



A Computational Comparison of Optimization Methods for the Golomb Ruler Problem

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Abstract. The Golomb ruler problem is defined as follows: Given a positive integer n , locate n marks on a ruler such that the distance between any two distinct pair of marks are different from each other and the total length of the ruler is minimized. The Golomb ruler problem has applications in information theory, astronomy and communications, and it can be seen as a challenge for combinatorial optimization algorithms. Although constructing high quality rulers is well-studied, proving optimality is a far more challenging task. In this paper, we provide a computational comparison of different optimization paradigms, each using a different model (linear integer, constraint programming and quadratic integer) to certify that a given Golomb ruler is optimal. We propose several enhancements to improve the computational performance of each method by exploring bound tightening, valid inequalities, cutting planes and branching strategies. We conclude that a certain quadratic integer programming model solved through a Benders decomposition and strengthened by two types of valid inequalities performs the best in terms of solution time for small-sized Golomb ruler problem instances. On the other hand, a constraint programming model improved by range reduction and a particular branching strategy could have more potential to solve larger size instances due to its promising parallelization features.

Keywords: Golomb ruler · Integer programming · Constraint programming

1 Introduction

For a given positive integer n , let us denote the positions of n marks on a ruler as x_1, x_2, \dots, x_n . Without loss of generality, we assume that the position of the first mark is zero, i.e. $x_1 = 0$, and the locations are ordered, i.e. $x_1 \leq x_2 \leq \dots \leq x_n$. A *Golomb ruler* satisfies the property that the pairwise distances between distinct marks are all different, in other words, $x_j - x_i \neq x_k - x_l$ unless $i = l$ and $j = k$. The *optimal* Golomb ruler is the one with the smallest length, that is, a

Golomb ruler with the minimum x_n . The Golomb ruler problem has interesting applications in several fields [3], including information theory [14], astronomy, and communications [1, 2, 4, 12].

In general, constructing a Golomb ruler with a given number of marks is an easy task, and there are many heuristic methods that provide high quality rulers. For instance, previous literature on heuristics has focused on affine and projective plane constructions [7, 15], genetic algorithms [19], and local search [6, 13] while exact methods based on constraint programming [8, 17] or hybrid methods [16] exist as well. Although not proven to be NP-hard yet, solving the Golomb ruler problem exactly proved to be notoriously difficult. For instance, the optimal rulers for $n = 24, 25, 26, 27$ have been proven by a parallel search with thousands of workstations coordinated by the website `distributed.net`, and it took approximately 4, 4, 1, and 5 years to complete, respectively. Currently, a search for the 28-mark problem is under way for more than 4 years.

As summarized above, most of the effort to prove that a given Golomb ruler is an optimal one is devoted to explicit enumeration techniques. However, such brute force approaches seem to be the only viable option since it is very difficult to establish strong valid lower bounds for the Golomb ruler problem.

At this point, we would like to state the main purpose of this paper, which is to *certify the optimality of a given Golomb ruler through optimization methods*. Most optimization algorithms inherently solve relaxations and hence, naturally provide lower bounds for minimization type problems. Therefore, it is worth focusing on optimization models to better understand the structure of the Golomb ruler problem, and hopefully, propose efficient methods which we can use to solve the Golomb ruler problem instances.

In this paper, we consider three classes of optimization problems to carry out the aforementioned analysis. In particular, we formulate the Golomb ruler problem as linear integer programming, constraint programming and quadratic integer programming problems. Some of these models exist in the literature while and the others are introduced, to the best of our knowledge, by us. Since the performance of the basic models is not satisfactory to solve instances with more than 10 marks, we propose several enhancements to improve the scalability of each method by means of bound tightening, valid inequalities, cutting planes and effective search strategies. Our computational experiments show that linear integer programming models scale up to 13 marks given a budget of 8 h while constraint programming models can solve up to 13-mark instances in about an hour and 14-mark problem in about 10 h. Quadratic integer programming models, on the other hand, are able to solve 14-mark instance in about four hours, all using a modest personal computer. As a comparison, it took 2.8 h for the constraint programming model in [8] to find an optimal ruler for the 13-mark instance and another 11.8 h to prove its optimality. The lean implementation of the search method in [16] reduced the respective computational effort to 0.6 and 1.3 h, albeit at the expense of a significantly larger search tree.

The rest of the paper is organized in three sections, which respectively cover the linear integer programming, constraint programming and quadratic integer

programming models in detail. Each section contains a formulation, enhancements and computational experiments subsections together with some discussions and comparisons of these different optimization paradigms.

2 Linear Integer Programming Models

2.1 Two Formulations

In this section, we present two known linear integer programming formulations for the Golomb ruler problem with n marks. One of these formulations is *exact* and the other one is only a *relaxation* but can be made exact by the use of additional features as detailed later. For both of the models, we assume that an upper bound, say L , on the optimal length is known (such a bound can be obtained as the length of any feasible Golomb ruler with n marks).

