

Dijkstra meets Steiner: a fast exact goal-oriented Steiner tree algorithm

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Received: 21 May 2015 / Accepted: 10 June 2016 / Published online: 14 July 2016
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Abstract We present a new exact algorithm for the Steiner tree problem in edge-weighted graphs. Our algorithm improves the classical dynamic programming approach by Dreyfus and Wagner. We achieve a significantly better practical performance via pruning and future costs, a generalization of a well-known concept to speed up shortest path computations. Our algorithm matches the best known worst-case run time and has a fast, often superior, practical performance: on some large instances originating from VLSI design, previous best run times are improved upon by orders of magnitudes. We are also able to solve larger instances of the d -dimensional rectilinear Steiner tree problem for $d \in \{3, 4, 5\}$, whose Hanan grids contain up to several millions of edges.

Keywords Graph algorithms · Steiner tree problem · Dynamic programming · Exact algorithm

Mathematics Subject Classification 05C85 · 68W35 · 90C27 · 90C39

1 Introduction

We consider the well-known Steiner tree problem (in graphs): Given an undirected graph G , costs $c : E(G) \rightarrow \mathbb{R}_{\geq 0}$ and a terminal set $R \subseteq V(G)$, find a tree T

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in G such that $R \subseteq V(T)$ and $c(E(T))$ is minimum. The decision version of the Steiner tree problem is one of the classical NP-complete problems [22]; it is even NP-complete in the special case that G is bipartite with $c \equiv 1$. Furthermore, it is NP-hard to approximate the Steiner tree problem within a factor of $\frac{96}{95}$ [6]. The currently best known approximation algorithm by Byrka et al. [5] uses polyhedral methods to achieve a 1.39-approximation. The Steiner tree problem has many applications, in particular in VLSI design [20], where electrical connections are realized by Steiner trees.

From now on, we will refer to $|V(G)|$ by n , $|E(G)|$ by m and $|R|$ by k . Dreyfus and Wagner [9] applied dynamic programming to the Steiner tree problem to obtain an exact algorithm with a run time of $\mathcal{O}(n(n \log n + m) + 3^k n + 2^k n^2)$ if implemented using Fibonacci heaps [14]. In 1987, Erickson, Monma and Veinott [11] improved the run time to $\mathcal{O}(3^k n + 2^k(n \log n + m))$ using a very similar approach. In 2006, Fuchs et al. [15] proposed an algorithm with a run time of $\mathcal{O}((2 + \delta)^k n^{(\ln(\frac{1}{\delta})/\delta)^\zeta})$ for every sufficiently small $\delta > 0$ and $\zeta > \frac{1}{2}$, improving the exponential dependence on k from 3^k to $(2 + \delta)^k$. Vygen [33] developed an algorithm with a worst-case run time of $\mathcal{O}(nk2^{k+\log_2(k)} \log_2(n))$, which is the fastest known algorithm if $f(n) < k < g(n)$ for some $f(n) = \text{polylog}(n)$ and $g(n) = \frac{n}{2} - \text{polylog}(n)$. However, for $k < 4 \log n$, the run time obtained by Erickson, Monma and Veinott [11] is still the best known. See [33] for a more detailed analysis of the run times mentioned above.

For graphs with treewidth t , one can solve the Steiner tree problem in time $\mathcal{O}(n2^{\mathcal{O}(t)})$ [4]. An implementation of this algorithm was evaluated in [12]. Polzin and Vahdati Daneshmand [26] proposed an algorithm with a worst-case run time of $\mathcal{O}(n2^{p \log p + 3p + \log p})$ where p is a parameter closely related to the pathwidth of G . They use this algorithm as a subroutine in their successful reduction-based Steiner tree solver [24, 32].

Except for the last mentioned algorithm, these results have played a very limited role in practice. Instead, empirically successful algorithms rely on preprocessing and reduction techniques, heuristics and branching: First, reductions [3, 10, 25, 31] are applied to reduce the size of the graph and the number of terminals, guaranteeing that optimum solutions of the reduced instance correspond to optimum solutions of the original instance. These reductions are not limited to simple local edge elimination tests, but may also rely on linear programming formulations and optimum solutions of partial instances. Primal and dual [2, 35] heuristics yield good upper and lower bounds, in many cases even resulting in a provably optimum solution. If these methods do not already solve the instance, enumerative algorithms are used. To this end, various authors [2, 7, 23] perform branch and cut. However, the solver by Polzin and Vahdati Daneshmand [24, 32], which achieved the best results so far, uses a branch and bound approach, where high effort is put into single branching nodes.

We propose a dynamic programming based algorithm with a worst-case run time of $\mathcal{O}(3^k n + 2^k(n \log n + m))$, matching the best known bound for small k , and which is fast in practice. Good practical performance is achieved by effectively pruning partial solutions and using *future cost* estimates. The latter are motivated by the similarity of our algorithm with Dijkstra's algorithm [8] and the well-known speed-up technique for Dijkstra's algorithm (first described by Hart, Nilsson and Raphael [17]) which uses reduced edge costs. More precisely, given an instance (G, c, s, t) of the shortest path

problem, where we assume G to be a directed graph, we use a feasible potential π , which is a function $\pi : V(G) \rightarrow \mathbb{R}_{\geq 0}$ with

$$\pi(t) = 0 \tag{1}$$

and

$$\pi(v) \leq \pi(w) + c((v, w)) \tag{2}$$

for all $(v, w) \in E(G)$. Define reduced costs c_π by

$$c_\pi(e) := c(e) + \pi(w) - \pi(v) \geq 0 \tag{3}$$

for every $e = (v, w) \in E(G)$. Then, run Dijkstra's algorithm on the instance (G, c_π, s, t) . The numbers $\pi(v)$ are lower bounds on the distance from v to t (we also say that $\pi(v)$ estimates the *future cost* at v). Moreover, the cost of every s - t -path changes by the same amount when going from c to c_π , namely $-\pi(s)$, so any shortest s - t -path in (G, c_π) is a shortest s - t -path in (G, c) . If the future costs are good lower bounds, only vertices close to a shortest path will be labeled by Dijkstra's algorithm before t is labeled permanently (i.e., the distance to t is known) and the algorithm can be stopped. This can lead to huge speedups.

The rest of this paper is organized as follows: In Sect. 2, we generalize this future cost idea from paths to Steiner trees and describe our algorithm. Examples of future cost estimates are given in Sect. 3. Section 4 introduces a pruning technique to further improve practical performance. Section 5 contains implementation details and computational results.

2 The algorithm

Now, let (G, c, R) be an instance of the Steiner tree problem, where G is an undirected graph, $c : E(G) \rightarrow \mathbb{R}_{\geq 0}$ is a cost function on the edges and R is the set of terminals to be connected. As usual, for a set $X \subseteq V(G)$, we denote by $\text{smt}(X)$, short for Steiner minimal tree, the cost of an optimum Steiner tree for the terminal set X . Our algorithm uses an arbitrary root terminal $r_0 \in R$. We will call the terminals in $R \setminus \{r_0\}$ source terminals. The algorithms by Dreyfus and Wagner [9] and Erickson et al. [11] as well as our algorithm use dynamic programming to compute $\text{smt}(\{v\} \cup I)$ for $(v, I) \in V(G) \times 2^{R \setminus \{r_0\}}$. Then, at termination, $\text{smt}(\{r_0\} \cup (R \setminus \{r_0\}))$ is the cost of an optimum Steiner tree.

The former two algorithms work as follows: They consider all $I \subseteq R \setminus \{r_0\}$ in order of non-decreasing cardinality and compute $\text{smt}(\{v\} \cup I)$ for all $v \in V(G)$. This way, it is guaranteed that when computing $\text{smt}(\{v\} \cup I)$, the values $\text{smt}(\{w\} \cup I')$ for all $w \in V(G)$ and $I' \subset I$ are already known. However, this leads to an exponential best case run time and memory consumption of $\Omega(2^k n)$. In contrast, our new algorithm considers all subsets of source terminals simultaneously, using a labeling technique

similar to Dijkstra’s algorithm. This way, we do not necessarily have to compute $\text{smt}(\{v\} \cup I)$ for all pairs (v, I) .

Our new algorithm labels from the source terminals towards the root r_0 . More precisely, the algorithm labels elements of $V(G) \times 2^{R \setminus \{r_0\}}$. Each label (v, I) represents the best Steiner tree for $\{v\} \cup I$ found so far. As in Dijkstra’s algorithm, each iteration selects one label (v, I) and declares it to be permanent. Each time a label (v, I) becomes permanent, all neighbors w of v are checked and updated if the Steiner tree represented by (v, I) plus the edge $\{v, w\}$ leads to a better solution for (w, I) than previously known. This operation is well-known from Dijkstra’s algorithm. In addition, for all sets $J \subseteq (R \setminus \{r_0\}) \setminus I$ it is checked whether the Steiner trees for (v, I) and (v, J) combined to a tree for $(v, I \cup J)$ lead to a better solution than previously known.

To allow a simpler presentation, we restrict ourselves to instances without edges of zero cost, as these can be contracted in a trivial preprocessing step.

Now, we introduce the notion of valid lower bounds, which are used by the algorithm to estimate the future cost of a label (v, I) .

Definition 1 Let (G, c, R) be an instance of the Steiner tree problem and $r_0 \in R$. A function $\mathcal{L} : V(G) \times 2^R \rightarrow \mathbb{R}_{\geq 0}$ is called a *valid lower bound* if

$$\mathcal{L}(r_0, \{r_0\}) = 0$$

and

$$\mathcal{L}(v, I) \leq \mathcal{L}(w, I') + \text{smt}((I \setminus I') \cup \{v, w\})$$

for all $v, w \in V(G)$ and $\{r_0\} \subseteq I' \subseteq I \subseteq R$.

Note that the values $\mathcal{L}(v, I)$ for $r_0 \notin I$ do not affect whether \mathcal{L} is a valid lower bound. Also note that by choosing $I' = \{r_0\}$ and $w = r_0$, we have $\mathcal{L}(v, I) \leq \text{smt}(I \cup \{v\})$, so a valid lower bound by definition indeed is a lower bound on the cost of an optimum Steiner tree. Moreover, if $e = \{v, w\} \in E(G)$ is an edge, by choosing $I' = I$, we have

$$\mathcal{L}(v, I) \leq \mathcal{L}(w, I) + \text{smt}(\{v, w\}) \leq \mathcal{L}(w, I) + c(e).$$

This shows that valid lower bounds generalize feasible potentials as defined in (1) and (2). In fact, our algorithm applied to the case $|R| = 2$ is identical to Dijkstra’s algorithm using future costs in the very same way.

Our new algorithm is described in Fig. 1. For each label $(v, I) \in V(G) \times 2^{R \setminus \{r_0\}}$, the algorithm stores the cost $l(v, I) \in \mathbb{R}_{\geq 0} \cup \{\infty\}$ of the cheapest Steiner tree for $\{v\} \cup I$ found so far as well as backtracking data $b(v, I) \subseteq V(G) \times 2^{R \setminus \{r_0\}}$ which is used to construct the Steiner tree represented by this label. If $b(v, I)$ is not empty, it will always either be of the form $b(v, I) = \{(w, I)\}$ where w is a neighbor of v or of the form $b(v, I) = \{(v, I_1), (v, I_2)\}$ where I_1 and I_2 form a partition of I (into nonempty disjoint sets). In the first case, i.e., $b(v, I) = \{(w, I)\}$, the Steiner tree represented by the label (v, I) contains exactly one edge incident to v , which is $\{v, w\}$. In the second case, i.e., $b(v, I) = \{(v, I_1), (v, I_2)\}$, the Steiner tree represented by (v, I) can be

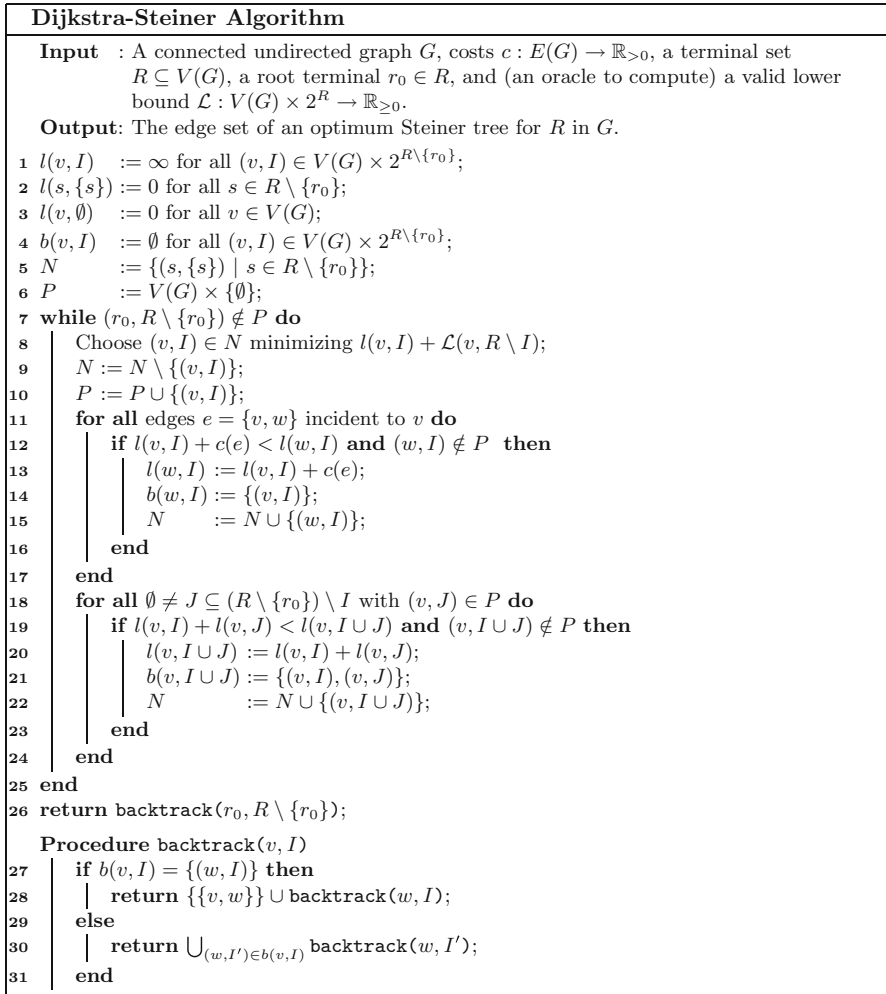


Fig. 1 The Dijkstra-Steiner Algorithm

split into two Steiner trees for the terminal sets $I_1 \cup \{v\}$ and $I_2 \cup \{v\}$, where I_1 and I_2 form a partition of I . Of course, the Steiner trees for $I_1 \cup \{v\}$ and $I_2 \cup \{v\}$ may in turn be split recursively into further trees. To be precise, it may happen that the subgraph of G corresponding to some label (v, I) contains cycles. However, since we ruled out edges of zero cost, this can only be the case as long as the label is not permanent, because—as we will show—permanent labels correspond to optimal Steiner trees.

We incorporate the valid lower bound \mathcal{L} into the algorithm as follows. First note that instead of running Dijkstra’s algorithm on reduced edge costs c_π as defined in (3), one can equivalently apply the following modification. For a vertex $v \in V(G)$, we denote by $l(v)$ the cost of a label v in Dijkstra’s algorithm, i.e., the cost of a shortest path connecting s with v found so far. Then, in each iteration, instead of choosing a non-

permanent vertex v minimizing $l(v)$ to become permanent, choose a non-permanent vertex minimizing $l(v) + \pi(v)$. We generalize this approach by always choosing a non-permanent label minimizing $l(v, I) + \mathcal{L}(v, R \setminus I)$.

By $P \subseteq V(G) \times 2^{R \setminus \{r_0\}}$ we denote the set of permanently labeled elements. We also maintain a set N of non-permanent labels which are candidates to be selected. The set N contains exactly the labels $(v, I) \in (V(G) \times 2^{R \setminus \{r_0\}}) \setminus P$ with $l(v, I) < \infty$. Note that $\mathcal{L} \equiv 0$ is always a valid lower bound, which may serve as an example to help understanding the algorithm. Other examples of valid lower bounds will be discussed in Sect. 3.

Theorem 2 *The Dijkstra–Steiner algorithm works correctly: Given an instance (G, c, R) of the Steiner tree problem, $r_0 \in R$, and a valid lower bound \mathcal{L} , it always returns the edge set of an optimum Steiner tree for R in G .*

Proof We will prove that the following invariants always hold when line 8 is executed:

(a) For each $(v, I) \in N \cup P$:

$$(a1) \quad l(v, I) = \begin{cases} c(\{v, w\}) + l(w, I) & \text{if } b(v, I) = \{(w, I)\}, \\ \sum_{(v, J) \in b(v, I)} l(v, J) & \text{otherwise,} \end{cases}$$

$$(a2) \quad I \cup \{v\} = \{v\} \cup \bigcup_{(w, J) \in b(v, I)} J,$$

(a3) $b(v, I) \subseteq P$, and `backtrack`(v, I) returns the edge set F of a connected subgraph of G containing $\{v\} \cup I$ with $c(F) \leq l(v, I)$.

(b) For each $(v, I) \in P$:

$$l(v, I) = \text{smt}(\{v\} \cup I).$$

(c) For each $(v, I) \in (V(G) \times 2^{R \setminus \{r_0\}}) \setminus P$:

$$(c1) \quad l(v, I) \geq \text{smt}(\{v\} \cup I),$$

(c2) If $I = \{v\}$, then $l(v, I) = 0$, otherwise

$$l(v, I) \leq \min_{\{v, w\} \in E(G), (w, I) \in P} (l(w, I) + c(\{v, w\})) \text{ and}$$

$$l(v, I) \leq \min_{\emptyset \neq I' \subset I \text{ and } (v, I'), (v, I \setminus I') \in P} (l(v, I') + l(v, I \setminus I')).$$

(c3) If $l(v, I) = \text{smt}(\{v\} \cup I)$, then $(v, I) \in N$.

(d) N is not empty and $N \cap P = \emptyset$.

Assuming (a)–(d), the correctness of the algorithm directly follows: Once we have $(r_0, R \setminus \{r_0\}) \in P$, (b) implies $l(r_0, R \setminus \{r_0\}) = \text{smt}(\{r_0\} \cup (R \setminus \{r_0\})) = \text{smt}(R)$. Furthermore, (a3) implies that the algorithm returns the edge set F of a connected subgraph of G containing R with $c(F) \leq l(r_0, R \setminus \{r_0\}) = \text{smt}(R)$. Since there are no edges of zero cost, F indeed is the edge set of a tree. Invariant (d) guarantees that in each iteration, a label $(v, I) \in N$ can be chosen and that the algorithm terminates, since $|P|$ is increased in each iteration.

Clearly, after line 6 these invariants hold. We have to prove that lines 8 to 24 preserve (a)–(d). Below, we first verify that (a) and (c) are preserved. Then, the main part of the proof shows that (b) is preserved. Finally, we will see that the latter argument also shows that (d) is preserved.

Let (v, I) be the label chosen in line 8 in some iteration. Clearly, lines 8–24 preserve (a2), (a3), (c2) and (c3). If a label $l(w, I)$ or $l(v, I \cup J)$ is decreased, it cannot be permanent, so (a1) is maintained.

