq \delta(z^+, z^-) \quad \Rightarrow \quad y(z^+, z^-) = \delta(z^+, z^-);$
- 2) $\delta(z^+, z^-) \leq \tilde{y} \leq \Delta(z^+, z^-) \quad \Rightarrow \quad y(z^+, z^-) = \tilde{y};$
- 3) $\Delta(z^+, z^-) \leq \tilde{y} \quad \Rightarrow \quad y(z^+, z^-) = \Delta(z^+, z^-).$

For case 2), plugging $y = \tilde{y} = z^+/(z^+ + z^-)$ into (9) gives

$$u \leq z^+ + z^- \leq \bar{u} \quad \text{and} \quad l \leq z^+ + z^- \leq -\bar{l} . \quad (17)$$

Therefore, under these conditions, the optimal objective function value $f^*(z^+, z^-) = f(z^+, z^-, \tilde{y})$ takes the particularly simple form

$$f^*(z^+, z^-) = f(z^+, z^-, z^+/(z^+ + z^-)) = (z^+ + z^-)^2,$$

i.e., (14). Hence, in the totally symmetric case $\bar{u} = -\bar{l}$, $l = u$ one has $\max\{\bar{u}, -\bar{l}\} = \min\{\bar{u}, -\bar{l}\}$ and $\max\{u, l\} = \min\{u, l\}$, only case 2) can happen: $g(z^+, z^-) = f^*(z^+, z^-)$. Note that, as claimed in the Theorem, (14) $\equiv f^*(z^+, z^-) \leq g(z^+, z^-)$ as it corresponds to *unconstrained* minimization over y .

With non-symmetric data, cases 1) and 3) has to be taken into account. The analysis has to be divided into several sub-cases.

1) $\tilde{y} \leq \delta(z^+, z^-)$. Because $\delta(z^+, z^-) = \max\{z^+/\bar{u}, 1 - z^-/l\}$, two sub-cases have to be separately considered:

1.1) $z^+/\bar{u} \geq 1 - z^-/l$ and $\tilde{y} \leq z^+/\bar{u}$; by simple algebraic manipulations, these two conditions boil down to

$$lz^+ + \bar{u}z^- \geq \bar{u}l \quad (18)$$

$$z^+ + z^- \geq \bar{u} \quad (19)$$

By rewriting (18) in the equivalent form

$$z^+ + z^-(\bar{u}/l) \geq \bar{u}$$

it is immediately evident that one among (18) and (19) is redundant when the other is imposed; this depends on which of the two conditions

$$\bar{u} \leq l \quad (20)$$

$$l \leq \bar{u} \quad (21)$$

holds. In particular,

* (20) $\Rightarrow$ (18) dominates (19);

* (21) $\Rightarrow$ (19) dominates (18).

In either case we have $y(z^+, z^-) = z^+/\bar{u}$, which finally leads to

$$f^*(z^+, z^-) = f(z^+, z^-, z^+/\bar{u}) = \bar{u}((z^-)^2/(\bar{u} - z^+) + z^+) . \quad (22)$$

Note that the objective function value is always positive, as $z^+ \leq \bar{u}$.

1.2) $z^+/\bar{u} \leq 1 - z^-/l$ and $\tilde{y} \leq 1 - z^-/l$; this gives

$$lz^+ + \bar{u}z^- \leq \bar{u}l \quad (23)$$

$$z^+ + z^- \leq l \quad (24)$$

Again, by rewriting (23) in the equivalent form

$$z^+(l/\bar{u}) + z^- \leq l$$

we see that one of these is redundant when the other is imposed, depending on *the same* conditions (20)/(21); that is,

- * (20) $\Rightarrow$ (23) dominates (24);
- * (21) $\Rightarrow$ (24) dominates (23).

In either case we have $y(z^+, z^-) = 1 - z^-/l$, which finally leads to

$$f^*(z^+, z^-) = f(z^+, z^-, 1 - z^-/l) = l((z^+)^2/(l - z^-) + z^-) . \quad (25)$$

Note that the objective function value is always positive, as $z^- \leq z^+ + z^- \leq l$.

- 3) $\Delta(z^+, z^-) \leq \tilde{y}$. Because $\Delta(z^+, z^-) = \min\{z^+/u, 1 + z^-/\bar{l}\}$, again this can happen in two different ways:

- 3.1) $z^+/u \leq 1 + z^-/\bar{l}$ and $\tilde{y} \geq z^+/u$; this is equivalent to

$$-\bar{l}z^+ + uz^- \leq -\bar{l}u \quad (26)$$

$$z^+ + z^- \leq u \quad (27)$$

where as usual (26) can be rewritten as $z^+ + z^-(u/\bar{l}) \leq u$. Thus, according to which among

$$-\bar{l} \leq u \quad (28)$$

$$u \leq -\bar{l} \quad (29)$$

holds, one of the constraints is useless; indeed,

- * (28) $\Rightarrow$ (26) dominates (27);
- * (29) $\Rightarrow$ (27) dominates (26).

In either case we have $y(z^+, z^-) = z^+/u$, which finally leads to

$$f^*(z^+, z^-) = f(z^+, z^-, z^+/u) = u((z^-)^2/(u - z^+) + z^+) . \quad (30)$$

Note that the objective function value is always positive, as $z^+ \leq z^+ + z^- \leq u$.