“ $d + e$ ” Formulation. We first present an exact linear integer programming model for the Golomb ruler problem [9]. In this formulation, there are two sets of decision variables: Let e_{ijv} be one if the distance between marks i and j is v , and zero otherwise. Also, we define d_{ij} as the distance between marks i and j . Then, the optimization problem is given as follows:

$$\min_{d,e} \sum_{i=1}^{n-1} d_{i,i+1} \tag{1a}$$

$$\text{s.t. } \sum_{v=1}^L e_{ijv} = 1 \quad 1 \leq i < j \leq n \tag{1b}$$

$$\sum_{i < j} e_{ijv} \leq 1 \quad v = 1, \dots, L \tag{1c}$$

$$\sum_{v=1}^L v e_{ijv} = d_{ij} \quad 1 \leq i < j \leq n \tag{1d}$$

$$\sum_{k=i}^{j-1} d_{k,k+1} = d_{ij} \quad 2 \leq i + 1 < j \leq n \tag{1e}$$

$$e_{ijv} \in \{0, 1\}, d_{ij} \in \mathbb{Z}_+ \quad 1 \leq i < j \leq n, v = 1, \dots, L. \tag{1f}$$

Here, the objective function (1a) minimizes the length of the Golomb ruler (alternatively, it can be simply given as $d_{1,n}$). Constraint (1b) assigns a distance between $1, \dots, L$ to every pair of marks i and j while constraint (1c) ensures that each distance between $1, \dots, L$ is assigned at most once. Constraint (1d) is simply a definition of the d variables in terms of the e variables. Finally, constraint (1e) is an identity guaranteeing that the distance between the marks i and j is the sum of the basic distances between consecutive marks. We note that d variables can be projected out by substituting the definition given in (1d) into constraint (1e) although the resulting lower dimensional model does not seem to be more advantageous empirically in terms of computational efficiency.

“ d ” Formulation. Now, we present a relaxation of the Golomb ruler problem by eliminating the e variables from the “ $d + e$ ” Formulation. The resulting optimization problem is defined as follows:

$$\min_d \sum_{i=1}^{n-1} d_{i,i+1} \quad (2a)$$

s.t. (1e)

$$\sum_{(i,j) \in R} d_{ij} \geq \frac{1}{2}|R|(|R| + 1) \quad R \subseteq \{(k,l) \in \mathbb{Z}^2 : 1 \leq k < l \leq n\}. \quad (2b)$$

The constraint set (2b), called “Subset Sum Inequalities”, was introduced in [9] to strengthen the integer programming (IP) formulation, and defines the facets of the convex hull of the all-different constraint [20]. In practice, the model (2) can be solved with a constraint generation scheme in which the subset sum inequalities are gradually added. We also note that the complexity of the separation of these inequalities is polynomial-time as it requires sorting $\binom{n}{2}$ many numbers.

As opposed to the “ $d + e$ ” Formulation, the “ d ” Formulation is not an exact representation of the Golomb ruler problem. However, it is known that the optimal value of the “ d ” Formulation is equal to the linear programming (LP) relaxation value of “ $d + e$ ” Formulation [11].

We note that even if the “ d ” Formulation is solved as an IP, it is still not an exact formulation since it does not guarantee that $d_{ij} \neq d_{kl}$ for $i \neq k$ and $j \neq l$, i.e., the uniqueness of the distances. However, this observation leads to a natural way to make the “ d ” Formulation exact: We can solve the problem (2) as an LP with two callbacks: Firstly, we add lazy constraint callbacks to ensure that subset sum inequalities (2b) are satisfied. Secondly, we add a branch callback such that the missing constraint $d_{ij} \neq d_{kl}$ is enforced by the solver as we go down the branch-and-bound tree. In particular, once $d_{ij} = d_{kl}$ for $i \neq k$ and $j \neq l$, we can create a dichotomy as $d_{ij} \leq d_{kl} - 1$ and $d_{ij} \geq d_{kl} + 1$.

2.2 Enhancements

We propose several enhancements to the models presented above based on bound tightening and branching strategies. We also carried out a preliminary polyhedral study of the Golomb ruler problem with the hope of obtaining strong valid inequalities. Although we have discovered several families of valid inequalities, they have not helped solving the problem more efficiently. Therefore, we leave this line of research as future work for further inquiry.

In the sequel, let G_m denote the length of the optimal Golomb ruler of order m , $m = 1, \dots, n - 1$. We assume that all the G_m values are known for $m < n$ when we are trying to solve the n -mark problem.