We now consider (c1). Since (c) held before the current iteration, we have $l(v, I) \geq \text{smt}(\{v\} \cup I)$. This directly implies

$$\begin{aligned} l(v, I) + c(\{v, w\}) &\geq \text{smt}(\{v\} \cup I) + c(\{v, w\}) \\ &\geq \text{smt}(\{v, w\} \cup I) \\ &\geq \text{smt}(\{w\} \cup I), \end{aligned}$$

so line 13 does not destroy (c1). Also, if $\emptyset \neq J \subseteq (R \setminus \{r_0\}) \setminus I$ is a set chosen in line 18 leading to the change of $l(v, I \cup J)$, we have

$$\begin{aligned} l(v, I \cup J) &= l(v, I) + l(v, J) \\ &\geq \text{smt}(\{v\} \cup I) + \text{smt}(\{v\} \cup J) \\ &\geq \text{smt}(\{v\} \cup I \cup J), \end{aligned}$$

so (c1) indeed is preserved.

In order to prove that (b) is preserved, we now show that $l(v, I) \leq \text{smt}(\{v\} \cup I)$, which together with (c1) yields the desired result. Since $l(v, \{v\}) = 0 = \text{smt}(\{v\})$, we can assume $I \neq \{v\}$. Let T be an optimum Steiner tree for $\{v\} \cup I$ in G . Then, all leaves of T are contained in $\{v\} \cup I$. For a vertex $w \in V(T)$, let T_w be the subtree of T containing all vertices x for which the unique x - v -path in T contains w .

We will now show that there is a vertex $w \in V(T)$, a nonempty terminal set $I' \subseteq I \cap V(T_w)$ and a subtree T' of T_w such that

- (I) $(w, I') \in N$,
- (II) $l(w, I') = c(T') = \text{smt}(\{w\} \cup I')$,
- (III) T' is a subtree of T_w containing $I' \cup \{w\}$,
- (IV) $T - T'$ is a tree containing $(I \setminus I') \cup \{v, w\}$.

Here, by $T - T'$, we refer to the graph $((V(T) \setminus V(T')) \cup \{w\}, E(T) \setminus E(T'))$. Assuming we have a triple (w, I', T') satisfying (I)–(IV), $l(v, I) \leq \text{smt}(\{v\} \cup I)$ can easily be proved: Since \mathcal{L} is a valid lower bound, we have

$$\begin{aligned} \mathcal{L}(w, R \setminus I') &\leq \mathcal{L}(v, R \setminus I) + \text{smt}((I \setminus I') \cup \{v, w\}) \\ &\leq \mathcal{L}(v, R \setminus I) + c(T - T') \\ &= \mathcal{L}(v, R \setminus I) + c(T) - c(T'). \end{aligned} \tag{4}$$

Adding (II) and (4) yields

$$l(w, I') + \mathcal{L}(w, R \setminus I') \leq c(T) + \mathcal{L}(v, R \setminus I).$$

By (I) and the choice of (v, I) in line 8 we have

$$l(v, I) + \mathcal{L}(v, R \setminus I) \leq l(w, I') + \mathcal{L}(w, R \setminus I'),$$

so

$$l(v, I) \leq c(T).$$

It remains to be shown that there is such a triple (w, I', T') . We call $w \in V(T)$ *proper* if $(w, I \cap V(T_w)) \in P$ before the execution of line 24. If we have a leaf $w \in V(T) \setminus \{v\}$ which is not proper, we set $I' = \{w\}$ and $T' = (\{w\}, \emptyset)$, satisfying (I)–(IV). Note that here (I) follows from (c3). Otherwise, since v is not proper, there is a vertex w in T which is not proper but all neighbors w_i of w in T_w are proper. We define

$$\mathcal{J} = \begin{cases} \{I \cap V(T_{w_i}) \mid w_i \text{ is neighbor of } w \text{ in } T_w\} \cup \{w\} & \text{if } w \in I, \\ \{I \cap V(T_{w_i}) \mid w_i \text{ is neighbor of } w \text{ in } T_w\} & \text{if } w \notin I. \end{cases}$$

Note that \mathcal{J} is a partition of $I \cap V(T_w)$. Let \mathcal{J}' be an inclusion-wise minimal subset of \mathcal{J} such that $(w, \bigcup_{J \in \mathcal{J}'} J) \notin P$. Since w is not proper and $(w, \emptyset) \in P$, \mathcal{J}' exists and \mathcal{J}' is not empty. For $J \in \mathcal{J}'$, let T_J be the unique minimum connected subgraph of T such that $(\{w\} \cup J) \subseteq V(T_J)$. By optimality of T , T_J is an optimum Steiner tree for $(\{w\} \cup J)$, as the only vertex in T_J which is incident to edges in $E(T) \setminus E(T_J)$ is w . We define

- (i) $I' = \bigcup_{J \in \mathcal{J}'} J$,
- (ii) $V(T') = \bigcup_{J \in \mathcal{J}'} V(T_J)$ and
- (iii) $E(T') = \bigcup_{J \in \mathcal{J}'} E(T_J)$.

See Fig. 2 for an illustration of this setting.

The conditions (III) and (IV) are satisfied by construction. We now show (II), which due to (c3) also implies (I). First, we deal with the case $|\mathcal{J}'| = 1$. If $\mathcal{J}' = \{\{w\}\}$, by (c2) clearly $l(w, I') = 0 = c(T')$. If $\mathcal{J}' = \{I \cap V(T_{w_i})\}$ for some neighbor w_i of w in T_w , by (c2), (b), and the fact that w_i is proper, we have

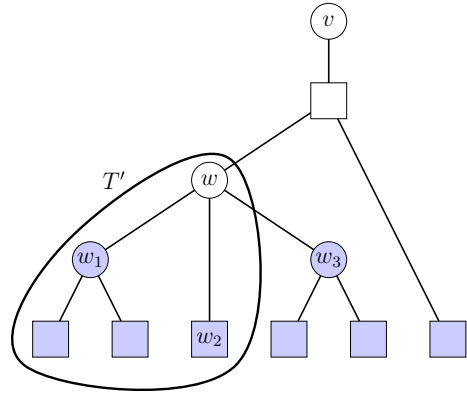
$$\begin{aligned} l(w, I') &\leq l(w_i, I') + c(\{w_i, w\}) \\ &= \text{smt}(\{w_i\} \cup I') + c(\{w_i, w\}) \\ &= c(T_{w_i}) + c(\{w_i, w\}) \\ &= c(T'). \end{aligned}$$

Otherwise, i.e., $|\mathcal{J}'| > 1$, choose an element $J \in \mathcal{J}'$ and see again by (c2), (b) and the minimality of \mathcal{J}' that

$$\begin{aligned} l(w, I') &\leq l(w, I' \setminus J) + l(w, J) \\ &= \text{smt}(\{w\} \cup (I' \setminus J)) + \text{smt}(\{w\} \cup J) \\ &= c(T' - T_J) + c(T_J) \\ &= c(T'). \end{aligned}$$

As T is an optimum Steiner tree for $\{v\} \cup I$, by (IV) we get $c(T') = \text{smt}(\{w\} \cup I')$, together with (c1) showing (II). By (c3), $(w, I') \in N$, so (I) holds as well, completing the proof that (b) is preserved by lines 8 to 24.

Fig. 2 A possible configuration with $\mathcal{J}' = \{I \cap V(T_{w_1}), I \cap V(T_{w_2})\}$. Vertices in I are drawn as squares, proper vertices are drawn in blue



To see that (d) is maintained, note that applying the previous argument to $(r_0, R \setminus \{r_0\})$ instead of (v, I) always yields a label $(w, I') \in N$, so N is not empty. Also, whenever a label (v, I) is inserted to P , it is removed from N . By (b), from then on $l(v, I)$ cannot be changed, so (v, I) is never inserted again into N . \square

Note that in line 8, one can actually choose any label $(v, I) \in N$ with $l(v, I) + \mathcal{L}(v, R \setminus I) \leq l(w, J) + \mathcal{L}(w, R \setminus J)$ for all $(w, J) \in (V(G) \times 2^I) \cap N$. This is a generalization of the choice as specified in the algorithm. However, in our implementation, we always choose a label minimizing $l(v, I) + \mathcal{L}(v, R \setminus I)$.

Theorem 3 *The Dijkstra–Steiner algorithm can be implemented to run in $\mathcal{O}(3^k n + 2^k(n \log n + m) + 2^k n f_{\mathcal{L}})$ time, where $n = |V(G)|$, $m = |E(G)|$, $k = |R|$, and $f_{\mathcal{L}}$ is an upper bound on the time required to evaluate \mathcal{L} .*

Proof Since $|P|$ increases in each iteration, we have at most $n2^{k-1}$ iterations. We use a Fibonacci heap [14] to store all labels $(v, I) \in N$, which allows updates in constant amortized time. Since the heap contains at most $2^{k-1}n$ elements, each execution of line 8 takes $\mathcal{O}(\log(2^{k-1}n)) = \mathcal{O}(k + \log(n))$ amortized time. Line 12 is executed at most $2^k m$ times and each execution takes $\mathcal{O}(1)$ amortized time. Furthermore, there are exactly 3^{k-1} pairs $I, J \subseteq R \setminus \{r_0\}$ with $I \cap J = \emptyset$, since every element in $R \setminus \{r_0\}$ can either be contained in I, J or $(R \setminus \{r_0\}) \setminus (I \cup J)$, independently of the others. Thus, line 18–24 take $\mathcal{O}(3^{k-1}n)$ time. By caching values of \mathcal{L} , we can achieve that we query \mathcal{L} at most once for each label, resulting in an additional run time of $\mathcal{O}(2^k n f_{\mathcal{L}})$. The run time of the backtracking clearly is dominated by the previous tasks, since `backtrack` is called at most $\mathcal{O}(kn)$ times and requires effort linear in the size of its output. We get a total run time of

$$\mathcal{O}\left(2^k n(\log n + k) + 2^k m + 3^k n + 2^k n f_{\mathcal{L}}\right) = \mathcal{O}\left(3^k n + 2^k(n \log n + m) + 2^k n f_{\mathcal{L}}\right),$$

since $2^k k = \mathcal{O}(3^k)$. \square

In Sect. 3, we will see that there are non-trivial valid lower bounds \mathcal{L} which can be used in the algorithm while still achieving a worst-case run time of $\mathcal{O}(3^k n + 2^k(n \log n + m))$, matching the bound of [11].

The memory consumption of our algorithm is obviously $\mathcal{O}(2^kn)$.

3 Lower bounds

Roughly speaking, the larger the valid lower bound \mathcal{L} is, the faster our algorithm will be. Before we describe examples of valid lower bounds, we note:

Proposition 4 *Let (G, c, R) be an instance of the Steiner tree problem and $\mathcal{L}, \mathcal{L}'$ be valid lower bounds. Furthermore, define $\max(\mathcal{L}, \mathcal{L}') : V(G) \times 2^R \rightarrow \mathbb{R}_{\geq 0}$ by*

$$\max(\mathcal{L}, \mathcal{L}')(v, I) := \max(\mathcal{L}(v, I), \mathcal{L}'(v, I))$$

for $v \in V(G)$ and $\{r_0\} \subseteq I \subseteq R$.

Then, $\max(\mathcal{L}, \mathcal{L}')$ also is a valid lower bound.

Proof Let $v, w \in V(G)$ and $I' \subseteq I \subseteq R$. Then

$$\begin{aligned} \mathcal{L}(v, I) &\leq \mathcal{L}(w, I') + \text{smt}((I \setminus I') \cup \{v, w\}) \\ &\leq \max(\mathcal{L}(w, I'), \mathcal{L}'(w, I')) + \text{smt}((I \setminus I') \cup \{v, w\}) \end{aligned}$$

and

$$\begin{aligned} \mathcal{L}'(v, I) &\leq \mathcal{L}'(w, I') + \text{smt}((I \setminus I') \cup \{v, w\}) \\ &\leq \max(\mathcal{L}(w, I'), \mathcal{L}'(w, I')) + \text{smt}((I \setminus I') \cup \{v, w\}), \end{aligned}$$

so

$$\max(\mathcal{L}(v, I), \mathcal{L}'(v, I)) \leq \max(\mathcal{L}(w, I'), \mathcal{L}'(w, I')) + \text{smt}((I \setminus I') \cup \{v, w\}).$$

□

Proposition 4 allows the combination of arbitrary valid lower bounds.

Now, we present three types of valid lower bounds. A simple valid lower bound can be obtained by considering terminal sets of bounded cardinality:

Definition 5 Let (G, c, R) be an instance of the Steiner tree problem, $r_0 \in R$ and let $j \geq 1$ be an integer. Then, \mathcal{L}_j is defined as

$$\mathcal{L}_j(v, I) = \max_{\{r_0\} \subseteq J \subseteq I \cup \{v\}, |J| \leq j+1} \text{smt}(J)$$

for $v \in V(G)$ and $\{r_0\} \subseteq I \subseteq R$. For $v \in V(G)$ and $I \subseteq R$ with $r_0 \notin I$, set $\mathcal{L}_j(v, I) = 0$.

Lemma 6 *Let (G, c, R) be an instance of the Steiner tree problem, $r_0 \in R$ and let $j \geq 1$ be an integer. Then, \mathcal{L}_j is a valid lower bound. Furthermore, we can implement \mathcal{L}_j such that after a preprocessing time of $\mathcal{O}(3^k + (2k)^{j-1}n + k^{j-1}(n \log n + m))$, we can evaluate $\mathcal{L}_j(v, I)$ for every $v \in V(G)$ and $\{r_0\} \subseteq I \subseteq R$ in time $\mathcal{O}(|I|^{j-1})$, where $n = |V(G)|$, $m = |E(G)|$ and $k = |R|$.*

Proof Let $v, w \in V(G)$ and $\{r_0\} \subseteq I' \subseteq I \subseteq R$. To prove that \mathcal{L}_j is a valid lower bound, we have to show

$$\max_{\substack{\{r_0\} \subseteq J \subseteq I \cup \{v\} \\ |J| \leq j+1}} \text{smt}(J) \leq \max_{\substack{\{r_0\} \subseteq J' \subseteq I' \cup \{w\} \\ |J'| \leq j+1}} \text{smt}(J') + \text{smt}((I \setminus I') \cup \{v, w\}).$$

Consider the map $f : I \cup \{v\} \rightarrow I' \cup \{w\}$ with $f(x) = w$ for $x \notin I'$ and $f(x) = x$ otherwise. Let J be a set with $\{r_0\} \subseteq J \subseteq I \cup \{v\}$ and $|J| \leq j + 1$. Set $J' = \{f(x) : x \in J\}$. Then, clearly $\{r_0\} \subseteq J' \subseteq I' \cup \{w\}$ and $|J'| \leq |J| \leq j + 1$. Moreover,

$$\text{smt}(J) \leq \text{smt}(J') + \text{smt}((I \setminus I') \cup \{v, w\}).$$

To achieve the given run time, we first compute $\text{smt}(\{v\} \cup I)$ for all $v \in V(G)$ and $I \subseteq R$ with $|I \setminus \{r_0\}| \leq j - 1$ in time $\mathcal{O}((2k)^{j-1}n + k^{j-1}(n \log n + m))$ using a modified variant of the Dijkstra–Steiner algorithm. More precisely, we do not use a lower bound, do not use a root terminal and consider terminal sets of increasing cardinality, very similar to [11]. There are $\mathcal{O}(k^{j-1})$ sets I with $I \subseteq R, |I \setminus \{r_0\}| \leq j - 1$. Since we consider terminal sets of increasing cardinality one after another, we always have at most n labels in the Fibonacci heap. As a set of cardinality j has 2^j subsets, there are $\mathcal{O}((2k)^{j-1}n)$ updates of supersets.

Then, to evaluate $\mathcal{L}_j(v, I)$, we exploit

$$\begin{aligned} \mathcal{L}_j(v, I) &= \max_{\{r_0\} \subseteq J \subseteq I \cup \{v\}, |J| \leq j+1} \text{smt}(J) \\ &= \max \left(\max_{J \subseteq I, |J| \leq j-1} \text{smt}(J \cup \{v, r_0\}), \max_{\{r_0\} \subseteq J \subseteq I, |J| \leq j+1} \text{smt}(J) \right), \end{aligned}$$

where the first expression can be computed in $\mathcal{O}(|I|^{j-1})$ time using the precomputed values $\text{smt}(\{v, r_0\} \cup J)$ and the second expression does not depend on v and can be computed in advance for every $I \subseteq R$ in $\mathcal{O}(3^k)$ time. □

Thus, for small j , e.g., $j \leq 3$, \mathcal{L}_j can be efficiently computed.

We now present a more effective lower bound. We will use the notion of *1-trees*, which have long been studied [19] as a lower bound for the traveling salesman problem. Given a complete graph H with metric edge costs and a special vertex $v \in V(H)$, a 1-tree for v and H is a spanning tree on $H - v$ together with two additional edges connecting v with the tree. A tour in H is a connected 2-regular subgraph of H . Since every tour consists of a path, which is a spanning tree, and a vertex connected to the endpoints of the path, every tour is a 1-tree. Thus, a 1-tree of minimum cost is a lower bound on the cost of a tour of minimum cost. Since such a tour of minimum cost is at most twice as expensive as a minimum Steiner tree, we can use 1-trees to get a lower bound for the Steiner tree problem.

For $v, w \in V(G)$, we denote by $d(v, w)$ the cost of a shortest path connecting v and w in G . Furthermore, for a set of vertices $X \subseteq V$, we denote by G_X the *distance graph* of X , which is the subgraph of the metric closure of G induced by X . Note that since the edge costs in G_X are the costs of shortest paths with respect to positive edge

costs in G , the edge costs in G_X are always metric. Moreover, for $X \subseteq V(G)$, we denote by $\text{mst}(X)$ the cost of a minimum spanning tree in G_X .

Definition 7 Let (G, c, R) be an instance of the Steiner tree problem and $r_0 \in R$. Then, the 1-tree bound $\mathcal{L}_{1\text{-tree}}$ is defined as

$$\mathcal{L}_{1\text{-tree}}(v, I) = \min_{i, j \in I: i \neq j \vee |I|=1} \frac{d(v, i) + d(v, j)}{2} + \frac{\text{mst}(I)}{2}$$

for $v \in V(G)$ and $\{r_0\} \subseteq I \subseteq R$. For $v \in V(G)$ and $I \subseteq R \setminus \{r_0\}$, we set $\mathcal{L}_{1\text{-tree}}(v, I) = 0$.

Lemma 8 Let (G, c, R) be an instance of the Steiner tree problem and $r_0 \in R$. Then, $\mathcal{L}_{1\text{-tree}}$ is a valid lower bound.

Proof Let $v, w \in V(G)$ and $\{r_0\} \subseteq I' \subseteq I \subseteq R$. We will show

$$2\mathcal{L}_{1\text{-tree}}(v, I) \leq 2\mathcal{L}_{1\text{-tree}}(w, I') + 2 \text{smt}((I \setminus I') \cup \{v, w\}),$$

which translates to

$$\begin{aligned} & \min_{i, j \in I: i \neq j \vee |I|=1} (d(v, i) + d(v, j)) + \text{mst}(I) \\ & \leq \min_{i, j \in I': i \neq j \vee |I'|=1} (d(w, i) + d(w, j)) + \text{mst}(I') + 2 \text{smt}((I \setminus I') \cup \{v, w\}). \end{aligned}$$

Consider a minimum spanning tree T_1 in $G_{I'}$ and a Steiner tree T_2 for $(I \setminus I') \cup \{v, w\}$. Furthermore, let $j_1, j_2 \in I'$ with $j_1 \neq j_2 \vee |I'| = 1$. This setting is illustrated in Fig. 3.

