



Master-Thesis

# High Quality Hypergraph Partitioning via Max-Flow-Min-Cut Computations

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## Abstract

In this thesis, we introduce a framework based on *Max-Flow-Min-Cut* computations for improving balanced  $k$ -way partitions of hypergraphs. Currently, variations of the *FM* heuristic [17] are used as *local search* algorithms in all state-of-the-art multilevel hypergraph partitioners. Such *move*-based heuristics have the disadvantage that they only incorporate *local* information about the problem structure and if many *moves* of vertices have an equal impact on the solution quality, the outcome mainly depends on random choices made within the algorithm [15, 31, 36]. *Flow*-based approaches are not *move*-based and they are able to find a *global* minimum cut separating two vertices  $s$  and  $t$  [18].

Our framework is inspired by the work of Sanders and Schulz [44] who successfully integrate a *flow*-based refinement algorithm into a multilevel graph partitioner. We generalize many ideas such that they are applicable in the multilevel hypergraph partitioning context. We develop several techniques to sparsify the hypergraph flow network, which reduces the resulting problem size by a factor of 2 on average compared to the state-of-the-art representation [33]. Additionally, we show how to configure a flow problem on a subhypergraph such that the quality achievable with a *Max-Flow-Min-Cut* computation is significantly better than with the modeling approach of Sanders and Schulz. Finally, we integrate our work as refinement strategy into the  $n$ -level hypergraph partitioner *KaHyPar* [25].

We tested our framework on a large benchmark set with 3216 instances. In comparison to 5 different systems, our new configuration outperforms the tested state-of-the-art hypergraph partitioners on 73% of the instances. In comparison to the latest version of *KaHyPar*, our new approach improves quality by 2.5% while only incurring a performance slowdown by a factor of 2. However, our algorithm is still as fast as the direct  $k$ -way version of *hMetis* and outperforms it on 84% of the benchmarks.

## Zusammenfassung

In dieser Arbeit wird ein Framework basierend auf *Max-Flow-Min-Cut* Berechnungen vorgestellt, zur Verbesserung einer balancierten  $k$ -teilige Aufteilung eines Hypergraphen. Aktuell werden Varianten des *FM* Algorithmus [17] in allen modernen *Multilevel Hypergraph Partitionierer* als lokaler Suchalgorithmus verwendet. Solche *bewegungsbasierenden* Heuristiken haben den Nachteil, dass sie nur *lokale* Informationen über die Problemstruktur in die Berechnungen miteinfließen lassen. Wenn viele Knotenbewegungen den selben Einfluss auf die Lösungsqualität haben, dann hängt das Ergebnis oft von zufälligen Entscheidungen ab, welche der Algorithmus selbst trifft [15, 31, 36]. Flussbasierende Ansätze sind nicht *bewegungsbasiert* und finden einen *globalen* minimalen Schnitt, welcher zwei Knoten  $s$  und  $t$  eines Graphen trennt [18].

Unser Framework ist durch die Arbeit von Sanders und Schulz [44] inspiriert. Diese integrierten eine *flussbasierende* Heuristik erfolgreich in Ihren *Multilevel Graph Partitionierer*. Wir generalisieren viele Ihrer Ideen, sodass sie im *Multilevel Hypergraph Partitionierung*-Kontext anwendbar sind. Wir entwickeln mehrere Techniken, um das aktuelle *Hypergraph Flussnetzwerk* zu verkleinern, welche die resultierende Problemgröße im Vergleich zu der aktuellen Representation [33], um den Faktor 2 reduziert. Zusätzlich zeigen wir, wie ein Flussproblem auf einem *Subhypergraphen* konfiguriert werden kann, sodass das eine *Max-Flow-Min-Cut* Berechnung eine bessere Qualität erzielt, als die Modellierung von Sanders und Schulz. Am Ende haben wir unsere Arbeit als Verbesserungsstrategie in den  $n$ -level *Hypergraph Partitionierer KaHyPar* integriert [25].

Wir haben unser Framework auf 3216 verschiedenen Instanzen getestet. Im Vergleich mit 5 verschiedenen Systemen erzielt unsere neue Konfiguration, auf 73% der Instanzen, die besten Ergebnisse. Im Vergleich zu der aktuellen Variante von *KaHyPar* ist die Qualität der Lösungen um 2.5% gestiegen, während die Laufzeit lediglich um den Faktor 2 langsamer ist. Jedoch hat unser Algorithmus eine vergleichbare Laufzeit mit *hMetis* und erzielt auf 84% der Instanzen bessere Ergebnisse.

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A good mentor is important for staying motivated and to have the feeling to work on something meaningful. Since my bachelor thesis, I work together with Sebastian Schlag in the research area of *Hypergraph Partitioning*. The decision to further work on this topic was not only a matter of interest, it was mainly a decision based on our outstanding interpersonal working relationship. Our intellectual discussions were characterized by the right balance of fun and the necessary seriousness to work towards a common goal. I think here is the right place to thank you for the endless time, which I have spent in your office over the last three years and which have made me a better computer scientist.

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## 1. Introduction

Hypergraphs are a generalization of graphs where each (hyper)edge can connect more than two (hyper)nodes. The  $k$ -way hypergraph partitioning problem is to partition the vertices of a hypergraph into  $k$  disjoint, non-empty blocks such that the size of each block is smaller than  $(1 + \epsilon)$  times the average block size, while simultaneously minimizing an objective function on the hypergraph.

Classical application areas are in *VLSI* design, parallelization of the sparse matrix-vector multiplication and simplifying *SAT* formulas [29, 36, 39]. The goal in *VLSI* design is to partition a circuit into smaller units such that the wires between the gates are as short as possible [9]. A wire can connect more than two gates, therefore a hypergraph models a circuit more accurately than a graph. In *SAT* solving, hypergraph partitioning is used to decompose a formula into smaller subformulas, which can be solved more easily [36].

Hypergraph partitioning is an NP-hard problem [34] and it is even NP-hard to find a good approximation [8]. The most common heuristic used in state-of-the-art hypergraph partitioners is the *multilevel paradigm* [10, 25, 29]. First, a sequence of smaller hypergraphs is generated by contracting matchings or clusterings in each step (*coarsening phase*). If the hypergraph is small enough, we can use expensive heuristics to *initially partition* it into  $k$  blocks. Afterwards, the sequence of smaller hypergraphs is *uncontracted* in reverse order and, at each level, a local search heuristic is used to improve the quality of the partition (*refinement phase*).

There exist several local search heuristics for improving hypergraph partitions. Currently, variations of the *FM* heuristic [17] are used as local search algorithms in all state-of-the-art multilevel hypergraph partitioners. All such approaches have in common that they greedily move hypernodes between blocks of a partition according to an associated *gain* value that depends on the local structure around a vertex. The *FM* heuristic is generally intuitive, easily adaptable to different optimization objectives and relatively fast [51].

However, the gain of moving a hypernode to another block only depends on the state of the incident hyperedges. Therefore, *FM* has no *global* view on the structure of the problem. A move is performed *locally* and *greedily*. Consequently, the algorithm tends to find locally optimal solutions, whose quality heavily depends on the initial partition [15]. If we execute *FM* in the multilevel context, we partially solve the problem. A move of a vertex in a coarsened hypergraph corresponds to a movement of a subset of the hypernodes on the *original* hypergraph, which allows a more effective exploration of the solution space [39]. The quality of the solution then depends more on the quality of the coarsening rather than on the initial partition.

A move of a node only influences the gain function if the state of an incident hyperedge changes *immediately* after a move. If a hyperedge contains vertices from two different blocks, where only one hypernode is contained in the first and all remaining hypernodes are in the second block, then a move of that node contributes to the gain if the objective is e.g., *cut* (sum of the weights of hyperedges which contain vertices of more than one block). Especially for large hyperedges, a sequence of nodes have to be moved such that a single move of a node finally contributes to the gain. Therefore, the gain of most vertices is equal to zero in such cases [36]. Krishnamurthy [31] points out that the quality in such situations highly depends on random choices made within the algorithm. Therefore, he enhanced the *FM* algorithm with a look-ahead scheme such that in case of ties one can incorporate *future gains* into the decision [31]. However, this *forecast* is limited by a predefined parameter.

*FM*-based local search algorithms have the above-mentioned disadvantages, because they are move-based and only incorporate local informations about the structure of the problem. Finding a balanced global minimum cut of a (hyper)graph is NP-hard, but if we ask for a minimum cut separating two vertices  $s$  and  $t$ , the problem becomes solvable in polynomial time [16]. The

well-known *max-flow min-cut* theorem [18] relates the maximum flow from a source  $s$  to a sink  $t$  to the minimum cut separating  $s$  and  $t$  in a graph. *Flow-based* approaches are not move-based and incorporate the *global* structure of the problem. Therefore, they overcome the drawbacks of the *FM* algorithm. However, they were overlooked for a long time because it was perceived as computationally expensive and impractical for (hyper)graph partitioning [35].

Sanders and Schulz [44] successfully integrated a *flow-based* refinement algorithm into their multilevel *graph* partitioner. They combine the strength of *flow-based* refinement and *FM* local search by executing both algorithms alternating throughout the multilevel hierarchy. As a result their multilevel graph partitioner produces the best partitions for a wide range of graph partitioning benchmarks. Recently, several algorithms were developed to obtain a balanced bipartition of a hypergraph with *Max-Flow-Min-Cut* computations [35, 40, 50]. A balanced  $k$ -way hypergraph partition with such an approach is currently only obtainable by applying the bipartitioning algorithm recursively [50]. The impact of a *flow-based* refinement algorithm on the solution quality of a multilevel hypergraph partitioner has not been studied yet.

## 1.1. Problem Statement

Motivated by the results of Sanders and Schulz [44], this thesis integrates such an approach into the  $n$ -level hypergraph partitioner *KaHyPar* [25]. One of the fundamental questions of this work is how *Max-Flow-Min-Cut* computations can be used to improve a given bipartition of hypergraphs. Therefore, the hypergraph must be modeled as a flow network such that each minimum cut separating two vertices  $s$  and  $t$  is computable with a maximum  $(s, t)$ -flow. The bipartitioning algorithm is the theoretical foundation for a framework to improve balanced  $k$ -way partitions of hypergraphs. The last step is to integrate the framework into the  $n$ -level hypergraph partitioner *KaHyPar* [25] and evaluate the performance on a large benchmark set in comparison to different state-of-the-art multilevel hypergraph partitioners. A major goal of this work is to outperform the latest version of *KaHyPar* on most of the benchmark instances and simultaneously ensure that the running time remaining competitive.

## 1.2. Contributions

We present several techniques to sparsify the hypergraph flow network representation proposed by Lawler [33]. Our experiments indicate that maximum flow algorithms are up to a factor of 2 faster on our new networks. Our *Max-Flow-Min-Cut* refinement framework is inspired by algorithmic ideas of Sanders and Schulz [44]. However, we generalize many results of their work such that they are applicable to hypergraph partitioning. We show how to configure a flow problem on a subhypergraph such that a maximum  $(S, T)$ -flow improves a given bipartition. Further, we show theoretically and practically that with our modeling approach better minimum cuts are achievable compared to the results of Sanders and Schulz. Additionally, we implement several heuristics to prevent unpromising *Max-Flow-Min-Cut* computations throughout the multilevel hierarchy and show that they speed-up the framework by factor of 2 while maintaining the solution quality. We integrate our *flow-based* refinement algorithm into the  $n$ -level hypergraph partitioner *KaHyPar* and show that the combination of *flow-based* refinement and *FM* algorithm produces the best partitions on a majority of real world benchmarks in comparison to other state-of-the-art hypergraph partitioners. Compared to 5 different systems, we achieve the best partitions on 73% of 3216 benchmark instances. In comparison to the latest version of *KaHyPar*, our new approach improves quality by 2.5% on average, while only incurring a slowdown by a factor of 2. However, our algorithm is still as fast the direct  $k$ -way version of *hMetis* and outperforms it on 84% of the benchmark instances.

### 1.3. Outline

We first introduce necessary notations and summarize related work in Sections 2 and 3. Afterwards, we describe techniques to sparsify the flow network proposed by Lawler [33] in Section 4. In Section 5 we present our source and sink set modeling approach and describe the integration of our *flow-based* refinement framework into the  $n$ -level hypergraph partitioner *KaHyPar*. The experimental evaluation of our algorithm is presented in Section 6. Section 7 concludes this thesis.

## 2. Preliminaries

### 2.1. Graphs

A directed weighted graph  $G = (V, E, c, \omega)$  is a set of nodes  $V$  and a set of edges  $E$  with a node weight function  $c : V \rightarrow \mathbb{R}$  and an edge weight function  $\omega : E \rightarrow \mathbb{R}$ . An edge  $e = (u, v)$  is a relation between two nodes  $u, v \in V$ .  $G_{V'} = (V', E_{V'}, c, \omega)$  is a subgraph of a graph  $G$  induced by  $V' \subseteq V$  with  $E_{V'} = \{(u, v) \in E \mid u, v \in V'\}$ . Two vertices  $u$  and  $v$  are *adjacent*, if there exists an edge  $(u, v) \in E$ . Two edges  $e_1$  and  $e_2$  are *incident* to each other if they share a node.  $N(v)$  denotes the set of all *adjacent* nodes of  $v$ . The *degree* of a node  $v$  is  $d(v) = |N(v)|$ .

**Definition 2.1** (Contraction). *Given a directed graph  $G = (V, E)$ . A contraction of two nodes  $u$  and  $v$  results in a new graph  $G_{(u,v)} = (V \setminus \{v\}, E')$ , where each edge of the form  $(v, w)$  or  $(w, v)$  in  $E$  is replaced with an edge  $(u, w)$  or  $(w, u)$  in  $E'$ .*

A *path*  $P = (v_1, \dots, v_k)$  is a sequence of nodes, where for each  $i \in [1, k - 1] : (v_i, v_{i+1}) \in E$ . A *cycle* is a path  $P = (v_1, \dots, v_k)$  with  $v_1 = v_k$ . A *strongly connected component*  $C \subseteq V$  is a set of nodes where for each  $u, v \in C$  exists a *path* from  $u$  to  $v$ . We can enumerate all *strongly connected components* (*SCCs*) in a directed graph  $G$  with a linear time algorithm proposed by Tarjan [47]. A directed graph  $G$  without any *cycles* is called *directed acyclic graph* (*DAG*). On such graphs we can define a *topological order*  $\gamma : V \rightarrow \mathbb{N}_+$  such that for each  $(u, v) \in E : \gamma(u) < \gamma(v)$ . A *topological order* of a *DAG* can be found in linear time with Kahn's algorithm [28]. We can transform a general directed graph  $G$  into a *DAG* by contracting each *strongly connected component*. *Strongly connected components* and a *topological order* of a graph are illustrated in Fig. 1.

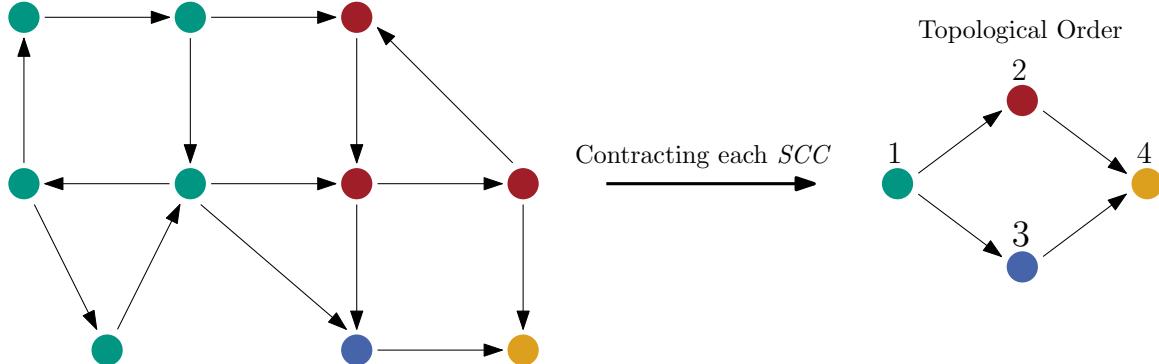


Figure 1: Example of *strongly connected components* in a directed graph and a *topological order* of a *directed acyclic graph*. Each *SCC* is marked with the same color.

### 2.2. Flows and Applications

Given a graph  $G = (V, E, u)$  with capacity function  $u : E \rightarrow \mathbb{R}_+$  and a source  $s \in V$  and a sink  $t \in V$ , the maximum flow problem is to find the maximum value of flow from  $s$  to  $t$  in  $G$ . A flow is a function  $f : E \rightarrow \mathbb{R}_+$ , which has to satisfy the following constraints:

- (i)  $\forall (u, v) \in E : f(u, v) \leq u(u, v)$  (capacity constraint)
- (ii)  $\forall v \in V \setminus \{s, t\} : \sum_{(u,v) \in E} f(u, v) = \sum_{(v,u) \in E} f(v, u)$  (conservation of flow constraint)

The capacity constraint restricts the flow on edge  $(u, v)$  by its capacity  $u(u, v)$ , whereas the conservation of flow constraint ensures that the amount of flow entering a node  $v \in V \setminus \{s, t\}$

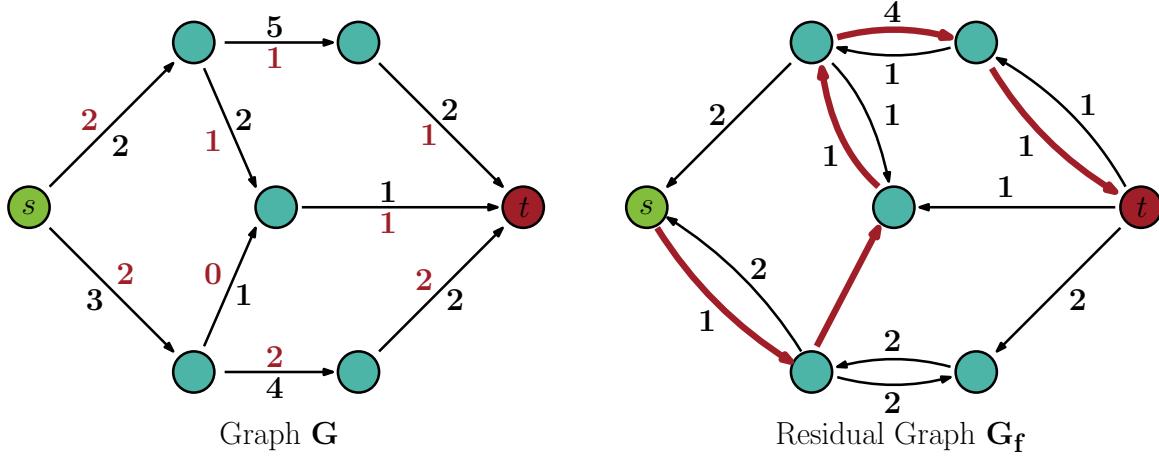


Figure 2: Illustrates concepts related to the maximum flow problem. A flow function  $f$  (red values) from  $s$  to  $t$  of a graph  $G$  is shown on the left side. The corresponding *residual graph*  $G_f$  with its *residual capacities* (black values) is illustrated on the right side. The red highlighted path is an *augmenting path*.

$\{s, t\}$  is the same as the amount leaving a node. The value of the flow is defined as  $|f| = \sum_{(s,v) \in E} f(s, v) = \sum_{(v,t) \in E} f(v, t)$ . A flow  $f$  is maximal, if there exists no other flow  $f'$  with  $|f'| > |f|$ .

The *residual capacity*  $r_f : V \times V \rightarrow \mathbb{R}_+$  of a flow function  $f$  is defined as follows:

- (i)  $\forall (u, v) \in E : r_f(u, v) = u(u, v) - f(u, v)$
- (ii)  $\forall (u, v) \in E : \text{If } f(u, v) > 0 \text{ and } u(v, u) = 0, \text{ then } r_f(v, u) = f(u, v)$

For an edge  $e = (u, v) \in E$  the residual capacity  $r_f(u, v)$  is the remaining amount of flow which can be send over edge  $e$ . For each reverse edge  $\overleftarrow{e} \notin E$  the residual capacity  $r_f(\overleftarrow{e})$  is the amount of flow which is send over  $e$ . The *residual graph*  $G_f = (V, E_f, r_f)$  is the network containing all  $(u, v) \in V \times V$  with  $r_f(u, v) > 0$ . More formally  $E_f = \{(u, v) \in V \times V \mid r_f(u, v) > 0\}$ . An *augmenting path*  $P = \{v_1, \dots, v_k\}$  is a path in  $G_f$  with  $v_1 = s$  and  $v_k = t$  [16]. Fig. 2 illustrates all presented concepts.

The *Max-Flow-Min-Cut-Theorem* is fundamental for many applications related to the maximum flow problem [18].