Bound Tightening. Bound tightening is a widely used strategy in optimization algorithms to reduce the range of the decision variables in order to save

computational effort. It can also be used as a way to strengthen relaxations and improve the performance of search methods (see [8] for an application to the Golomb ruler problem). Our bound tightening procedure starts with the following simple observation: If the difference between marks i and j is small (large), then d_{ij} cannot be too large (small). In particular, we can infer the following initial bounds on d_{ij} variables:

$$G_{j-i+1} =: \underline{d}_{ij} \leq d_{ij} \leq \bar{d}_{ij} := L - G_i - G_{n-j+1}. \quad (3)$$

After this initialization step, we can further improve the bounds \underline{d}_{ij} and \bar{d}_{ij} by solving bounding LPs. In particular, we can minimize/maximize d_{ij} variables over a suitable relaxation (for instance, over the feasible region of the LP relaxation of (1)) to try to improve the bounds iteratively. Once new bounds \underline{d}_{ij} and \bar{d}_{ij} are obtained after rounding up and down the minimum and maximum values, we repeat this procedure until the fixed point is reached, that is, none of the bounds are improved further. We will refer to this procedure as *LP Bounding*.

As an additional mechanism to tighten the variable bounds on the d variables, we extend the LP Bounding approach in the following sense. Now, we optimize the d variables over the feasible region of (1) (not its LP relaxation as in the LP Bounding approach) with a limited computational budget. We will refer to this procedure as *IP Bounding*. Although this approach requires an additional non-trivial effort, it pays off in terms of reducing the solution time of the “ $d + e$ ” formulation.

We also use the bounds \underline{d}_{ij} and \bar{d}_{ij} to fix some of the binary variables e_{ijv} to zero as follows:

$$e_{ijv} = 0 \text{ if } v < \underline{d}_{ij} \text{ or } v > \bar{d}_{ij}.$$

This procedure reduces the total range of the d variables and the number of e variables considerably although it does not improve the LP relaxation bound.

Branching Strategies. The choice of branching strategies may significantly affect the computational performance of the mixed-integer programming solvers. Branching decisions made by the solvers can be altered by either explicitly choosing the variables to be branched on through branch callbacks, or implicitly by assigning priorities to the integer variables. We experimented with both of these choices by exploiting the structure of the Golomb ruler problem.

In terms of imposing explicit branching decisions, we experimented with two strategies which can be applied to both “ $d + e$ ” and “ d ” Formulations. The first strategy, which we will call as “Left Branching”, is described as follows: We first branch on the variable d_{12} by creating $\bar{d}_{12} - \underline{d}_{12} + 1$ many child nodes, each taking an integer from the interval $[\underline{d}_{ij}, \bar{d}_{ij}]$. Then, we proceed by solving the node relaxations. Whenever we have to make another branching decision, we decide on the next variable still undecided from the left of the ruler (for instance, the second variable would be d_{23}). Such an algorithm is based on the intuition that the classical dichotomy branching is probably ineffective for the Golomb ruler problem since assigning particular values to d_{ij} variables can

help detecting infeasibility of more branches than simply branching on d_{ij} by assigning intervals, or traditional binary branching on the e_{iju} variables. The shortcoming of this strategy is of course the increased number of child nodes for each level of the branch-and-bound tree.

Table 1. Results of the “ $d+e$ ” Formulation with LP and IP Bounding strategies. Here, BTT, OT, TT and #BBN respectively represent the bound tightening, optimization, total time (in seconds unless otherwise stated), and the number of branch-and-bound nodes.

n	LP Bounding				IP Bounding after LP Bounding			
	BTT	OT	TT	#BBN	BTT	OT	TT	#BBN
9	0.10	0.36	0.46	0	41.35	0.60	42.05	615
10	0.11	1.42	1.53	333	37.69	0.68	38.48	337
11	0.12	199.87	199.99	155,421	20.55	140.38	161.05	138,820
12	0.19	297.62	297.81	153,244	68.27	208.39	276.85	126,405
13	0.26	32,435.04	32,435.30	13,949,679	2,874.62	24,993.13	27,868.01	13,363,776
14	0.32	>10 h	-	-	3,721.56	>10 h	-	-

The second strategy for imposing explicit branching decisions is called “Difference Branching”, and implemented with the inclusion of a branch callback function. Suppose that in a certain node in the branch-and-bound tree, we have two variables d_{ij} and d_{kl} , $i \neq k$ and $j \neq l$, such that $|d_{ij} - d_{kl}| \leq 1$. Then, we can branch on constraints $d_{ij} \leq d_{kl} - 1$ and $d_{ij} \geq d_{kl} + 1$ as this is a valid partitioning of the feasible region.