- 3.2) $z^+/u \geq 1 + z^-/\bar{l}$ and $\tilde{y} \geq 1 + z^-/\bar{l}$; one has

$$-\bar{l}z^+ + uz^- \geq -\bar{l}u \quad (31)$$

$$z^+ + z^- \geq -\bar{l} \quad (32)$$

According to which among (28)/(29) holds, one of the above (considering that (31) can be rewritten as $z^+(-\bar{l}/u) + z^- \geq -\bar{l}$) is irrelevant; that is,

- * (28) $\Rightarrow$ (31) dominates (32);
- * (29) $\Rightarrow$ (32) dominates (31).

In either case we have $y(z^+, z^-) = 1 + z^-/\bar{l}$, which finally leads to

$$f^*(z^+, z^-) = f(z^+, z^-, 1 + z^-/\bar{l}) = (-\bar{l})((z^+)^2/(-\bar{l} - z^-) + z^-) . \quad (33)$$

Again, the objective function value is always positive, as $z^- \leq -\bar{l}$.

From the above discussion we conclude, remembering that $0 \leq u \leq \bar{u}$ and $0 \leq l \leq -\bar{l}$, that the (z^+, z^-) space can be partitioned into several subsets, in each of which the objective function is uniquely determined. Again this requires a case-by-case discussion:

- If $\bar{u} \leq l$ (cf. (20)), then $\max\{l, u\} = l \geq \min\{\bar{u}, -\bar{l}\} = \bar{u}$; therefore, case 2) is not significant (cf. 17). Because (18) dominates (19) and (23) dominates (24), we have that for all $u \leq z^+ + z^- \leq -\bar{l}$

$$g(z^+, z^-) = \begin{cases} \bar{u}((z^-)^2/(\bar{u} - z^+) + z^+) & \text{if } lz^+ + \bar{u}z^- \geq \bar{u}l \\ l((z^+)^2/(l - z^-) + z^-) & \text{if } lz^+ + \bar{u}z^- \leq \bar{u}l \end{cases}.$$

- Analogously, if $-\bar{l} \leq u$ (cf. (28)), then $\max\{l, u\} = u \geq \min\{\bar{u}, -\bar{l}\} = -\bar{l}$; therefore, case 2) does not happen (cf. 17). Because (26) dominates (27) and (31) dominates (32), we have that for all $l \leq z^+ + z^- \leq \bar{u}$

$$g(z^+, z^-) = \begin{cases} u((z^-)^2/(u - z^+) + z^+) & \text{if } -\bar{l}z^+ + uz^- \leq -\bar{l}u \\ (-\bar{l})((z^+)^2/(-\bar{l} - z^-) + z^-) & \text{if } -\bar{l}z^+ + uz^- \geq -\bar{l}u \end{cases}.$$

If none of the above two “extreme” cases occur, then the “simple” inequalities (19), (24), (27) and (32) all dominate their “complex” companions (18), (23), (26) and (31), respectively. We can thus continue the discussion listing all other possible ways in which l , u , $-\bar{l}$ and $\bar{u}$ can be arranged along the line:

- If $l \leq u \leq \bar{u} \leq -\bar{l}$, then $\max\{l, u\} = u$ and $\min\{\bar{u}, -\bar{l}\} = \bar{u}$. Thus,

$$g(z^+, z^-) = \begin{cases} u((z^-)^2/(u - z^+) + z^+) & \text{if } l \leq z^+ + z^- \leq u \\ (z^+ + z^-)^2 & \text{if } u \leq z^+ + z^- \leq \bar{u} \\ \bar{u}((z^-)^2/(\bar{u} - z^+) + z^+) & \text{if } \bar{u} \leq z^+ + z^- \leq -\bar{l} \end{cases}$$

- If $l \leq u \leq -\bar{l} \leq \bar{u}$, then $\max\{l, u\} = u$ and $\min\{\bar{u}, -\bar{l}\} = -\bar{l}$. Thus,

$$g(z^+, z^-) = \begin{cases} u((z^-)^2/(u - z^+) + z^+) & \text{if } l \leq z^+ + z^- \leq u \\ (z^+ + z^-)^2 & \text{if } u \leq z^+ + z^- \leq -\bar{l} \\ (-\bar{l})((z^+)^2/(-\bar{l} - z^-) + z^-) & \text{if } -\bar{l} \leq z^+ + z^- \leq \bar{u} \end{cases}$$

- If $u \leq l \leq -\bar{l} \leq \bar{u}$, then $\max\{l, u\} = l$ and $\min\{\bar{u}, -\bar{l}\} = -\bar{l}$. Thus,

$$g(z^+, z^-) = \begin{cases} l((z^+)^2/(l - z^-) + z^-) & \text{if } u \leq z^+ + z^- \leq l \\ (z^+ + z^-)^2 & \text{if } l \leq z^+ + z^- \leq -\bar{l} \\ (-\bar{l})((z^+)^2/(-\bar{l} - z^-) + z^-) & \text{if } -\bar{l} \leq z^+ + z^- \leq \bar{u} \end{cases}$$

- If $u \leq l \leq \bar{u} \leq -\bar{l}$, then $\max\{l, u\} = l$ and $\min\{\bar{u}, -\bar{l}\} = \bar{u}$. Thus,

$$g(z^+, z^-) = \begin{cases} l((z^+)^2/(l - z^-) + z^-) & \text{if } u \leq z^+ + z^- \leq l \\ (z^+ + z^-)^2 & \text{if } l \leq z^+ + z^- \leq \bar{u} \\ \bar{u}((z^-)^2/(\bar{u} - z^+) + z^+) & \text{if } \bar{u} \leq z^+ + z^- \leq -\bar{l} \end{cases}$$

Thus, we have a total of 6 possible cases; in 4 of them the function has three pieces, two SOCP ones and a quadratic one, while in the remaining 2 the function has two pieces, all of them being SOCP. We have therefore completed the proof of Theorem 3.1.

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