**Theorem 2.1** (Max-Flow Min-Cut). *The value of a maximum  $(s, t)$ -flow obtainable in a graph  $G$  is equal to the weight of a minimum-weight cutset in  $G$  separating  $s$  and  $t$ .*

Let  $f$  be a maximum  $(s, t)$ -flow in a graph  $G = (V, E, \omega)$  with  $s \in V$  and  $t \in V$ . Further, let  $A$  be the set containing all  $v \in V$ , which are *reachable* from  $s$  in  $G_f$ . A node  $v$  is *reachable* from a node  $u$  if there exists a path from  $u$  to  $v$ . Then the set of all edges from nodes in  $A$  to nodes in  $V \setminus A$  is a minimum-weight  $(s, t)$ -cutset [19].  $A$  can be calculated with a *BFS* in  $G_f$  starting from  $s$ .

Many related problems can be solved with maximum flows. For example, maximum bipartite-matching, number of edge- or vertex-disjoint paths in a graph or to find a minimum-weight vertex separator. Solutions to those problems sometimes involve a transformation  $T$  of the graph  $G$  into a flow network  $T(G)$ , such that the *Max-Flow-Min-Cut-Theorem* is applicable. A problem essential for this work is to find a minimum-weight  $(s, t)$ -vertex separator in a graph  $G = (V, E, c)$  with  $c : V \rightarrow \mathbb{R}_+$ .

**Definition 2.2** (Vertex Separator). *Let  $G = (V, E, c)$  be a graph with  $c : V \rightarrow \mathbb{R}_+$ .  $S \subseteq V$  is a vertex separator for non-adjacent vertices  $s \in V$  and  $t \in V$  if the removal of  $S$  from*

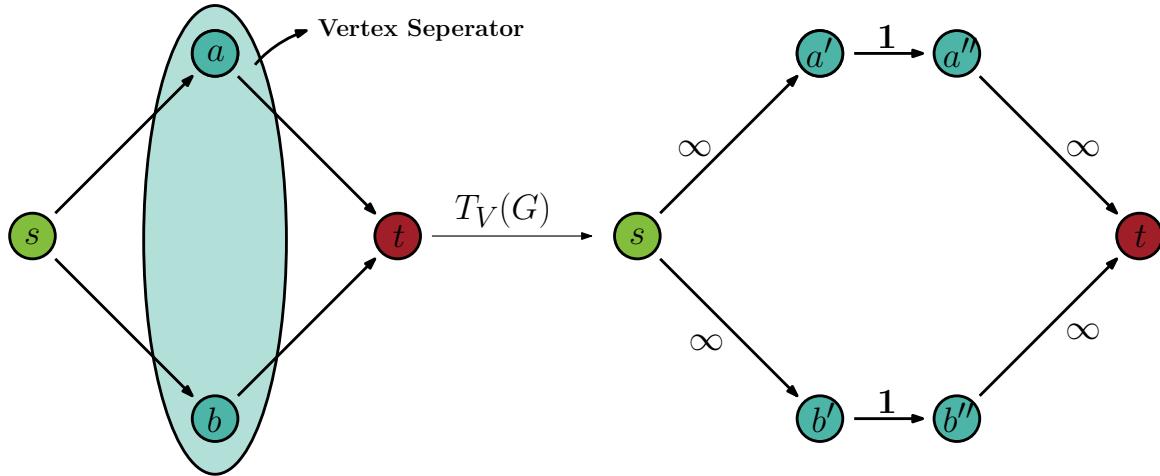


Figure 3: Illustration of the vertex separator problem and the flow network  $T_V(G)$  in which we can find a minimum  $(s, t)$ -vertex separator.

graph  $G$  separates  $s$  and  $t$  ( $s$  not reachable from  $t$ ). A vertex separator  $S$  is a minimum-weight  $(s, t)$ -vertex separator, if for all  $(s, t)$ -vertex separators  $S' \subseteq V$  it follows that  $c(S) \leq c(S')$ .

We can calculate a minimum-weight  $(s, t)$ -vertex separator with a maximum flow calculation on the following flow network [49]:

**Definition 2.3** (Vertex Separator Transformation). Let  $T_V$  be a transformation of a graph  $G = (V, E, c)$  into a flow network  $T_V(G) = (V_V, E_V, u_V)$  (with  $u_V : E_V \rightarrow \mathbb{R}_+$ ).  $T_V$  is defined as follows:

- (i)  $V_V = \bigcup_{v \in V} \{v', v''\}$
- (ii)  $\forall v \in V : \text{add a directed edge } (v', v'') \text{ with capacity } u_V(v', v'') = c(v)$
- (iii)  $\forall (u, v) \in E : \text{add two directed edges } (u'', v') \text{ and } (v'', u') \text{ with capacity } u_V(u'', v') = u_V(v'', u') = \infty$ .

The vertex separator problem and transformation  $T_V(G)$  is illustrated in Fig. 3. Obviously, no edge between two adjacent nodes in  $G$  can be in a minimum-capacity  $(s, t)$ -cutset of  $T_V(G)$ , because for all those edges the capacity is  $\infty$ . Therefore, the cutset must consist of edges of the form  $(v', v'')$ . A minimum-weight  $(s, t)$ -vertex separator can be calculated by finding a maximum  $(s, t)$ -flow of  $T_V(G)$  and the corresponding minimum  $(s, t)$ -cutset [37].

Given a set of sources  $S$  and sinks  $T$ . The *multi-source multi-sink* maximum flow problem is to find a maximum flow  $f$  from all source nodes  $s \in S$  to all sink nodes  $t \in T$ . We can transform such a problem into a *single-source single-sink* problem by adding two additional nodes  $s$  and  $t$ . We add a directed edge from  $s$  to all source nodes  $s' \in S$  and for all sink nodes  $t' \in T$  a directed edge to  $t$  with capacity  $u(s, s') = u(t', t) = \infty$ .

## 2.3. Hypergraphs

**Definition 2.4** (Hypergraph). An undirected weighted hypergraph  $H = (V, E, c, \omega)$  consists of a set of hypernodes  $V$  and a set of hyperedges  $E$  with a hypernode weight function  $c : V \rightarrow \mathbb{R}$  and a hyperedge weight function  $\omega : E \rightarrow \mathbb{R}$ . A hyperedge  $e$  is a subset of  $V$  (formally:  $\forall e \in E : e \subseteq V$ ).

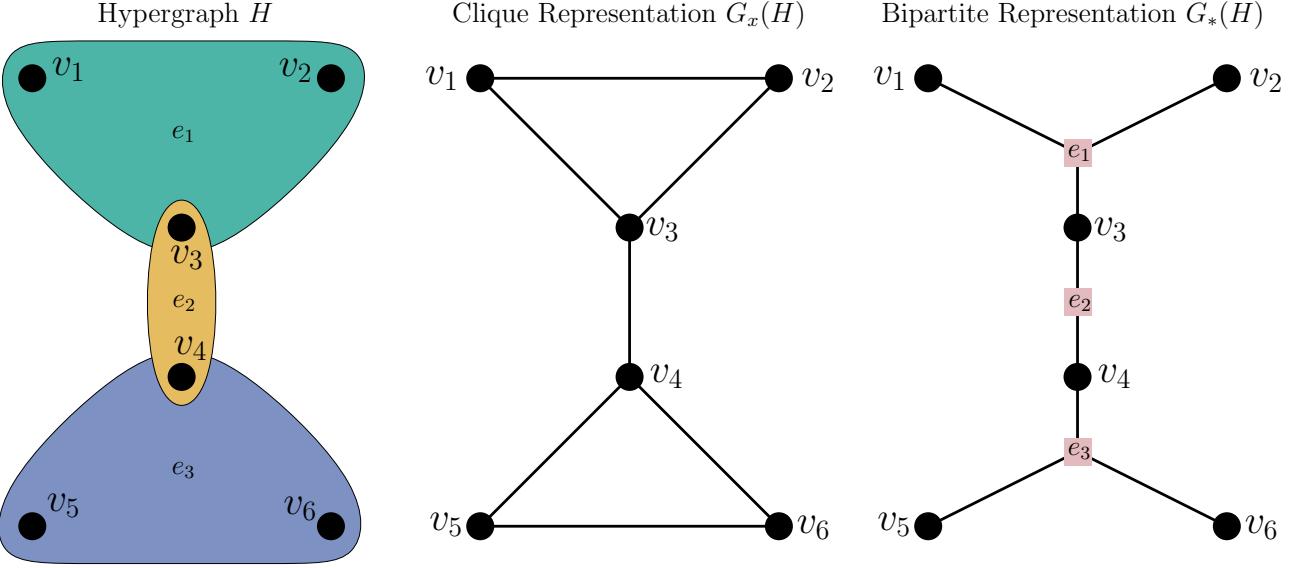


Figure 4: Example of a hypergraph  $H$  and its two corresponding graph representations.

A hypergraph generalizes a graph by extending the definition of an edge, which can contain more than two nodes. Hyperedges are also called *nets* and hypernodes are also called *vertices*. A vertex contained in a net is called *pin*. For a subset  $V' \subseteq V$  and  $E' \subseteq E$  we define

$$c(V') = \sum_{v \in V'} c(v)$$

$$\omega(E') = \sum_{e \in E'} \omega(e)$$

A vertex  $v$  is *incident* to a hyperedge  $e$  if  $v \in e$ . Two vertices  $u$  and  $v$  are *adjacent*, if there exists an  $e \in E$  such that  $u \in e$  and  $v \in e$ .  $I(v)$  denotes the set of all *incident* nets of  $v$ . The *degree* of a hypernode  $v$  is  $d(v) = |I(v)|$ . The size of a net  $e$  is its cardinality  $|e|$ .

**Definition 2.5** (Subhypergraph).  $H_{V'} = (V', E_{V'}, c, \omega)$  is a subhypergraph of a hypergraph  $H$  induced by  $V' \subseteq V$  with  $E_{V'} := \{e \cap V' \mid e \in E : e \cap V' \neq \emptyset\}$ .

**Definition 2.6** (Section Hypergraph). Given a subset  $A \subseteq V$  of hypergraph  $H = (V, E, c, \omega)$ . The section hypergraph  $H \times A$  is the hypergraph induced by subset  $A$  and contains all hyperedges  $e \in E$  which are fully contained in  $A$ . More formally,  $H \times A := (A, \{e \mid e \in E : e \subseteq A\}, \omega, c)$ .

A hypergraph  $H = (V, E, c, \omega)$  can be represented as an undirected graph. There are two standard transformations, called *clique* and *bipartite* representation [27]. The *clique* graph  $G_x(H) = (V, E_x)$  models each net  $e$  as a clique between its pins. The *bipartite* graph  $G_*(H) = (V \cup E, E_*)$  contains all hypernodes and hyperedges as nodes and connects each net  $e$  with an undirected edge  $\{e, v\}$  to all its pins  $v \in e$ . The two transformations are illustrated in Fig. 4.

## 2.4. Hypergraph Partitioning

**Definition 2.7** ( $k$ -way Partition). A  $k$ -way partition of a hypergraph  $H$  is a partition of its hypernodes into  $k$  disjoint blocks  $\Pi = \{V_1, \dots, V_k\}$  such that  $\bigcup_{i=1}^k V_i = V$  and  $V_i \neq \emptyset$ .

For a  $k$ -way partition  $\Pi = \{V_1, \dots, V_k\}$ , we define the *connectivity set* of a hyperedge  $e$  with  $\Lambda(e, \Pi) = \{V_i \in \Pi \mid V_i \cap e \neq \emptyset\}$ . The *connectivity* of a net  $e$  is  $\lambda(e, \Pi) = |\Lambda(e, \Pi)|$ . A hyperedge

$e$  is *cut*, if  $\lambda(e, \Pi) > 1$ .  $E(\Pi) = \{e \mid \lambda(e, \Pi) > 1\}$  is the set of all *cut* nets. We say two blocks  $V_i$  and  $V_j$  are adjacent, if there exists a hyperedge  $e$  with  $\{V_i, V_j\} \subseteq \Lambda(e, \Pi)$ . A  $k$ -way partition is  $\epsilon$ -balanced if each block  $V_i \in \Pi$  satisfies the *balance constraint*  $c(V_i) \leq (1 + \epsilon)\lceil \frac{c(V)}{k} \rceil$ .

**Definition 2.8** (Hypergraph Partitioning Problem). *The  $k$ -way hypergraph partitioning problem is to find an  $\epsilon$ -balanced  $k$ -way partition  $\Pi$  of a hypergraph  $H$  such that a certain objective function is minimized.*

There exists several objective functions in the hypergraph partitioning context. The most popular objective function is the cut metric (especially for *graph partitioning*), which is defined as

$$\omega_H(\Pi) = \sum_{e \in E(\Pi)} \omega(e)$$

The goal is to minimize the weight of all *cut* hyperedges. Another important metric for this work is the  $(\lambda - 1)$ -metric or *connectivity* metric, which is defined as

$$(\lambda - 1)_H(\Pi) = \sum_{e \in E} (\lambda(e, \Pi) - 1)\omega(e)$$

The idea behind this function is to minimize the *connectivity* of all hyperedges.

**Definition 2.9** (Quotient Graph).  *$Q = (\Pi, E')$  is a graph, which contains an edge between each pair of adjacent blocks of a  $k$ -way partition  $\Pi = \{V_1, \dots, V_k\}$  of a hypergraph  $H$ . More formally,  $E' = \{(V_i, V_j) \mid \exists e \in E : V_i, V_j \in \Lambda(e, \Pi)\}$ .*

### 3. Related Work

#### 3.1. Maximum Flow Algorithms

In Section 2.2 we introduce the concept of flows in a network. We will now present two approaches to solve the maximum flow problem.

##### 3.1.1. Augmenting-Path Algorithms

An *augmenting path*  $P = \{v_1, \dots, v_k\}$  is a path in the residual graph  $G_f$  with  $v_1 = s$  and  $v_k = t$  [16]. Fig. 5 illustrates such a path. For all edges  $(u, v) \in G_f$  it holds that  $r_f(u, v) > 0$ . Therefore we can increase the flow on all edges  $(v_i, v_{i+1})$  by  $\Delta f = \min_{i \in [1, \dots, k-1]} r_f(v_i, v_{i+1})$ . It can be shown that  $f$  is not a maximum flow if an augmenting path exists in  $G_f$  [16].

One way to calculate a maximum flow  $f$  is to find augmenting paths in  $G_f$  as long as there exists one. The algorithm was established by Ford and Fulkerson [18] and consists of two phases. First, we search for an augmenting path  $P = \{v_1, \dots, v_k\}$  from  $s$  to  $t$ , e.g., with a simple *DFS*. Afterwards, we increase the flow on each edge  $(v_i, v_{i+1})$  by  $\Delta f$  and decrease the flow on each reverse edge  $(v_{i+1}, v_i)$  by  $\Delta f$ . If the capacities are integral, the algorithm always terminates. Since we can find an augmenting path in  $G_f$  with a simple *DFS* in  $\mathcal{O}(|V| + |E|)$  time and increase the flow on every path by at least one, the running time of the algorithm can be bounded by  $\mathcal{O}(|E||f_{max}|)$ . We can construct instances where the running time is  $\mathcal{O}(|E||f_{max}|)$  or even instances where the maximum flow  $|f_{max}|$  is exponential in the problem size [16].

Edmond and Karp [16] improved Ford & Fulkerson's algorithm by increasing the flow along an augmenting path of minimal length. The shortest path from  $s$  to  $t$  in a graph with unit lengths can be found with a simple *BFS*. It can be shown that the total number of *augmentations* is in  $\mathcal{O}(|V||E|)$ . The running time of Edmond & Karp's maximum flow algorithm is  $\mathcal{O}(|V||E|^2)$ . An exemplary execution of the algorithm is presented in Fig. 5.

Boykov and Kolmogorov proposed a maximum flow algorithm based on augmenting path especially designed for applications in computer vision [7]. Their basic idea is to grow two search trees simultaneously. One is starting from the source and one from the sink. The two search trees maintain the invariant that all edges in the tree are non-saturated. More formally, for an edge  $e$  the residual capacity  $r_f(e)$  must be greater than zero. A node is added to one of the two trees if a non-saturated edge exists that connects the node with one of the nodes in the search trees. If the two trees touch at a given node, we found an augmenting path from the source to the sink. After we increase the flow along this path, some of the edges in the two search trees are saturated. Therefore, the algorithm tries to restore the search tree invariant by finding a new non-saturated edge for each node which is connected through a saturated edge to the tree. If this is not possible, then the node is removed from the tree. The algorithm has no polynomial complexity (worst case  $\mathcal{O}(|E||V|^2|f|)$ ), but it outperforms many state-of-the-art maximum flow algorithms on computer vision benchmarks [7].

An extension of the algorithm of Boykov & Kolmogorov is the *incremental breadth-first search* algorithm [21], which guarantees polynomial running time ( $\mathcal{O}(|V|^2|E|)$ ). The algorithm maintains two distance labels  $d_s$  and  $d_t$  for each node. For some values  $D_s$  and  $D_t$ , the source tree contains all nodes up to a distance  $D_s$  and the sink tree up to distance  $D_t$ . Furthermore it maintains the invariant that  $L = D_s + D_t + 1$  is a lower bound for the shortest augmenting path. Initially,  $d_s(s) = d_t(t) = 0$  and  $D_s = D_t = 0$ . The algorithm works in passes and in a pass one of the two trees is chosen to grow. Assume, we have chosen the source tree. Each node  $u$  contained in the source tree with distance label  $d_s(u) = D_s$  is marked as *active*. In a pass all *active* nodes are processed. If an *active* node  $u$  is adjacent to a node  $v$  not contained

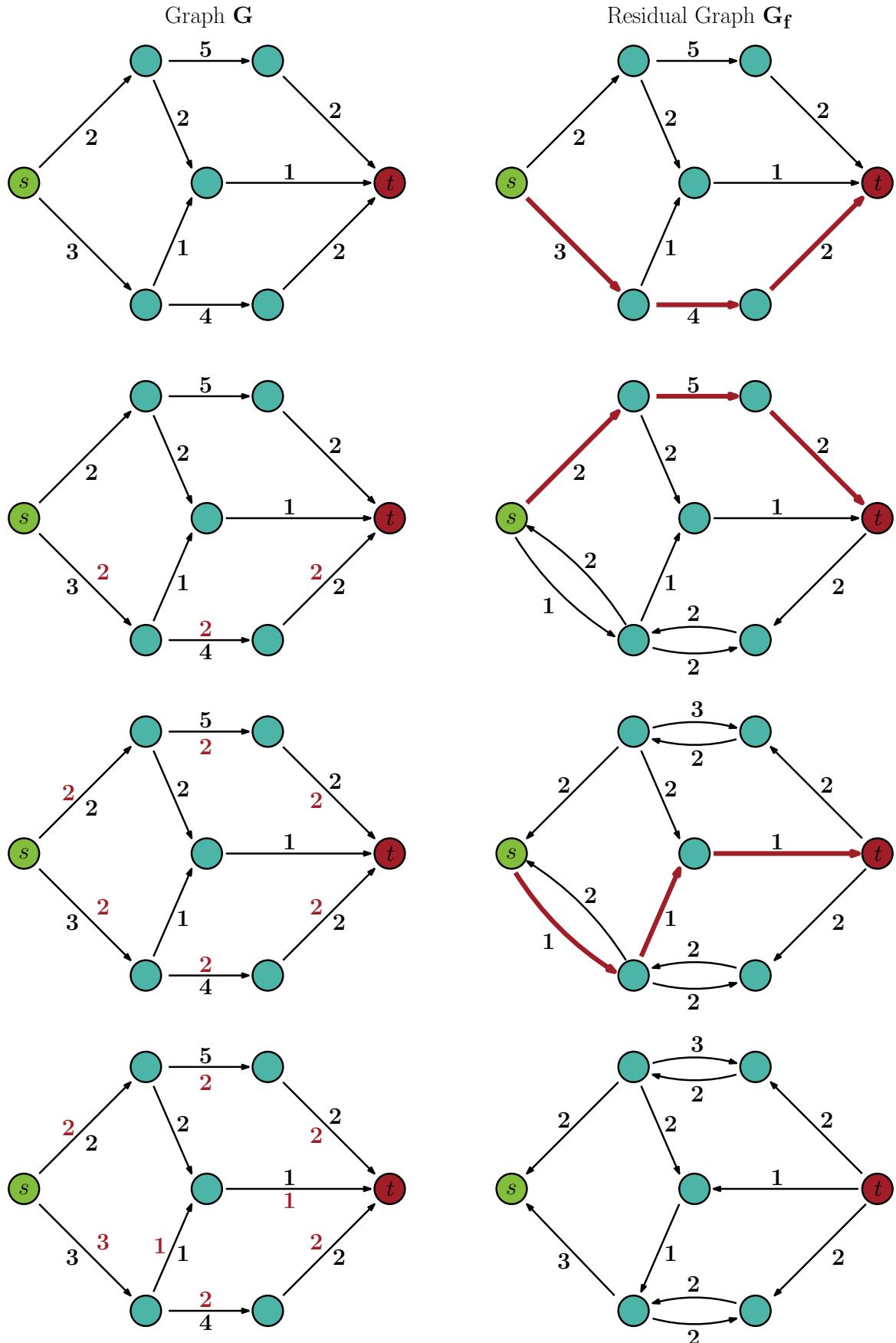


Figure 5: Execution of Edmond & Karps maximum flow algorithm [16]. The network  $G$  with its capacities  $c$  (black values) and flow  $f$  (red values) is illustrated on the left side. The residual graph  $G_f$  with its *residual capacities*  $r_f$  (black values) is presented on the right side. In each step the current augmenting path in  $G_f$  is highlighted by a red path.

in any of the two trees, we add  $v$  to the source tree and set  $d_s(v) = d_s(u) + 1$ . If  $v$  is in the sink tree, we have found an augmenting path. After augmenting along that path some of the nodes are not connected to the tree through a non-saturated edge. For such a node  $v$  the adjacency list is scanned and if an adjacent node  $u$  exist with  $d_s(u) = d_s(v) - 1$  and  $r_f(u, v) > 0$ , the parent of  $v$  is set to  $u$ . If such a node is not found, we search for an adjacent node  $u$  for which  $d_s(u)$  is minimal and  $r_f(u, v) > 0$ . If such a node is found, we set the parent of  $v$  to  $u$  and  $d_s(v) = d_s(u) + 1$ . Otherwise,  $v$  is removed from the source tree. If after a pass a node  $v$  exists with  $d_s(v) = D_s + 1$ ,  $D_s$  is set to  $D_s + 1$ , otherwise the algorithm terminates.