In terms of imposing implicit branching decisions, we experimented with different priority assignment strategies. The most successful strategy seems to be the one that assigns higher priorities to e_{iju} variables with smaller u indices. Here, the intuition is that if smaller distances are decided first, then we can either find feasible solutions or detect infeasibility faster.

2.3 Computations

We first report the results of our computational experiments with the “ $d+e$ ” formulation in Table 1 for $n = 9, \dots, 14$. We compare the following two settings (we note that the bound tightening techniques are only applied at the root node assuming that $L = G_n$):

- LP Bounding: Bound tightening is applied over the LP Relaxation of the “ $d+e$ ” formulation in parallel for five rounds.
- IP Bounding after LP Bounding: Bound tightening is applied over the “ $d+e$ ” formulation with a budget of 1 s for $n \leq 12$ and 1 min for $n \geq 13$ in parallel for five rounds.

CPLEX 12.8 is used as the mixed-integer linear programming (MILP) solver on a 64-bit computer with Intel Core i7 CPU 2.60GHz processor and 16 GB RAM. Since our aim to prove the optimality of the n -mark ruler of length G_n , we set $L = G_n - 1$ while solving the MILPs.

We note that the LP Bounding scheme is quite cheap to obtain better variable bounds than the initial bounds derived in (3). On the other hand, IP Bounding requires an additional nontrivial effort to further improve those bounds. We observe that this additional computational effort can be justified when $n \geq 12$ as the reduction in the optimization step outweighs the increase in the bound tightening step and the 13-mark instance can be solved in less than 8 h in total. Due to the sharp increase in the CPU time necessary, we were not able to solve the Golomb ruler problem with 14 marks in less than 10 h.

Table 2. Results of the “ d ” Formulation with different variable bounding and branching strategies.

n	LP Bounding				IP Bounding after LP Bounding			
	Diff. Branching		Left Branching		Diff. Branching		Left Branching	
	TT	#BBN	TT	#BBN	TT	#BBN	TT	#BBN
9	1.45	3,277	3.05	5310	42.59	3,257	44.45	5,338
10	0.55	805	2.00	3248	38.21	785	39.74	3,297
11	9,915.67	4,256,165	1,920.96	1,651,695	9,785.72	4,285,299	1,862.69	1,655,038

We report the results of our experiments with the “ d ” formulation in Table 2 for $n = 9, 10, 11$. We compare the Difference (Diff.) Branching and Left Branching strategies as introduced in Sect. 2.2 in combination with LP Bounding and IP Bounding. We observe that the Left Branching becomes significantly better than the Difference Branching approach as the number of marks increases. Since we were able to solve only very small Golomb ruler problem instances with the “ d ” Formulation in comparison to the “ $d + e$ ” Formulation, we have not pursued this direction further. Nevertheless, the Left Branching strategy has proved to be quite effective and is utilized multiple times in this paper.

3 Constraint Programming Model

In the previous section, we presented two linear integer programming models to solve the Golomb ruler problem. Although several enhancement of these models are introduced and the computational effort is reduced significantly, we were not able prove the optimality of a given 14-mark ruler in a reasonable amount of time. In this section, we switch our attention to constraint programming models which prove to be more successful for the Golomb ruler problem.

3.1 Formulation

A constraint programming model of the Golomb ruler problem can be formulated as follows [16, 18]:

$$\min_d d_{1,n} \tag{4a}$$

$$\text{s.t. alldiff}(\{d_{ij} : 1 \leq i < j \leq n\}) \tag{4b}$$

$$d_{ij} + d_{jk} = d_{ik} \quad 1 \leq i < j < k \leq n \tag{4c}$$

$$d_{ij} \in \{\underline{d}_{ij}, \dots, \bar{d}_{ij}\} \quad 1 \leq i < j \leq n. \tag{4d}$$

Here, constraint (4b) ensures that each distance d_{ij} are different from each other. Constraint (4c) guarantees that the distances respect the “triangle” constraint, that is, the distance between marks i, k is the sum of the distances between marks i, j and j, k , where j is strictly between i and k . Finally, constraint (4d) specifies the ranges of the decision variables.

3.2 Enhancements

The constraint programming model (4) can easily solve small instances of the Golomb ruler problem, e.g., $n \leq 10$, but runs into slow convergence issues for even slightly larger instances. Similar to the integer programming models considered in the previous sections, we propose some enhancements to improve the scalability of the constraint programming model. These enhancements utilize bound tightening, table constraints and search strategies.

Bound Tightening. The bound tightening procedures proposed in Sect. 2.2 based on LPs and IPs are quite effective in reducing the ranges of the d variables. We now discuss another similar procedure based on constraint programming techniques (see [10] for a related method called “shaving”). The proposed idea is quite simple: We fix a d_{ij} variable to its current lower or upper bound and solve the feasibility version of the constraint programming model (4) for a limited amount of time. If the infeasibility of this restricted model can be proven, this implies that we can tighten the range of the d_{ij} variable by excluding the value that we have fixed. We will refer to this procedure as *CP Bounding*. This approach is implemented in an iterative fashion with limited computational budget and proved to be helpful to further reduce the range of the decision variables.