First, we construct a tour C in $G_{(I \setminus I') \cup \{v, w\}}$ of cost at most $2c(T_2)$ using the standard double tree argument: If we double each edge in T_2 , the graph becomes Eulerian and we can find a Eulerian cycle. If we visit the vertices in the order the Eulerian cycle visits them and skip already visited vertices, we obtain a tour of at most the same cost exploiting that the edge costs in the distance graph are metric.

We can decompose the tour into two paths P_1 and P_2 in $G_{I \cup \{v, w\}}$ with endpoints v and w such that $(I \setminus I') \cup \{v, w\} = V(P_1) \cup V(P_2)$ and $c(P_1) + c(P_2) = c(C)$. Now, for $i \in \{1, 2\}$, we define $P'_i = (V(P_i) \cup \{j_i\}, E(P_i) \cup \{\{w, j_i\}\})$, which is the path obtained by appending the edge $\{w, j_i\}$ to P_i .

If $I_1 := (I \setminus I') \cap V(P_1)$ is empty, let $j'_1 = j_1$, else, let j'_1 be the first terminal in I_1 when traversing P_1 from v to w .

Similarly, if $I_2 := (I \setminus I') \cap V(P_2)$ is empty, set $j'_2 = j_2$, else let j'_2 be the first terminal in I_2 when traversing P_2 from v to w .

Since I_1 and I_2 are disjoint and do not contain $j_1, j_2 \in I'$, we have

$$j'_1 = j'_2 \implies (j_1 = j'_1 = j'_2 = j_2 \wedge I \setminus I' = \emptyset),$$

which together with

$$j_1 = j_2 \implies |I'| = 1$$

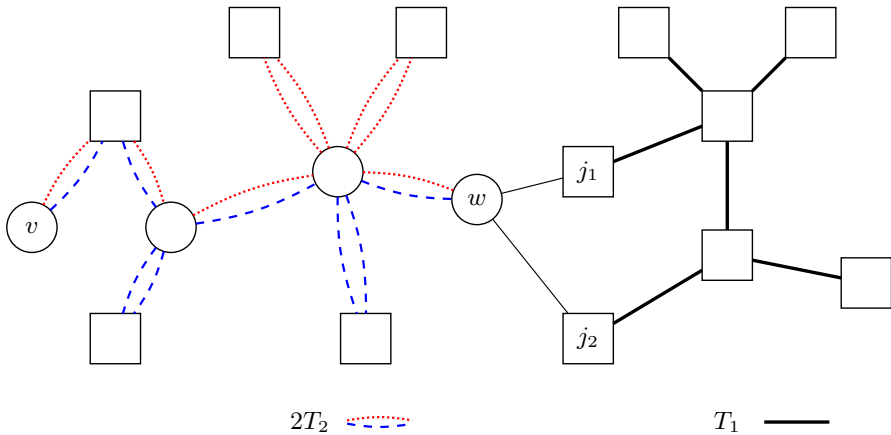


Fig. 3 The minimum spanning tree T_1 , the double Steiner tree $2T_2$ and the edges $\{w, j_1\}$ and $\{w, j_2\}$. Edges in $2T_2$ contributing to P_1 are colored red and edges contributing to P_2 are colored blue. Vertices in I are drawn as squares

implies that

$$j'_1 = j'_2 \implies |I| = 1.$$

Then, let Q_i be the path in G_I obtained from the subpath of P'_i from j'_i to j_i by skipping w . This is illustrated in Fig. 4. We have

$$d(v, j'_1) + d(v, j'_2) + d(Q_1) + d(Q_2) \leq d(w, j_1) + d(w, j_2) + 2c(T_2).$$

Also, we have $(I \setminus I') \cup \{j_1, j_2\} \subseteq V(Q_1) \cup V(Q_2)$ and clearly, we can find a spanning tree in G_I with cost at most $d(Q_1) + d(Q_2) + d(T_1)$ by attaching Q_1 and Q_2 to T_1 . Therefore,

$$\begin{aligned} \min_{i, j \in I: i \neq j \vee |I|=1} (d(v, i) + d(v, j)) + \text{mst}(I) &\leq d(v, j'_1) + d(v, j'_2) \\ &+ d(Q_1) + d(Q_2) + d(T_1) \leq d(w, j_1) + d(w, j_2) + d(T_1) + 2c(T_2). \end{aligned}$$

□

Note that we could also use half the cost of a minimum spanning tree for $I \cup \{v\}$ to obtain a valid lower bound. However, the 1-tree lower bound is always larger and hence leads to better run times.

Lemma 9 Let (G, c, R) be an instance of the Steiner tree problem and $r_0 \in R$. Then, we can implement $\mathcal{L}_{1\text{-tree}}$ such that after a preprocessing time of $\mathcal{O}(k(n \log n + m) + 2^k k^2)$, we can evaluate $\mathcal{L}_{1\text{-tree}}$ for every $v \in V(G)$ and $\{r_0\} \subseteq I \subseteq R$ in time $\mathcal{O}(|I|)$, where $n = |V(G)|$, $m = |E(G)|$ and $k = |R|$.

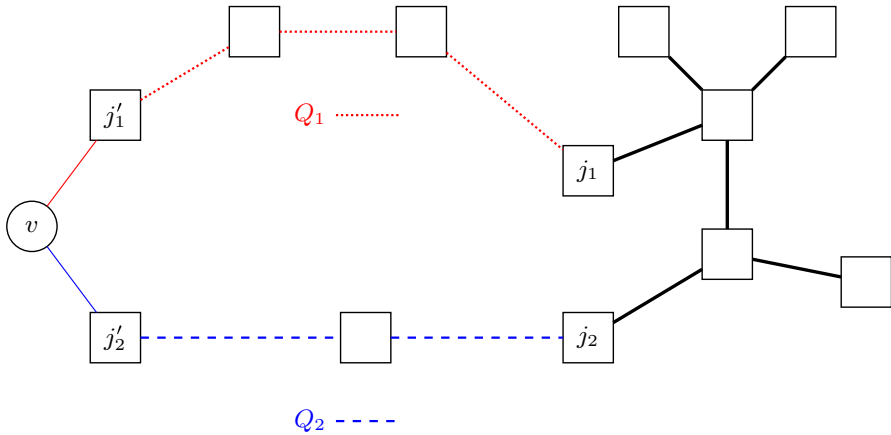


Fig. 4 j'_1, j'_2, Q_1 and Q_2 in the same setting as in Fig. 3

Proof First, for every terminal $s \in R$, we compute $d(v, s)$ for all $v \in V(G)$ in $\mathcal{O}(n \log n + m)$ time using Dijkstra’s algorithm implemented with a Fibonacci heap [14]. For every $I \subseteq R$, we compute $\text{mst}(I)$ in $\mathcal{O}(|I|^2)$ time using Prim’s algorithm [28]. This results in a total preprocessing time of $\mathcal{O}(k(n \log n + m) + 2^k k^2)$. Clearly,

$$\min_{i, j \in I: i \neq j \vee |I|=1} (d(v, i) + d(v, j))$$

can be evaluated in $\mathcal{O}(|I|)$ time if $d(v, i)$ is known for all $v \in V(G)$ and $i \in I$. \square

Of course, in practice we do not compute minimum spanning trees for all sets of terminals in advance, but compute them dynamically when needed.

Theorem 10 *Let $j \in \mathbb{N}$ be a constant. Let (G, c, R) be an instance of the Steiner tree problem and $r_0 \in R$. Then, we can compute $\text{smt}(R)$ in time $\mathcal{O}(3^k n + 2^k(n \log n + m))$ using the Dijkstra–Steiner algorithm with $\mathcal{L} = \max(\mathcal{L}_j, \mathcal{L}_{1\text{-tree}})$.*

The 1-tree lower bound exploits the fact that 1-trees can be used to compute lower bounds on the minimum cost of a tour, which in turn is at most twice as expensive as a minimum cost Steiner tree. Using more preprocessing and evaluation time, we can eliminate the loss of approximating tours by 1-trees by using *optimum tours* to get lower bounds. While it may sound unreasonable to use optimum solutions for an NP-hard problem to speed up another algorithm, it turns out we can compute optimum tours for the union of sets of terminals and at most one vertex quite fast if there are only few terminals. This is due to the fact that the cost of an optimum tour in $G_{I \cup \{v\}}$ only depends on the distances from terminals to v and shortest Hamiltonian paths with given endpoints in G_I , which can be computed in advance. For a set of vertices $X \subseteq V(G)$, we denote by $\text{tsp}(X)$ the minimum cost of a Hamiltonian circuit in G_X .

Definition 11 Let (G, c, R) be an instance of the Steiner tree problem and $r_0 \in R$. Then, the TSP bound \mathcal{L}_{TSP} is defined as

$$\mathcal{L}_{\text{TSP}}(v, I) = \frac{\text{tsp}(I \cup \{v\})}{2}$$

for $v \in V(G)$ and $I \subseteq R$.

Lemma 12 Let (G, c, R) be an instance of the Steiner tree problem and $r_0 \in R$. Then, \mathcal{L}_{TSP} is a valid lower bound. Moreover, after a preprocessing time of $\mathcal{O}(k(n \log n + m) + 2^k k^3)$, we can evaluate $\mathcal{L}_{\text{TSP}}(v, I)$ in time $\mathcal{O}(|I|^2)$ for all $v \in V(G)$ and $I \subseteq R$.

Proof Let $v, w \in V(G)$ and $\{r_0\} \subseteq I' \subseteq I \subseteq R$. We will show

$$2\mathcal{L}_{\text{TSP}}(v, I) \leq 2\mathcal{L}_{\text{TSP}}(w, I') + 2 \text{smt}((I \setminus I') \cup \{v, w\}),$$

which is equivalent to

$$\text{tsp}(I \cup \{v\}) \leq \text{tsp}(I' \cup \{w\}) + 2 \text{smt}((I \setminus I') \cup \{v, w\}).$$

First, we choose an optimal tour C_1 in $G_{I' \cup \{w\}}$. Then, we construct a tour C_2 in $G_{(I \setminus I') \cup \{v, w\}}$ of cost at most $2 \text{smt}((I \setminus I') \cup \{v, w\})$ by doubling the edges of an optimum Steiner tree, finding a Eulerian walk and taking shortcuts. We have $I \cup \{v\} = V(C_1) \cup V(C_2)$ and $w \in V(C_1) \cap V(C_2)$, so we can construct a tour in $G_{I \cup \{v\}}$ by inserting C_2 into C_1 after w and taking shortcuts, which results in a tour of cost of at most

$$\text{tsp}(I' \cup \{w\}) + 2 \text{smt}((I \setminus I') \cup \{v, w\}).$$

We achieve the given run time using a dynamic programming approach very similar to the TSP algorithm by Held and Karp [18]. The idea is to compute shortest Hamiltonian paths in the distance graph of the terminals for all possible pairs of endpoints. Then, one can evaluate $\mathcal{L}_{\text{TSP}}(v, I)$ in $\mathcal{O}(|I|^2)$ time by enumerating all possible pairs of neighbors of v in the tour. □

4 Pruning

In this section, we present techniques to speed up the algorithm further by discarding labels (v, I) for which we can prove that they cannot contribute to an optimum solution. This affects the number of iterations, since these labels then are not chosen in line 8 of the algorithm. Also, it speeds up the execution of line 18, since we only have to consider existing labels in the merge step. First, we show how to identify labels that cannot contribute to an optimum solution. Then we show that we can indeed safely discard them in our algorithm.

Definition 13 Let (G, c, R) be an instance of the Steiner tree problem, $(v, I) \in V(G) \times 2^R$ and T be a Steiner tree for R . A tree T_1 is said to be a (v, I) -subtree of T if there exists a tree T_2 such that

- (i) $V(T_1) \cup V(T_2) = V(T)$,
- (ii) $V(T_1) \cap V(T_2) = \{v\}$,
- (iii) T_1 is a subtree of T containing $\{v\} \cup I$ and
- (iv) T_2 is a subtree of T containing $\{v\} \cup (R \setminus I)$.

For a tree T and a (v, I) -subtree T_1 of T , we will also refer to the corresponding subtree T_2 by $T - T_1$.

Lemma 14 *Let (G, c, R) be an instance of the Steiner tree problem and $r_0 \in R$. Let \mathcal{L} be a valid lower bound and $U \geq \text{smt}(R)$. Furthermore, let $v \in V(G)$, $I \subseteq R \setminus \{r_0\}$ and T_1 be a tree in G containing $\{v\} \cup I$ with*

$$c(T_1) + \mathcal{L}(v, R \setminus I) > U.$$

Then, there is no optimum Steiner tree for R containing T_1 as a (v, I) -subtree.

Proof Let T be a Steiner tree for R such that T_1 is a (v, I) -subtree of T . Then,

$$\begin{aligned} c(T) &= c(T_1) + c(T - T_1) \\ &\geq c(T_1) + \text{smt}(\{v\} \cup (R \setminus I)) \\ &= c(T_1) + \text{smt}(\{v, r_0\} \cup ((R \setminus I) \setminus \{r_0\})) + \mathcal{L}(r_0, \{r_0\}) \\ &\geq c(T_1) + \mathcal{L}(v, R \setminus I) \\ &> U \\ &\geq \text{smt}(R). \end{aligned}$$

□

Lemma 14 is a trivial exploitation of the lower bound \mathcal{L} . Its effect on the run time of the algorithm is rather limited, since we only discard labels that would never have been labeled permanently anyway. In contrast, the following lemma allows significant run time improvements of our algorithm, in particular on geometric instances. An application is illustrated in Fig. 5.

Lemma 15 *Let (G, c, R) be an instance of the Steiner tree problem, $v \in V(G)$, $I \subset R$ and $\emptyset \neq S \subseteq R \setminus I$. Furthermore, let T_1 be a Steiner tree for $\{v\} \cup I$ and H be a subgraph of G with*

- (i) $(I \cup S) \subseteq V(H)$,
- (ii) each connected component of H contains a terminal in S and
- (iii) $c(H) < c(T_1)$.

Then, there is no optimum Steiner tree for R in G containing T_1 as a (v, I) -subtree.

Proof Let T be a Steiner tree for R in G containing T_1 as a (v, I) -subtree. Then, there exists a tree T_2 containing $\{v\} \cup (R \setminus I)$ with $c(T) = c(T_1) + c(T_2)$. We construct a subgraph T' of G containing R by $T' = T_2 + H$. As H contains a path from every

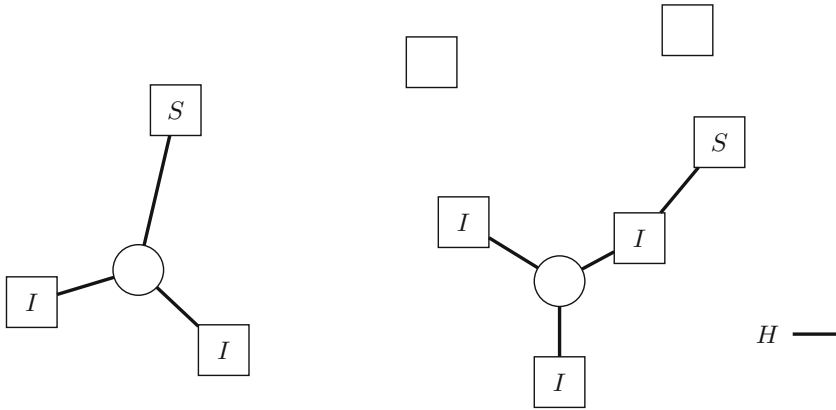


Fig. 5 By Lemma 15, no label for the set I with cost strictly larger than $c(H)$ can be part of an optimum solution. Terminals are drawn as squares, elements of I and S are labeled with the respective set

vertex in H to some vertex in S , T_2 is connected and $S \subseteq R \setminus I \subseteq V(T_2)$, T' is connected. Thus,

$$\begin{aligned}
 \text{smt}(R) &\leq c(T') \\
 &\leq c(T_2) + c(H) \\
 &= c(T) - c(T_1) + c(H) \\
 &< c(T).
 \end{aligned}$$

□

In Sect. 5, we will explain how suitable graphs H can be found. Lemmata 14 and 15 allow us to identify labels that cannot contribute to an optimum solution. Theorem 17 shows that we can discard these labels without affecting the correctness of the algorithm. First, we prove an auxiliary lemma used in the proof of Theorem 17:

Lemma 16 *Let (G, c, R) be an instance of the Steiner tree problem and $r_0 \in R$. Let $O \subseteq V(G) \times 2^{R \setminus \{r_0\}}$ be the set of pairs (v, I) with the property that there is an optimum Steiner tree for R containing a (v, I) -subtree. Furthermore, let $(v, I) \in O$ and T_1 be a tree containing $\{v\} \cup I$ with $c(T_1) = \text{smt}(\{v\} \cup I)$. Then, there is an optimum Steiner tree T for R containing T_1 as a (v, I) -subtree.*

Proof Since $(v, I) \in O$, there is an optimum Steiner tree T' for R and a tree T'_1 which is a (v, I) -subtree of T' . Set $T = (T' - T'_1) + T_1$. Then, since $T' - T'_1$ is a tree containing $\{v\} \cup (R \setminus I)$ and T_1 is a tree containing $\{v\} \cup I$, T is a connected subgraph of G containing $\{v\} \cup R$. Furthermore, we have

$$\begin{aligned}
 \text{smt}(R) &\leq c(T) \leq c(T' - T'_1) + c(T_1) \\
 &= c(T' - T'_1) + \text{smt}(\{v\} \cup I)
 \end{aligned}$$

$$\begin{aligned}
 &= c(T') - c(T'_1) + \text{smt}(\{v\} \cup I) \\
 &\leq c(T') \\
 &= \text{smt}(R).
 \end{aligned}$$

Since we do not have edges of zero cost, this shows T is an optimum Steiner tree and T_1 is a (v, I) -subtree of T . □

We now formalize a general method of pruning:

<p>Procedure <code>prune</code> (v, I)</p> <p>1 if we can prove that there is no optimum Steiner tree T for R such that <code>backtrack</code>(v, I) is the edge set of a (v, I)-subtree of T then</p> <p>2 $N := N \setminus \{(v, I)\};$</p> <p>3 end</p>
--

Note that when considering a not permanently labeled element $(v, I) \in N$, we cannot guarantee that `backtrack` (v, I) is the edge set of a tree, since it may contain cycles. However, if it is not a tree, we can prune (v, I) obviously.

Theorem 17 *The Dijkstra–Steiner algorithm still works correctly if we modify it to execute `prune` (w, I) after line 15 and `prune` $(v, I \cup J)$ after line 22.*

Proof Let $O \subseteq V(G) \times 2^{R \setminus \{r_0\}}$ be the set of pairs (v, I) with the property that there is an optimum Steiner tree for R containing a (v, I) -subtree. It suffices that the modified algorithm is correct on O , which we will now prove.

To this end, we modify invariants (a)–(d) as defined in the proof of Theorem 2 by restricting (a)–(c) to labels $(v, I) \in O$ and not changing (d). We call these new invariants (a')–(d').