### 3.1.2. Push-Relabel Algorithm

Goldberg and Tarjan [23] proposed a maximum flow algorithm not based on finding an augmenting path in the *residual graph*. Instead, the idea is to maintain a *preflow* during the execution of the algorithm which satisfies the capacity constraints, but only a weakened form of the conservation of flow constraint:

$$\forall v \in V \setminus \{s, t\} : \sum_{u \in V} f(v, u) \leq \sum_{u \in V} f(u, v)$$

The algorithm maintains a *distance labeling*  $d : V \rightarrow \mathbb{N}$  and an *excess function*  $e_f : V \rightarrow \mathbb{N}$ . The *distance labeling* satisfies the following conditions:  $d(s) = |V|$ ,  $d(t) = 0$  and for each  $(u, v) \in E_f$ ,  $d(u) \leq d(v) + 1$ . We say an residual edge  $(u, v)$  is *admissible* if  $d(u) = d(v) + 1$ . A node  $v$  is *active* if  $v \notin \{s, t\}$  and  $e_f(v) > 0$ .

Initially, all *labels* and *excess* values are set to zero except for the source node  $s$  will be set to  $d(s) = 1$  and  $e_f(s) = \infty$ . For each *active* node  $u$  the algorithm performs two update operations, called *push* and *relabel*. The first operation pushes flow over each *admissible* edge  $(u, v)$ . After a *push*  $e_f(u) = e_f(u) - \min(e_f(u), r_f(u, v))$  and  $e_f(v) = e_f(v) + \min(e_f(u), r_f(u, v))$ . If there is no *admissible* edge, a *relabel* operation is performed, which replaces  $d(u)$  by  $\min_{(u,v) \in E_f} d(v) + 1$ . The algorithm terminates, if none of the nodes is *active*. The worst case complexity of the algorithm is  $\mathcal{O}(n^3)$ . The running time can be reduced to  $\mathcal{O}(n^2 \log n)$  with *Dynamic Trees* [23, 46], but this implementation is not practical due to a large hidden constant factor.

The *push-relabel* algorithm is one of the fastest maximum flow algorithms in practice because there exist several speed-up techniques. The first one is the *global relabeling* heuristic which frequently updates the *distance labels* by computing the shortest path in the residual graph from all nodes to the sink [12]. This can be done with a backward *BFS* in linear time. This technique is performed periodically, e.g., after  $n$  *relabel* operations.

The second heuristic is the *gap heuristic* [11, 14]. If at a particular stage of the algorithm there is no node  $u$  with  $d(u) = g < n$ , then for each node  $v$  with  $g < d(v) < n$  the sink is not reachable anymore. Therefore, we can increase the *distance label* of all those nodes to  $n$ . To implement this heuristic, the algorithm maintains a linked list of nodes with distance label  $i$ .

## 3.2. Modeling Flows on Hypergraphs

Finding a minimum  $(s, t)$ -cutset of a hypergraph  $H = (V, E, c, \omega)$  is close related to the problem of finding a minimum  $(s, t)$ -vertex separator of the corresponding *bipartite graph* representation  $G_*(H)$  (see Section 2.3). Hu and Moerder [27] introduce node capacities in  $G_*(H)$ . Each hyperedge  $e$  has a capacity equal to  $\omega(e)$  and each hypernode has infinite capacity. Further, they show that a minimum-weight  $(s, t)$ -vertex separator in  $G_*(H)$  is equal to a minimum-weight  $(s, t)$ -cutset of a hypergraph  $H$ . Finding such a separator is a flow problem and can be calculated with the flow network  $T_L(H)$  presented by Lawler [33]:

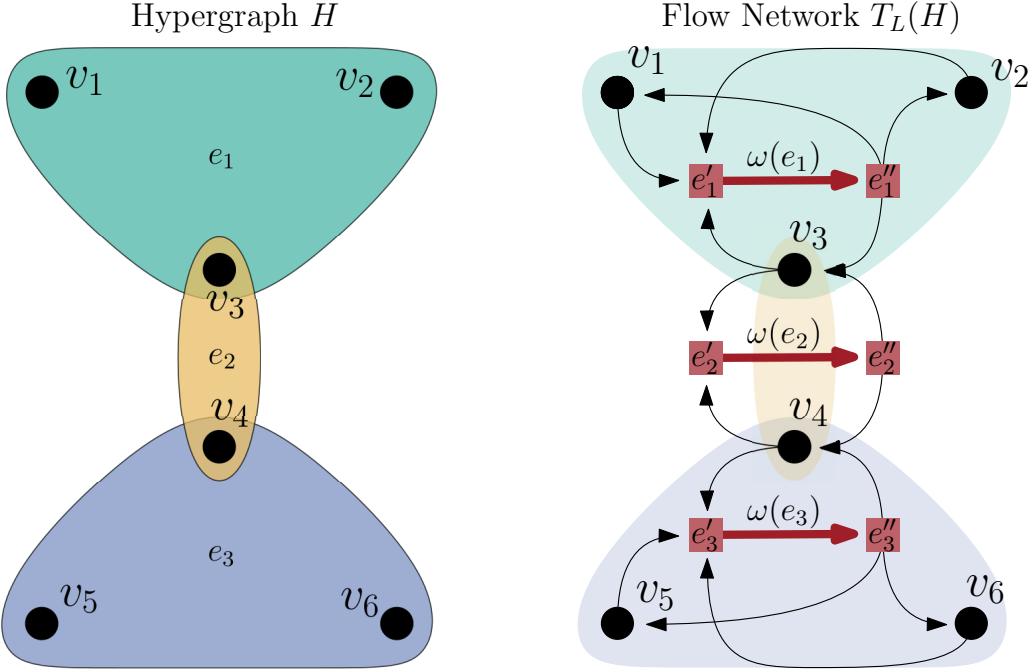


Figure 6: Transformation of a hypergraph into the flow network  $T_L(H)$  [33]. The capacity of the black edges in the flow network is  $\infty$ .

**Definition 3.1** (Lawler Transformation). Let  $T_L$  be the transformation of a hypergraph  $H = (V, E, c, \omega)$  into a flow network  $T_L(H) = (V_L, E_L, u_L)$  proposed by Lawler [33].  $T_L(H)$  is defined as follows:

- (i)  $V_L = V \cup \bigcup_{e \in E} \{e', e''\}$
- (ii)  $\forall e \in E : we add a directed edge (e', e'') with capacity u_L(e', e'') = \omega(e)$
- (iii)  $\forall v \in V \text{ and } \forall e \in I(v) : we add two directed edges (v, e') and (e'', v) with capacity u_L(v, e') = u_L(e'', v) = \infty.$

An example of this transformation is shown in Fig. 6.  $T_L(H)$  is nearly equivalent to the transformation  $T_V(G)$  described in Definition 2.3 except that we do not have to split the hypernodes  $v \in V$ . For all  $e \in E$  there exist two corresponding nodes  $e', e'' \in V_L$ .  $e'$  is called *incoming hyperedge node* and  $e''$  is called *outgoing hyperedge node*.

A hypernode cannot be in a minimum-capacity  $(s, t)$ -vertex separator because each  $v \in V$  has infinity capacity [27]. Therefore, a minimum-capacity  $(s, t)$ -cutset of  $T_L(H)$  is equal to a minimum  $(s, t)$ -vertex separator of  $G_*(H)$ . The resulting graph  $T_L(H)$  has  $|V_L| = |V| + 2|E|$  nodes and  $|E_L| = (2\bar{e} + 1)|E|$  edges, where  $\bar{e}$  is the average size of a hyperedge [42]. Using Edmond-Karps maximum flow algorithm (see Section 3.1.1) on flow network  $T_L(H)$  takes time  $\mathcal{O}(|V|^2|E|^2)$  [33].

A minimum-weight  $(s, t)$ -cutset of  $H$  can be found by simply mapping the minimum-capacity  $(s, t)$ -cutset to their corresponding hyperedges in  $H$  (see Section 2.2). The minimum-weight  $(s, t)$ -bipartition consists of all vertices  $v \in V$  reachable from  $s$  in the residual graph of  $T_L(H)$  and all hypernodes not reachable from  $s$ .

In Fig. 7 we illustrate the structure of  $T_L(H)$  and demonstrate what happens after we augment along a path in the Lawler-Network. This figure can be used as a reference to illustrate the proofs of Section 4.

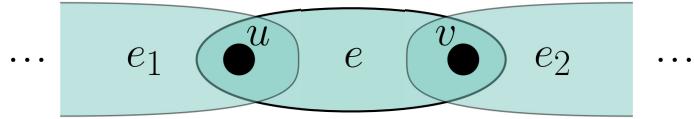
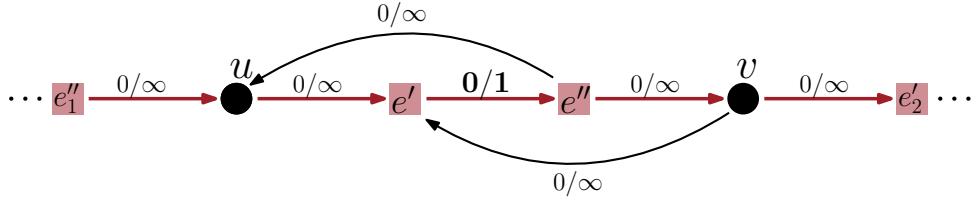
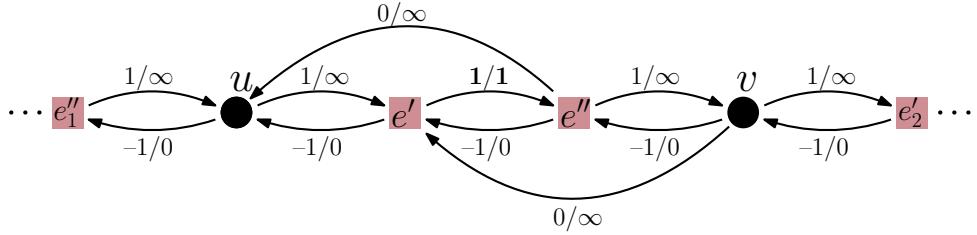
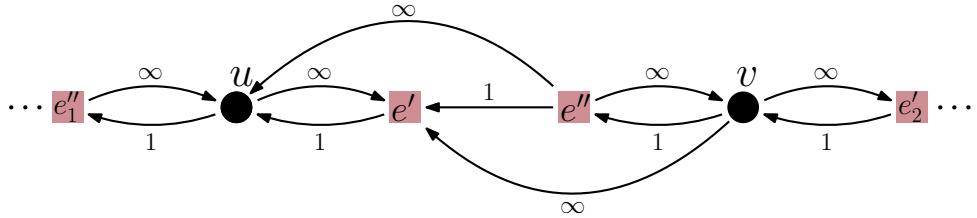
Hypergraph  $H$ 

 Flow Network  $T_L(H)$ 

 Flow Network  $T_L(H)$  after augmentation

 Residual Graph of  $T_L(H)$  after augmentation


Figure 7: Illustration of the structure of a hyperedge  $e$  in  $T_L(H)$  and the effect of augmenting along a path in the network. The labeling on an edge represents the flow  $f(x, y)$  and the capacity  $u(x, y)$  denoted with  $f(x, y)/u(x, y)$ . The labeling of the edges in the residual graph corresponds to the residual capacity  $r_f(x, y)$ . The red highlighted path represents an augmenting path.

### 3.3. Flow-based Refinement for Graph Partitioning

It seems natural to utilize maximum flow computations to improve the cut metric of a given partition of a graph. Lang and Rao [32] use an approach, called *Max-Flow Quotient-cut Improvement* (MQI) to improve the quality of a graph partition when metrics such as *expansion* or *conductance* are used. For a given bipartition  $(S, \bar{S})$ , they find the best improvement among all bipartitions  $(S', \bar{S}')$  such that  $S' \subset S$  by solving a flow problem. Andersen and Lang [4] suggested a flow-based improvement algorithm, called *Improve*, which works similar as MQI, but does not restrict the output of the partition to  $S' \subset S$ . However, both techniques can not guarantee that the resulting bipartition is balanced and are only applicable for  $k = 2$ .

Schulz and Sanders [44] integrate a flow-based refinement algorithm in the *multilevel graph*

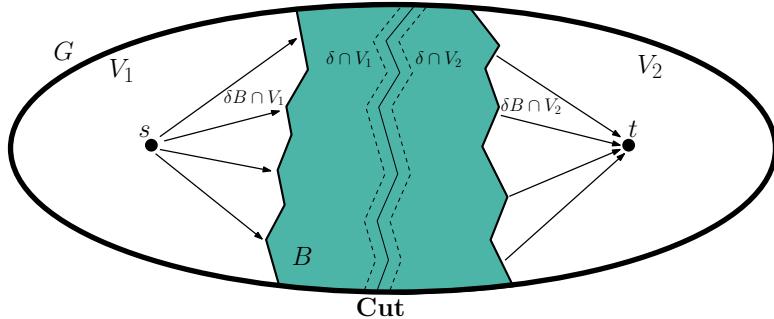


Figure 8: Configuration of a flow problem around the cut of graph  $G$  [44].

*partitioner KaFFPa*. Their basic idea is to extract a region  $B$  around the cut of the graph and connect the *border* of  $B$  with the source resp. sink.  $B$  is defined in such a way that the flow computation yields a feasible cut according to the *balance constraint*. Many ideas of this work are used in this thesis and adapted to hypergraphs. Therefore we will give a detailed description of the concepts and advanced techniques to improve graph partitions.

### 3.3.1. Balanced Bipartitioning

Let  $(V_1, V_2)$  be a balanced bipartition of a graph  $G = (V, E, c, \omega)$ . Further, let  $P(v) = 1$ , if  $v \in V_1$  and  $P(v) = 2$  otherwise. We now explain how a given bipartition can be improved with flow computations. The technique can also be applied on a  $k$ -way partition by applying the approach on two adjacent blocks [44].

Let  $\delta := \{u \mid \exists(u, v) \in E : P(u) \neq P(v)\}$  be the set of nodes around the cut of  $G$ . For a set  $B \subseteq V$  we define its border  $\delta B := \{u \in B \mid \exists(u, v) \in E : v \notin B\}$ . The basic idea is to build a region  $B$  around  $\delta$  and connect all nodes in  $\delta B \cap V_1$  to the source node  $s$  and all nodes in  $\delta B \cap V_2$  to the sink node  $t$ .

We can construct  $B := B_1 \cup B_2$  with two *Breadth First Searches (BFS)*. One is initialized with all nodes in  $\delta \cap V_1$  and stops if  $c(B_1)$  would exceed  $(1 + \epsilon) \lceil \frac{c(V)}{2} \rceil - c(V_2)$ . The second is initialized with all nodes in  $\delta \cap V_2$  and stops if  $c(B_2)$  would exceed  $(1 + \epsilon) \lceil \frac{c(V)}{2} \rceil - c(V_1)$ . The two *BFSs* only touch nodes of  $V_1$  resp.  $V_2$  such that  $B_1 \subseteq V_1$  and  $B_2 \subseteq V_2$ . The constraints for the weights of  $B_1$  and  $B_2$  guarantee that the bipartition is still balanced after a *Max-Flow-Min-Cut* computation. Connecting  $s$  resp.  $t$  to all border nodes  $\delta B \cap V_1$  resp.  $\delta B \cap V_2$  ensures that a non-cut edge not contained in  $G_B$  is not a cut edge after assigning the minimum  $(s, t)$ -bipartition of subgraph  $G_B$  to  $G$ . Consequently, each minimum  $(s, t)$ -cutset in  $G_B$  leads to a cut smaller or equal to the old cut of  $G$ . All concepts are illustrated in Fig. 8.

### 3.3.2. Adaptive Flow Iterations

Sanders and Schulz [44] introduce several techniques to improve this basic approach. If the *Max-Flow-Min-Cut* computation on  $G_B$  leads to an improved cut, we can apply the method again. An extension of this approach is to iteratively adapt the size of the flow problem based on the result of the maximum flow computation. We define  $\epsilon' := \alpha\epsilon$  for a  $\alpha \geq 1$  and let the size of  $B$  depend on  $\epsilon'$  rather than on  $\epsilon$ . If we find an improvement, we increase  $\alpha$  to  $\min\{2\alpha, \alpha'\}$  where  $\alpha'$  is a predefined upper bound for  $\alpha$ . If not, we decrease the size of  $\alpha$  to  $\max\{\frac{\alpha}{2}, 1\}$ . The approach is called *adaptive flow iterations* [44].

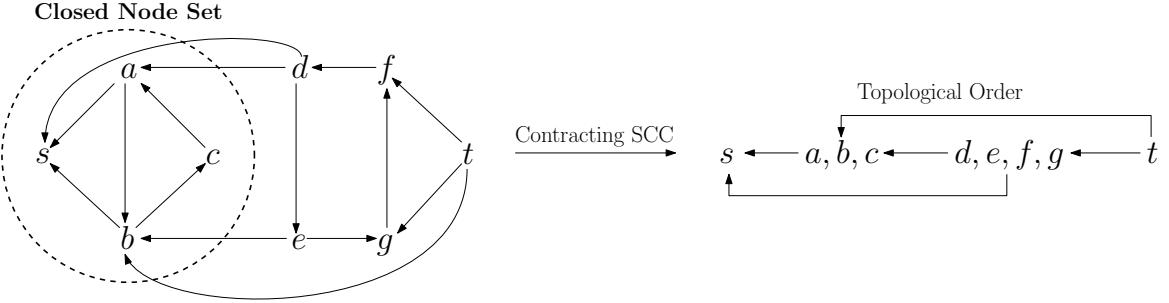


Figure 9:  $C = \{s, a, b, c\}$  is a *closed node set* of graph  $G$  (left side). After contracting all *Strongly Connected Components*, we can enumerate all *closed node sets* of  $G$  by sweeping over the contracted graph in reverse topological order (right side).

### 3.3.3. Most Balanced Minimum Cut

Picard and Queyranne [41] show that all minimum  $(s, t)$ -cuts are computable with one maximum  $(s, t)$ -flow computation. An important concept used by them is the definition of a *closed node set*  $C \subseteq V$  of a graph  $G$ .

**Definition 3.2** (Closed Node Set). *Let  $G = (V, E)$  be a graph and  $C \subseteq V$ .  $C$  is called a *closed node set* iff the condition  $u \in C$  implies that for all edges  $(u, v) \in E$  also  $v \in C$ .*

A *closed node set* is illustrated in Fig. 9. A simple observation is that all nodes on a cycle have to be in the same *closed node set* per definition. Therefore we can contract all *Strongly Connected Components* (SCC) of  $G$  with a linear time algorithm proposed by Tarjan [47] and sweep over the contracted graph in reverse topological order to enumerate all *closed node sets*. If we contract all SCCs of  $G$  the resulting graph is a *directed acyclic graph* (DAG). Therefore, a topological order exists.

With the Theorem of Picard and Queyranne [41] we can enumerate all minimum  $(s, t)$ -cuts of  $G$  with one maximum flow computation.

**Theorem 3.1.** *There is a 1-1 correspondence between the minimum  $(s, t)$ -cuts of a graph and the closed node sets containing  $s$  in the residual graph of a maximum  $(s, t)$ -flow.*

All *closed node sets* in the residual graph of  $G$  induce a minimum  $(s, t)$ -cutset on  $G$ . They can be calculated with the algorithm described above using the residual graph of  $G$  as input. The running time of the algorithm is  $\mathcal{O}(|V| + |E|)$ .