Table Constraints. Table constraints can be crucial to speed up constraint programming solvers. By exploiting the specific structure of the Golomb ruler problem, we also define certain “forbidden assignments”. The construction is as follows: Consider the subruler with marks numbered as $\{i, \dots, i + 4\}$. We first enumerate the set S_j of all triplets $(d_{j,j+1}, d_{j+1,j+2}, d_{j+2,j+3})$ that constitute a feasible subruler with respect to the variable bounds and all-different constraints, for $j = i$ and $j = i + 1$. Now, suppose that for some $(\bar{d}_{i,i+1}, \bar{d}_{i+1,i+2},$

$\bar{d}_{i+2,i+3}) \in S_i$, there does not exist any $\bar{d}_{i+3,i+4}$ such that $(\bar{d}_{i+1,i+2}, \bar{d}_{i+2,i+3}, \bar{d}_{i+3,i+4})$ belongs to the set S_{i+1} . In this case, we can declare the triplet $(\bar{d}_{i,i+1}, \bar{d}_{i+1,i+2}, \bar{d}_{i+2,i+3})$ as “forbidden”. We can repeat this procedure for a few rounds across different subrulers to identify more forbidden assignments.

Table 3. Results with LP Bounding, IP Bounding and CP Bounding strategies.

n	LP Bounding		IP Bounding after LP		CP Bounding after LP and IP		
	OT	TT	OT	TT	BTT	OT	TT
9	2.82	2.92	0.27	41.71	1.03	0.06	42.54
10	11.95	12.06	0.28	38.08	1.17	0.07	39.04
11	140.30	140.42	19.63	40.30	11.85	0.54	33.07
12	554.71	554.90	23.39	91.85	27.77	1.52	97.75
13	11,615.19	11,615.45	1,780.54	4,655.42	1,665.97	209.87	4,750.71
14	>10 h	-	31,839.14	35,561.02	3,872.62	29,795.25	37,389.74

Search Strategies. Search strategies are extremely important in constraint programming as they significantly alter the performance of the solvers. Inspired by the Left Branching for the linear integer programming model and its adaptation to the quadratic integer model, we have decided to employ a variable selection rule based on lexicographical ordering. We also set the search phase parameter to depth first search as our aim is to prove the optimality of a given ruler efficiently. Finally, we experiment with different value selection strategies and decide to use the one based on the smallest impact.

3.3 Computations

We report the results of our computational experiments with the constraint programming formulation in Table 3 for $n = 9, \dots, 14$. In addition to the “LP Bounding” and “IP Bounding after LP Bounding” settings introduced in Sect. 2.3, we also experimented with the following version:

- CP Bounding after LP and IP Bounding: Bound tightening is applied over the constraint programming formulation with a budget of 1 s for $n \leq 12$ and 1 min for $n \geq 13$ in parallel for five rounds. This includes the generation of forbidden assignments based on the table constraints.

CPLEX CP Optimizer is used as the constraint programming solver with the default settings unless otherwise stated.

We now summarize our observations: Firstly, a comparison with Tables 1 and 3 indicates that the constraint programming formulation takes less time than the “ $d + e$ ” formulation under the same version of bounding for $n \geq 11$. This allows us to solve the 14-mark problem with the constraint programming approach

with IP Bounding in 10 h, which was not possible with the “ $d + e$ ” formulation. Secondly, the overhead of the CP Bounding approach is quite large, hence, the reduction in the optimization time compared to the IP Bounding may not be fully justified always. However, we believe that further inquiry along this direction should be pursued. For instance, we extended the CP Bounding approach for the 14-mark problem by allowing 10 min of budget for each subruler length. This increases the total bounding time to 18,251 s but reduces the optimization time to 16,851 s. Although the total time remains more or less unchanged, this additional experiment shows that a carefully executed bounding mechanism may have a potential to be efficient overall.

4 Quadratic Integer Programming Models

So far, we presented classical linear integer and constraint programming formulations for the Golomb ruler problem. In this section, we focus on a less-explored approach based on quadratic integer programming.

4.1 Two Formulations

In this section, we discuss two possible quadratic integer programming formulations for the Golomb ruler problem with n marks, one based on an *optimization* model and the other based on a *feasibility* version. To the best of our knowledge, such formulations have not been proposed before in the literature.

Let us define a single set of binary variables y_l , which takes value one if there is a mark at location l and zero otherwise, $l = 1, \dots, L$. Here, L is again an upper bound on the length of a shortest Golomb ruler with n marks.