Since $(r_0, R \setminus \{r_0\}) \in O$, the algorithm is correct assuming that these invariants hold. They clearly hold after the initialization.

Moreover, (a'), (c1') and (c2') are clearly preserved. To see that (c3') is preserved, recall that `prune` only removes labels (v, I) from N if there is no optimum Steiner tree T for R such that `backtrack` (v, I) is the edge set of a (v, I) -subtree of T . However, if $(v, I) \in O$ and $l(v, I) = \text{smt}(\{v\} \cup I)$, by (a3') and Lemma 16 the label (v, I) cannot be pruned, so (c3') is preserved as well.

The argument showing that (b) is preserved remains unchanged: (c') can be applied to (w, I') , because if $(v, I) \in O$, then (w, I') is in O as well. This directly implies that the same argument as in the proof of Theorem 2 can be used to prove that (d') is preserved, since $(r_0, R \setminus \{r_0\}) \in O$. □

Of course, in practice we just avoid the creation of such labels instead of removing them immediately after creation. Moreover, whenever a label (v, I) is selected in line 8, we also try to prune it. This is not redundant, since after $l(v, I)$ was updated the last time, bounds used to prune may have improved. Moreover, we could have pruned (v, I) immediately after the last update of $l(v, I)$ with an equivalent impact on the execution of the algorithm, so the algorithm still works correctly.

5 Implementation and results

We implemented the algorithm using the C++ programming language. In our implementation, we use a binary heap instead of a Fibonacci heap, since binary heaps performed better in our experiments.

Our implementation is limited to instances with less than 64 terminals, allowing us to uniquely represent terminal sets by 64-bit words using the canonical bijection $2^R \rightarrow \{0, \dots, 2^{|R|} - 1\}$. Basic operations on sets like union and intersection can be performed using a single bitwise instruction.

For each vertex $v \in V(G)$, we maintain an array containing the labels (v, I) with $l(v, I) < \infty$ and a lookup table storing for each label its index in the array, if it exists. This enables us to access labels very quickly and traverse over the existing labels in linear time, which is important for an efficient implementation of the merge step:

To implement line 18, we have two options. Either we explicitly enumerate all sets $J \subseteq (R \setminus \{r_0\}) \setminus I$ and check whether the label (v, J) exists, or we traverse over all existing labels at v and omit the labels (v, J) with $J \cap I \neq \emptyset$. We always choose the option resulting in fewer sets to be considered.

We implement the pruning rule of Lemma 14 using a shortest-paths Steiner tree heuristic similar to Prim's algorithm [28], maintaining and extending one component at a time. This takes $\mathcal{O}(k(n \log n + m))$ time. Then, we use the cost of that Steiner tree as an upper bound and apply Lemma 14 each time we create a new label.

To implement Lemma 15, we maintain an upper bound $U(I)$ on the cost of labels for each set $I \subseteq R \setminus \{r_0\}$ of terminals, which is initially set to infinity. For each occurring set $I \subseteq R \setminus \{r_0\}$, we compute the distance $d(I, R \setminus I) = \min_{x \in I, y \in R \setminus I} d(x, y)$. Then, each time we extract a label (v, I) from the heap, we update $U(I)$ by

$$U(I) := \min(U(I), l(v, I) + \min(d(I, R \setminus I), d(v, R \setminus I))).$$

Also, we keep track of the set $S(I)$ that was used to generate the currently best upper bound for the set I . In the routine described above, we always have $|S| = 1$. However, when merging two sets I_1 and I_2 , we can use the sum of their upper bounds as an upper bound for the set $I_1 \cup I_2$ if $S(I_1) \cap I_2 = \emptyset$ or $S(I_2) \cap I_1 = \emptyset$, resulting in $S(I_1 \cup I_2) = (S(I_1) \cup S(I_2)) \setminus (I_1 \cup I_2)$.

Lacking a good selection strategy for general instances, we always choose the last terminal of the instance w.r.t. the order in the instance file as root terminal.

The rest of this section is organized as follows: First, in Sect. 5.1, we demonstrate the impact of lower bounds and pruning on the practical run time of the algorithm and compare our algorithm with the dynamic programming algorithm by Erickson et al. [11] which achieves the same worst-case run time. Then, in Sect. 5.2, we compare our algorithm with the state-of-the-art algorithm by Polzin and Vahdati Daneshmand [27]. Finally, in Sect. 5.3, we consider the special case of the d -dimensional rectilinear Steiner tree problem for $d \in \{3, 4, 5\}$. All results of our algorithm were achieved single-threaded on a computer with 3.33 GHz Intel Xeon W5590 CPUs, which produced a score of 391 for the DIMACS benchmark.

5.1 Impact of lower bounds and pruning

Now, we compare the algorithm by Erickson et al. with our algorithm and discuss the impact of lower bounds and pruning. We reimplemented the algorithm by Erickson et al. using the same terminal set representation and the same heap as used in the implementation of our algorithm. Recall that this algorithm considers all sets $I \subseteq R \setminus \{r_0\}$ in order of non-decreasing cardinality and computes $\text{smt}(\{v\} \cup I)$ for all $v \in V(G)$, leading to a run time of $\Theta(3^k n) + \mathcal{O}(2^k(n \log n + m))$ and memory consumption of $\Theta(2^k n)$.

For these experiments, we implemented the lookup table in our algorithm storing indices of labels (v, I) for each $v \in V(G)$ using an array of length 2^{k-1} . We compare three lower bound configurations for our algorithm: The trivial lower bound $\mathcal{L} \equiv 0$, the lower bound $\max(\mathcal{L}_{1\text{-tree}}, \mathcal{L}_2)$ which can be evaluated in $\mathcal{O}(k)$ time and $\max(\mathcal{L}_{\text{TSP}}, \mathcal{L}_3)$ which can be evaluated in $\mathcal{O}(k^2)$ time. For each of these configurations, we test the algorithm with and without pruning. Despite all edge costs being integral, the 1-tree bound and the TSP bound may be non-integral. Note that if all costs are integral, a valid lower bound stays valid when rounded up. Hence, we round $\mathcal{L}_{1\text{-tree}}$ and \mathcal{L}_{TSP} up, leading to slightly improved bounds and allowing exact integer arithmetic.

Computational results on instances of the 11th DIMACS implementation challenge [1] are given in Table 1. For each instance, we give its name, the number of vertices, edges, terminals and its type. Then, we provide results for the algorithm by Erickson et al. [11] as well as the Dijkstra–Steiner algorithm, indicated by DS. For the latter, we further indicate which lower bound was used and whether pruning was enabled. For each result, we give the number of permanent labels (v, I) at the termination of the algorithm. For the Dijkstra–Steiner algorithm, this coincides with the number of iterations of the algorithm. Furthermore, we give the number of encountered terminal sets and the run time in seconds.

Not surprisingly, running the Dijkstra–Steiner algorithm without lower bounds and pruning leads to significantly worse run times compared to the algorithm by Erickson et al. (except for es20fst10). This is caused by the number of permanent labels decreasing only slightly for lin24 and staying the same for wrp3-17 and cc3-5p, while the run time per label is increased in our algorithm. Note that our algorithm is more complicated than the algorithm by Erickson et al. Also, the implementation of our algorithm is tuned for the case that much less than 2^{k-1} labels are created per vertex: Instead of storing the labels directly in a table, we store them in a separate array for fast traversal and only store indices to that array in a lookup table, slowing down access to labels.

Except for the artificial instance cc3-5p, lower bounds significantly reduce the number of labels. As expected, the stronger lower bound leads to even less labels. In particular, the variant using the strongest lower bound $\max(\mathcal{L}_{\text{TSP}}, \mathcal{L}_3)$ is faster than the algorithm by Erickson et al. Note that on the instance es20fst10, the preprocessing run time of $\Theta(2^k k^3)$ dominates the run time for the TSP bound.

On the geometric instances lin24 and es20fst10, pruning is extremely effective. Even without lower bounds, the number of labels and hence the run time is reduced by orders of magnitudes. In contrast, on the group Steiner tree instance wrp3-17, our pruning implementation has nearly no effect. This can be explained as follows. Although these instances are based on VLSI-derived grid graphs with holes as well, they have been modified to model the groups as terminals: For each group of the

Table 1 Impact of lower bounds and pruning

Instance	$ V $	$ E $	$ R $	Solver	\mathcal{L}	Prune	Labels	Sets	Time (s)
lin24	7998	14734	16	[11] DS DS DS	0 0 $\max(\mathcal{L}_1\text{-tree}, \mathcal{L}_2)$	No Yes No	262,070,466 260,911,042 77,126	32,767 32,767 445	684.24 5241.77 0.43
Type: VLSI-derived grid graph with holes				DS DS DS	$\max(\mathcal{L}_1\text{-tree}, \mathcal{L}_2)$ $\max(\mathcal{L}_1\text{-tree}, \mathcal{L}_2)$ $\max(\mathcal{L}_{TSP}, \mathcal{L}_3)$ $\max(\mathcal{L}_{TSP}, \mathcal{L}_3)$	Yes No Yes	31,447,839 73,900 4,781,074 61,503	32,767 445 31,690 423	1220.21 0.48 115.91 1.50
es20fst10	49	67	20	[11] DS DS	0 0	No Yes	25,690,063 7,098,990 1069	524,287 374,815 247	285.58 105.71 0.05
Type: Rectilinear instance after FST-preprocessing by GeoSteiner				DS DS DS	$\max(\mathcal{L}_1\text{-tree}, \mathcal{L}_2)$ $\max(\mathcal{L}_1\text{-tree}, \mathcal{L}_2)$ $\max(\mathcal{L}_{TSP}, \mathcal{L}_3)$ $\max(\mathcal{L}_{TSP}, \mathcal{L}_3)$	No Yes No Yes	322,620 1029 40,216 754	285,750 247 64,747 237	8.28 0.05 10.83 10.32

Table 1 continued

Instance	$ V $	$ E $	$ R $	Solver	\mathcal{L}	Prune	Labels	Sets	Time (s)
wrp3-17	177	354	17	[11]			11,599,695	65,535	37.88
				DS	0	No	11,599,695	65,535	125.12
				DS	0	Yes	11,403,289	65,535	215.49
				DS	$\max(\mathcal{L}_{1\text{-tree}}, \mathcal{L}_2)$	No	5,177,416	65,535	193.50
				DS	$\max(\mathcal{L}_{1\text{-tree}}, \mathcal{L}_2)$	Yes	5,174,919	65,535	284.01
Type: Group Steiner tree instance				DS	$\max(\mathcal{L}_{\text{TSP}}, \mathcal{L}_3)$	No	14,523	3180	0.86
				DS	$\max(\mathcal{L}_{\text{TSP}}, \mathcal{L}_3)$	Yes	14,526	3179	0.89
				[11]			511,875	4095	0.22
				DS	0	No	511,875	4095	2.33
cc3-5p	125	750	13	DS	0	Yes	343,916	4095	1.18
				DS	$\max(\mathcal{L}_{1\text{-tree}}, \mathcal{L}_2)$	No	506,462	4095	3.90
				DS	$\max(\mathcal{L}_{1\text{-tree}}, \mathcal{L}_2)$	Yes	332,103	4095	1.87
				DS	$\max(\mathcal{L}_{\text{TSP}}, \mathcal{L}_3)$	No	483,683	4095	4.46
				DS	$\max(\mathcal{L}_{\text{TSP}}, \mathcal{L}_3)$	Yes	310,999	4095	2.27
Type: Artificial instance from the hard PUC testset				DS	0	Yes	343,916	4095	1.18
				DS	$\max(\mathcal{L}_{1\text{-tree}}, \mathcal{L}_2)$	No	506,462	4095	3.90
				DS	$\max(\mathcal{L}_{1\text{-tree}}, \mathcal{L}_2)$	Yes	332,103	4095	1.87
				DS	$\max(\mathcal{L}_{\text{TSP}}, \mathcal{L}_3)$	No	483,683	4095	4.46
				DS	$\max(\mathcal{L}_{\text{TSP}}, \mathcal{L}_3)$	Yes	310,999	4095	2.27

group Steiner tree instance, a new terminal is added to the graph and connected to the elements of the group by edges of very high cost. By choosing the cost of these new edges sufficiently large, one can guarantee that an optimum Steiner tree in the new instance corresponds to an optimum group Steiner tree in the original instance and vice versa, since each terminal will be a leaf of the Steiner tree. To prune a label $(v, I) \in V(G) \times 2^{R \setminus \{r_0\}}$, our implementation needs to connect the terminal set I to at least one additional terminal $s \in R \setminus I$ with cost strictly less than the cost of the label (v, I) . However, on these instances, connecting to an additional terminal is always much more expensive than any path in the original graph. Hence, no labels are pruned at non-terminals. On the artificial instance cc3-5p, pruning roughly halves run time, which still leads to a worse run time compared to the classical dynamic programming approach.

When combining lower bounds and pruning, albeit slightly improving the number of labels, run times are not improved compared to only using pruning on the geometric instances. However, on the group Steiner tree instance wrp3-17, where our pruning implementation has no effect, lower bounds still reduce the number of labels, with the stronger lower bound $\max(\mathcal{L}_{\text{TSP}}, \mathcal{L}_3)$ improving the run time significantly. Note that the 1-tree bound and the TSP bound completely incorporate the expensive edges incident to terminals.

In summary, on some instance classes including geometric instances, our algorithm significantly improves upon the classical dynamic programming algorithm by Erickson et al. This becomes even more evident in the results in Tables 2 and 3, where instances with more than 40 terminals are solved. For these instances, the Erickson et al. best-case run time of $\Omega(3^k n)$ clearly is impractical.

5.2 Comparison with the state of the art

Despite the TSP bound being significantly stronger on some instances, its required preprocessing leads to an exponential best-case run time. Hence, in the following experiments, we use the 1-tree bound as a lower bound. Also, in order to avoid the exponential best-case memory consumption, we replace the array of length 2^{k-1} by a hash table as lookup table for labels. This modification improves the run time on lin24, where much less than $2^{k-1}n$ labels are generated, but leads to worse run times on wrp3-17 and cc3-5p, where the used lower bound and pruning have little effect.

We now compare our results with those obtained by the state-of-the-art algorithm by Polzin and Vahdati Daneshmand [27] on instances of the 11th DIMACS implementation challenge [1]. Their results were obtained using one thread on a computer with a 2.66 GHz Intel i7 920 CPU which produced a score of 307 in the DIMACS benchmark. The algorithm by Polzin and Vahdati Daneshmand successively performs various optimality-preserving reductions combined with a branch and bound approach.

In Table 2, we show results on multiple instance classes (a)–(e). For each instance, we give its name, the number of vertices, edges and terminals. Then, we state the cost of an optimum solution as reported by our algorithm and the run time in seconds. Moreover, for each instance, we give the run time reported by Polzin and Vahdati Daneshmand. For the lin testset, Polzin and Vahdati Daneshmand improved run times

Table 2 Results on various instance types

Instance	$ V $	$ E $	$ R $	Opt	Time (s)	Time PV (s)
(a) VLSI-derived grid graphs with holes						
diw0779	11,821	22,516	50	4440	1.60	1.26
diw0819	10,553	20,066	32	3399	0.29	0.52
diw0820	11,749	22,384	37	4167	1.50	1.06
lin23	3716	6750	52	17,560	11.08	0.54
lin24	7998	14,734	16	15,076	0.10	1.73
lin30	19,091	35,644	31	27,684	0.68	14.74
lin32	19,112	35,665	53	39,832	150.20	816.51
lin34	38,282	71,521	34	45,018	12.93	1848.24
lin35	38,294	71,533	45	50,559	26.90	1911.09
lin36	38,307	71,546	58	55,608	47.59	39,931.77
(b) Rectilinear obstacle-avoiding instances preprocessed by ObSteiner						
ind5	114	228	33	1341	0.02	0.01
rc03	109	202	50	54,160	0.15	0.00
rt02	788	1938	50	45,852	0.70	1.99
(c) Group Steiner tree instances						
wrp3-14	128	247	14	1,400,250	3.78	0.01
wrp3-15	138	257	15	1,500,422	51.16	0.01
wrp3-16	204	374	16	1,600,208	11.62	0.03
wrp3-17	177	354	17	1,700,442	422.08	0.02
wrp3-19	189	353	19	1,900,439	1765.72	0.03
(d) Random graphs with so-called incidence costs						
i160-141	160	2544	12	2549	3.40	0.01
i320-111	320	1845	17	4273	1706.67	0.03
i640-022	640	204,480	9	1756	4.03	0.52
i640-031	640	1280	9	3278	0.07	0.00
i640-043	640	40,896	9	1931	0.89	0.13
(e) Artificial instances from the hard PUC testset						
cc3-4p	64	288	8	2338	0.01	1.99
cc3-4u	64	288	8	23	0.01	1.37
cc3-5p	125	750	13	3661	3.45	87.98
cc3-5u	125	750	13	36	4.64	115.83
cc6-2p	64	192	12	3271	0.17	0.40
cc6-2u	64	192	12	32	0.28	0.90

by modifying their algorithm to use stronger reductions. With default settings, their algorithm did not solve lin36 within a time limit of 24 h.

On instances (a) and (b), both arising from rectilinear VLSI problems, our algorithm is much faster than the worst-case bound tells. This is primarily caused by the high impact of our pruning method as seen in Table 1. In particular, on instances with large

underlying graphs, our algorithm performs very well, beating the reduction-based solver.

On group Steiner tree instances (c), our pruning implementation has no effect. Here, the reduction-based solver yields much better results. Note that the stronger TSP bound still improves run time significantly on these instances as seen in Table 1. On incidence cost instances (d), where edges incident to terminals are assigned larger costs, a similar effect can be observed.

Although neither pruning nor lower bounds do have a significant effect on instances from the hard PUC testset (e), our algorithm performs very well on instances with few terminals. This is caused by the strong worst-case run time guarantee, which, albeit exponential in the number of terminals, is quasilinear in the size of the graph. Note that on these instances, the classical algorithm by Erickson et al. [11] yields even better run times. Detailed further computational results can be found in Appendix 1.

5.3 d -dimensional rectilinear Steiner tree problem

We also applied our algorithm to the d -dimensional rectilinear Steiner tree problem for $d \in \{3, 4, 5\}$. For $d = 2$, instances with thousands of terminals can be solved by the GeoSteiner algorithm [34], which works by generating a candidate set of full Steiner trees for subsets of terminals and then concatenating a subset of these candidates to form an optimum Steiner tree. A full Steiner tree is a Steiner tree where each terminal has degree 1. The concatenation phase works by either solving a Steiner tree problem in graphs or a minimum spanning tree problem in hypergraphs. Exploiting a result by Hwang [21], the GeoSteiner algorithm only has to consider full Steiner trees following a special structure, which allows a significant reduction of the number of generated candidates. In contrast, for higher dimensions, eliminating possible full Steiner trees is much harder, as Hwang's result does not apply and complicated full Steiner trees have to be considered [36]. An implementation of the GeoSteiner algorithm for higher dimension is only able to solve instances with up to around 15 terminals in dimension 3 and up to around 10 terminals in dimensions 4, 5 and 6 [36]. The situation is similar in the Euclidean case, where huge instances can be solved for $d = 2$ using the GeoSteiner algorithm, but only instances with up to around 17 terminals for $d \geq 3$, using very different algorithms [13].