A common problem of the *adaptive flow iteration* approach (see Section 3.3.2) is that using a large  $\alpha$  often leads to cuts in  $G$  that violate the balanced constraint. We can enumerate all minimum  $(s, t)$ -cuts with one maximum flow computation and therefore have a higher probability to find a feasible partition after a *Max-Flow-Min-Cut* computation. We refer to this method as *Most Balanced Minimum Cut* [44].

### 3.3.4. Active Block Scheduling

*Active Block Scheduling* is a *quotient graph style refinement* technique for  $k$ -way partitions [26, 44]. The algorithm is organized in rounds and executes a two-way local improvement algorithm on each pair of adjacent blocks in the *quotient graph* where at least one of both is *active*. Initially all blocks are *active*. A block becomes *inactive* if none of its nodes move in a round. The algorithm terminates, if all blocks are *inactive*.

Fiduccia and Mattheyses [17] introduce a linear time two-way local search heuristic, called *FM*

heuristic, which is fundamental for many graph partitioning algorithms. They define the gain  $g(v)$  of a node  $v \in V$  as the reduction of the cut metric when moving  $v$  from its current block to the other block. By maintaining the gains of the nodes in a special data structure, called *bucket queue*, they can find a maximum gain node in constant time. After moving a maximum gain node, they are also able to update the data structure in time equal to the number of adjacent nodes.

The local improvement algorithm (for *Active Block Scheduling*) can either be an *FM* local search or a flow-based approach or even a combination of both as proposed by Sanders and Schulz [44].

## 3.4. Hypergraph Partitioning

In this section, we review how most hypergraph partitioners solve the *hypergraph partitioning problem*. The most successful approach is the *multilevel paradigm* [3, 5, 39] which we describe in Section 3.4.1. The algorithms presented in this thesis are integrated into  $n$ -level hypergraph partitioner *KaHyPar*. Therefore, we give a brief overview of implementation details of this framework in Section 3.4.2.

### 3.4.1. Multilevel Paradigm

The *multilevel paradigm* is a three phase algorithm to solve the *hypergraph partitioning problem* (see Fig. 10). In the first stage, called *coarsening phase*, vertex matchings or clusterings are calculated which are contracted. This process is repeated until a predefined number of hypernodes remains. The sequence of successively smaller hypergraphs is called *levels*. If the hypergraph  $H$  is small enough, expensive algorithms can be used to initially partition  $H$  into  $k$  blocks (*Initial Partitioning*). Afterwards, we *uncontract* each *level* in reverse order of *contraction* by projecting the partition to the next *level*. After *uncontraction* a *refinement* heuristic can be used to improve the quality of the current partition according to an objective function. The most commonly used *refinement* algorithm is the *FM* algorithm [17].

### 3.4.2. $n$ -Level Hypergraph Partitioning

*KaHyPar* is a multilevel hypergraph partitioner in its most extreme version, which removes only a single vertex in one *level* of the hierarchy. It seems to be the method of choice for optimizing cut- and the  $(\lambda - 1)$ -metric unless speed is more important than quality [25]. The framework provides a *direct k-way* [1] and a *recursive bisection* mode, which recursively calculates bipartitions (with multilevel paradigm) until the hypergraph is divided into  $k$  blocks [45]. *KaHyPar* consists of four phases: *Preprocessing* and the three phases of the *multilevel paradigm*.

In the *preprocessing* step community structures of the hypergraph are detected. The hypergraph is transformed into a bipartite graph  $G_*(H)$  (see Section 2.3) and a community detection algorithm is executed which optimizes *modularity* [20, 25]. During the *coarsening phase* contractions are restricted to vertices within the same community. The contraction partners are chosen according to the *heavy-edge* rating function  $r(u, v) := \sum_{e \in I(u) \cap I(v)} \frac{\omega(e)}{|e|-1}$  [29]. The function prefers vertices which share a large number of heavy nets with small size. The contraction algorithm works in passes. At the beginning of each pass a random permutation of the vertices is generated and for each vertex  $u$ , the contraction partner  $v$  is determined according to the *heavy-edge* rating function [45]. A pass ends if each vertex was involved in a contraction. The passes are repeated until only  $t = 160k$  hypernodes remain. The *initial partitioning* phase uses the *recursive bisection* approach to calculate a  $k$ -way partition in combination with a portfolio

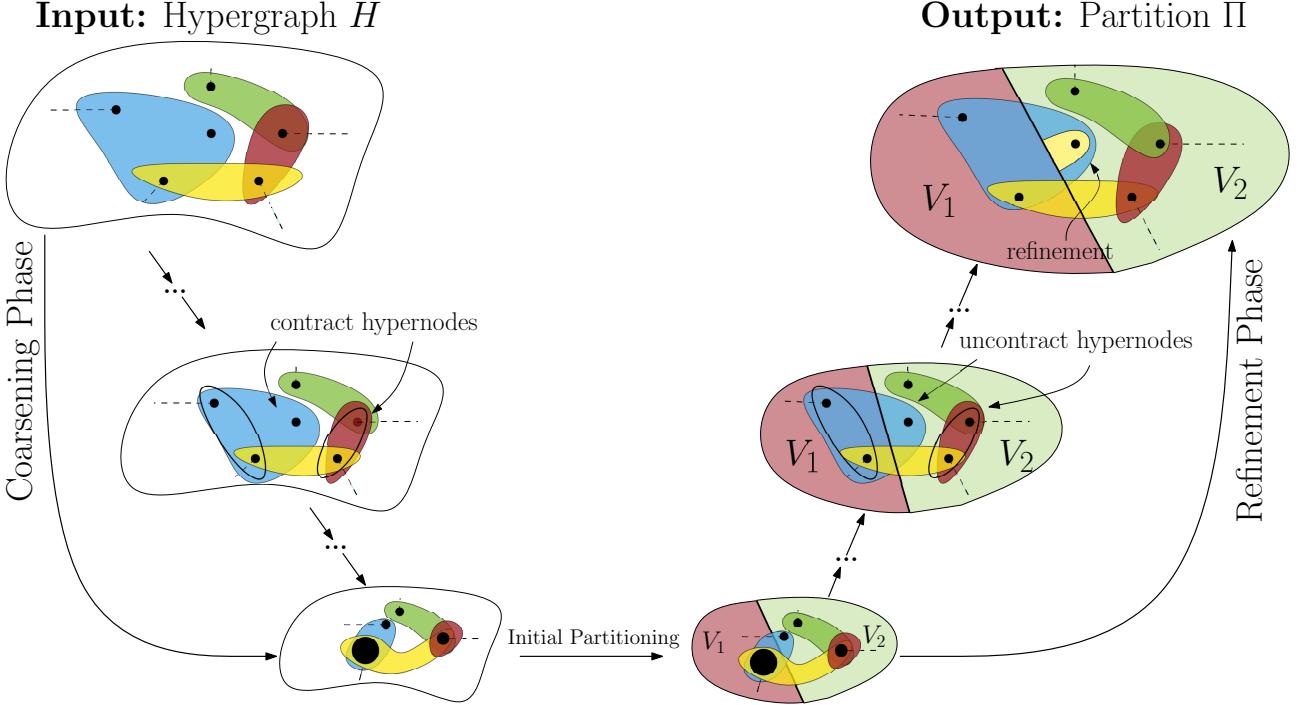


Figure 10: Multilevel Hypergraph Partitioning

of initial partitioning techniques [24]. In the *refinement phase*, a localized *FM* search is started [17], initialized with the current uncontracted vertices. The *local search* maintains  $k$  *priority queues* (PQ) for each block  $V_i$  exactly one [1]. After a move, the gains of all adjacent hypernodes are updated with a *delta-gain* update strategy [39]. The recalculation of all gain values at the beginning of a *FM* pass is one of the main bottlenecks of the algorithm [39]. Therefore, Schlag et al. [1, 45] introduce a *gain cache*, which prevents expensive recalculations of the corresponding gain function. The *gain cache* is maintained with *delta-gain* updates in the same way as the PQs. Further, the *local search* is stopped as soon as an improvement during an *FM* pass becomes unlikely. This model is called *adaptive stopping rule* [1].

## 4. Hypergraph Flow Networks

In Section 3.2 we have shown how a hypergraph  $H$  can be transformed into a flow network  $T_L(H)$  such that each minimum-capacity  $(S, T)$ -cutset of  $T_L(H)$  is a minimum-weight  $(S, T)$ -cutset of  $H$  [33]. However, the resulting flow network has significantly more nodes and edges than the original hypergraph. The running time of a maximum flow algorithm depends heavily on the problem size. Therefore, different modeling approaches, which reduce the number of nodes and edges, can have a crucial impact on the running time of the flow algorithm.

We will present techniques to sparsify the flow network proposed by Lawler. First, we will show how *any subset  $V' \subseteq V$  of hypernodes* can be removed from  $T_L(H)$  (see Section 4.1). This approach minimizes the number of nodes, but in some cases the number of edges can be significantly higher than in  $T_L(H)$ . The basic idea of this technique can still be applied to remove low degree hypernodes from the Lawler-Network *without* increasing the number of edges (see Section 4.2). Additionally, we show how every hyperedge  $e$  of size 2 can be removed by inserting an undirected flow edge between the corresponding nodes (see Section 4.3). Finally, we combine the two suggested approaches into a Hybrid-Network (see Section 4.4). The presented transformations are illustrated in Fig. 11.

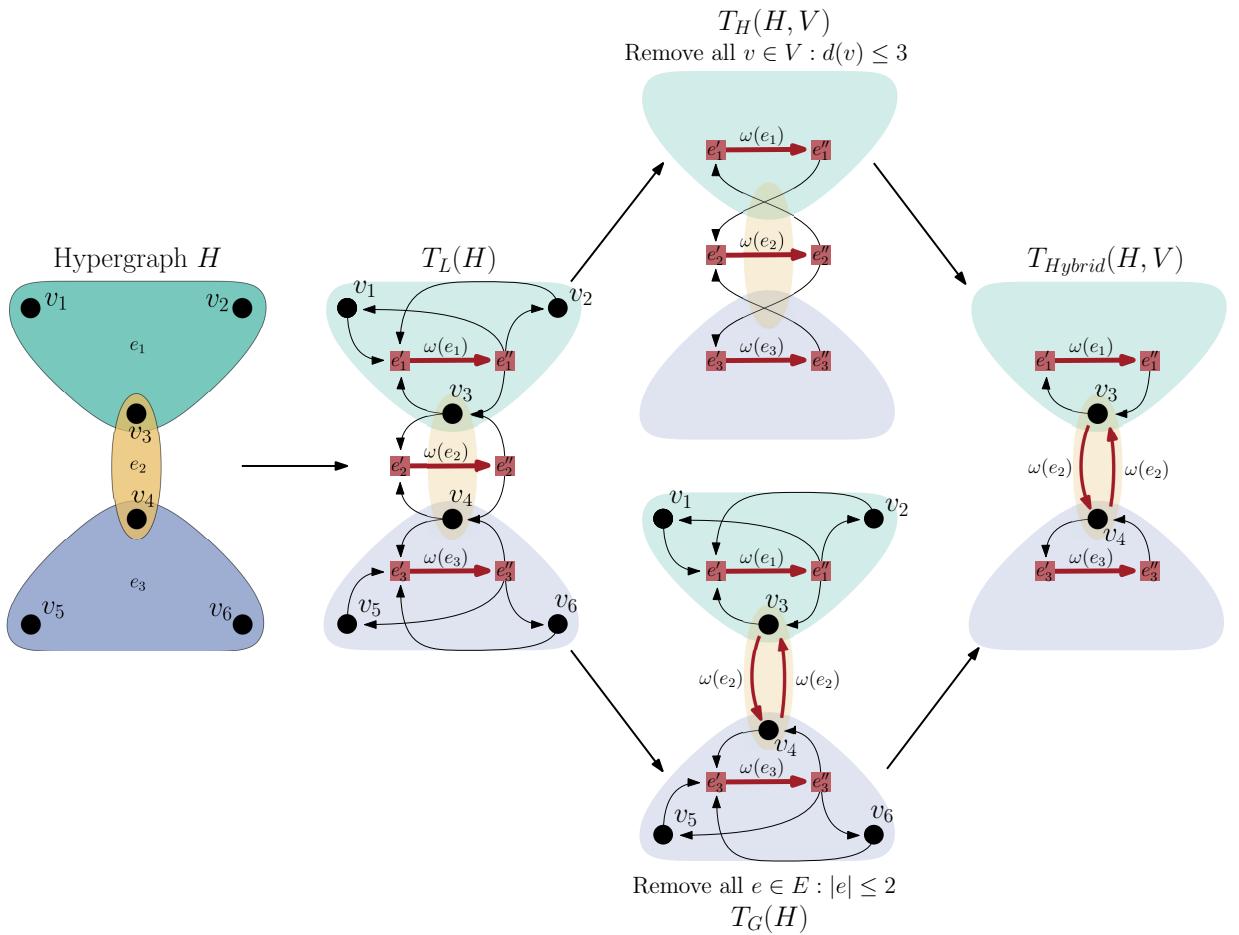


Figure 11: Illustration of all presented techniques to sparsify the flow network of a hypergraph. Transformation from  $T_L(H)$  to  $T_H(H, V)$  follows with Lemma 4.1. Transformation from  $T_L(H)$  to  $T_G(H)$  follows with Lemma 4.4.

## 4.1. Removing Hypernodes

In this section we show how all hypernodes of  $T_L(H)$  can be removed such that a maximum  $(S, T)$ -flow on the new network induces a minimum-weight  $(S, T)$ -cutset on  $H$ . If a hypernode  $v \in V$  occurs in an augmenting path  $P$  the previous node in the path must be a hyperedge node, either  $e'$  or  $e''$ . Further, for all  $e' \in I(v)$  the capacity  $u_L(v, e')$  is  $\infty$ . Therefore, we can push a positive flow entering node  $v$  to any  $e' \in I(v)$  during the whole maximum flow computation because  $u_L(v, e') = \infty$ . The idea is to remove the hypernode  $v$  from the flow network  $T_L(H)$  and insert *shortcut* edges between all incident hyperedge nodes in the flow network. The following lemma is central to our first sparsifying technique and is illustrated in Fig. 12. Given a graph  $G = (V, E)$  we define the two sets  $in(u) := \{v \mid (v, u) \in E\}$  and  $out(u) := \{v \mid (u, v) \in E\}$  with  $u \in V$ .

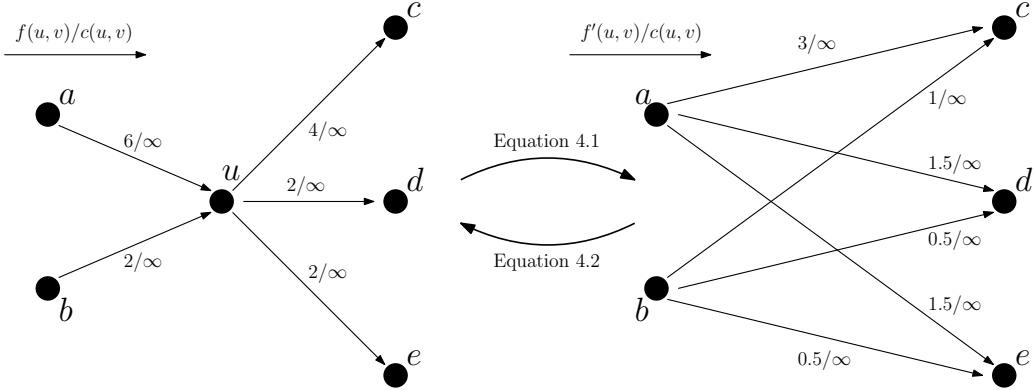


Figure 12: Illustration of Lemma 4.1 and Equation 4.1 and 4.2.

**Lemma 4.1** (Shortcut Edges). *Let  $G = (V, E, u)$  be a flow network and  $u \in V$  a node where all incoming and outgoing edges have capacity  $\infty$ . Further, let  $G(u) = (V \setminus \{u\}, E_u, u_u)$  be the flow network obtained by removing  $u$  and inserting a shortcut edge between each  $v \in in(u)$  and  $w \in out(u)$  with  $u_u(v, w) = \infty$ . If  $f$  is a maximum  $(S, T)$ -flow of  $G$  with  $|f| < \infty$ , then  $|f|$  is equal to the value of a maximum  $(S, T)$ -flow  $f'$  of  $G(u)$  with  $u \notin S \cup T$ .*

*Proof.* Let  $f$  be a maximum  $(S, T)$ -flow of  $G$ . We define a maximum  $(S, T)$ -flow  $f'$  of  $G(u)$  as follows:

$$f'(v, w) = \begin{cases} \frac{f(v, u)f(u, w)}{\sum_{w \in out(u)} f(u, w)}, & \text{if } v \in in(u), w \in out(u) \\ f(v, w), & \text{otherwise} \end{cases} \quad (4.1)$$

$f'$  is chosen in such a way that for all  $v \in in(u) : \sum_{w \in out(u)} f'(v, w) = f(v, u)$  and for all  $w \in out(u) : \sum_{v \in in(u)} f'(v, w) = f(u, w)$ . Therefore,  $f'$  satisfies the flow conservation constraint and since all capacities are equal to  $\infty$ ,  $f'$  also satisfies the capacity constraint. Consequently,  $f'$  is a valid flow function. Further  $u$  is not contained in  $S \cup T$  which implies that  $|f| = |f'|$ . Let  $f'$  be a maximum  $(S, T)$ -flow of  $G(u)$ . We define a maximum  $(S, T)$ -flow  $f$  of  $G$  as follows:

$$\begin{aligned} f(u, w) &= \sum_{x \in in(u)} f'(x, w) \\ f(v, u) &= \sum_{x \in out(u)} f'(v, x) \\ f(x, y) &= f'(x, y) \text{ if } x \neq u \neq y \end{aligned} \quad (4.2)$$

The amount of flow from each  $v \in in(u)$  to each  $w \in out(u)$  of flow function  $f'$  is redirected over  $u$  in  $f$ . Therefore,  $f$  is a valid flow function. Since  $u \notin S \cup T$ , it follows that  $|f| = |f'|$ .  $\square$

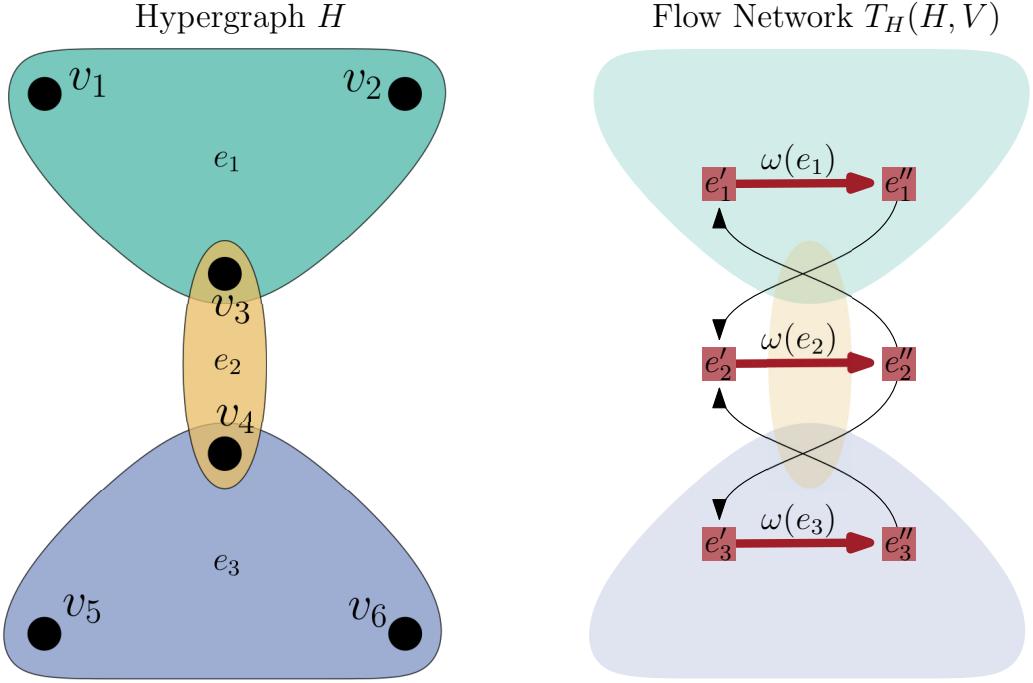


Figure 13: Transformation of a hypergraph  $H$  into the flow network  $T_H(H, V)$  by removing all hypernodes of  $T_L(H)$ . Note, capacity of the black edges in the flow network is  $\infty$ .