Optimality Version. We first present an alternative integer programming formulation of the Golomb ruler problem as follows:

$$\min_y \max_{l=1, \dots, L} l \times y_l \tag{5a}$$

$$\text{s.t. } \sum_{l=0}^{L-v} y_l y_{l+v} \leq 1 \qquad v = 1, \dots, L \tag{5b}$$

$$y_l \in \{0, 1\} \qquad l = 1, \dots, L. \tag{5c}$$

Here, the objective (5a) minimizes the position of the last mark on a ruler of length L , which corresponds to the length of an optimal ruler. We note that the objective function can be easily linearized using an auxiliary variable and enforcing L additional constraints. Constraint (5b) guarantees that each distance v is used at most once in a feasible solution. Observe that the model (5) can be reformulated as a quadratically constrained program, which contains two types of nonconvexities, one due to the bilinear inequalities (5b), and another due to the integrality of the y variables.

Convexification techniques can be utilized to solve or approximate the non-convex problem (5). We note that this formulation admits a straightforward semidefinite programming (SDP) relaxation given as follows:

$$\min_{y,z,Y} z \tag{6a}$$

$$\text{s.t. } l \times y_l \leq z \quad l = 1, \dots, L \tag{6b}$$

$$\sum_{l=0}^{L-v} Y_{l,l+v} \leq 1 \quad v = 1, \dots, L \tag{6c}$$

$$0 \leq y_l \leq 1 \quad l = 1, \dots, L \tag{6d}$$

$$\begin{bmatrix} 1 & y^T \\ y & Y \end{bmatrix} \succeq 0. \tag{6e}$$

Unfortunately, the dual bound obtained from solving the SDP relaxation (6) is extremely weak (for instance, the bound obtained for the 10-mark instance is only 15.14 while the length of the optimal Golomb ruler is 55). Therefore, we have not pursued this line of research direction further.

Feasibility Version. Now, we consider a “complementary” version of the problem defined as follows: Given the length of a ruler L , maximize the number of marks that can be located onto such a ruler that satisfies the Golomb ruler requirements. This version of the problem can be formulated as follows:

$$n_L := \max_y \sum_{l=0}^L y_l \tag{7a}$$

$$\text{s.t. (5b) – (5c).} \tag{7b}$$

Note that the formulation (7) can be seen as the feasibility version of the model (5) in the following sense: If $n_L = n$ but $n_{L-1} = n - 1$, then we can certify that $G_n = L$. Hence, in order to obtain the length of a shortest Golomb ruler with n marks, that is G_n , we can first solve problem (7) with $L = G_{n-1}$, and then increase the value of L until we can locate all of the n marks. Such a procedure gives an indirect way of solving the Golomb ruler problem.

Problem (7) is again a nonconvex, quadratically constrained integer program. Below, we propose two linearization methods that can be used to solve problem (7) via an appropriate branch-and-bound method.

Linearization via SDP The problem (7) can be reformulated as a mixed-integer SDP as follows:

$$\max_{y,Y} \sum_{l=0}^L y_l$$

$$\text{s.t. (6c), (6e), (5c).} \tag{8a}$$

Since the problems in this class are not typically supported by commercial solvers, we implemented our own branch-and-bound algorithm. In this algorithm, we solve the SDP relaxation of the model (8), which replaces the binary restriction (5c) with its continuous relaxation (6d), at each node of the tree. Our algorithm decides which y variables to choose for branching, which is discussed in more detail in Sect. 4.2.

Linearization via LP. The problem (7) can be also reformulated as a mixed-integer LP as follows:

$$\begin{aligned} \max_{y, Y} \quad & \sum_{l=0}^L y_l & (9a) \\ \text{s.t.} \quad & (6c), (5c) \\ & y_l + y_k - 1 \leq Y_{lk} & l, k = 1, \dots, L & (9b) \\ & 0 \leq Y_{lk} \leq y_l & l, k = 1, \dots, L. & (9c) \end{aligned}$$

Here, constraints (9b)–(9c) correspond to the McCormick envelopes for the equation $Y_{lk} = y_l y_k$. In general, solving problem (9) directly as an MILP is quite expensive, partly due to the fact that its LP relaxation is highly degenerate. Therefore, we adopt a Benders decomposition approach, whose problem specific details are presented in Sect. 4.2.

4.2 Enhancements

We again propose some enhancements to speed up the solution procedure of the feasibility version of the quadratic formulation of the Golomb ruler problem. In particular, we develop two types of valid inequalities, Benders decomposition for the linearized model (9) and branching strategies. Improved variable bounds obtained via the bound tightening procedure presented in Sect. 2.2 are also used whenever applicable.

Valid Inequalities. In this section, we present two families of valid inequalities, which we refer to as “Golomb” and “Clique” inequalities. Below, we present their precise formulations together with the intuition behind them.