It is well-known that to compute an optimum rectilinear Steiner tree in dimension 2, it suffices to compute an optimum Steiner tree in the so-called Hanan grid [16]. The Hanan grid is the graph obtained by drawing axis-parallel lines through each terminal, taking intersections of these lines as vertex set and segments between intersections as edges. This result was later generalized to arbitrary dimension by Snyder [30], leading to a grid graph with $\mathcal{O}(k^d)$ vertices and $\mathcal{O}(dk^d)$ edges for a d -dimensional instance with k terminals.

Using this reduction, we ran our algorithm on instances from the CARIOCA [1] testset, which contains randomly generated instances for $d \in \{3, 4, 5\}$ with between 11 and 20 terminals. To test our algorithm on larger instances, we generated new random instances (using the prefix “bonn”), as other available testsets do not contain sufficiently many instances which are neither too small nor too large. For these new

Table 3 Results on d -dimensional rectilinear instances

Instance	d	$ V $	$ E $	$ R $	Opt	Time (s)
carioca_3_11_01	3	1331	3630	11	311,221,222	0.02
carioca_3_11_02	3	1331	3630	11	466,149,453	0.02
carioca_3_20_01	3	8000	22,800	20	638,376,617	1.61
carioca_3_20_02	3	8000	22,800	20	477,950,448	0.15
bonn_3_40_1	3	64,000	187,200	40	9024	25.44
bonn_3_40_2	3	57,798	168,909	40	9633	710.09
bonn_3_55_3	3	154,548	455,004	55	12,138	6201.10
carioca_4_11_01	4	14,641	53,240	11	627,022,001	0.43
carioca_4_11_02	4	14,641	53,240	11	636,772,154	0.22
carioca_4_20_01	4	160,000	608,000	20	889,180,827	82.72
carioca_4_20_02	4	160,000	608,000	20	822,698,792	101.11
carioca_5_11_01	5	161,051	732,050	11	925,163,690	34.55
carioca_5_11_02	5	161,051	732,050	11	844,673,618	13.02
carioca_5_15_01	5	759,375	3,543,750	15	1,011,895,745	1046.36
carioca_5_15_02	5	759,375	3,543,750	15	1,067,623,193	888.81
carioca_5_18_03	5	1,889,568	8,922,960	18	1,177,091,608	1081.01

instances, coordinates were chosen uniformly at random from $\{0, 1, \dots, 999\}$. In particular for the larger instances, coordinates may appear multiple times, leading to grid graphs with slightly less than k^d vertices. Coordinates of instances from the CARIOCA testset were scaled by 10^8 to obtain integral coordinates. For these instances, we chose a terminal as close as possible to the center of gravity of all terminals as root terminal, improving results compared to a random choice.

Excerpts of experimental results are given in Table 3, the full results can be found in Appendix 1. In dimension 3, we are able to solve all tested instances with up to 34 terminals. Many of the larger instances with up to 40 terminals are solved as well, and additionally one instance with 55 terminals. In dimension 4, we solve all instances of the CARIOCA testset as well. Experiments with larger instances are not reported here, since we were only able to solve instances with up to 22 terminals. In dimension 5, all instances with up to 15 terminals are solved. The largest solved instance *carioca_5_18_03* has 18 terminals and nearly 9 million edges. Solving it required approximately 20 GB of memory.

We also tried to exploit the geometric structure of these instances by using geometric lower bounds. For example, consider the bounding box bound $\mathcal{L}_{\text{BBox}}$ given by

$$\mathcal{L}_{\text{BBox}}(v, I) := \sum_{i=1}^d \left(\max_{x \in \{v\} \cup I} x_i - \min_{x \in \{v\} \cup I} x_i \right).$$

One can easily verify that $\mathcal{L}_{\text{BBox}}$ is a valid lower bound. Also note that $\mathcal{L}_{\text{BBox}} \leq \mathcal{L}_{\text{TSP}}$ and $\mathcal{L}_{\text{BBox}} \leq \mathcal{L}_{2d}$, but $\mathcal{L}_{\text{BBox}}$ can be larger than $\mathcal{L}_{1-\text{tree}}$. However, using $\mathcal{L}_{\text{BBox}}$ did not lead to better run times.

6 Discussion

Note that due to the dynamic programming nature of our algorithm, it can also be used to compute all optimum Steiner trees or even all Steiner trees up to a given cost. If we enumerate all Steiner trees up to a cost of $\text{Opt} + \Delta$, we have to relax the pruning implementations by Δ and continue labeling until all labels (v, I) with $l(v, I) \leq \text{Opt} + \Delta$ are permanent. Also, we have to save all predecessors instead of only one optimum predecessor. Then, we can recursively combine Steiner trees for subsets of terminals. In practice, the additional effort is linear in the size of the output, allowing the enumeration of millions of near-optimum Steiner trees in seconds. See [29] for details.

The dynamic programming idea by Dreyfus and Wagner has been used extensively to obtain Steiner tree algorithms with fast theoretical worst-case behavior. However, in the field of practical solving, it has rather been disregarded prior to this work. Compared to other exact algorithms, our algorithm depends much less on effective preprocessing and performs well on large graphs. Our approach is very general and not limited to the lower bounds and pruning strategies proposed in this paper.

Appendix 1: Results on graphic DIMACS instances

We present detailed computational results on DIMACS testsets. Our implementation is limited to instances with less than 64 terminals, so we exclude instances with more terminals.

The implementation of our algorithm is written in the C++ programming language and compiled using the GCC 4.8.2 compiler.

The experiments were performed single-threaded on a machine with 3.33 GHz Intel Xeon W5590 CPUs and 144 GB main memory which produced a score of 391.372724 using the DIMACS benchmark code.

For these experiments, we limited the memory consumption of the algorithm to 100 GB and set the time limit to 7200 s. The reported run times do not include the time to read the instance file from disk (Tables 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46).

Table 4 Results on the testset ALUE

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
alue2087	1244	1971	34	1049	1.075
alue2105	1220	1858	34	1032	0.204
alue7066	6405	10,454	16	2256	0.068
alue7229	940	1474	34	824	0.036

Type: VLSI-derived grid graphs with holes

Table 5 Results on the testset ALUT

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
alut0787	1160	2089	34	982	1.769
alut0805	966	1666	34	958	0.258
alut2764	387	626	34	640	0.042

Type: VLSI-derived grid graphs with holes

Table 6 Results on the testset DIW

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
diw0234	5349	10,086	25	1996	0.096
diw0250	353	608	11	350	0.002
diw0260	539	985	12	468	0.003
diw0313	468	822	14	397	0.003
diw0393	212	381	11	302	0.002
diw0445	1804	3311	33	1363	0.061
diw0459	3636	6789	25	1362	0.042
diw0460	339	579	13	345	0.004
diw0473	2213	4135	25	1098	0.065
diw0487	2414	4386	25	1424	0.373
diw0495	938	1655	10	616	0.006
diw0513	918	1684	10	604	0.006
diw0523	1080	2015	10	561	0.005
diw0540	286	465	10	374	0.002
diw0559	3738	7013	18	1570	0.089
diw0778	7231	13,727	24	2173	0.139
diw0779	11,821	22,516	50	4440	1.603
diw0795	3221	5938	10	1550	0.024
diw0801	3023	5575	10	1587	0.024
diw0819	10,553	20,066	32	3399	0.291
diw0820	11,749	22,384	37	4167	1.504

Type: VLSI-derived grid graphs with holes

Table 7 Results on the testset DMXA

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
dmxa0296	233	386	12	344	0.002
dmxa0368	2050	3676	18	1017	0.019
dmxa0454	1848	3286	16	914	0.012
dmxa0628	169	280	10	275	0.002
dmxa0734	663	1154	11	506	0.006
dmxa0848	499	861	16	594	0.041

Table 7 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
dmxa0903	632	1087	10	580	0.008
dmxa1010	3983	7108	23	1488	0.104
dmxa1109	343	559	17	454	0.007
dmxa1200	770	1383	21	750	0.069
dmxa1304	298	503	10	311	0.002
dmxa1516	720	1269	11	508	0.003
dmxa1721	1005	1731	18	780	0.012
dmxa1801	2333	4137	17	1365	0.049

Type: VLSI-derived grid graphs
with holes

Table 8 Results on the testset
GAP

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
gap1307	342	552	17	549	0.057
gap1413	541	906	10	457	0.007
gap1500	220	374	17	254	0.003
gap1810	429	702	17	482	0.013
gap1904	735	1256	21	763	0.042
gap2007	2039	3548	17	1104	0.051
gap2119	1724	2975	29	1244	0.460
gap2740	1196	2084	14	745	0.011
gap2800	386	653	12	386	0.003
gap2975	179	293	10	245	0.001
gap3036	346	583	13	457	0.013
gap3100	921	1558	11	640	0.007

Type: VLSI-derived grid graphs
with holes

Table 9 Results on the testset
LIN

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
lin01	53	80	4	503	0.000
lin02	55	82	6	557	0.000
lin03	57	84	8	926	0.001
lin04	157	266	6	1239	0.001
lin05	160	269	9	1703	0.002
lin06	165	274	14	1348	0.004
lin07	307	526	6	1885	0.002
lin08	311	530	10	2248	0.002
lin09	313	532	12	2752	0.004
lin10	321	540	20	4132	0.017
lin11	816	1460	10	4280	0.013

Table 9 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
lin12	818	1462	12	5250	0.017
lin13	822	1466	16	4609	0.017
lin14	828	1472	22	5824	0.023
lin15	840	1484	34	7145	0.088
lin16	1981	3633	12	6618	0.032
lin17	1989	3641	20	8405	0.051
lin18	1994	3646	25	9714	0.475
lin19	2010	3662	41	13,268	10.966
lin20	3675	6709	11	6673	0.029
lin21	3683	6717	20	9143	0.062
lin22	3692	6726	28	10,519	0.129
lin23	3716	6750	52	17,560	11.080
lin24	7998	14,734	16	15,076	0.104
lin25	8007	14,743	24	17,803	0.291
lin26	8013	14,749	30	21,757	0.319
lin27	8017	14,753	36	20,678	1.577
lin29	19,083	35,636	24	23,765	1.746
lin30	19,091	35,644	31	27,684	0.681
lin31	19,100	35,653	40	31,696	34.061
lin32	19,112	35,665	53	39,832	150.201
lin34	38,282	71,521	34	45,018	12.930
lin35	38,294	71,533	45	50,559	26.904
lin36	38,307	71,546	58	55,608	47.590

Type: VLSI-derived grid graphs
with holes

Table 10 Results on the testset
MSM

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
msm0580	338	541	11	467	0.006
msm0654	1290	2270	10	823	0.007
msm0709	1442	2403	16	884	0.010
msm0920	752	1264	26	806	0.041
msm1008	402	695	11	494	0.008
msm1234	933	1632	13	550	0.007
msm1477	1199	2078	31	1068	0.259
msm1707	278	478	11	564	0.001
msm1844	90	135	10	188	0.001
msm1931	875	1522	10	604	0.003
msm2000	898	1562	10	594	0.004
msm2152	2132	3702	37	1590	0.269
msm2326	418	723	14	399	0.003

Table 10 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
msm2492	4045	7094	12	1459	0.035
msm2525	3031	5239	12	1290	0.016
msm2601	2961	5100	16	1440	0.042
msm2705	1359	2458	13	714	0.017
msm2802	1709	2963	18	926	0.028
msm3277	1704	2991	12	869	0.021
msm3676	957	1554	10	607	0.006
msm3727	4640	8255	21	1376	0.079
msm3829	4221	7255	12	1571	0.042
msm4038	237	390	11	353	0.003
msm4114	402	690	16	393	0.004
msm4190	391	666	16	381	0.005
msm4224	191	302	11	311	0.002
msm4312	5181	8893	10	2016	0.042
msm4414	317	476	11	408	0.003
msm4515	777	1358	13	630	0.013

Type: VLSI-derived grid graphs
with holes

Table 11 Results on the testset
TAQ

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
taq0023	572	963	11	621	0.007
taq0365	4186	7074	22	1914	0.079
taq0431	1128	1905	13	897	0.017
taq0631	609	932	10	581	0.008
taq0739	837	1438	16	848	0.019
taq0741	712	1217	16	847	0.024
taq0751	1051	1791	16	939	0.032
taq0891	331	560	10	319	0.003
taq0910	310	514	17	370	0.010
taq0920	122	194	17	210	0.003
taq0978	777	1239	10	566	0.005

Type: VLSI-derived grid graphs
with holes

Table 12 Results on the testset 1R

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
1r111	1250	4704	6	28,000	0.006
1r112	1250	4704	6	28,000	0.005
1r113	1250	4704	6	26,000	0.005
1r121	1250	4704	6	36,000	0.004
1r122	1250	4704	6	45,000	0.006
1r123	1250	4704	6	40,000	0.004
1r131	1250	4704	6	43,000	0.005
1r132	1250	4704	6	37,000	0.005
1r133	1250	4704	6	36,000	0.004
1r211	1250	4704	31	77,000	0.344
1r212	1250	4704	30	81,000	0.066
1r213	1250	4704	29	70,000	0.720
1r221	1250	4704	31	79,000	0.147
1r222	1250	4704	31	68,000	0.059
1r223	1250	4704	31	77,000	0.097
1r231	1250	4704	30	80,000	0.146
1r232	1250	4704	29	86,000	0.307
1r233	1250	4704	31	71,000	1.551
1r311	1250	4704	56	–	Timeout
1r312	1250	4704	60	113,000	1276.770
1r313	1250	4704	58	106,000	496.549
1r321	1250	4704	59	–	Timeout
1r322	1250	4704	60	113,000	1612.443
1r323	1250	4704	60	–	Timeout
1r331	1250	4704	58	103,000	1.107
1r332	1250	4704	58	109,000	50.351
1r333	1250	4704	58	113,000	1708.425

Type: 2D grid graphs

Table 13 Results on the testset 2R

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
2r111	2000	11,600	9	28,000	0.015
2r112	2000	11,600	9	32,000	0.013
2r113	2000	11,600	9	28,000	0.011
2r121	2000	11,600	9	28,000	0.011
2r122	2000	11,600	9	29,000	0.011
2r123	2000	11,600	9	25,000	0.009
2r131	2000	11,600	9	27,000	0.012
2r132	2000	11,600	9	33,000	0.016
2r133	2000	11,600	9	29,000	0.011

Table 13 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
2r211	2000	11,600	50	–	Memout
2r212	2000	11,600	49	80,000	2819.259
2r213	2000	11,600	48	76,000	3152.193
2r221	2000	11,600	50	–	Timeout
2r222	2000	11,600	50	–	Timeout
2r223	2000	11,600	49	–	Timeout
2r231	2000	11,600	50	–	Timeout
2r232	2000	11,600	49	–	Timeout
2r233	2000	11,600	47	–	Timeout

Type: 3D grid graphs

Table 14 Results on the testset ES10FST

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
es10fst01	18	20	10	22,920,745	0.000
es10fst02	14	13	10	19,134,104	0.000
es10fst03	17	20	10	26,003,678	0.000
es10fst04	18	20	10	20,461,116	0.000
es10fst05	12	11	10	18,818,916	0.000
es10fst06	17	20	10	26,540,768	0.000
es10fst07	14	13	10	26,025,072	0.000
es10fst08	21	28	10	25,056,214	0.000
es10fst09	21	29	10	22,062,355	0.000
es10fst10	18	21	10	23,936,095	0.000
es10fst11	14	13	10	22,239,535	0.000
es10fst12	13	12	10	19,626,318	0.000
es10fst13	18	21	10	19,483,914	0.000
es10fst14	24	32	10	21,856,128	0.000
es10fst15	16	18	10	18,641,924	0.000

Type: Rectilinear instances after FST-preprocessing by GeoSteiner

Table 15 Results on the testset ES20FST

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
es20fst01	29	28	20	33,703,886	0.004
es20fst02	29	28	20	32,639,486	0.001
es20fst03	27	26	20	27,847,417	0.001
es20fst04	57	83	20	27,624,394	0.003
es20fst05	54	77	20	34,033,163	0.002
es20fst06	29	28	20	36,014,241	0.001
es20fst07	45	59	20	34,934,874	0.002
es20fst08	52	74	20	38,016,346	0.014

Table 15 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)	
es20fst09	36	42	20	36,739,939	0.003	
es20fst10	49	67	20	34,024,740	0.002	
es20fst11	33	36	20	27,123,908	0.001	
es20fst12	33	36	20	30,451,397	0.005	
es20fst13	35	40	20	34,438,673	0.003	
Type: Rectilinear instances after FST-preprocessing by GeoSteiner	es20fst14	36	44	20	34,062,374	0.009
	es20fst15	37	43	20	32,303,746	0.003

Table 16 Results on the testset
ES30FST

Instance	$ V $	$ E $	$ R $	Opt	Time (s)	
es30fst01	79	115	30	40,692,993	0.037	
es30fst02	71	97	30	40,900,061	0.029	
es30fst03	83	120	30	43,120,444	0.019	
es30fst04	80	115	30	42,150,958	0.010	
es30fst05	58	71	30	41,739,748	0.007	
es30fst06	83	119	30	39,955,139	0.053	
es30fst07	53	64	30	43,761,391	0.007	
es30fst08	69	93	30	41,691,217	0.008	
es30fst09	43	44	30	37,133,658	0.010	
es30fst10	48	52	30	42,686,610	0.009	
es30fst11	79	112	30	41,647,993	0.007	
es30fst12	46	48	30	38,416,720	0.013	
es30fst13	65	84	30	37,406,646	0.005	
Type: Rectilinear instances after FST-preprocessing by GeoSteiner	es30fst14	53	58	30	42,897,025	0.021
	es30fst15	118	188	30	43,035,576	0.070

Table 17 Results on the testset
ES40FST

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
es40fst01	93	127	40	44,841,522	0.036
es40fst02	82	105	40	46,811,310	0.016
es40fst03	87	116	40	49,974,157	0.093
es40fst04	55	55	40	45,289,864	0.013
es40fst05	121	180	40	51,940,413	0.133
es40fst06	92	123	40	49,753,385	0.046
es40fst07	77	95	40	45,639,009	0.109
es40fst08	98	137	40	48,745,996	0.016
es40fst09	107	153	40	51,761,789	0.040
es40fst10	107	152	40	57,136,852	0.117

Table 17 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
es40fst11	97	135	40	46,734,214	0.027
es40fst12	67	75	40	43,843,378	0.029
es40fst13	78	95	40	51,884,545	0.030
es40fst14	98	134	40	49,166,952	0.030
es40fst15	93	129	40	50,828,067	0.050

Type: Rectilinear instances after
FST-preprocessing by
GeoSteiner

Table 18 Results on the testset
ES50FST

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
es50fst01	118	160	50	54,948,660	0.053
es50fst02	125	177	50	55,484,245	0.474
es50fst03	128	182	50	54,691,035	0.075
es50fst04	106	138	50	51,535,766	0.348
es50fst05	104	135	50	55,186,015	0.280
es50fst06	126	182	50	55,804,287	0.539
es50fst07	143	211	50	49,961,178	0.049
es50fst08	83	96	50	53,754,708	0.089
es50fst09	139	202	50	53,456,773	0.538
es50fst10	139	207	50	54,037,963	3.006
es50fst11	100	131	50	52,532,923	0.019
es50fst12	110	149	50	53,409,291	0.172
es50fst13	92	116	50	53,891,019	0.032
es50fst14	120	167	50	53,551,419	0.082
es50fst15	112	147	50	52,180,862	0.105