In  $T_L(H)$  all incoming and outgoing edges of a hypernode  $v$  have capacities equal to  $\infty$ . For all  $e \in I(v)$  there is an edge from  $v$  to  $e'$  and from  $e''$  to  $v$ . Consequently,  $in(v) = \bigcup_{e \in I(v)} e''$  and  $out(v) = \bigcup_{e \in I(v)} e'$ . Therefore, we can remove  $v$  and add a *shortcut* edge  $(u, w)$  between each  $u \in in(v)$  and  $w \in out(v)$ . The removal of a hypernode induces  $d(v)^2$  edges in the new network where  $d(v)$  is the degree of hypernode  $v$ . However, we can proof that  $d(v)(d(v) - 1)$  edges are sufficient to model the problem with the same *min-cut* properties, which means that the value of a maximum  $(S, T)$ -flow in both networks are equal. In Appendix B we proof that we can remove a node  $v$  with *infinite* weight of a graph by adding a clique between all adjacent nodes of  $v$ , if we want to find a minimum-weight  $(s, t)$ -vertex separator. Using the vertex separator transformation (see Definition 2.3) results in a flow network where the removal of a hypernode induces  $d(v)(d(v) - 1)$  instead of  $d(v)^2$  edges. The technique is illustrated in Fig. 22. The removed edges are exactly the edges between the *outgoing* and *incoming* hyperedge node of a hyperedge. More formally,  $\forall e \in I(v)$  we can remove edge  $(e'', e')$  of Lemma 4.1. Therefore, we can construct the following network with Lemma 4.1:

**Definition 4.1.** Let  $T_H$  be a transformation that converts a hypergraph  $H = (V, E, c, \omega)$  into a flow network  $T_H(H, V') = (V_H, E_H, u_H)$  with  $V' \subseteq V$ .  $T_H(H, V')$  is defined as follows:

- (i)  $V_H = V \setminus V' \bigcup_{e \in E} \{e', e''\}$
- (ii)  $\forall v \in V'$  and  $\forall e_1, e_2 \in I(v)$  with  $e_1 \neq e_2$  we add a directed edge  $(e''_1, e'_2)$  with capacity  $u_H(e''_1, e'_2) = \infty$  (Lemma 4.1).
- (iii) Let  $H_{V \setminus V'}$  be the subhypergraph without the hypernodes  $v \in V'$ , then we add all edges of  $T_L(H_{V \setminus V'})$  to  $E_H$  with their corresponding capacities.

An example of the transformation is shown in Fig. 13. We have to proof that a minimum-capacity  $(S, T)$ -cutset of  $T_H(H, V')$  is equal to a minimum-weight  $(S, T)$ -cutset of  $H$ . We will use the following lemma in the correctness proof.

**Lemma 4.2** (Source/Sink Node Removal). *Let  $G = (V, E, u)$  be a flow network and  $f$  a maximum  $(S, T)$ -flow of  $G$  with  $|f| < \infty$ . If  $s \in S$  is a source node where all outgoing edges*

have infinite capacity and  $t \in T$  is a sink node where all incoming edges have infinite capacity, then  $|f|$  is equal to the value of a maximum  $(S', T)$ -flow  $f_s$  of  $G(s)$  and a maximum  $(S, T')$ -flow  $f_t$  of  $G(t)$ , where  $S' = (S \setminus \{s\}) \cup \text{out}(s)$  and  $T' = (T \setminus \{t\}) \cup \text{in}(t)$ .

*Proof.* First we note that the flow over an incoming edge of a source node  $s \in S$  is zero. More formally,  $\forall v \in \text{in}(s) : f(v, s) = 0$ . Edmond and Karp [16] show that we can find a maximum  $(s, t)$ -flow if we augment in each step along a shortest path. Assume we find an augmenting path  $P$  which contains an edge  $(v, s)$ . We can obtain a shorter path if we split  $P$  after edge  $(v, s)$  and use the second part as augmenting path. Therefore,  $f(v, s) = 0$ . The same holds for all outgoing edges of a sink node. Consequently, we can remove all incoming resp. outgoing edges of a source resp. sink node.

In Section 2.2 we described how to solve a *multi-source multi sink* flow problem by adding a super source node  $a$  and super sink node  $b$  to the network.  $a$  is connected to all nodes  $s' \in S$  and all nodes  $t' \in T$  to  $b$  where all edges have capacity  $\infty$ . With Lemma 4.1 follows, that we can remove  $s$  from  $G$  and insert a directed edge from  $a$  to each  $v \in \text{out}(s)$  (equal to  $G(s)$ ) and  $|f| = |f_s|$ . The new flow problem corresponds to the *multi-source multi-sink* problem with  $S'$  and  $T$  as source and sink set. The proof for  $G(t)$  is equivalent.  $\square$

As a consequence of this lemma, we can remove a source hypernode  $v \in S$  of  $T_L(H)$  and instead add all incoming hyperedge nodes  $e' \in I(v)$  as sources to the flow problem. Because for all incoming resp. outgoing edges of vertices  $v$  of  $T_L(H)$  the capacity is  $\infty$ .

**Theorem 4.1.** *A minimum-weight  $(S, T)$ -cutset of a hypergraph  $H = (V, E, c, \omega)$  (with  $S, T \subseteq V, S \cap T = \emptyset$ ) is equivalent to a minimum-capacity  $(S', T')$ -cutset of the flow network  $T_H(H, V')$  ( $V' \subseteq V$ ) with  $S' = S \setminus V' \cup \bigcup_{e \in I(V' \cap S)} \{e'\}$  and  $T' = T \setminus V' \cup \bigcup_{e \in I(V' \cap T)} \{e''\}$ .*

*Proof.* Applying Lemma 4.1 and 4.2 on all nodes  $v \in V'$  of flow network  $T_L(H)$  yields network  $T_H(H, V')$  with  $S'$  and  $T'$  as source and sink sets. A maximum  $(S, T)$ -flow  $f_L$  of  $T_L(H)$  is then equal to a maximum  $(S', T')$ -flow  $f_H$  of  $T_H(H, V')$ . Since  $|f_L| < \infty$ , only edges between hyperedge nodes are contained in a minimum-capacity  $(S, T)$ -cutset of  $T_L(H)$ . Since  $|f_L| = |f_H|$ , the same holds for a minimum-capacity  $(S', T')$ -cutset of  $T_H(H, V')$ , which is equal to a minimum-weight  $(S, T)$ -cutset of  $H$ .  $\square$

Consequently, we can find a minimum-weight  $(S, T)$ -cutset of  $H$  by calculating a minimum-capacity  $(S', T')$ -cutset of  $T_H(H, V')$ . Finally, we have to find the corresponding minimum-weight  $(S, T)$ -bipartition. In  $T_L(H)$  all hypernodes reachable from source nodes in the residual graph are part of the first and all hypernodes not reachable are part of the second block of the bipartition. Since we removed all hypernodes  $v \in V'$  in our new network, we have to reconstruct the bipartition using the following lemma.

**Lemma 4.3** (Reachability of Hypernodes). *Let  $f$  be a maximum  $(S, T)$ -flow of  $T_L(H)$ . If a hypernode  $v \notin S$  is reachable from a node  $s \in S$  in the residual graph of  $T_L(H)$ , then there must exist at least one net  $e \in I(v)$  where  $e''$  is reachable from  $s$  in the residual graph of  $T_L(H)$ .*

*Proof.* Let  $A$  be the set of all nodes reachable from the source nodes  $S$  in the residual graph of  $T_L(H)$ . We will proof the lemma by contradiction. If  $v \in A$  and  $\forall e \in I(v)$  the outgoing hyperedge node  $e''$  is not contained in  $A$ , then all edges  $(v, e'')$  are not contained in the residual graph of  $T_L(H)$ . More formally,  $\forall e \in I(v) : r_f(v, e'') = 0$ . Otherwise,  $e''$  would be in  $A$  because  $v \in A$ . Since  $r_f(v, e'') = f(e'', v) = 0$ , there is no flow entering node  $v$  and due to the

conservation of flow constraint there cannot be any flow leaving node  $v$ . Therefore, there is no path from any  $s \in S$  to  $v$  over a node  $e'$ , because  $\forall e \in I(v) : r_f(e', v) = f(v, e') = 0$  and no path over  $e''$  because  $\forall e \in I(v) : e'' \notin A$ . Therefore,  $v$  is not reachable from any  $s \in S$ , which is a contradiction to the assumption that  $v \in A$ .  $\square$

Lemma 4.3 gives us an alternative construction for the minimum-weight  $(S, T)$ -bipartition of  $H$  for both networks  $T_L(H)$  and  $T_H(H, V')$ . Let  $E''$  be the set of all *outgoing* hyperedge nodes  $e''$  reachable from a source node  $s \in S$ . Then,  $(A := \bigcup_{e \in E''} e, V \setminus A)$  is a minimum-weight  $(S, T)$ -bipartition of  $H$ .

## 4.2. Low-Degree Hypernodes

The resulting flow network  $T_H(H, V)$  proposed in Section 4.1 has significantly fewer nodes than the network  $T_L(H)$  proposed by Lawler. On the other hand, the number of edges can be much larger.

Consider a hypernode  $v \in V$ . We replace  $v$  in  $T_L(H)$  with *shortcut* edges between all  $e''$  and  $e'$  which are incident to  $v$ . The number of edges added to  $T_H(H, V)$  depends on the degree of  $v$ . Each vertex  $v \in V$  induces  $d(v)(d(v) - 1)$  edges in  $T_H(H, V)$ . In  $T_L(H)$ , a hypernode adds  $2d(v)$  edges and one additional node to the network. A simple observation is that for all hypernodes with  $d(v) \leq 3$  the inequality  $d(v)(d(v) - 1) \leq 2d(v)$  holds. Removing such low degree hypernodes not only reduces the number of nodes, but also the number of edges.

Let  $V_d(n) = \{v \in V \mid d(v) \leq n\}$  be the set of all hypernodes with degree smaller or equal  $n$ . Then our suggested flow network is  $T_H(H, V_d(3))$ .

## 4.3. Modeling Small Hyperedges

If we want to find a minimum-weight  $(S, T)$ -cutset of a graph  $G = (V, E, \omega)$ , we do not have to transform  $G$  into an equivalent flow network. We can directly operate on the graph with capacities  $u(e) = \omega(e)$  for all  $e \in E$  [18]. Hypergraphs are a generalization of graphs, where an edge can consist of more than two nodes. However, a hyperedge  $e$  of size 2 is equivalent to a graph edge connecting two nodes. Instead of modeling those edges as described by Lawler [33] (see hyperedge  $e_2$  in Fig. 6), we can add an undirected flow edge between  $v_1, v_2 \in e$  (with  $v_1 \neq v_2$ ) with capacity  $u(\{v_1, v_2\}) = \omega(e)$ . In the following, we will proof the opposite. We will show that each undirected graph can be modeled as a directed graph with the same *min-cut* properties. The transformation used in the proof of an undirected to an directed edge will be equal to the modeling of a hyperedge of size two in the Lawler-Network. As a consequence, if we define the network where each hyperedge of size two is modeled with an undirected flow edge, we can use the following lemma to show that both networks have the same value of a maximum  $(S, T)$ -flow.

**Lemma 4.4** (Transformation of Undirected to Directed Networks). *Let  $G = (V, E, u)$  be an undirected flow network with capacity function  $u : E \rightarrow \mathbb{N}_+$ .  $G$  can be transformed into a directed graph  $G'$  such that the value of a maximum  $(s, t)$ -flow  $f$  of  $G$  is equal to the value of a maximum  $(s, t)$ -flow  $f'$  of  $G'$ . More formally,  $|f| = |f'|$ .*

*Proof.* Assume  $\forall e \in E : u(e) = 1$ . According to Menger's Theorem [37], a maximum  $(s, t)$ -flow is then equal to the maximum number of edge-disjoint paths between  $s$  and  $t$  in a directed graph. This theorem can also be proven for undirected graphs if we replace each undirected edge  $e = \{u, v\}$  by five directed edges  $(v, x'), (w, x'), (x', x''), (x'', v), (x'', w)$  (see Fig. 14) [37]. Obviously, we can map each set of edge-disjoint paths from  $s$  to  $t$  from  $G'$  to  $G$  and vice versa.

Therefore, the maximum number of edge-disjoint paths from  $s$  to  $t$  in  $G'$  is then the same as in  $G$  and therefore,  $|f| = |f'|$ .

Consider the general case where  $\forall e \in E : u(e) \in \mathbb{N}_+$ . We can transform the weighted undirected graph  $G$  into an unweighted directed multigraph by replacing each undirected edge  $e = \{u, v\}$  with  $u(e)$  undirected edges of weight 1 (see Fig. 14). Afterwards, we can use the transformation to an unweighted directed multigraph the same way as before. Again, we can apply Menger’s Theorem to show that  $|f| = |f'|$ . Newman [38] showed that there is an one-to-one correspondence between a maximum  $(s, t)$ -flow of an unweighted multigraph and its corresponding weighted graph where the weight of each edge  $(u, v)$  is the number of parallel edges between  $u$  and  $v$  of the multigraph.  $\square$

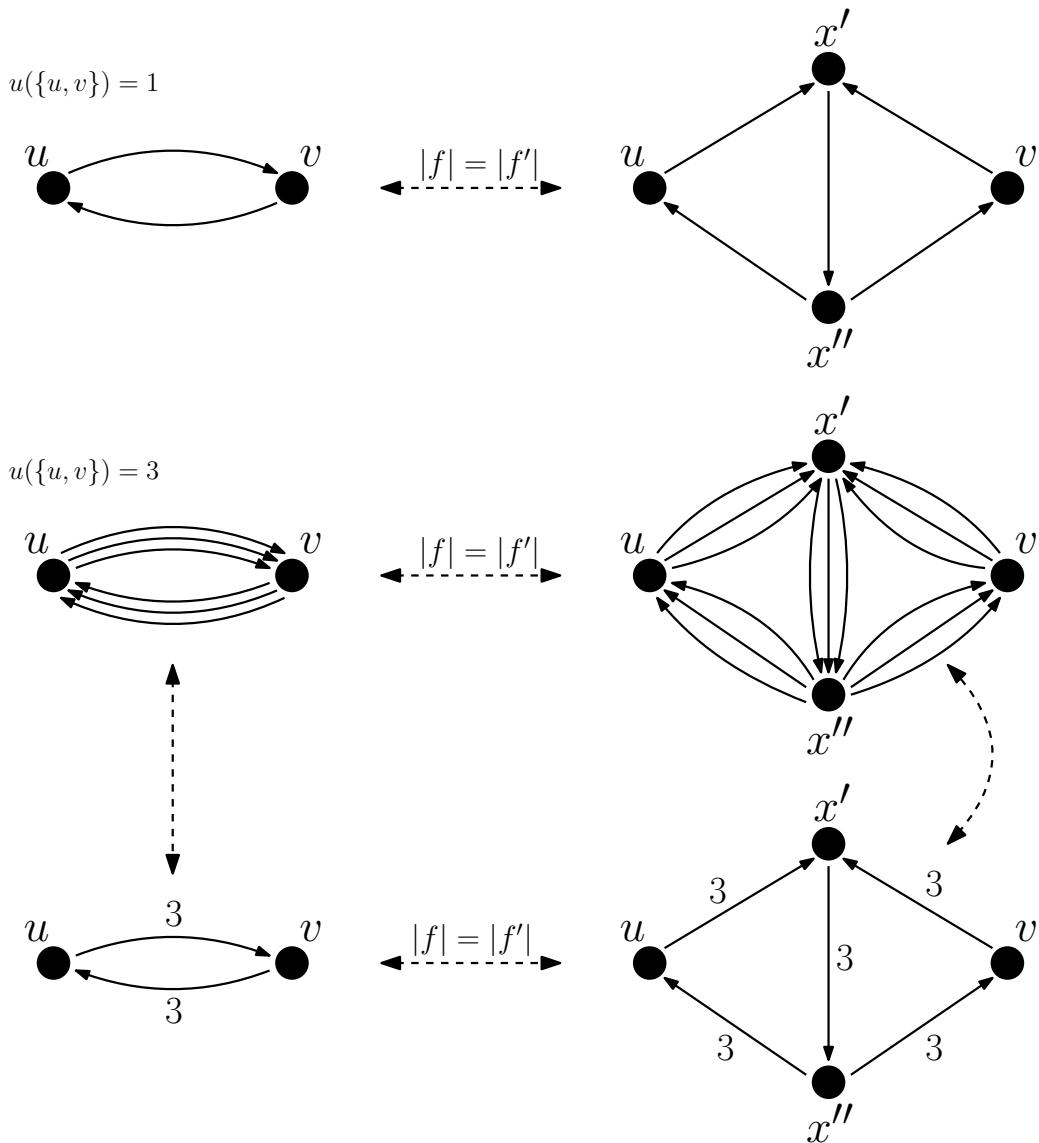


Figure 14: Illustration of the transformation of an unweighted or weighted undirected graph into an unweighted or weighted directed graph. The equivalence of a maximum  $(s, t)$ -flow of a unweighted multigraph and the corresponding weighted graph is a result of a work by Newman [38].

As a consequence of the construction of the proof of Lemma 4.4 the weighted directed graph illustrated on the right side of Fig. 14 can be transformed into a single undirected edge with

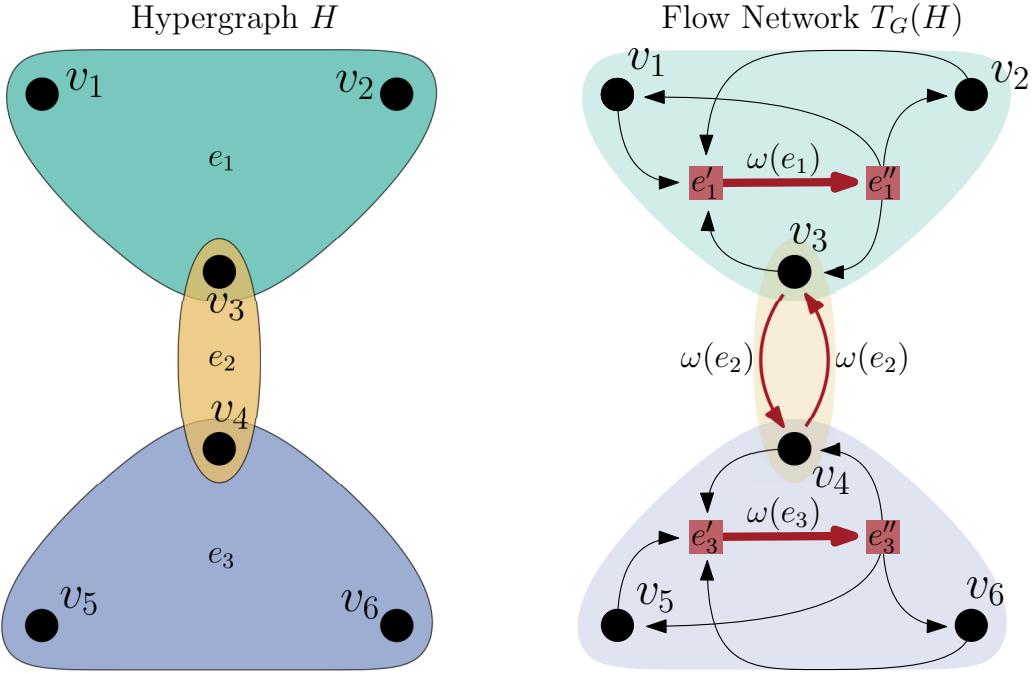


Figure 15: Transformation of a hypergraph into the flow network  $T_G(H)$  by inserting an undirected edge with capacity  $\omega(e)$  for each hyperedge of size 2. Note, capacity of the black edges in the flow network is  $\infty$ .

weight  $u(\{u, v\}) = u(x', x'')$ . Each hyperedge  $e$  with  $|e| = 2$  has exactly this structure in  $T_L(H)$ . Therefore, we can construct the following network:

**Definition 4.2.** Let  $T_G$  be a transformation that converts a hypergraph  $H = (V, E, c, \omega)$  into a flow network  $T_G(H) = (V_G, E_G, u_G)$ .  $T_G(H)$  is defined as follows:

- (i)  $V_G = V \cup \bigcup_{e \in E: |e|=2} \{e', e''\}$
- (ii)  $\forall e \in E \text{ with } |e| = 2 \text{ and } e = \{v_1, v_2\} \text{ we add two directed edges } (v_1, v_2) \text{ and } (v_2, v_1) \text{ to } E_G \text{ with capacity } u_G(v_1, v_2) = \omega(e) \text{ and } u_G(v_2, v_1) = \omega(e)$
- (iii) Let  $H' = (V, E', c, \omega)$  be the hypergraph with  $E' = \{e \mid e \in E \wedge |e| \neq 2\}$ , then we add all edges of  $T_L(H')$  to  $E_G$  with their corresponding capacities.

An example of transformation  $T_G(H)$  is shown in Fig. 15. A hyperedge  $e$  of size 2 consists exactly of 4 nodes and 5 edges in  $T_L(H)$  (see Fig. 6). The same hyperedge induces 2 nodes and 2 edges in  $T_G(H)$  (see Fig. 11).