Golomb Inequalities. Since the number of marks that can be placed onto any subruler of length t is upper bounded by n_t , the following inequalities are valid and are added to the root node relaxation:

$$\sum_{j=l}^{l+\min\{G_{i+1}, L\}+1} y_j \leq i \quad i = 2, \dots, n_L; \quad l = 0, \dots, L - (\min\{G_{i+1}, L\} + 1). \quad (10)$$

More inequalities of this kind can be obtained as follows: Instead of summing the consecutive y variables, we can consider any subset of these variables whose indices are separated by exactly the same integer c , $c = 2, \dots, \lfloor L/2 \rfloor$, such as $y_j, y_{j+c}, y_{j+2c}, \dots$

Clique Inequalities In order to better explain the construction of the clique inequalities, it is more suitable to present the Golomb ruler problem as a special *maximum cardinality clique problem* defined as follows: Let us consider a complete graph $G = (V, E)$, where the set of vertices is $V := \{0, \dots, L\}$. We partition the edge set E into L subsets E_l defined as $E_l := \{(i, i+l) : i = 0, \dots, L-l\}$ for $l = 1, \dots, L$. Then, in order to solve the Golomb ruler problem, we search for a largest clique $G' = (V', E')$ in this graph such that at most one edge from each subset E_l belongs to E' , that is, $|E_l \cap E'| \leq 1$.

Motivated by the above construction, let us introduce the clique inequalities, which are easily implementable in a cutting plane framework. Consider a fractional solution \tilde{y} , and construct two sets $\mathcal{L}_1 := \{l : \tilde{y}_l = 1\}$ and $\mathcal{L}_f := \{l : \tilde{y}_l \in (0, 1)\}$. Let us define the distances induced by the solution \tilde{y} as $\mathcal{D} := \{|k-l| : k, l \in \mathcal{L}_1\}$. We will now construct an auxiliary graph $\tilde{G} = (\tilde{V}, \tilde{E})$, where $\tilde{V} := \mathcal{L}_f$ and $\tilde{E} := \{(k, l) \in \tilde{V} \times \tilde{V} : |k-l| \in \mathcal{D}\}$. We also associate node weights \tilde{y}_l for each $l \in \tilde{E}$. Then, each maximal clique \tilde{C} in the graph \tilde{G} whose weight is more than 1 gives rise to a cutting plane of the following form:

$$\sum_{l \in \tilde{C}} y_l \leq 1. \tag{11}$$

We note that the set of all maximal cliques in a graph can be found by the Bron-Kerbosch algorithm [5] in reasonable time for such small graphs, and the inequalities (11) can be added as local user cuts in a branch-and-cut algorithm.

Benders Decomposition. Since we observe that solving problem (9) directly is not computationally efficient, we employ a Benders decomposition technique instead. In this approach, we solve the following master problem

$$\max_y \sum_{l=0}^L y_l \tag{12a}$$

s.t. (5c)

$$\sum_{l \in C} |C_u(l)| y_l \leq \frac{|C|}{2} + 1 \quad C \subseteq \{0, \dots, L\}, u = 1, \dots, L, \tag{12b}$$

where constraints (12b) are added in lazy fashion until feasibility is proven. Here, $C_u(l) := \{k : |k-l| = u\}$. This is achieved through the separation procedure (feasibility check) described as follows: Given a binary vector \tilde{y} , we first define the set of marks as $M := \{l : \tilde{y}_l = 1\}$. For this candidate ruler to be a Golomb ruler, the distances between each pair of mark should be distinct. Therefore, the cardinality of the set $M_u(l) := \{k \in M : |k-l| = u\}$ should be 1 for $l \in M$ and $u = 1, \dots, L$. Otherwise, we detect infeasibility and can add the following cut:

$$\sum_{l \in M} |M_u(l)| y_l \leq \frac{|M|}{2} + 1. \tag{13}$$

In other words, we expand the constraint set (12b) by the inclusion of the set M_u . We note that our approach allows to add multiple cuts of the form (13) corresponding to different u values for a given solution.

What we described so far amounts to a classical implementation of the Benders decomposition technique in which a “multi-tree” approach is employed, that is, at each iteration, we solve the master problem (12) as an MILP. Therefore, multiple branch-and-bound trees are created. An alternative approach would be to use a single branch-and-bound tree, and add the Benders feasibility cuts (13) via lazy constraint callbacks. Such an approach is commonly referred to as a “one-tree” approach, branch-and-cut or “branch-and-check” and works much better than its multi-tree counterpart for model (12).