Type: Rectilinear instances after
FST-preprocessing by
GeoSteiner

Table 19 Results on the testset
ES60FST

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
es60fst01	123	159	60	53,761,423	0.436
es60fst02	186	280	60	55,367,804	3.033
es60fst03	113	142	60	56,566,797	0.066
es60fst04	162	238	60	55,371,042	0.118
es60fst05	119	148	60	54,704,991	0.059
es60fst06	130	174	60	60,421,961	1.064
es60fst07	188	280	60	58,978,041	0.073
es60fst08	109	133	60	58,138,178	0.366
es60fst09	151	216	60	55,877,112	0.493
es60fst10	133	177	60	57,624,488	0.039
es60fst11	121	154	60	56,141,666	0.523

Table 19 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
es60fst12	176	257	60	59,791,362	3.289
es60fst13	157	226	60	61,213,533	0.091
es60fst14	118	149	60	56,035,528	0.058
es60fst15	117	151	60	56,622,581	0.104

Type: Rectilinear instances after FST-preprocessing by GeoSteiner

Table 20 Results on the testset TSPFST

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
att48fst	139	202	48	30,236	0.453
berlin52fst	89	104	52	6760	33.108
eil51fst	181	289	51	409	513.690

Type: Rectilinear instances after FST-preprocessing by GeoSteiner

Table 21 Results on the testset Copenhagen14

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
ind1	18	31	10	604	0.001
ind2	31	57	10	9500	0.001
ind3	16	23	10	600	0.000
ind4	74	146	25	1086	0.023
ind5	114	228	33	1341	0.021
rc01	21	35	10	25,980	0.000
rc02	87	176	30	41,350	0.029
rc03	109	202	50	54,160	0.153
rt01	262	740	10	2146	0.002
rt02	788	1938	50	45,852	0.703

Type: Instances of the Obstacle-avoiding rectilinear Steiner tree problem after FSTpreprocessing by ObSteiner and merging the FSTs into a single graph

Table 22 Results on the testset WRP3

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
wrp3-11	128	227	11	1,100,361	0.099
wrp3-12	84	149	12	1,200,237	0.123
wrp3-13	311	613	13	1,300,497	20.014
wrp3-14	128	247	14	1,400,250	3.780
wrp3-15	138	257	15	1,500,422	51.156
wrp3-16	204	374	16	1,600,208	11.622
wrp3-17	177	354	17	1,700,442	422.079
wrp3-19	189	353	19	1,900,439	1765.723
wrp3-20	245	454	20	–	Timeout
wrp3-21	237	444	21	–	Timeout
wrp3-22	233	431	22	–	Timeout

Table 22 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
wrp3-23	132	230	23	–	Timeout
wrp3-24	262	487	24	–	Timeout
wrp3-25	246	468	25	–	Memout
wrp3-26	402	780	26	–	Memout
wrp3-27	370	721	27	–	Timeout
wrp3-28	307	559	28	–	Memout
wrp3-29	245	436	29	–	Memout
wrp3-30	467	896	30	–	Memout
wrp3-31	323	592	31	–	Timeout
wrp3-33	437	838	33	–	Memout
wrp3-34	1244	2474	34	–	Memout
wrp3-36	435	818	36	–	Memout
wrp3-37	1011	2010	37	–	Memout
wrp3-38	603	1207	38	–	Timeout
wrp3-39	703	1616	39	–	Memout
wrp3-41	178	307	41	–	Memout
wrp3-42	705	1373	42	–	Memout
wrp3-43	173	298	43	–	Memout
wrp3-45	1414	2813	45	–	Memout
wrp3-48	925	1738	48	–	Memout
wrp3-49	886	1800	49	–	Memout
wrp3-50	1119	2251	50	–	Memout
wrp3-52	701	1352	52	–	Memout
wrp3-53	775	1471	53	–	Memout
wrp3-55	1645	3186	55	–	Memout
wrp3-56	853	1590	56	–	Memout
wrp3-60	838	1763	60	–	Memout
wrp3-62	670	1316	62	–	Memout

Type: Group Steiner tree instances arising from VLSI design modeled as Steiner tree instances by connecting each terminal to the vertices of its group by edges of very high cost

Table 23 Results on the testset WRP4

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
wrp4-11	123	233	11	1,100,179	0.241
wrp4-13	110	188	13	1,300,798	0.019
wrp4-14	145	283	14	1,400,290	2.798
wrp4-15	193	369	15	1,500,405	8.193
wrp4-16	311	579	16	1,601,190	149.542
wrp4-17	223	404	17	1,700,525	69.524

Table 23 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
wrp4-18	211	380	18	1,801,464	1212.777
wrp4-19	119	206	19	1,901,446	0.925
wrp4-21	529	1032	21	–	Timeout
wrp4-22	294	568	22	–	Timeout
wrp4-23	257	515	23	–	Memout
wrp4-24	493	963	24	–	Memout
wrp4-25	422	808	25	–	Memout
wrp4-26	396	781	26	–	Memout
wrp4-27	243	497	27	–	Memout
wrp4-28	272	545	28	–	Memout
wrp4-29	247	505	29	–	Memout
wrp4-30	361	724	30	–	Memout
wrp4-31	390	786	31	–	Memout
wrp4-32	311	632	32	–	Memout
wrp4-33	304	571	33	–	Timeout
wrp4-34	314	650	34	–	Memout
wrp4-35	471	954	35	–	Memout
wrp4-36	363	750	36	–	Memout
wrp4-37	522	1054	37	–	Memout
wrp4-38	294	618	38	–	Memout
wrp4-39	802	1553	39	–	Memout
wrp4-40	538	1088	40	–	Memout
wrp4-41	465	955	41	–	Memout
wrp4-42	552	1131	42	–	Memout
wrp4-43	596	1148	43	–	Timeout
wrp4-44	398	788	44	–	Memout
wrp4-45	388	815	45	–	Memout
wrp4-46	632	1287	46	–	Memout
wrp4-47	555	1098	47	–	Memout
wrp4-48	451	825	48	–	Timeout
wrp4-49	557	1080	49	–	Memout
wrp4-50	564	1112	50	–	Memout
wrp4-51	668	1306	51	–	Memout
wrp4-52	547	1115	52	–	Memout
wrp4-53	615	1232	53	–	Memout
wrp4-54	688	1388	54	–	Memout
wrp4-55	610	1201	55	–	Memout

Table 23 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
wrp4-56	839	1617	56	–	Memout
wrp4-58	757	1493	58	–	Memout
wrp4-59	904	1806	59	–	Memout
wrp4-60	693	1370	60	–	Memout
wrp4-61	775	1538	61	–	Timeout
wrp4-62	1283	2493	62	–	Memout
wrp4-63	1121	2227	63	–	Memout

Type: Group Steiner tree instances arising from VLSI design modeled as Steiner tree instances by connecting each terminal to the vertices if its group by edges of very high cost

Table 24 Results on the testset vienna-i-advanced

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
I052a	160	237	23	13,309,487	0.013
I054a	540	817	25	15,841,596	0.021
I056a	290	439	34	14,171,206	0.086

Type: Realworld telecommunication networks after an “advanced” preprocessing routine. We report the cost of an optimum solution in the original instance, computed as the sum of an optimum solution in the reduced instance and the fixed cost induced by the reductions

Table 25 Results on the testset vienna-i-simple

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
I052	2363	3761	40	–	Timeout
I054	3803	6213	38	–	Timeout
I056	1991	3176	51	–	Timeout

Type: Real-world telecommunication networks after a “simple” preprocessing routine

Table 26 Results on the testset X

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
berlin52	52	1326	16	1044	0.013
brasil58	58	1653	25	13,655	0.005

Type: Complete graphs with Euclidean costs

Table 27 Results on the testset P4E

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
p455	100	4950	5	1138	0.001
p456	100	4950	5	1228	0.001
p457	100	4950	10	1609	0.001
p458	100	4950	10	1868	0.002
p459	100	4950	20	2345	0.003
p460	100	4950	20	2959	0.005
p461	100	4950	50	4474	0.030
p463	200	19,900	10	1510	0.005
p464	200	19,900	20	2545	0.012
p465	200	19,900	40	3853	0.066

Type: Complete graphs with
Euclidean costs

Table 28 Results on the testset P4Z

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
p401	100	4950	5	155	0.001
p402	100	4950	5	116	0.001
p403	100	4950	5	179	0.001
p404	100	4950	10	270	0.001
p405	100	4950	10	270	0.002
p406	100	4950	10	290	0.003
p407	100	4950	20	590	0.257
p408	100	4950	20	542	0.154
p409	100	4950	50	963	4350.849
p410	100	4950	50	1010	245.304

Type: Complete graphs with
random costs

Table 29 Results on the testset P6E

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
p619	100	180	5	7485	0.001
p620	100	180	5	8746	0.001
p621	100	180	5	8688	0.001
p622	100	180	10	15,972	0.001
p623	100	180	10	19,496	0.002
p624	100	180	20	20,246	0.003
p625	100	180	20	23,078	0.003
p626	100	180	20	22,346	0.011

Table 29 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
p627	100	180	50	40,647	0.023
p628	100	180	50	40,008	0.052
p629	100	180	50	43,287	0.043
p630	200	370	10	26,125	0.001
p631	200	370	20	39,067	0.010
p632	200	370	40	56,217	0.038

Type: Sparse graphs with
Euclidean costs

Table 30 Results on the testset
P6Z

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
p602	100	180	5	8083	0.001
p603	100	180	5	5022	0.001
p604	100	180	10	11,397	0.001
p605	100	180	10	10,355	0.001
p606	100	180	11	13,048	0.001
p607	100	180	21	15,358	0.003
p608	100	180	21	14,439	0.002
p609	100	180	20	18,263	0.004
p610	100	180	50	30,161	0.034
p611	100	180	50	26,903	0.090
p612	100	180	50	30,258	0.107
p613	200	370	10	18,429	0.001
p614	200	370	20	27,276	0.017
p615	200	370	40	42,474	0.049

Type: Sparse graphs with
random costs

Table 31 Results on the testset
B

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
b01	50	63	9	82	0.001
b02	50	63	13	83	0.003
b03	50	63	25	138	0.136
b04	50	100	9	59	0.001
b05	50	100	13	61	0.008
b06	50	100	25	122	0.256
b07	75	94	13	111	0.005
b08	75	94	19	104	0.004
b09	75	94	38	220	1858.382
b10	75	150	13	86	0.006
b11	75	150	19	88	0.019
b12	75	150	38	174	98.165

Table 31 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
b13	100	125	17	165	0.111
b14	100	125	25	235	1.704
b15	100	125	50	318	176.192
b16	100	200	17	127	0.008
b17	100	200	25	131	266.814
b18	100	200	50	218	3228.991

Type: Random sparse graphs
with random costs

Table 32 Results on the testset C

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
c01	500	625	5	85	0.002
c02	500	625	10	144	0.005
c06	500	1000	5	55	0.003
c07	500	1000	10	102	0.024
c11	500	2500	5	32	0.004
c12	500	2500	10	46	0.012
c16	500	12,500	5	11	0.005
c17	500	12,500	10	18	0.011

Type: Random sparse graphs
with random costs

Table 33 Results on the testset D

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
d01	1000	1250	5	106	0.004
d02	1000	1250	10	220	0.052
d06	1000	2000	5	67	0.004
d07	1000	2000	10	103	0.010
d11	1000	5000	5	29	0.007
d12	1000	5000	10	42	0.016
d16	1000	25,000	5	13	0.011
d17	1000	25,000	10	23	0.072

Type: Random sparse graphs
with random costs

Table 34 Results on the testset E

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
e01	2500	3125	5	111	0.007
e02	2500	3125	10	214	0.045
e06	2500	5000	5	73	0.008
e07	2500	5000	10	145	0.230
e11	2500	12,500	5	34	0.009
e12	2500	12,500	10	67	0.161
e16	2500	62,500	5	15	0.016
e17	2500	62,500	10	25	0.124

Type: Random sparse graphs
with random costs

Table 35 Results on the testset I080

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i080-001	80	120	6	1787	0.001
i080-002	80	120	6	1607	0.000
i080-003	80	120	6	1713	0.000
i080-004	80	120	6	1866	0.000
i080-005	80	120	6	1790	0.001
i080-011	80	350	6	1479	0.001
i080-012	80	350	6	1484	0.001
i080-013	80	350	6	1381	0.001
i080-014	80	350	6	1397	0.001
i080-015	80	350	6	1495	0.001
i080-021	80	3160	6	1175	0.004
i080-022	80	3160	6	1178	0.004
i080-023	80	3160	6	1174	0.004
i080-024	80	3160	6	1161	0.004
i080-025	80	3160	6	1162	0.004
i080-031	80	160	6	1570	0.001
i080-032	80	160	6	2088	0.001
i080-033	80	160	6	1794	0.001
i080-034	80	160	6	1688	0.001
i080-035	80	160	6	1862	0.001
i080-041	80	632	6	1276	0.001
i080-042	80	632	6	1287	0.001
i080-043	80	632	6	1295	0.001
i080-044	80	632	6	1366	0.001
i080-045	80	632	6	1310	0.001
i080-101	80	120	8	2608	0.001
i080-102	80	120	8	2403	0.001
i080-103	80	120	8	2603	0.002
i080-104	80	120	8	2486	0.002
i080-105	80	120	8	2203	0.001
i080-111	80	350	8	2051	0.008
i080-112	80	350	8	1885	0.006
i080-113	80	350	8	1884	0.004
i080-114	80	350	8	1895	0.005
i080-115	80	350	8	1868	0.004
i080-121	80	3160	8	1561	0.023
i080-122	80	3160	8	1561	0.023
i080-123	80	3160	8	1569	0.023

Table 35 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i080-124	80	3160	8	1555	0.022
i080-125	80	3160	8	1572	0.024
i080-131	80	160	8	2284	0.001
i080-132	80	160	8	2180	0.003
i080-133	80	160	8	2261	0.002
i080-134	80	160	8	2070	0.002
i080-135	80	160	8	2102	0.001
i080-141	80	632	8	1788	0.009
i080-142	80	632	8	1708	0.009
i080-143	80	632	8	1767	0.016
i080-144	80	632	8	1772	0.015
i080-145	80	632	8	1762	0.013
i080-201	80	120	16	4760	0.128
i080-202	80	120	16	4650	0.111
i080-203	80	120	16	4599	0.891
i080-204	80	120	16	4492	8.025
i080-205	80	120	16	4564	0.615
i080-211	80	350	16	3631	108.657
i080-212	80	350	16	3677	104.799
i080-213	80	350	16	3678	106.887
i080-214	80	350	16	3734	107.154
i080-215	80	350	16	3681	107.424
i080-221	80	3160	16	3158	111.565
i080-222	80	3160	16	3141	113.026
i080-223	80	3160	16	3156	112.402
i080-224	80	3160	16	3159	114.264
i080-225	80	3160	16	3150	114.489
i080-231	80	160	16	4354	32.829
i080-232	80	160	16	4199	26.645
i080-233	80	160	16	4118	16.691
i080-234	80	160	16	4274	0.898
i080-235	80	160	16	4487	2.326
i080-241	80	632	16	3538	146.827
i080-242	80	632	16	3458	141.589
i080-243	80	632	16	3474	139.922
i080-244	80	632	16	3466	143.147
i080-245	80	632	16	3467	142.418
i080-301	80	120	20	5519	38.991

Table 35 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i080-302	80	120	20	5944	10.556
i080-303	80	120	20	5777	19.155
i080-304	80	120	20	5586	6.392
i080-305	80	120	20	5932	201.235
i080-311	80	350	20	–	Timeout
i080-312	80	350	20	–	Timeout
i080-313	80	350	20	–	Timeout
i080-314	80	350	20	–	Timeout
i080-315	80	350	20	–	Timeout
i080-321	80	3160	20	–	Timeout
i080-322	80	3160	20	–	Timeout
i080-323	80	3160	20	–	Timeout
i080-324	80	3160	20	–	Timeout
i080-325	80	3160	20	–	Timeout
i080-331	80	160	20	5226	814.502
i080-332	80	160	20	5362	902.230
i080-333	80	160	20	5381	541.448
i080-334	80	160	20	5264	920.974
i080-335	80	160	20	4953	1004.156
i080-341	80	632	20	–	Timeout
i080-342	80	632	20	–	Timeout
i080-343	80	632	20	–	Timeout
i080-344	80	632	20	–	Timeout
i080-345	80	632	20	–	Timeout

Type: Random graphs with so-called incidence costs, designed to defy preprocessing

Table 36 Results on the testset I160

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i160-001	160	240	7	2490	0.004
i160-002	160	240	7	2158	0.001
i160-003	160	240	7	2297	0.002
i160-004	160	240	7	2370	0.002
i160-005	160	240	7	2495	0.002
i160-011	160	812	7	1677	0.007

Table 36 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i160-012	160	812	7	1750	0.008
i160-013	160	812	7	1661	0.005
i160-014	160	812	7	1778	0.008
i160-015	160	812	7	1768	0.009
i160-021	160	12,720	7	1352	0.055
i160-022	160	12,720	7	1365	0.057
i160-023	160	12,720	7	1351	0.056
i160-024	160	12,720	7	1371	0.058
i160-025	160	12,720	7	1366	0.054
i160-031	160	320	7	2170	0.003
i160-032	160	320	7	2330	0.003
i160-033	160	320	7	2101	0.005
i160-034	160	320	7	2083	0.003
i160-035	160	320	7	2103	0.004
i160-041	160	2544	7	1494	0.013
i160-042	160	2544	7	1486	0.013
i160-043	160	2544	7	1549	0.016
i160-044	160	2544	7	1478	0.011
i160-045	160	2544	7	1554	0.015
i160-101	160	240	12	3859	0.082
i160-102	160	240	12	3747	0.205
i160-103	160	240	12	3837	0.093
i160-104	160	240	12	4063	0.014
i160-105	160	240	12	3563	0.034
i160-111	160	812	12	2869	1.430
i160-112	160	812	12	2924	2.304
i160-113	160	812	12	2866	1.575
i160-114	160	812	12	2989	1.949
i160-115	160	812	12	2937	1.436
i160-121	160	12,720	12	2363	5.395
i160-122	160	12,720	12	2348	5.355
i160-123	160	12,720	12	2355	5.418
i160-124	160	12,720	12	2352	5.330
i160-125	160	12,720	12	2351	5.459
i160-131	160	320	12	3356	0.306
i160-132	160	320	12	3450	0.205
i160-133	160	320	12	3585	0.345
i160-134	160	320	12	3470	0.095