**Theorem 4.2.** A minimum-weight  $(S, T)$ -cutset of a hypergraph  $H = (V, E, c, \omega)$  (with  $S, T \subseteq V, S \cap T = \emptyset$ ) is equal to a minimum-capacity  $(S, T)$ -cutset of the flow network  $T_G(H) = (V_G, E_G, u_G)$ .

*Proof.* Consider a hyperedge  $e = \{u, v\}$ . The capacity of  $(u, e')$ ,  $(v, e')$ ,  $(e'', u)$  and  $(e'', v)$  is  $\infty$  in flow network  $T_L(H)$ . Before we can apply Lemma 4.4 on all hyperedges  $e$  with  $|e| = 2$ , we have to show how to handle the infinite capacity edges. The flow leaving  $e'$  is restricted by  $u(e', e'') = \omega(e)$ . Therefore, the flow entering  $e'$  is restricted by  $f(u, e') + f(v, e') \leq u(e', e'') = \omega(e)$ . Consequently,  $f(u, e') \leq \omega(e)$  and  $f(v, e') \leq \omega(e)$ . The same holds for  $f(e'', u)$  and  $f(e'', v)$ . Therefore, we can replace each infinite capacity of an edge entering  $e'$  or leaving  $e''$  with  $\omega(e)$  without changing the value of a maximum  $(S, T)$ -flow. We call the capacity adapted network  $T_{L'}(H)$ .

Applying the transformation of Lemma 4.4 on each undirected edge of  $T_G(H)$  results in flow network  $T_{L'}(H)$ . It follows that a maximum  $(S, T)$ -flow of  $T_G(H)$  is equal to a maximum  $(S, T)$ -flow of  $T_{L'}(H)$  and  $T_L(H)$ . Consequently, a minimum-capacity  $(S, T)$ -cutset of  $T_G(H)$  is equal to a minimum-weight  $(S, T)$ -cutset of  $H$ .

□

A minimum-weight  $(S, T)$ -cutset of  $H$  can also be calculated with  $T_G(H)$ . Each edge  $(v_1, v_2)$  with  $v_1, v_2 \in V$  of the minimum-capacity  $(S, T)$ -cutset of  $T_G(H)$  can be mapped to the corresponding hyperedge. Since there exists a one-one correspondence between the hypernodes of  $T_L(H)$  and  $T_G(H)$  the corresponding bipartition consists of all hypernodes *reachable* from all nodes in  $S$  and all nodes not *reachable* from  $S$  in the *residual graph* of  $T_G(H)$ .

#### 4.4. Combining Techniques

The density of a hypergraph  $H = (V, E)$  is defined as follows:

$$d := \frac{\overline{d(v)}}{\overline{|e|}} = \frac{|P|/|V|}{|P|/|E|} = \frac{|E|}{|V|}$$

where  $\overline{d(v)}$  is the average hypernode degree,  $\overline{|e|}$  is the average hyperedge size and  $|P|$  is the number of pins. Many real world benchmark instances have either a low or high density. For an example, consider the summary of our benchmark set in Table 8. Hypergraphs with high density have usually an average hypernode degree significantly greater than the average hyperedge size, whereas the opposite behavior can be observed on instances with low density. High density hypergraphs often have many graph edges and low density hypergraphs often have many low degree hypernodes.

Currently, we have two different modeling approaches which either perform better on hypergraphs with many low degree hypernodes or small hyperedges. Taking our observation from real-world instances into account means that  $T_G(H)$  is significantly smaller on high density hypergraphs and  $T_H(H, V_d(3))$  on low density hypergraphs. It would be preferable to combine the two approaches into one network.

**Definition 4.3.** Let  $T_{\text{Hybrid}}$  be a transformation that converts a hypergraph  $H = (V, E, c, \omega)$  into a flow network  $T_{\text{Hybrid}}(H, V') = (V_{\text{Hybrid}}, E_{\text{Hybrid}}, u_{\text{Hybrid}})$ , where  $V' = \{v \in V_d(3) \mid \forall e \in I(v) : |e| \neq 2\}$ .  $T_{\text{Hybrid}}(H, V')$  is defined as follows:

- (i)  $V_{\text{Hybrid}} = V \setminus V' \cup \bigcup_{\substack{e \in E \\ |e| \neq 2}} \{e', e''\}$
- (ii)  $\forall v \in V'$  we add a directed edge  $(e''_1, e'_2)$ ,  $\forall e_1, e_2 \in I(v)$  ( $e_1 \neq e_2$ ) with capacity  $u_{\text{Hybrid}}(e''_1, e'_2) = \infty$  (Lemma 4.1).
- (iii)  $\forall e \in E$  with  $|e| = 2$  and  $e = \{v_1, v_2\}$  we add two directed edges  $(v_1, v_2)$  and  $(v_2, v_1)$  with capacity  $u_{\text{Hybrid}}(v_1, v_2) = \omega(e)$  and  $u_{\text{Hybrid}}(v_2, v_1) = \omega(e)$  (Lemma 4.4)
- (iv)  $\forall e \in E$  with  $|e| \neq 2$  we add a directed edge  $(e', e'')$  with capacity  $u_{\text{Hybrid}}(e', e'') = \omega(e)$  (same as in  $T_L(H)$ ).
- (v)  $\forall v \in V \setminus V'$  we add for each incident hyperedge  $e \in I(v)$  with  $|e| \neq 2$  two directed edges  $(v, e')$  and  $(e'', v)$  with capacity  $u_{\text{Hybrid}}(v, e') = u_{\text{Hybrid}}(e'', v) := \infty$  (same as in  $T_L(H)$ ).

Fig. 11 summarizes all explained transformations of this section. We can prove the correctness of  $T_{\text{Hybrid}}(H, V')$  with Lemmas 4.1, 4.2 and 4.4 as used in the proof of Theorem 4.1 and

**4.2.** A minimum-weight  $(S, T)$ -cutset of  $H$  is equal to a minimum-capacity  $(S', T')$ -cutset of  $T_{\text{Hybrid}}(H, V')$ .

Per definition of  $T_{\text{Hybrid}}(H, V')$  we prefer hyperedge removal over hypernode removal. If a hypernode has a degree smaller than or equal to 3, we only remove it, if there is no hyperedge  $e \in I(v)$  with  $|e| = 2$ . The reason for this is that hyperedge removal always removes more nodes and edges than hypernode removal.

The minimum-weight  $(S, T)$ -cutset of  $H$  can be calculated using the technique described in Section 4.3. Let  $(A, V \setminus A)$  be the corresponding bipartition.  $A$  is the union of all reachable hypernodes from  $S'$  and the union of all reachable *outgoing hyperedge nodes*  $e''$  from  $S'$  (see Section 4.1 and Lemma 4.3).

## 5. Max-Flow-Min-Cut Refinement Framework

We now present our direct  $k$ -way *flow-based* refinement framework. We use similar techniques as proposed by Sanders and Schulz [44]. The basic concepts of the framework are illustrated in Fig. 16. The algorithm can be integrated into a *multilevel hypergraph partitioner* by executing the following algorithm in a level of the multilevel hierarchy.

We perform a *flow-based* refinement on two adjacent blocks of a  $k$ -way partition  $\Pi = \{V_1, \dots, V_k\}$ . The pairwise refinements are embedded into the *active block scheduling* strategy (see Section 3.3.4). The algorithm starts by constructing the quotient graph  $Q$  of  $\Pi$ . Afterwards, we iterate over all edges of  $Q$  in random order. For each edge  $(V_i, V_j)$  of  $Q$ , we build a flow problem around the cut of the bipartition induced by  $V_i$  and  $V_j$ . To construct the flow problem, we use two *BFSs*. The first only touches hypernodes of  $V_i$  and the second only touches hypernodes of  $V_j$ . The *BFS* is initialized with all hypernodes contained in cut hyperedges of the bipartition  $(V_i, V_j)$ . We will denote all hypernodes touched by the two *BFSs* with  $V' \subseteq V_i \cup V_j$ . We embed the pairwise *flow-based* refinement into an *adaptive flow iteration* strategy (as described in Section 3.3.2), which also determines the number of hypernodes touched by the two *BFSs*.

We will use the subhypergraph  $H_{V'}$  to construct one of the flow networks proposed in Section 4. We define the corresponding sources  $S$  and sinks  $T$  of the flow network of  $H_{V'}$  in such way that a *Max-Flow-Min-Cut* computation yields an improved  $k$ -way partition according to our objective function. After we determine a maximum  $(S, T)$ -flow on the flow network, we iterate over the minimum  $(S, T)$ -bipartitions of  $H_{V'}$  and choose the *Most Balanced Minimum Cut* according to our balance constraint (as described in Section 3.3.3).

If a *Max-Flow-Min-Cut* computation yields an improved partition of  $H$ , we apply the new partition and execute the algorithm on the same blocks again, but double the flow problem size according to the *adaptive flow iteration* strategy. If we cannot improve the partition, we decrease the flow problem size by a factor of 2 and execute the algorithm on the same blocks again. The pairwise *flow-based* refinements stop if the *adaptive flow iteration* scaling parameter  $\alpha$  is smaller than 1 (see Section 3.3.2).

### 5.1. Flow Algorithms

We implement two maximum flow algorithms. One is the *augmenting path* algorithm of Edmond & Karp (EDMONDKARP) [16] and the second is the *Push-Relabel* algorithm of Goldberg & Tarjan (GOLDBERGTARJAN) [12, 23]. The EDMONDKARP algorithm finds one *augmenting path* with one *BFS* computation in each step. Since we have a *Multi-Source-Multi-Sink* problem, we can find several *augmenting paths* with one *BFS*. After we execute a *BFS* on the residual graph, we search as many edge-disjoint paths as possible in the resulting *BFS-tree* connecting a source  $s$  with a sink  $t$ . Our Goldberg & Tarjan implementation uses a *FIFO* queue and the *global relabeling* and *gap* heuristic [12].

Further, we integrate two third-party maximum flow algorithms. The first algorithm is due to Boykov & Kolmogorov [7] (BOYKOVKOLMOGOROV<sup>1</sup>) and the second is the *incremental breadth-first search* (IBFS<sup>2</sup>) algorithm of Goldberg et. al [22]. Before we call the algorithms, we map our internal flow network representation to the one of the third-party implementation. Afterwards, we map the flow of each edge back to our flow network.

<sup>1</sup> Available at <https://github.com/gerddie/maxflow> (Accessed at 14.12.2017)

<sup>2</sup> Available at <http://www.cs.tau.ac.il/~sagihed/ibfs/code.html> (Accessed at 16.12.2017)

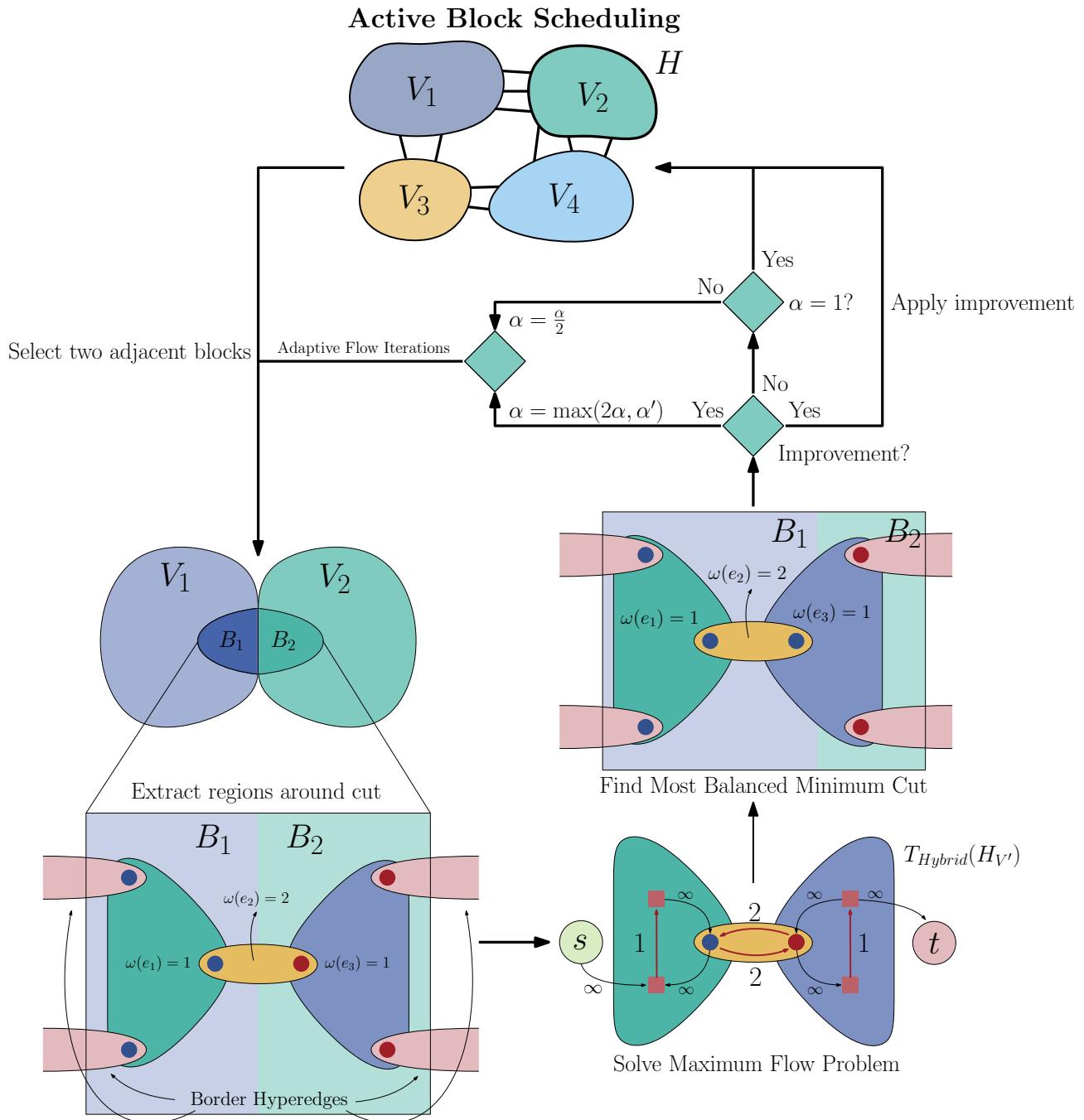


Figure 16: Illustration of our *flow-based* refinement framework for direct  $k$ -way hypergraph partitioning.

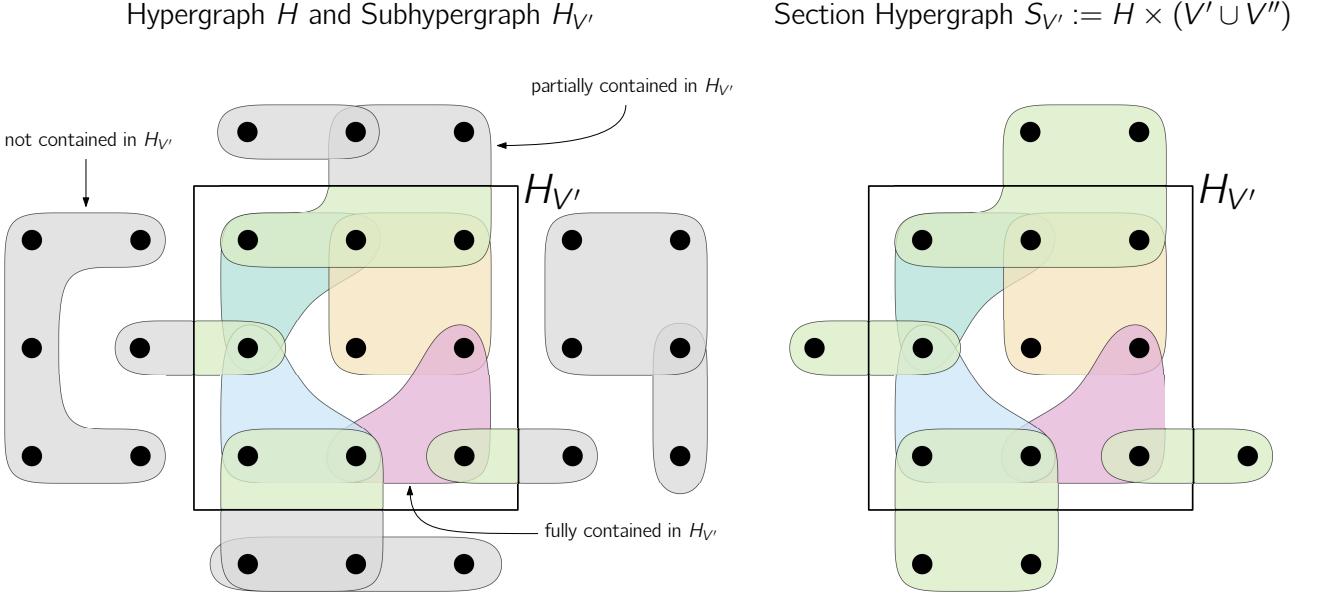


Figure 17: Illustration of the *section hypergraph*  $S_{V'}$ . Each hyperedge of the the hypergraph  $H$  which is fully or partially contained in  $H_{V'}$  is fully contained in  $S_{V'}$ . The nodes not contained in the rectangle of the right figure are part of  $V''$ .

## 5.2. Source and Sink Configuration

Let  $\Pi_1$  be the bipartition of a hypergraph  $H = (V, E, c, \omega)$ . In the following, we show how to configure the source set  $S$  and sink set  $T$  of the flow network  $T_L(H_{V'})$  of a subhypergraph  $H_{V'}$  induced by  $V' \subseteq V$ . The goal is to improve  $\Pi_1$  with a maximum  $(S, T)$ -flow calculation on  $T_L(H_{V'})$  such that after applying the minimum  $(S, T)$ -bipartition of  $H_{V'}$  to  $H$  the resulting bipartition  $\Pi_2$  has a cut less than or equal to the cut of  $\Pi_1$ . An important concept of this section will be the definition of the following *section hypergraph*.

**Definition 5.1** (Extension of a Subhypergraph). *Given a subset  $V' \subseteq V$  of a hypergraph  $H = (V, E)$ . The section hypergraph  $S_{V'} := H \times (V' \cup V'')$  is a hypergraph where  $V''$  contains all pins  $u \notin V'$  of hyperedges incident to a vertex  $v \in V'$ . More formally,*

$$V'' := \bigcup_{e \in I(V')} e \setminus V'$$

$S_{V'}$  can be seen as an *extension* of subhypergraph  $H_{V'}$ . Each hyperedge, which is partially or fully contained in  $H_{V'}$  is fully contained in  $S_{V'}$  (see Fig. 17). The source and sink set of  $T_L(H_{V'})$  should be chosen in such a way that the two conditions of following problem statement are satisfied:

**Problem 5.1.** *Given a subhypergraph  $H_{V'} (V' \subseteq V)$  and bipartition  $\Pi_1$  of hypergraph  $H$ . How should  $S$  and  $T$  be defined such that after a maximum  $(S, T)$ -flow calculation on  $T_L(H_{V'})$  (with  $f$  as maximum flow) the resulting minimum  $(S, T)$ -bipartition  $\Pi_2$  of  $H$  satisfies the following conditions:*

- (i)  $\omega_H(\Pi_2) \leq \omega_H(\Pi_1)$
- (ii)  $\Delta_H := \omega_H(\Pi_1) - \omega_H(\Pi_2) = \omega_{S_{V'}}(\Pi_1) - |f| =: \Delta_{H_{V'}}$

The first condition ensures that a *Max-Flow-Min-Cut* computation on  $T_L(H_{V'})$  never increases the cut of  $H$ , while the second condition allows us to update the cut metric in constant time via  $\omega_H(\Pi_2) = \omega_H(\Pi_1) - \Delta_{H_{V'}}$ , instead of having to sum up the weight of all cut hyperedges.

Since we have to build the subhypergraph  $H_{V'}$  before each maximum flow computation, we can implicitly calculate  $\omega_{S_{V'}}(\Pi_1)$ .

Note that we define  $\Delta_{H_{V'}}$  over the cut of the *section hypergraph*  $S_{V'}$ . If only hypernodes contained in  $V'$  can change their block after a *Max-Flow-Min-Cut* computation then the equality

$$\Delta_H := \omega_H(\Pi_1) - \omega_H(\Pi_2) = \omega_{S_{V'}}(\Pi_1) - \omega_{S_{V'}}(\Pi_2) =: \Delta_{H_{V'}}$$

holds, because all hyperedges, which can change their state from non-cut to cut or vice versa, are fully contained in  $S_{V'}$ . For example, if a *Max-Flow-Min-Cut* computation on  $H_{V'}$  removes hyperedge  $e$  from the cut in  $H_{V'}$ , but  $e$  is still cut in  $H$ , then the equality would not hold if we would have defined  $\Delta_{H_{V'}}$  over the cut of  $H_{V'}$ , because  $\Delta_{H_{V'}}$  would be equal to 1 and  $\Delta_H$  equal to 0. Further, if we can show that  $|f| = \omega_{S_{V'}}(\Pi_2)$ , we simultaneously show that our source and sink set modeling approach satisfies condition (ii)  $\Delta_H = \Delta_{H_{V'}}$ .