Table 4. Results of the “ y ” Formulation (linearization via LP) with and without Golomb and Clique cuts using one-tree Benders decomposition. Total time and branch-and-nodes for each mark n and different ruler lengths L are reported.

n	L	without Golomb Cuts				with Golomb Cuts			
		w/o Clique Cuts		with Clique Cuts		w/o Clique Cuts		with Clique Cuts	
		TT	#BBN	TT	#BBN	TT	#BBN	TT	#BBN
9	35–43	7.91	17,753	2.63	278	5.73	12,630	3.49	597
10	45–54	32.24	81,036	11.45	354	17.73	59,770	5.80	846
11	56–71	3,850.04	1,712,947	730.56	824	619.7	1,384,860	35.49	2,101
12	73–84	>10 h	-	5,576.83	674	4,119.82	4,710,139	57.80	1,661
13	86–105	>10 h	-	>10 h	-	>10 h	-	1,689.52	4,869
14	107–126	>10 h	-	>10 h	-	>10 h	-	12,960.17	7,776

Branching Strategy. The branching decisions are extremely important for both the SDP and LP based branch-and-bound algorithms. Following the intuition from Left Branching idea from linear integer programming models as mentioned in Sect. 2.2, we propose a similar scheme that decides the next mark from the left of the ruler. In particular, suppose that the first m marks from the left are located at the positions ℓ_1, \dots, ℓ_m . Then, the location of the mark $m + 1$ can be chosen from the set

$$\{v : \underline{d}_{1,m+1} \leq v \leq \bar{d}_{1,m+1}, v - \ell_k \notin \{\ell_j - \ell_i : 1 \leq i < j \leq m\} \forall k = 1, \dots, m\}.$$

Therefore, we again prefer to create multiple child nodes rather than the more traditional dichotomous branching.

4.3 Computations

We report the results of our computational experiments with the quadratic integer programming formulation with LP linearization in Table 4 for $n = 9, \dots, 14$. Since quadratic integer programming formulations are based on feasibility version of the Golomb ruler problem, we solve a sequence of models with increasing

ruler length to certify that a given ruler is optimal (see the explanation at the end of Sect. 4.1). For instance, to prove that $G_9 = 44$, we solve problem (9) with $L = 35, \dots, 43$ and certify that $n_L = 8$ (here, we assume that G_8 is known as 34). We report the computational results with and without the Golomb and Cliques cuts giving rise to four different settings.

We observe that both types of cuts are quite effective to solve the subproblems from different perspectives: Golomb cuts are especially helpful in reducing the computational time more directly whereas Clique cuts significantly lowers the number of branch-and-bound nodes and indirectly reduces the total time. The reason that these two cuts behave differently is that Golomb cuts are added from scratch and their number is limited whereas Clique cuts are added on the fly at each node of the tree and their number can be quite large. We believe that the separation of Clique cuts can be made more efficient and selective so that the total computational effort can be further improved.

Finally, we report the results of our computational experiments with the quadratic integer programming formulation with SDP linearization in Table 5 for $n = 9, 10, 11$ with and without Golomb cuts (MOSEK 8.1 is used as the SDP solver). Although the total number of branch-and-bound nodes is reduced by solving the SDP relaxation of the model (8) at each node, the total time increases quite significantly which prevents this line of research to be practical. However, we point out that our implementation is quite naïve and perhaps the value of stronger relaxations provided by the SDP relaxations can be made useful.

Table 5. Results of the “ y ” Formulation (linearization via SDP) with and without Golomb cuts.

n	L	w/o Golomb Cuts		with Golomb Cuts	
		TT	#BBN	TT	#BBN
9	35–43	21.38	227	22.58	209
10	45–54	33.03	231	40.77	200
11	56–71	6,776.11	25,591	6,607.07	24,737

5 Concluding Remarks

In this paper, we provided a comprehensive comparison of computational methods to solve the Golomb ruler problem using optimization techniques. In particular, we analyzed three formulations based on linear integer programming, constraint programming and quadratic integer programming, and proposed several enhancements based on valid inequalities, variable bounding and branching strategies. According to our experiments with a budget of 10 h, integer linear programming models can solve up to 13-mark instances whereas constraint programming and quadratic integer programming formulations can scale up to 14-mark instance, with the latter being faster. We observed that proposed

enhancements significantly alter the solution procedures and provide substantial savings in terms of computational effort.

Although the methods in this paper can solve relatively small-size instances of the Golomb ruler problem, we think that there are some promising research directions which might utilize them more effectively. As an example, if a large number of processors is available, then bound tightening subproblems can be parallelized asynchronously so that they can exchange information whenever a new bound is improved. Since the availability of tight variable bounds seems to accelerate the constraint programming solver, this can potentially enable us to solve larger instances. Another potential line of research would be to make the cut generation procedure for the quadratic integer programming model more efficient and selective so that the overhead associated with solving large MILPs is reduced while keeping the strength of the relaxations intact.

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