Table 36 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i160-135	160	320	12	3716	0.286
i160-141	160	2544	12	2549	3.398
i160-142	160	2544	12	2562	3.434
i160-143	160	2544	12	2557	2.955
i160-144	160	2544	12	2607	3.238
i160-145	160	2544	12	2578	3.451
i160-201	160	240	24	–	Timeout
i160-202	160	240	24	–	Timeout
i160-203	160	240	24	7243	4173.679
i160-204	160	240	24	–	Timeout
i160-205	160	240	24	–	Timeout
i160-211	160	812	24	–	Timeout
i160-212	160	812	24	–	Timeout
i160-213	160	812	24	–	Timeout
i160-214	160	812	24	–	Timeout
i160-215	160	812	24	–	Timeout
i160-221	160	12,720	24	–	Timeout
i160-222	160	12,720	24	–	Timeout
i160-223	160	12,720	24	–	Timeout
i160-224	160	12,720	24	–	Timeout
i160-225	160	12,720	24	–	Timeout
i160-231	160	320	24	–	Timeout
i160-232	160	320	24	–	Timeout
i160-233	160	320	24	–	Timeout
i160-234	160	320	24	–	Timeout
i160-235	160	320	24	–	Timeout
i160-241	160	2544	24	–	Timeout
i160-242	160	2544	24	–	Timeout
i160-243	160	2544	24	–	Timeout
i160-244	160	2544	24	–	Timeout
i160-245	160	2544	24	–	Timeout
i160-301	160	240	40	–	Memout
i160-302	160	240	40	–	Memout
i160-303	160	240	40	–	Memout
i160-304	160	240	40	–	Memout
i160-305	160	240	40	–	Memout

Table 36 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i160-311	160	812	40	–	Memout
i160-312	160	812	40	–	Memout
i160-313	160	812	40	–	Memout
i160-314	160	812	40	–	Memout
i160-315	160	812	40	–	Memout
i160-321	160	12,720	40	–	Memout
i160-322	160	12,720	40	–	Memout
i160-323	160	12,720	40	–	Memout
i160-324	160	12,720	40	–	Memout
i160-325	160	12,720	40	–	Memout
i160-331	160	320	40	–	Memout
i160-332	160	320	40	–	Memout
i160-333	160	320	40	–	Memout
i160-334	160	320	40	–	Memout
i160-335	160	320	40	–	Memout
i160-341	160	2544	40	–	Memout
i160-342	160	2544	40	–	Memout
i160-343	160	2544	40	–	Memout
i160-344	160	2544	40	–	Memout
i160-345	160	2544	40	–	Memout

Type: Random graphs with so-called incidence costs, designed to defy preprocessing

Table 37 Results on the testset I320

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i320-001	320	480	8	2672	0.003
i320-002	320	480	8	2847	0.004
i320-003	320	480	8	2972	0.004
i320-004	320	480	8	2905	0.007
i320-005	320	480	8	2991	0.006
i320-011	320	1845	8	2053	0.031
i320-012	320	1845	8	1997	0.023
i320-013	320	1845	8	2072	0.039
i320-014	320	1845	8	2061	0.035
i320-015	320	1845	8	2059	0.040
i320-021	320	51,040	8	1553	0.366
i320-022	320	51,040	8	1565	0.414
i320-023	320	51,040	8	1549	0.373
i320-024	320	51,040	8	1553	0.360
i320-025	320	51,040	8	1550	0.360

Table 37 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i320-031	320	640	8	2673	0.011
i320-032	320	640	8	2770	0.010
i320-033	320	640	8	2769	0.010
i320-034	320	640	8	2521	0.005
i320-035	320	640	8	2385	0.007
i320-041	320	10,208	8	1707	0.061
i320-042	320	10,208	8	1682	0.050
i320-043	320	10,208	8	1723	0.059
i320-044	320	10,208	8	1681	0.067
i320-045	320	10,208	8	1686	0.056
i320-101	320	480	17	5548	16.131
i320-102	320	480	17	5556	10.289
i320-103	320	480	17	6239	178.463
i320-104	320	480	17	5703	108.739
i320-105	320	480	17	5928	84.748
i320-111	320	1845	17	4273	1706.674
i320-112	320	1845	17	4213	1872.720
i320-113	320	1845	17	4205	1464.609
i320-114	320	1845	17	4104	1581.733
i320-115	320	1845	17	4238	1747.827
i320-121	320	51,040	17	3321	2381.939
i320-122	320	51,040	17	3314	2336.603
i320-123	320	51,040	17	3332	2379.991
i320-124	320	51,040	17	3323	2342.527
i320-125	320	51,040	17	3340	2353.655
i320-131	320	640	17	5255	343.942
i320-132	320	640	17	5052	33.234
i320-133	320	640	17	5125	44.197
i320-134	320	640	17	5272	374.938
i320-135	320	640	17	5342	211.986
i320-141	320	10,208	17	3606	2246.125
i320-142	320	10,208	17	3567	2305.369
i320-143	320	10,208	17	3561	2244.354
i320-144	320	10,208	17	3512	2244.792
i320-145	320	10,208	17	3601	2261.946
i320-201	320	480	34	–	Memout
i320-202	320	480	34	–	Memout
i320-203	320	480	34	–	Memout

Table 37 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i320-204	320	480	34	–	Memout
i320-205	320	480	34	–	Memout
i320-211	320	1845	34	–	Memout
i320-212	320	1845	34	–	Memout
i320-213	320	1845	34	–	Memout
i320-214	320	1845	34	–	Memout
i320-215	320	1845	34	–	Memout
i320-221	320	51,040	34	–	Memout
i320-222	320	51,040	34	–	Memout
i320-223	320	51,040	34	–	Memout
i320-224	320	51,040	34	–	Memout
i320-225	320	51,040	34	–	Memout
i320-231	320	640	34	–	Memout
i320-232	320	640	34	–	Memout
i320-233	320	640	34	–	Memout
i320-234	320	640	34	–	Memout
i320-235	320	640	34	–	Memout
i320-241	320	10,208	34	–	Memout
i320-242	320	10,208	34	–	Memout
i320-243	320	10,208	34	–	Memout
i320-244	320	10,208	34	–	Memout
i320-245	320	10,208	34	–	Memout

Type: Random graphs with so-called incidence costs, designed to defy preprocessing

Table 38 Results on the testset I640

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i640-001	640	960	9	4033	0.042
i640-002	640	960	9	3588	0.030
i640-003	640	960	9	3438	0.024
i640-004	640	960	9	4000	0.070
i640-005	640	960	9	4006	0.055
i640-011	640	4135	9	2392	0.163
i640-012	640	4135	9	2465	0.271
i640-013	640	4135	9	2399	0.205
i640-014	640	4135	9	2171	0.038
i640-015	640	4135	9	2347	0.126
i640-021	640	204,480	9	1749	4.426
i640-022	640	204,480	9	1756	4.031
i640-023	640	204,480	9	1754	4.499

Table 38 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i640-024	640	204,480	9	1751	4.081
i640-025	640	204,480	9	1745	4.452
i640-031	640	1280	9	3278	0.065
i640-032	640	1280	9	3187	0.056
i640-033	640	1280	9	3260	0.062
i640-034	640	1280	9	2953	0.015
i640-035	640	1280	9	3292	0.033
i640-041	640	40,896	9	1897	0.957
i640-042	640	40,896	9	1934	0.811
i640-043	640	40,896	9	1931	0.889
i640-044	640	40,896	9	1938	0.975
i640-045	640	40,896	9	1866	0.403
i640-101	640	960	25	–	Timeout
i640-102	640	960	25	–	Timeout
i640-103	640	960	25	–	Timeout
i640-104	640	960	25	–	Timeout
i640-105	640	960	25	–	Timeout
i640-111	640	4135	25	–	Memout
i640-112	640	4135	25	–	Memout
i640-113	640	4135	25	–	Memout
i640-114	640	4135	25	–	Memout
i640-115	640	4135	25	–	Memout
i640-121	640	204,480	25	–	Memout
i640-122	640	204,480	25	–	Memout
i640-123	640	204,480	25	–	Memout
i640-124	640	204,480	25	–	Memout
i640-125	640	204,480	25	–	Memout
i640-131	640	1280	25	–	Timeout
i640-132	640	1280	25	–	Timeout
i640-133	640	1280	25	–	Timeout
i640-134	640	1280	25	–	Timeout
i640-135	640	1280	25	–	Timeout
i640-141	640	40,896	25	–	Memout
i640-142	640	40,896	25	–	Memout
i640-143	640	40,896	25	–	Memout
i640-144	640	40,896	25	–	Memout
i640-145	640	40,896	25	–	Memout

Table 38 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
i640-201	640	960	50	–	Memout
i640-202	640	960	50	–	Memout
i640-203	640	960	50	–	Memout
i640-204	640	960	50	–	Memout
i640-205	640	960	50	–	Memout
i640-211	640	4135	50	–	Memout
i640-212	640	4135	50	–	Memout
i640-213	640	4135	50	–	Memout
i640-214	640	4135	50	–	Memout
i640-215	640	4135	50	–	Memout
i640-221	640	204,480	50	–	Memout
i640-222	640	204,480	50	–	Memout
i640-223	640	204,480	50	–	Memout
i640-224	640	204,480	50	–	Memout
i640-225	640	204,480	50	–	Memout
i640-231	640	1280	50	–	Memout
i640-232	640	1280	50	–	Memout
i640-233	640	1280	50	–	Memout
i640-234	640	1280	50	–	Memout
i640-235	640	1280	50	–	Memout
i640-241	640	40,896	50	–	Memout
i640-242	640	40,896	50	–	Memout
i640-243	640	40,896	50	–	Memout
i640-244	640	40,896	50	–	Memout
i640-245	640	40,896	50	–	Memout

Type: Random graphs with so-called incidence costs, designed to defy preprocessing

Table 39 Results on the testset PUC

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
bipe2p	550	5013	50	–	Memout
bipe2u	550	5013	50	–	Memout
cc3-10p	1000	13,500	50	–	Memout
cc3-10u	1000	13,500	50	–	Memout
cc3-11p	1331	19,965	61	–	Memout
cc3-11u	1331	19,965	61	–	Memout
cc3-4p	64	288	8	2338	0.006
cc3-4u	64	288	8	23	0.008
cc3-5p	125	750	13	3661	3.450
cc3-5u	125	750	13	36	4.637

Table 39 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
cc5-3p	243	1215	27	–	Memout
cc5-3u	243	1215	27	–	Memout
cc6-2p	64	192	12	3271	0.166
cc6-2u	64	192	12	32	0.279
hc6p	64	192	32	–	Memout
hc6u	64	192	32	–	Memout

Type: Artificial instances designed to be hard for existing solvers

Table 40 Results on the testset SPG-PUCN

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
cc3-10n	1000	13,500	50	–	Memout
cc3-11n	1331	19,965	61	–	Memout
cc3-4n	64	288	8	13	0.002
cc3-5n	125	750	13	20	0.563
cc5-3n	243	1215	27	–	Memout
cc6-2n	64	192	12	18	0.047

Type: Unweighted instances of the PUC testset, which contains artificial instances designed to be hard for existing solvers

Table 41 Results on the testset SP

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
antiwheel5	10	15	5	7	0.000
design432	8	20	4	9	0.000
oddcycle3	6	9	3	4	0.000
oddwheel3	7	9	4	5	0.000
se03	13	21	4	12	0.000

Type: Artificial instances

Table 42 Results on the testset MC

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
mc2	120	7140	60	–	Memout
mc3	97	4656	45	–	Timeout

Type: Artificial instances

Table 43 Results on the testset csd

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
csd02	3	2	1	0	0.000
csd03	6	6	3	4	0.000
csd04	10	12	6	8	0.000
csd05	15	20	10	13	0.007
csd06	21	30	15	19	2.724
csd07	28	42	21	26	6138.678
csd08	36	56	28	–	Timeout
csd09	45	72	36	–	Memout
csd10	55	90	45	–	Memout
csd11	66	110	55	–	Memout

Type: Artificial instances arising from generalizations of Steiner tree LP gap examples

Table 44 Results on the testset goemans

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
g01-00	7	9	3	8	0.000
g01-01	8	10	4	9	0.000
g01-02	9	11	5	10	0.000
g01-03	10	12	6	11	0.000
g01-04	11	13	7	12	0.000
g01-05	12	14	8	13	0.001
g01-06	13	15	9	14	0.004
g01-07	14	16	10	15	0.007
g01-08	15	17	11	16	0.016
g01-09	16	18	12	17	0.067
g01-10	17	19	13	18	0.172
g01-11	18	20	14	19	0.490
g01-12	19	21	15	20	2.220
g01-13	20	22	16	21	18.637
g01-14	21	23	17	22	42.576
g01-15	22	24	18	23	39.915
g02-00	9	16	4	14	0.000
g02-01	10	17	5	15	0.000
g02-02	11	18	6	16	0.000
g02-03	12	19	7	17	0.000
g02-04	13	20	8	18	0.001
g02-05	14	21	9	19	0.004
g02-06	15	22	10	20	0.013
g02-07	16	23	11	21	0.035
g02-08	17	24	12	22	0.135
g02-09	18	25	13	23	0.352
g02-10	19	26	14	24	1.354
g02-11	20	27	15	25	6.346
g02-12	21	28	16	26	25.602
g02-13	22	29	17	27	114.366
g02-14	23	30	18	28	300.818
g02-15	24	31	19	29	1171.010
g03-00	11	25	5	22	0.000
g03-01	12	26	6	23	0.000
g03-02	13	27	7	24	0.000
g03-03	14	28	8	25	0.001
g03-04	15	29	9	26	0.004

Table 44 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
g03-05	16	30	10	27	0.016
g03-06	17	31	11	28	0.067
g03-07	18	32	12	29	0.145
g03-08	19	33	13	30	0.417
g03-09	20	34	14	31	1.536
g03-10	21	35	15	32	6.411
g03-11	22	36	16	33	28.536
g03-12	23	37	17	34	106.674
g03-13	24	38	18	35	407.020
g03-14	25	39	19	36	1414.010
g03-15	26	40	20	37	4935.897
g04-00	13	36	6	32	0.000
g04-01	14	37	7	33	0.001
g04-02	15	38	8	34	0.002
g04-03	16	39	9	35	0.007
g04-04	17	40	10	36	0.022
g04-05	18	41	11	37	0.062
g04-06	19	42	12	38	0.155
g04-07	20	43	13	39	0.424
g04-08	21	44	14	40	1.571
g04-09	22	45	15	41	6.114
g04-10	23	46	16	42	26.880
g04-11	24	47	17	43	103.263
g04-12	25	48	18	44	379.413
g04-13	26	49	19	45	1380.378
g04-14	27	50	20	46	4854.754
g04-15	28	51	21	–	Timeout
g05-00	15	49	7	44	0.001
g05-01	16	50	8	45	0.002
g05-02	17	51	9	46	0.007
g05-03	18	52	10	47	0.023
g05-04	19	53	11	48	0.065
g05-05	20	54	12	49	0.164
g05-06	21	55	13	50	0.417
g05-07	22	56	14	51	1.502
g05-08	23	57	15	52	5.839
g05-09	24	58	16	53	22.368

Table 44 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
g05-10	25	59	17	54	89.853
g05-11	26	60	18	55	331.230
g05-12	27	61	19	56	1183.867
g05-13	28	62	20	57	4559.627
g05-14	29	63	21	–	Timeout
g05-15	30	64	22	–	Timeout
g06-00	17	64	8	58	0.002
g06-01	18	65	9	59	0.006
g06-02	19	66	10	60	0.022
g06-03	20	67	11	61	0.061
g06-04	21	68	12	62	0.150
g06-05	22	69	13	63	0.403
g06-06	23	70	14	64	1.441
g06-07	24	71	15	65	5.374
g06-08	25	72	16	66	20.749
g06-09	26	73	17	67	80.435
g06-10	27	74	18	68	307.301
g06-11	28	75	19	69	1129.370
g06-12	29	76	20	70	4294.387
g06-13	30	77	21	–	Timeout
g06-14	31	78	22	–	Timeout
g06-15	32	79	23	–	Timeout
g07-00	19	81	9	74	0.003
g07-01	20	82	10	75	0.011
g07-02	21	83	11	76	0.037
g07-03	22	84	12	77	0.112
g07-04	23	85	13	78	0.390
g07-05	24	86	14	79	1.370
g07-06	25	87	15	80	5.032
g07-07	26	88	16	81	19.383
g07-08	27	89	17	82	76.224
g07-09	28	90	18	83	276.931
g07-10	29	91	19	84	1064.745
g07-11	30	92	20	85	4173.155
g07-12	31	93	21	–	Timeout
g07-13	32	94	22	–	Timeout
g07-14	33	95	23	–	Timeout

Table 44 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
g07-15	34	96	24	–	Timeout
g08-00	21	100	10	92	0.009
g08-01	22	101	11	93	0.032
g08-02	23	102	12	94	0.108
g08-03	24	103	13	95	0.383
g08-04	25	104	14	96	1.309
g08-05	26	105	15	97	4.942
g08-06	27	106	16	98	18.081
g08-07	28	107	17	99	68.314
g08-08	29	108	18	100	262.768
g08-09	30	109	19	101	1019.464
g08-10	31	110	20	102	3956.305
g08-11	32	111	21	–	Timeout
g08-12	33	112	22	–	Timeout
g08-13	34	113	23	–	Timeout
g08-14	35	114	24	–	Timeout
g08-15	36	115	25	–	Timeout
g09-00	23	121	11	112	0.028
g09-01	24	122	12	113	0.150
g09-02	25	123	13	114	0.383
g09-03	26	124	14	115	1.291
g09-04	27	125	15	116	4.625
g09-05	28	126	16	117	17.479
g09-06	29	127	17	118	66.582
g09-07	30	128	18	119	240.706
g09-08	31	129	19	120	939.553
g09-09	32	130	20	121	3748.635
g09-10	33	131	21	–	Timeout
g09-11	34	132	22	–	Timeout
g09-12	35	133	23	–	Timeout
g09-13	36	134	24	–	Timeout
g09-14	37	135	25	–	Timeout
g09-15	38	136	26	–	Timeout
g10-00	25	144	12	134	0.126
g10-01	26	145	13	135	0.351
g10-02	27	146	14	136	1.228
g10-03	28	147	15	137	4.474
g10-04	29	148	16	138	17.188

Table 44 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
g10-05	30	149	17	139	63.640
g10-06	31	150	18	140	223.035
g10-07	32	151	19	141	878.752
g10-08	33	152	20	142	3612.406
g10-09	34	153	21	–	Timeout
g10-10	35	154	22	–	Timeout
g10-11	36	155	23	–	Timeout
g10-12	37	156	24	–	Timeout
g10-13	38	157	25	–	Timeout
g10-14	39	158	26	–	Timeout
g10-15	40	159	27	–	Timeout
g11-00	27	169	13	158	0.369
g11-01	28	170	14	159	1.147
g11-02	29	171	15	160	4.529
g11-03	30	172	16	161	16.525
g11-04	31	173	17	162	61.300
g11-05	32	174	18	163	216.074
g11-06	33	175	19	164	845.014
g11-07	34	176	20	165	3514.339
g11-08	35	177	21	–	Timeout
g11-09	36	178	22	–	Timeout
g11-10	37	179	23	–	Timeout
g11-11	38	180	24	–	Timeout
g11-12	39	181	25	–	Timeout
g11-13	40	182	26	–	Timeout
g11-14	41	183	27	–	Timeout
g11-15	42	184	28	–	Timeout
g12-00	29	196	14	184	0.626
g12-01	30	197	15	185	4.491
g12-02	31	198	16	186	15.098
g12-03	32	199	17	187	59.824
g12-04	33	200	18	188	201.250
g12-05	34	201	19	189	790.252
g12-06	35	202	20	190	3361.075
g12-07	36	203	21	–	Timeout
g12-08	37	204	22	–	Timeout
g12-09	38	205	23	–	Timeout
g12-10	39	206	24	–	Timeout