We will now define our source and sink set for the flow network  $T_L(H_{V'})$  such that we satisfy the two conditions of Problem 5.1.

**Theorem 5.1.** *Let  $\Pi_1 = (V_1, V_2)$  be the bipartition of  $H$ . The resulting bipartition  $\Pi_2$  of  $H$  of a maximum  $(S, T)$ -flow computation on  $T_L(H_{V'})$  with*

$$\begin{aligned} S &= \{e' \mid e \in I(V'' \cap V_1)\} \\ T &= \{e'' \mid e \in I(V'' \cap V_2)\} \end{aligned}$$

satisfies the following two conditions:

- (i)  $\omega_H(\Pi_2) \leq \omega_H(\Pi_1)$
- (ii)  $\Delta_H = \Delta_{H_{V'}}$

*Proof.* We first define  $S$  and  $T$  for flow network  $T_L(S_{V'})$ , because for each maximum  $(S, T)$ -flow  $f$  of  $T_L(S_{V'})$  and its corresponding minimum  $(S, T)$ -bipartition  $\Pi_2$  the equality  $|f| = \omega_{S_{V'}}(\Pi_2)$  holds due to the *max-flow-min-cut* theorem [18]. Defining a hypernode  $v \in V_1$  resp.  $v \in V_2$  as source resp. sink means that it cannot change its block after a *Max-Flow-Min-Cut* computation. However, we do not want that a hypernode  $v \notin V'$  can change its block after a *Max-Flow-Min-Cut* computation on  $T_L(S_{V'})$ , because such hypernodes cannot move if we solve a flow problem on subhypergraph  $H_{V'}$ . Therefore, we define all hypernodes of  $V''$  contained in block  $V_1$  as sources and all hypernodes of  $V''$  contained in block  $V_2$  as sinks. More formally:

$$\begin{aligned} S' &= V'' \cap V_1 \\ T' &= V'' \cap V_2 \end{aligned}$$

With  $S'$  and  $T'$  we ensure that only hyperedges fully contained in  $S_{V'}$  can change their state from cut to non-cut or vice versa. Therefore, it follows with the *max-flow-min-cut* theorem [18] that  $|f| = \omega_{S_{V'}}(\Pi_2) \leq \omega_{S_{V'}}(\Pi_1)$  and

$$\Delta_H = \omega_H(\Pi_1) - \omega_H(\Pi_2) = \omega_{S_{V'}}(\Pi_1) - |f| = \Delta_{H_{V'}} \geq 0,$$

because only hypernodes contained in  $V'$  can change their block. Since  $\Delta_H \geq 0$ , it holds that  $\omega_H(\Pi_2) \leq \omega_H(\Pi_1)$ .

The value of a maximum  $(S', T')$ -flow of  $T_L(S_{V'})$  is equal to the value of a maximum  $(S, T)$ -flow

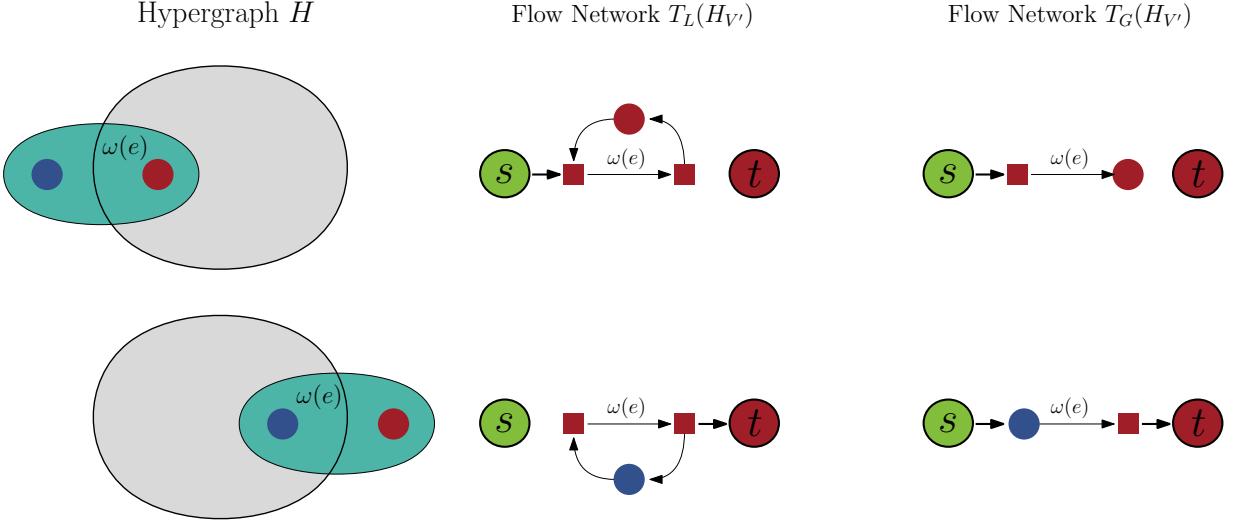


Figure 18: Illustration of modeling hyperedges of size one of the flow network if the incoming or outgoing hyperedge node is a source or a sink node of the flow problem.

of  $T_H(S_{V'}, V'')$  according to Theorem 4.1 with

$$S = \overbrace{S' \setminus V''}^{\neq \emptyset} \cup \bigcup_{\substack{e \in I(V'' \cap S') \\ = V'' \cap V_1}} \{e'\} = \{e' \mid e \in I(V'' \cap V_1)\}$$

$$T = \overbrace{T' \setminus V''}^{\neq \emptyset} \cup \bigcup_{\substack{e \in I(V'' \cap T') \\ = V'' \cap V_2}} \{e''\} = \{e'' \mid e \in I(V'' \cap V_2)\}$$

Since each  $v \in V''$  is either a source or sink node of  $T_L(S_{V'})$ , the removal of  $v$  does not induce any additional edges in  $T_H(S_{V'}, V'')$  (see Lemma 4.2). Therefore,  $T_H(S_{V'}, V'') = T_L(H_{V'})$ .  $\square$

The value of a maximum  $(S', T')$ -flow of  $T_L(S_{V'})$  and a maximum  $(S, T)$ -flow of  $T_L(H_{V'})$  are equal. Since  $S'$  and  $T'$  satisfy conditions (i) and (ii) of our problem statement, also  $S$  and  $T$  satisfy the two conditions. In general, each hyperedge partially contained in  $H_{V'}$ , which contains at least one pin  $v \notin V'$  of block  $V_1$  resp.  $V_2$  is a source resp. sink node. Furthermore, no hypernode of  $T_L(H_{V'})$  is either a source or sink node. Consequently, all hypernodes of  $V'$  can change their block after a *Max-Flow-Min-Cut* computation. According to the *max-flow-min-cut* theorem, the value of the cut of bipartition  $\Pi_2$  is the minimum weight cut of all possible bipartitions with the restriction that only hypernodes of  $V'$  can move.

Additionally, we can model hyperedges of size one more efficiently (see Fig. 18). If the incoming hyperedge node  $e'$  is a source node, we can replace the hyperedge of size one with a directed edge  $(e', v)$  with  $v \in e \cap V'$  and capacity  $\omega(e)$ . If the outgoing hyperedge node  $e''$  is a sink node, we add a directed edge  $(v, e'')$  with capacity  $\omega(e)$ . If  $e'$  and  $e''$  is neither a source nor sink node, we can remove the hyperedge from the flow problem.

With the given approach we can optimize the cut metric of a given bipartition of a hypergraph  $H$ . We can transfer those results to improve the connectivity metric of a  $k$ -way partition  $\Pi = (V_1, \dots, V_k)$ . Let  $V' \subseteq V_i \cup V_j$  be a subset of the hypernodes of two adjacent blocks  $V_i$  and  $V_j$ . If we optimize the cut of subhypergraph  $H_{V'}$  we simultaneously optimize the connectivity metric of  $H$ . The reduction of the cut of  $H_{V'}$  is then equal with the decrease in the connectivity metric of  $H$ .

**Implications for Graph Partitioning.** If we compare our source and sink set modeling approach with the one of Sanders and Schulz [44] (see Section 3.3.1), we can show that with our technique better minimum  $(S, T)$ -bipartitions are achievable. They define each node of the graph as source resp. sink, which is adjacent to a node not contained in the flow problem of block  $V_1$  resp.  $V_2$ . Consequently, a non-cut edge of the graph partially contained in the flow problem cannot become a cut edge. Therefore, their modeling approach satisfies condition (i) of our problem statement. However, a movement of a node adjacent to a non-cut edge can still improve the cut, if the number of adjacent non-cut edges is smaller than the number of adjacent cut edges. If we interpret a graph as hypergraph, we can use our modeling approach on network  $T_L(H_{V'})$  or  $T_G(H_{V'})$  with  $S$  and  $T$  as source and sink set. All nodes incident to a non-cut edge which is partially contained in the flow problem are now able to change their block and the corresponding minimum  $(S, T)$ -bipartition is minimum among all possible bipartitions where only nodes of  $V'$  can move.

### 5.3. Most Balanced Minimum Cuts on Hypergraphs

Picard and Queyranne [41] show that all minimum  $(s, t)$ -cuts of a graph  $G$  are computable with one maximum  $(s, t)$ -flow computation by iterating through all *closed node sets* of the residual graph of  $G$ .

We can apply the same algorithm on hypergraphs. A minimum-capacity  $(s, t)$ -cutset of  $T_L(H)$  is equal with a minimum-weight  $(s, t)$ -cutset of  $H$ . With the algorithm of Section 3.3.3 we can find all minimum-capacity  $(s, t)$ -cutsets of  $T_L(H)$ , which are also minimum-weight  $(s, t)$ -cutsets of  $H$ . The corresponding minimum-weight  $(s, t)$ -bipartitions are all *closed node sets* of the residual graph of  $T_L(H)$ . However, when we use e.g.,  $T_H(H, V')$  (see Section 4.1) or  $T_{\text{Hybrid}}(H, V')$  (see Section 4.4) as underlying flow network, some hypernodes are removed from the flow problem. If an *outgoing* hyperedge node  $e''$  is part of a *closed node set*, than all hypernodes  $v \in e$  must be part of it too, which is a consequence of Lemma 4.3. The *Most Balanced Minimum Cut* heuristic consists of many stages, which we then have to adapt if we enumerate the minimum-weight  $(S, T)$ -bipartitions. Since the algorithm has a linear running time, we simply reinsert all removed hypernodes with the corresponding edges of the Lawler-Network before computing the *Most Balanced Minimum Cut*.

**Lemma 5.1.** *Let  $T_L(H) = (V, E_L, u_L)$  be the Lawler-Network and  $T_H(H, V') = (V \setminus V', E_H, u_H)$  be the flow network proposed in Section 4.1 of hypergraph  $H = (V, E, c, \omega)$  with  $V' \subseteq V$ . If  $f$  is a maximum  $(S, T)$ -flow of  $T_H(H, V')$ , then  $f$  is also a maximum  $(S, T)$ -flow of the flow network  $T = (V, E_L \cup E_H, u)$  with  $u(v, w) = u_L(v, w)$ , if  $(v, w) \in E_L$  and  $u(v, w) = u_H(v, w)$ , otherwise.*

*Proof.* The main statement of the lemma is that we can calculate a maximum  $(S, T)$ -flow  $f$  of  $T_H(H, V')$  and then reinsert all removed hypernodes with their corresponding edges of the Lawler-Network. The flow  $f$  is also a maximum  $(S, T)$ -flow on the resulting flow network  $T$ . Assume, that there still exists an *augmenting path* in the residual graph of  $T$ . If we remove a hypernode  $v$  from the flow network  $T_L(H)$ , we insert *shortcut* edges between all incident hyperedges  $e \in I(v)$ . However, if the *augmenting path*  $P = (s, \dots, e'_1, v, e'_2, \dots, t)$  contains a reinserted hypernode  $v \in V'$ , we can simply remove it from the path. After removing all  $v \in V'$  from  $P$ , we obtain a valid path in  $T_H(H, V')$ . The resulting path then contains the *shortcut* edges  $(e''_1, e'_2)$  instead of the two inserted edges  $(e''_1, v)$  and  $(v, e'_2)$ . All involved edges have capacity equal to  $\infty$ . Therefore, it must be an *augmenting path* in  $T_H(H, V')$ , which is a contradiction that  $f$  is a maximum  $(S, T)$ -flow.  $\square$

Consequently, if we remove a hypernode from the flow network, we can reinsert it with the corresponding incident edges of the Lawler-Network after a maximum  $(S, T)$ -flow computation.

All minimum  $(S, T)$ -cutsets of the resulting flow network  $T$  have the same value as all minimum  $(S, T)$ -cutsets of  $T_H(H, V')$ , because the value of a maximum  $(S, T)$ -flow is the same in both networks.

## 5.4. Integration into KaHyPar

**Flow Execution Policies.** Since *KaHyPar* is an  $n$ -level hypergraph partitioner, local searches are executed after each uncontraction of a single vertex (see Section 3.4.2). Using our *flow-based refinement* algorithm in each level would be too expensive. Therefore, we introduce *Flow Execution Policies*, which control the total number of *flow-based refinements* throughout the multilevel hierarchy. The first policy is to execute our *flow-based refinement* on each level  $i$  where  $i = \beta \cdot j$  with  $j \in \mathbb{N}_+$  and  $\beta$  as a predefined tuning parameter. Another approach is to simulate a multilevel partitioner with  $\log(n)$  hierarchies. A *flow-based refinement* is then executed on each level  $i$  where  $i = 2^j$  with  $j \in \mathbb{N}_+$ . Each policy also performs the *active block scheduling* refinement strategy on the last level of the hierarchy. In all remaining levels where no flow is executed, we can use the *FM* algorithm [1, 17, 43] (see Section 3.3.4).

**Combining Flow-Based Refinements with the FM algorithm.** The *FM* algorithms integrated into *KaHyPar* use a *gain cache* to maintain the gain values of moves throughout the multilevel hierarchy. The concept prevents expensive recalculations of gain values if a *FM* local search is instantiated. However, if we use *flow-based refinement* in combination with the *FM* algorithm, we have to ensure that the *gain cache* contains valid entries at each time. Therefore, we undo all changes after a *flow-based refinement* and simulate the moves with the *FM* algorithm to ensure that all entries in the *gain cache* are valid.

**Speedup Heuristics.** An observation during early experiments was that only a minority of the pairwise refinements based on flows leads to an improvement on hypergraph  $H$ . Thus, we introduce several rules which help to prevent *unpromising* flow executions to speed-up the running time.

- (R1) The *active block scheduling* refinement strategy is executed in rounds. In each round we use *flows* to improve the bipartition of two adjacent blocks, where one of the two is *active*. Initially, all blocks are *active*. A block becomes *inactive*, if its border does not change in a round. However, we introduce a second criterion when to use *flow-based refinement* on two adjacent blocks. For each pair of adjacent blocks, we count how many times we found an improvement on these blocks throughout the multilevel hierarchy. The first round of *active block scheduling* is executed as before. In all remaining rounds, we only execute a pairwise *flow-based refinement*, if one of the two blocks is *active* and if we found at least one improvement before on the corresponding blocks.
- (R2) If the cut between two adjacent blocks is small (e.g.  $\leq 10$ ) we skip the *flow-based refinement* on the blocks except on the last level of the hierarchy.
- (R3) If the value of the cut of a minimum  $(S, T)$ -bipartition of  $H_{V'}$  is the same as the cut before, we stop the *adaptive flow iteration* strategy.

## 6. Experimental Results

In this Section, we evaluate the performance of our flow-based refinement framework. First, we show the effects of our sparsification techniques of the Lawler-Network [33] on the running time of maximum flow algorithms. Afterwards, we analyze how the maximum flow problem size influences the solution quality of different configurations of our framework. Finally, we compare the new version of *KaHyPar* with *Max-Flow-Min-Cut* computations with state-of-the-art hypergraph partitioners.

### 6.1. Instances

Our full benchmark set consists of 488 hypergraphs from three different application areas. For VLSI design, we use instances from the *ISPD98 VLSI Circuit Benchmark Suite* (ISPD98) [2] and add more recent instances of the *DAC 2012 Routability-Driven Placement Contest* (DAC) [48]. We interpret the Sparse Matrix instances of the *Florida Sparse Matrix Collection* (SPM) [13] as hypergraphs using the row-net model [10]. The rows of each matrix are treated as hyperedges and the columns are the vertices of the hypergraph. Our last benchmark type are SAT formulas of the *International SAT Competition 2014* [6]. A common representation of a SAT formula as hypergraph is to define the literals as vertices and each clause as a net (LITERAL) [39]. Mann and Papp [36] suggested two other hypergraph representations, called PRIMAL and DUAL. The PRIMAL representation treats each variable as vertex and each clause as hyperedge. The DUAL representation treats each clause as vertex and the variables induce nets containing all clauses where the corresponding variable occurs. A summary of the different instance types is presented in Table 8.

We divide our full benchmark set into two smaller subsets. Our *parameter tuning* benchmark set consists of 25 hypergraphs (see Table 6), 5 of each instance type (except DAC). Additionally, we choose a benchmark subset of 165 instances (see Table 7). If we test the quality of our partitioner, we partition each hypergraph into  $k \in \{2, 4, 8, 16, 32, 64, 128\}$  blocks and use 10 different *seeds* for each  $k$  and an imbalance of  $\epsilon = 3\%$ .

### 6.2. System and Methodology

Our experiments run on a single core of a machine consisting of two *Intel Xeon E5- 2670 Octa-Core* processors clocked at 2.6 GHz. The machine has 64 GB main memory, 20 MB L3- and  $8 \times 256$  KB L2-Cache. The code is written in C++ and compiled using g++-5.2 with flags `-O3 -mtune=native -march=native`. We refer to our new implementation of *KaHyPar* with (*M*)ax-(*F*)low-*Min-Cut* computations as *KaHyPar-MF* and the latest configuration with (*C*)ommunity-(*A*)ware coarsening as *KaHyPar-CA*.

We compare *KaHyPar-MF* with the state-of-the-art hypergraph partitioners *hMetis* [29, 30] and *PaToH* [10]. *hMetis* provides a direct  $k$ -way (*hMetis-K*) and recursive bisection (*hMetis-R*) implementation. Further, we use the default configuration (*PaToH-D*) and quality preset (*PaToH-Q*) of *PaToH*. We configure *hMetis* to optimize the *sum-of-external-degrees-metric* (SOED) and calculate  $(\lambda - 1)(\Pi) = \text{SOED}(\Pi) - \text{cut}(\Pi)$ . This is also suggested by the authors of *hMetis* [30]. Additionally, we have to adapt the imbalance definition of *hMetis-R*. An imbalance value of 5 means that the weight of each bisected block is allowed to be between  $0.45 \cdot c(V)$  and  $0.55 \cdot c(V)$ . To ensure that *hMetis-R* produces a valid  $\epsilon$ -balanced partition after  $\log_2(k)$  bisections we have to adapt  $\epsilon$  to

$$\epsilon' = 100 \cdot \left( \left( (1 + \epsilon) \frac{\lceil \frac{c(V)}{k} \rceil}{c(V)} \right)^{\frac{1}{\log_2(k)}} - 0.5 \right).$$

If we evaluate the performance of a hypergraph partitioner, we first summarize the results by calculating the arithmetic mean (or minimum) of a specific metric for the different *seeds* of a hypergraph partitioned into  $k$  blocks. Afterwards, we calculate the *geometric mean* of all instances to give each instance comparable influence on the final result. To compare the performance of different hypergraph partitioners in more detail we use performance plots introduced in [45]. In the following, we call a  $k$ -way partition of a hypergraph an *instance*. For each algorithm we determine the instance with the best quality (of the 10 different *seeds*). Each color in the plot corresponds to one algorithm. The  $x$ -axis represents the number of instances and the  $y$ -axis represents the quality ratio produced by an algorithm for an instance relative to the partition of the best algorithm. For example, partitioner  $P_1$  produces a partition for an instance  $X$  with quality 100 and partitioner  $P_2$  produces a partition for the same instance of quality 105. Then, the  $y$ -value for instance  $X$  of partitioner  $P_2$  is  $1 - \frac{100}{105} \approx 0.048$  and for partitioner  $P_1$  is  $1 - \frac{100}{100} = 0$ , which means that the partition of partitioner  $P_2$  for instance  $X$  is  $\approx 4.8\%$  worse than the best partition produced for instance  $X$ . A value of zero indicates that the algorithm produced the best partition. A point close to one indicates that the partition produced by the corresponding partitioner was considerably worse than the partition produced by the best algorithm. Before we add the points to the grid, we sort them in decreasing order according to the  $y$ -values. An algorithm is considered to outperform another algorithm if its corresponding ratio values are below those of the other algorithm. A point with an  $y$ -value greater than one corresponds to an infeasible solution that violated the balanced constraint.