Table 44 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
g12-11	40	207	25	–	Timeout
g12-12	41	208	26	–	Timeout
g12-13	42	209	27	–	Timeout
g12-14	43	210	28	–	Timeout
g12-15	44	211	29	–	Timeout
g13-00	31	225	15	212	1.815
g13-01	32	226	16	213	14.468
g13-02	33	227	17	214	56.674
g13-03	34	228	18	215	195.572
g13-04	35	229	19	216	728.650
g13-05	36	230	20	217	3214.443
g13-06	37	231	21	–	Timeout
g13-07	38	232	22	–	Timeout
g13-08	39	233	23	–	Timeout
g13-09	40	234	24	–	Timeout
g13-10	41	235	25	–	Timeout
g13-11	42	236	26	–	Timeout
g13-12	43	237	27	–	Timeout
g13-13	44	238	28	–	Timeout
g13-14	45	239	29	–	Timeout
g13-15	46	240	30	–	Timeout
g14-00	33	256	16	242	6.512
g14-01	34	257	17	243	53.631
g14-02	35	258	18	244	189.942
g14-03	36	259	19	245	696.400
g14-04	37	260	20	246	2918.275
g14-05	38	261	21	–	Timeout
g14-06	39	262	22	–	Timeout
g14-07	40	263	23	–	Timeout
g14-08	41	264	24	–	Timeout
g14-09	42	265	25	–	Timeout
g14-10	43	266	26	–	Timeout
g14-11	44	267	27	–	Timeout
g14-12	45	268	28	–	Timeout
g14-13	46	269	29	–	Timeout
g14-14	47	270	30	–	Timeout
g14-15	48	271	31	–	Timeout
g15-00	35	289	17	274	22.458

Table 44 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
g15-01	36	290	18	275	181.218
g15-02	37	291	19	276	653.425
g15-03	38	292	20	277	2738.780
g15-04	39	293	21	–	Timeout
g15-05	40	294	22	–	Timeout
g15-06	41	295	23	–	Timeout
g15-07	42	296	24	–	Timeout
g15-08	43	297	25	–	Timeout
g15-09	44	298	26	–	Timeout
g15-10	45	299	27	–	Timeout
g15-11	46	300	28	–	Timeout
g15-12	47	301	29	–	Timeout
g15-13	48	302	30	–	Timeout
g15-14	49	303	31	–	Timeout
g15-15	50	304	32	–	Timeout

Type: Artificial instances arising from generalizations of Steiner tree LP gap examples

Table 45 Results on the testset skutella

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
s1	15	35	8	10	0.003
s2	106	399	50	–	Memout

Type: artificial instances arising from generalizations of Steiner tree LP gap examples

Table 46 Results on the testset smc

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
smc01	2	1	1	0	0.000
smc02	3	3	2	2	0.000
smc03	4	6	3	3	0.000
smc04	5	10	4	4	0.000
smc05	6	15	5	5	0.000
smc06	7	21	6	6	0.000
smc07	8	28	7	7	0.000
smc08	9	36	8	8	0.001
smc09	10	45	9	9	0.001
smc10	11	55	10	10	0.002
smc11	12	66	11	11	0.003
smc12	13	78	12	12	0.012
smc13	14	91	13	13	0.046
smc14	15	105	14	14	0.134
smc15	16	120	15	15	0.313

Type: artificial instances arising from generalizations of Steiner tree LP gap examples

Appendix 2: Results on rectilinear instances

For these experiments, the setup is identical to the one described in Appendix 1. For each instance, first, the Hanan grid was computed and written to an instance file describing an instance of the Steiner tree problem in graphs. The latter instance was then solved. The reported run times only include the time to solve the graphic instance, in particular, the time needed to read in the Hanan grid is not included (Tables 47, 48, 49, 50).

Table 47 Results on the testset CARIOCA

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
carioca_3_11_01	1331	3630	11	311,221,222	0.020
carioca_3_11_02	1331	3630	11	466,149,453	0.019
carioca_3_11_03	1331	3630	11	439,391,117	0.058
carioca_3_11_04	1331	3630	11	413,409,501	0.054
carioca_3_11_05	1331	3630	11	387,407,782	0.009
carioca_3_12_01	1728	4752	12	494,141,224	0.032
carioca_3_12_02	1728	4752	12	443,366,694	0.024
carioca_3_12_03	1728	4752	12	429,706,282	0.083
carioca_3_12_04	1728	4752	12	486,545,112	0.031
carioca_3_12_05	1728	4752	12	444,438,614	0.016
carioca_3_13_01	2197	6084	13	452,770,450	0.037
carioca_3_13_02	2197	6084	13	462,700,327	0.238
carioca_3_13_03	2197	6084	13	474,263,794	0.153
carioca_3_13_04	2197	6084	13	442,802,506	0.019
carioca_3_13_05	2197	6084	13	547,158,862	0.032
carioca_3_14_01	2744	7644	14	438,382,690	0.150
carioca_3_14_02	2744	7644	14	495,879,854	0.136
carioca_3_14_03	2744	7644	14	480,652,934	0.048
carioca_3_14_04	2744	7644	14	473,370,979	0.097
carioca_3_14_05	2744	7644	14	408,691,456	0.048
carioca_3_15_01	3375	9450	15	603,071,413	0.352
carioca_3_15_02	3375	9450	15	528,575,469	0.279
carioca_3_15_03	3375	9450	15	490,905,559	0.154
carioca_3_15_04	3375	9450	15	540,300,331	0.201
carioca_3_15_05	3375	9450	15	535,330,648	0.126
carioca_3_16_01	4096	11,520	16	527,653,658	0.181
carioca_3_16_02	4096	11,520	16	500,606,262	0.213
carioca_3_16_03	4096	11,520	16	468,414,684	0.130
carioca_3_16_04	4096	11,520	16	539,655,260	0.239
carioca_3_16_05	4096	11,520	16	540,126,099	0.140
carioca_3_17_01	4913	13,872	17	555,032,119	0.236

Table 47 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
carioca_3_17_02	4913	13,872	17	527,737,314	0.936
carioca_3_17_03	4913	13,872	17	562,083,809	0.405
carioca_3_17_04	4913	13,872	17	589,257,703	0.230
carioca_3_17_05	4913	13,872	17	612,582,645	3.852
carioca_3_18_01	5832	16,524	18	556,545,528	0.291
carioca_3_18_02	5832	16,524	18	549,027,056	1.392
carioca_3_18_03	5832	16,524	18	649,390,363	0.710
carioca_3_18_04	5832	16,524	18	554,907,444	0.800
carioca_3_18_05	5832	16,524	18	509,234,906	0.408
carioca_3_19_01	6859	19,494	19	561,743,715	6.788
carioca_3_19_02	6859	19,494	19	608,506,796	1.957
carioca_3_19_03	6859	19,494	19	574,021,347	0.398
carioca_3_19_04	6859	19,494	19	630,525,105	0.342
carioca_3_19_05	6859	19,494	19	650,204,402	6.354
carioca_3_20_01	8000	22,800	20	638,376,617	1.613
carioca_3_20_02	8000	22,800	20	477,950,448	0.148
carioca_3_20_03	8000	22,800	20	746,979,341	8.890
carioca_3_20_04	8000	22,800	20	653,809,733	10.096
carioca_3_20_05	8000	22,800	20	678,171,940	1.649

Type: Random 3-d rectilinear instances with coordinates scaled by 10^8

Table 48 Results on the testset CARIOCA

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
carioca_4_11_01	14,641	53,240	11	627,022,001	0.425
carioca_4_11_02	14,641	53,240	11	636,772,154	0.223
carioca_4_11_03	14,641	53,240	11	607,879,790	1.779
carioca_4_11_04	14,641	53,240	11	638,743,359	1.166
carioca_4_11_05	14,641	53,240	11	545,419,447	1.883
carioca_4_12_01	20,736	76,032	12	641,297,479	0.350
carioca_4_12_02	20,736	76,032	12	619,890,840	1.143
carioca_4_12_03	20,736	76,032	12	618,169,838	1.152
carioca_4_12_04	20,736	76,032	12	573,580,734	0.791
carioca_4_12_05	20,736	76,032	12	690,707,456	0.907
carioca_4_13_01	28,561	105,456	13	668,457,902	1.776
carioca_4_13_02	28,561	105,456	13	732,093,506	5.151
carioca_4_13_03	28,561	105,456	13	667,816,953	1.369
carioca_4_13_04	28,561	105,456	13	618,023,300	1.465

Table 48 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
carioca_4_13_05	28,561	105,456	13	816,676,045	9.274
carioca_4_14_01	38,416	142,688	14	678,015,050	1.967
carioca_4_14_02	38,416	142,688	14	770,189,931	32.560
carioca_4_14_03	38,416	142,688	14	774,041,179	7.656
carioca_4_14_04	38,416	142,688	14	753,394,327	15.256
carioca_4_14_05	38,416	142,688	14	668,149,161	6.908
carioca_4_15_01	50,625	189,000	15	867,047,412	3.505
carioca_4_15_02	50,625	189,000	15	747,749,078	2.624
carioca_4_15_03	50,625	189,000	15	797,161,324	41.344
carioca_4_15_04	50,625	189,000	15	682,701,539	9.475
carioca_4_15_05	50,625	189,000	15	816,563,142	5.407
carioca_4_16_01	65,536	245,760	16	877,600,183	53.440
carioca_4_16_02	65,536	245,760	16	840,957,543	11.185
carioca_4_16_03	65,536	245,760	16	769,487,137	7.469
carioca_4_16_04	65,536	245,760	16	883,810,994	40.603
carioca_4_16_05	65,536	245,760	16	844,364,805	26.792
carioca_4_17_01	83,521	314,432	17	778,812,798	46.322
carioca_4_17_02	83,521	314,432	17	885,687,619	96.926
carioca_4_17_03	83,521	314,432	17	866,496,021	345.275
carioca_4_17_04	83,521	314,432	17	961,783,573	22.303
carioca_4_17_05	83,521	314,432	17	926,268,906	107.808
carioca_4_18_01	104,976	396,576	18	951,149,709	99.353
carioca_4_18_02	104,976	396,576	18	842,404,966	98.72303
carioca_4_18_03	104,976	396,576	18	848,447,422	1431.374
carioca_4_18_04	104,976	396,576	18	956,109,307	212.732
carioca_4_18_05	104,976	396,576	18	893,733,310	143.342
carioca_4_19_01	130,321	493,848	19	917,950,857	186.383
carioca_4_19_02	130,321	493,848	19	825,014,078	49.409
carioca_4_19_03	130,321	493,848	19	945,521,812	25.660
carioca_4_19_04	130,321	493,848	19	912,019,383	160.591
carioca_4_19_05	130,321	493,848	19	963,415,391	1625.465
carioca_4_20_01	160,000	608,000	20	889,180,827	82.724
carioca_4_20_02	160,000	608,000	20	822,698,792	101.107
carioca_4_20_03	160,000	608,000	20	884,633,836	125.995
carioca_4_20_04	160,000	608,000	20	948,878,450	2618.045
carioca_4_20_05	160,000	608,000	20	984,006,649	82.545

Type: Random 4-d rectilinear instances with coordinates scaled by 10^8

Table 49 Results on the testset CARIOCA

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
carioca_5_11_01	161,051	732,050	11	925,163,690	34.547
carioca_5_11_02	161,051	732,050	11	844,673,618	13.019
carioca_5_11_03	161,051	732,050	11	867,510,918	6.297
carioca_5_11_04	161,051	732,050	11	906,103,201	14.043
carioca_5_11_05	161,051	732,050	11	795,198,510	30.521
carioca_5_12_01	248,832	1,140,480	12	953,491,398	59.408
carioca_5_12_02	248,832	1,140,480	12	985,601,088	102.106
carioca_5_12_03	248,832	1,140,480	12	844,385,082	57.499
carioca_5_12_04	248,832	1,140,480	12	879,014,839	93.151
carioca_5_12_05	248,832	1,140,480	12	815,604,529	15.595
carioca_5_13_01	371,293	1,713,660	13	881,473,517	132.662
carioca_5_13_02	371,293	1,713,660	13	873,559,091	177.287
carioca_5_13_03	371,293	1,713,660	13	1,005,775,838	184.838
carioca_5_13_04	371,293	1,713,660	13	922,258,018	237.882
carioca_5_13_05	371,293	1,713,660	13	879,174,698	46.431
carioca_5_14_01	537,824	2,497,040	14	1,080,307,930	1038.209
carioca_5_14_02	537,824	2,497,040	14	1,082,279,116	150.913
carioca_5_14_03	537,824	2,497,040	14	931,463,937	284.221
carioca_5_14_04	537,824	2,497,040	14	1,037,634,219	821.468
carioca_5_14_05	537,824	2,497,040	14	1,072,793,454	1224.013
carioca_5_15_01	759,375	3,543,750	15	1,011,895,745	1046.361
carioca_5_15_02	759,375	3,543,750	15	1,067,623,193	888.808
carioca_5_15_03	759,375	3,543,750	15	1,093,631,593	1258.172
carioca_5_15_04	759,375	3,543,750	15	890,715,927	66.472
carioca_5_15_05	759,375	3,543,750	15	1,112,392,828	638.515
carioca_5_16_01	1,048,576	4,915,200	16	1,140,155,635	3259.377
carioca_5_16_02	1,048,576	4,915,200	16	1,114,675,222	2047.700
carioca_5_16_03	1,048,576	4,915,200	16	1,097,447,396	464.254
carioca_5_16_04	1,048,576	4,915,200	16	–	Timeout
carioca_5_16_05	1,048,576	4,915,200	16	1,034,250,551	815.794
carioca_5_17_01	1,419,857	6,681,680	17	1,084,906,998	803.613
carioca_5_17_02	1,419,857	6,681,680	17	–	Memout
carioca_5_17_03	1,419,857	6,681,680	17	1,030,965,254	845.502
carioca_5_17_04	1,419,857	6,681,680	17	1,154,984,533	3195.596
carioca_5_17_05	1,419,857	6,681,680	17	–	Timeout
carioca_5_18_01	1,889,568	8,922,960	18	–	Memout

Table 49 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
carioca_5_18_02	1,889,568	8,922,960	18	–	Memout
carioca_5_18_03	1,889,568	8,922,960	18	1,177,091,608	1081.015
carioca_5_18_04	1,889,568	8,922,960	18	–	Timeout
carioca_5_18_05	1,889,568	8,922,960	18	–	Memout

Type: Random 5-d rectilinear instances with coordinates scaled by 10^8 . Instances with 19 and 20 terminals omitted

Table 50 Results on the testset bonn-3d

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
bonn_3_21_1	8820	25,179	21	6217	1.542
bonn_3_21_2	8820	25,179	21	6729	1.944
bonn_3_21_3	8820	25,179	21	5738	0.948
bonn_3_22_1	10,648	30,492	22	6681	842.792
bonn_3_22_2	10,648	30,492	22	6797	3.242
bonn_3_22_3	10,164	29,084	22	6941	4.239
bonn_3_23_1	12,167	34,914	23	6195	1.530
bonn_3_23_2	12,167	34,914	23	6094	2.275
bonn_3_23_3	11,638	33,373	23	6398	12.394
bonn_3_24_1	13,824	39,744	24	6622	4.948
bonn_3_24_2	13,248	38,064	24	7136	14.769
bonn_3_24_3	13,248	38,064	24	7014	7.010
bonn_3_25_1	15,625	45,000	25	6928	12.241
bonn_3_25_2	15,625	45,000	25	7249	9.195
bonn_3_25_3	15,625	45,000	25	7504	36.022
bonn_3_26_1	17,576	50,700	26	8184	11.849
bonn_3_26_2	17,576	50,700	26	7172	6.536
bonn_3_26_3	16,900	48,724	26	7732	7.608
bonn_3_27_1	18,252	52,676	27	7504	12.941
bonn_3_27_2	19,683	56,862	27	7032	20.365
bonn_3_27_3	18,954	54,729	27	7688	21.094
bonn_3_28_1	21,168	61,208	28	8106	1795.931
bonn_3_28_2	21,168	61,208	28	7774	384.240
bonn_3_28_3	21,952	63,504	28	7307	22.964
bonn_3_29_1	22,736	65,800	29	8231	248.490
bonn_3_29_2	23,548	68,179	29	8542	37.717
bonn_3_29_3	22,736	65,800	29	8053	23.270

Table 50 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
bonn_3_30_1	26,100	75,660	30	8141	181.245
bonn_3_30_2	26,100	75,660	30	7897	25.814
bonn_3_30_3	26,100	75,660	30	8527	63.451
bonn_3_31_1	27,869	80,848	31	8664	16.913
bonn_3_31_2	28,830	83,669	31	8409	328.879
bonn_3_31_3	28,830	83,669	31	7583	45.304
bonn_3_32_1	31,744	92,224	32	9483	59.047
bonn_3_32_2	31,744	92,224	32	8828	2371.743
bonn_3_32_3	31,744	92,224	32	8261	8.539
bonn_3_33_1	33,792	98,240	33	9588	46.329
bonn_3_33_2	35,937	104,544	33	9658	465.676
bonn_3_33_3	31,744	92,224	33	8902	83.404
bonn_3_34_1	37,026	107,745	34	9045	410.333
bonn_3_34_2	38,148	111,044	34	9664	1822.087
bonn_3_34_3	37,026	107,745	34	9105	959.836
bonn_3_35_1	41,650	121,345	35	–	Timeout
bonn_3_35_2	40,460	117,844	35	9372	513.599
bonn_3_35_3	40,460	117,844	35	9803	528.187
bonn_3_36_1	42,768	124,632	36	9353	2906.588
bonn_3_36_2	45,360	132,264	36	9118	87.813
bonn_3_36_3	44,100	128,555	36	–	Timeout
bonn_3_37_1	49,284	143,819	37	9379	811.912
bonn_3_37_2	47,915	139,786	37	9596	1602.806
bonn_3_37_3	49,284	143,819	37	8768	113.704
bonn_3_38_1	53,428	156,028	38	–	Timeout
bonn_3_38_2	52,022	151,885	38	9895	317.967
bonn_3_38_3	52,022	151,885	38	–	Timeout
bonn_3_39_1	54,834	160,171	39	9757	581.362
bonn_3_39_2	54,834	160,171	39	–	Timeout
bonn_3_39_3	57,798	168,909	39	–	Timeout
bonn_3_40_1	64,000	187,200	40	9024	25.440
bonn_3_40_2	57,798	168,909	40	9633	710.092
bonn_3_40_3	59,280	173,278	40	10,696	1183.496
bonn_3_45_1	89,100	261,315	45	–	Timeout

Table 50 continued

Instance	$ V $	$ E $	$ R $	Opt	Time (s)
bonn_3_45_2	89,100	261,315	45	–	Timeout
bonn_3_45_3	85,140	249,613	45	–	Timeout
bonn_3_50_1	110,544	324,721	50	–	Memout
bonn_3_50_2	117,600	345,598	50	–	Timeout
bonn_3_50_3	112,800	331,394	50	–	Memout
bonn_3_55_1	160,380	472,284	55	–	Timeout
bonn_3_55_2	151,470	445,881	55	–	Timeout
bonn_3_55_3	154,548	455,004	55	12,138	6201.104
bonn_3_60_1	198,417	585,044	60	–	Timeout
bonn_3_60_2	201,898	595,369	60	–	Timeout
bonn_3_60_3	198,476	585,220	60	–	Memout

Type: Random 3-d rectilinear instances. Coordinates were chosen uniformly at random from $\{0, 1, \dots, 999\}$

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