### 6.3. Flow Algorithms and Networks

In the first experiment, we evaluate the effect of our sparsification techniques on the performance of the maximum flow algorithms EDMONDKARP, GOLDBERG-TARJAN, BOYKOV-KOLMOGOROV and IBFS. We refer to the Lawler-Network as  $T_L$ , which is our baseline flow network. In Section 4 we present several techniques to reduce the number of nodes and edges of  $T_L$ .  $T_H$  represents our flow network in which we remove all hypernodes with a degree smaller or equal to 3. The network  $T_G$  models each hyperedge of size 2 as undirected graph edge between the corresponding pins. Finally,  $T_{\text{Hybrid}}$  combines both networks.

We evaluate the performance of our maximum flow algorithms on flow problems with  $|V'| \in \{500, 1000, 5000, 10000, 25000\}$  hypernodes. The instances are generated by executing *KaHyPar* on our benchmark subset (see Table 7) for  $k = 2$  and five different seeds. After an instance is bipartitioned, we generate flow problems with the above-mentioned sizes and execute each possible combination of flow algorithm and flow network on it.

Fig. 19 shows the average number of nodes and edges of the resulting flow networks for flow problems with 25000 hypernodes. As expected,  $T_H$  reduces the number of nodes more significantly on instances with low degree hypernodes (DUAL) and  $T_G$  on instances with small hyperedges (PRIMAL and LITERAL). Further,  $T_{\text{Hybrid}}$  combines the advantages of both networks and reduces the number of nodes and edges of nearly each benchmark type by at least a factor of 2, except on SPM instances. If we compare the sizes of the resulting flow problems, we can observe that instances with a high density ( $d = \frac{|E|}{|V'|}$ ), like PRIMAL or LITERAL, yields large flow problem and instances with a low density yield small flow problems (see DUAL instances).

In Fig. 20 we compare the performance of our maximum flow algorithms on different flow networks. A bar in the plot indicates the speed-up of the corresponding algorithm executed on  $T_H$ ,  $T_G$  or  $T_{\text{Hybrid}}$  relative to the execution on  $T_L$ . The main observation is that the speed-ups are nearly proportional to the reduction of the number of nodes and edges of the corresponding flow network. For example,  $T_{\text{Hybrid}}$  reduces the size of the flow problems of nearly each benchmark type by at least factor of 2 compared to  $T_L$ . Consequently, the speed-ups of our

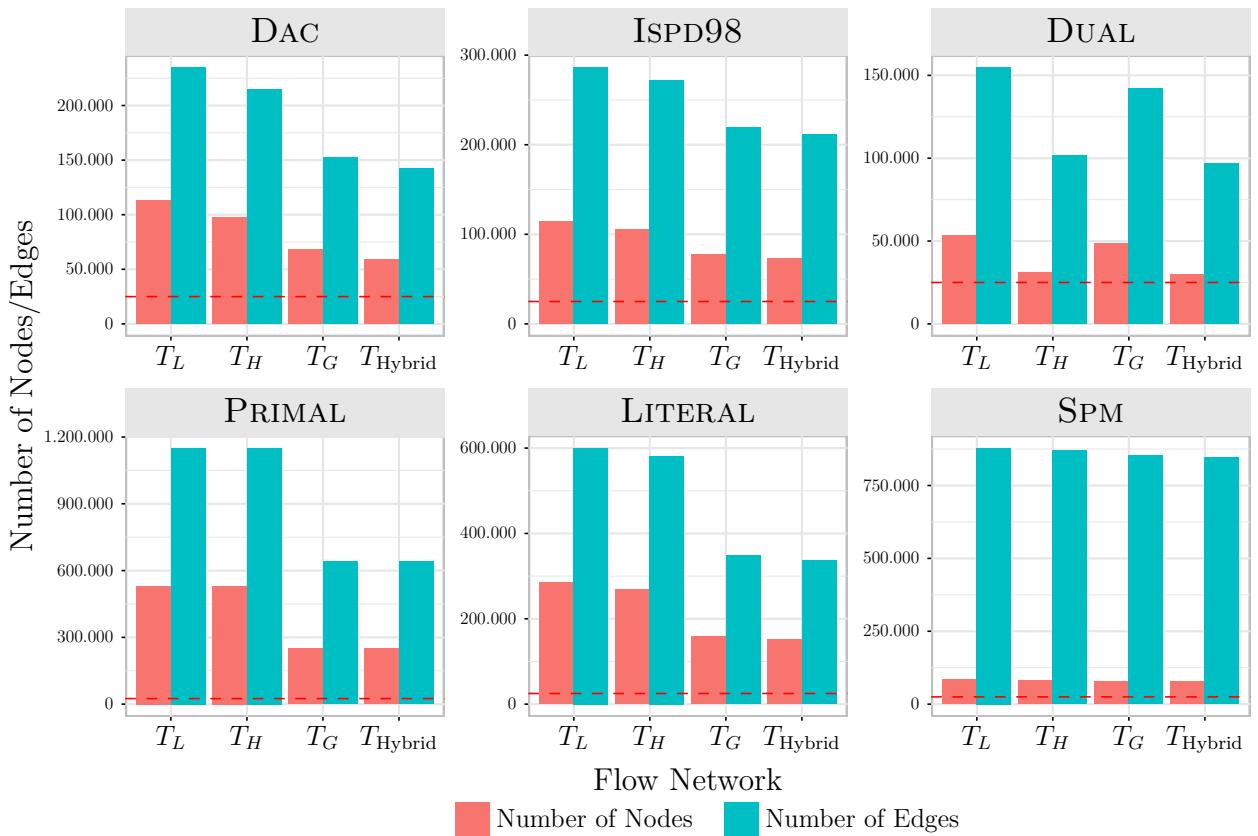


Figure 19: Comparison of the number of nodes and edges induced by flow problems of size  $|V'| = 25000$  on our flow networks for different benchmark types. The red dashed lines indicate 25000 nodes.

maximum flow algorithms on  $T_{\text{Hybrid}}$  are nearly up to a factor of 2 on each benchmark type. Our GOLDBERG-TARJAN implementation benefits most from our sparsification techniques. The algorithm is around 3 to 4 times faster on  $T_{\text{Hybrid}}$  than on  $T_L$ . All algorithms perform best on  $T_{\text{Hybrid}}$ . In conclusion, our sparsification techniques not only reduce the size of the flow problems, they also improve the running time of several maximum flow algorithms significantly.

In Table 1, we compare the absolute running times of the algorithms on our fastest flow network  $T_{\text{Hybrid}}$ . The IBFS algorithm works best on large instances ( $|V'| > 1000$ ). For smaller benchmarks ( $|V'| \leq 1000$ ) BOYKOV-KOLMOGOROV and EDMOND-KARP are faster than the IBFS algorithm. However, we are currently not able to use the IBFS algorithm in our flow-based local search algorithm. The data structure of the algorithm is not optimized for multiple executions on different flow networks, because the allocated memory of the old flow network is not deleted if we build a new flow network. However, we currently work on a reimplementation of the algorithm such that it can be used. Therefore, we use the BOYKOV-KOLMOGOROV maximum flow algorithm in combination with our flow network  $T_{\text{Hybrid}}$  in the following experiments.

## 6.4. Configuring direct $k$ -way Flow-Based Refinement

In this section, we analyze the quality of our  $k$ -way flow-based refinement algorithm with different configurations on our parameter tuning benchmark subset. There are several configurations and tuning parameters that we have to evaluate:

- *Max-(F)low-Min-Cut* computations as refinement algorithm

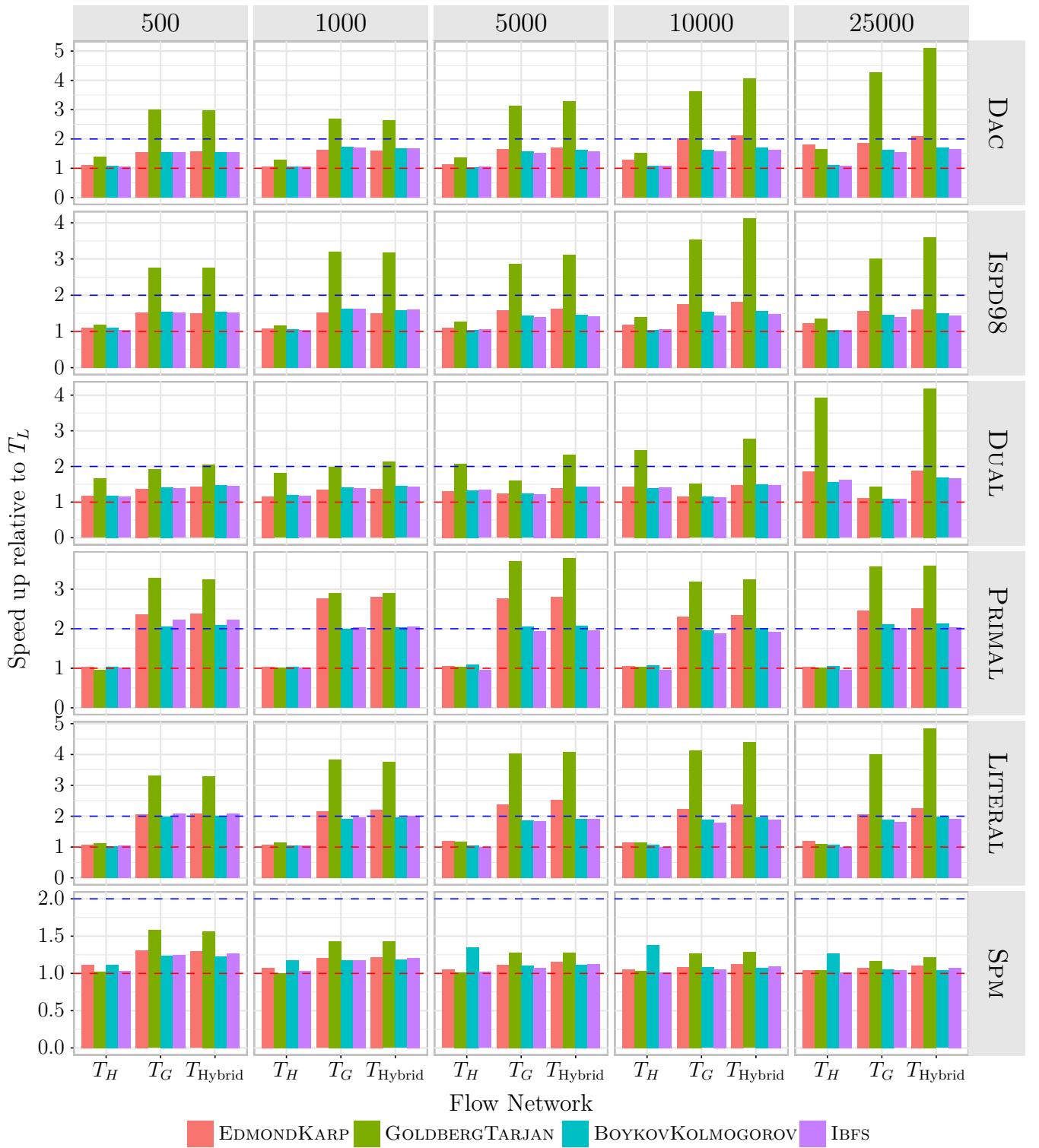


Figure 20: Speed-ups of the flow algorithms on different flow networks relative to execution on  $T_L$  for different problem sizes and types. The red resp. blue dashed line indicate a speed-up of 1 resp. 2.

$ V' $	IBFS $t[ms]$	BOYKOV-KOLMOGOROV $t[%]$	GOLDBERG-TARJAN $t[%]$	EDMOND-KARP $t[%]$
500	0.81	1.79	24.56	<b>-7.36</b>
1000	<b>1.91</b>	12.92	26.88	13.90
5000	<b>13.52</b>	38.11	63.68	108.43
10000	<b>28.40</b>	53.52	92.56	182.79
25000	<b>64.18</b>	50.19	95.25	157.03

Table 1: Average running times of our maximum flow algorithms on flow network  $T_{\text{Hybrid}}$ . Note, all values in the table are in percentage relative to the running time of the IBFS algorithm. In each line the fastest variant is marked bold.

- *Adaptive Flow Iteration* parameter  $\alpha'$  (see Section 3.3.2)
- *(M)ost Balanced Minimum Cut* heuristic (see Section 5.3)
- Combining *Max-(F)low-Min-Cut* computations with *(FM)* refinement

In the following, we denote a configuration for example with  $(+F,-M,-FM)$  that indicates which heuristic resp. technique is enabled (+) or disabled (-). The meaning of the abbreviations is explained in the enumeration above (see letters inside parentheses). We evaluate each configuration for  $k \in \{2, 4, 8, 16, 32, 64, 128\}$ ,  $\alpha' \in \{1, 2, 4, 8, 16\}$  and 10 different seeds and an imbalance of  $\epsilon = 3\%$ . We execute a *flow-based refinement* on each level  $i$  with  $i = 2^j$  ( $j \in \mathbb{N}_+$ ). Additionally, we add configuration  $(+F,+M,+FM)$  with *flow execution policy*  $i = 128j$  ( $j \in \mathbb{N}_+$ ). This configuration has a prohibitively large running time, but it is used as an upper bound for the quality achievable with *Max-Flow-Min-Cut* computations in combination with *FM* refinement. We refer to this variant as **CONSTANT128**. We use KaHyPar-CA as reference [25] and refer to it as  $(-F,-M,+FM)$ .

Config.	$(+F,-M,-FM)$		$(+F,+M,-FM)$		$(+F,+M,+FM)$		CONSTANT128	
$\alpha'$	Avg[%]	$t[s]$	Avg[%]	$t[s]$	Avg[%]	$t[s]$	Avg[%]	$t[s]$
1	-6.10	13.51	-5.62	14.22	0.23	15.19	0.53	55.75
2	-3.20	16.89	-2.08	18.23	0.74	17.97	1.09	87.93
4	-1.82	22.23	-0.20	24.29	1.21	22.50	1.61	144.42
8	-0.85	31.49	0.98	34.43	1.71	30.58	2.16	257.41
16	-0.20	48.66	1.75	53.23	2.21	45.04	2.69	498.29
Ref.	$(-F,-M,+FM)$		6373.88	13.73				

Table 2: Table contains results for different configurations of our flow-based refinement framework for increasing  $\alpha'$ . The quality in column *Avg.* is relative to our baseline configuration  $(-F,-M,+FM)$ .

The results are summarized in Table 2. The values in column *Avg* are improvements relative to our baseline configuration  $(-F,-M,+FM)$ . The running time are absolute values in seconds. The first observation is that flows only are not strong enough to outperform the *FM* heuristic. Our strongest configuration with  $\alpha' = 16$  is 0.2% worse than the *FM* baseline. Enabling the *Most Balanced Minimum Cut* heuristic significantly improves the quality compared to the configuration  $(+F,-M,-FM)$ . The quality improvements are more significant for large  $\alpha'$ . The

Config.	(+F,-M,-FM)		(+F,+M,-FM)		(+F,+M,+FM)	
$\alpha'$	M1 - Avg [%]	M2 - Avg [%]	M1 - Avg [%]	M2 - Avg [%]	M1 - Avg [%]	M2 - Avg [%]
1	-15.48	-6.10	-15.26	-5.62	0.14	0.23
2	-10.50	-3.20	-10.12	-2.08	0.36	0.74
4	-5.98	-1.82	-5.08	-0.20	0.67	1.21
8	-3.22	-0.85	-1.64	0.98	1.25	1.71
16	-1.52	-0.20	0.51	1.75	1.87	2.21
Ref.	(-F,-M,+FM)		6373.88			

Table 3: Comparison on quality of our framework with different source and sink set modeling approaches. M1 represents the approach of Sanders and Schulz [44] and M2 is our new variant proposed in Section 5.2.

larger the flow problem size, the larger is the number of different minimum  $(S, T)$ -cutsets and this increases the possibility to find a feasible solution that respects the balance constraint. Also it outperforms our baseline *FM* configuration for  $\alpha' = 16$  by 1.75%. If we enable *FM* refinement, we improve the solution quality by 2.21% (for  $\alpha' = 16$ ). Also, the running time of this variant is faster than all previous flow configurations because we transfer more work to the *FM* refinement. Consequently, a block becomes *inactive* faster during the *active block scheduling* algorithm and this decreases the number of rounds of complete pairwise flow-based refinements. Finally, CONSTANT128 gives us an upper bound of the quality achievable with a combination of *flow-based* and *FM* refinement. Flows are executed in each 128th level of the multilevel hierarchy. The quality is 2.69% better than our baseline configuration, but roughly 50 times slower. Compared to  $(+F,+M,+FM)$  for  $\alpha = 16$ , CONSTANT128 is only 0.48% better and around roughly 10 times slower.

Our best configuration is  $(+F,+M,+FM)$  with  $\alpha' = 16$ . It is also the most effective one (see Effectiveness Test in Appendix D). For further experiments, we refer to this variant as KaHyPar-MF.

At the end of Section 5.2, we compare our source and sink set modeling approach (M2) with the one of Sanders and Schulz [44] (M1). The main result is that our approach should theoretically yield to better minimum cuts, because we do not restrict all hypernodes contained in a non-cut hyperedge, which is partially contained in the flow problem, to stay in the same block after a *Max-Flow-Min-Cut* computation. In Table 3 we compare the two modeling approaches in practice. The quality of our *flow-based* configurations without the *FM* algorithm are up to 5% to 10% better for  $\alpha' \leq 4$ . For  $\alpha' > 4$  the improvement is around 1.5% to 2.5%. For small  $\alpha'$  most of the hypernodes of the flow problem are incident to a non-cut hyperedge partially contained in the flow problem. Therefore, M1 restricts them to stay in the same block after a *Max-Flow-Min-Cut* computation. M2 allows them to change its block, if it yields a smaller minimum cut.

## 6.5. Speed-Up Heuristics

At the end of Section 5.4, we presented several heuristics which help to prevent *unpromising* flow executions during active block scheduling ((R1)-(R3)). The main assumption is that only a minority of *Max-Flow-Min-Cut* computations lead to an improvement. To verify this assumption, we execute KaHyPar-MF in combination with different speed-up heuristics on our

benchmark subset (see Table 7).

Table 4 summarizes the results of the experiment. The indices of the different variants of KaHyPar-MF describe which speed-up heuristic is enabled. On average, enabling all speed-up heuristics worsen the quality of KaHyPar-MF only by 0.07%. On the other hand, the framework is significantly faster by a factor of 2. In its final configuration, KaHyPar-MF<sub>(R1,R2,R3)</sub> computes partitions with 2.41% better quality than KaHyPar-CA, while only incurring a slowdown of a factor of 2. In the following, we denote our final configuration KaHyPar-MF<sub>(R1,R2,R3)</sub> as KaHyPar-MF.

Variant	Avg [%]	Min [%]	$t_{\text{flow}}[s]$	$t[s]$
KaHyPar-CA	7077.20	6820.17	-	29.26
KaHyPar-MF	-2.48	-2.13	51.76	81.02
KaHyPar-MF <sub>(R1)</sub>	-2.41	-2.05	41.21	70.47
KaHyPar-MF <sub>(R1,R2)</sub>	-2.40	-2.04	35.56	64.82
KaHyPar-MF <sub>(R1,R2,R3)</sub>	-2.41	-2.05	26.64	55.90

Table 4: Results of our flow-based refinement framework with different speedup heuristics.

## 6.6. Comparison with other Hypergraph Partitioners

Finally, we compare our new approach KaHyPar-MF with different state-of-the-art hypergraph partitioners on the full benchmark set. We excluded 200 instances of 3416 either because PaToH-Q could not allocate enough memory or other partitioners did not finish in time. The excluded instances are shown in Table 10.

Fig. 21 summarizes the results of the experiment. KaHyPar-MF produces the best partitions on 72.9% of all benchmark instances. It is followed by hMetis-R (12.3%), hMetis-K (10.3%), KaHyPar-CA (1.3%), PaToH-Q (1.8%) and PaToH-D (1.4%). KaHyPar-MF improves the quality of KaHyPar-CA by 2.49% (see Table 14). Comparing KaHyPar-MF with each partitioner individually, KaHyPar-MF produces better partitions than KaHyPar-CA, hMetis-R, hMetis-K, PaToH-Q, PaToH-Q on 97%, 82%, 84%, 95%, 95% of the benchmark instances. Especially on *VLSI* instances, KaHyPar-MF calculates significantly better partitions than all other hypergraph partitioners (see DAC and ISPD98 in Fig. 21).

Table 13 shows the running time of all partitioners for different benchmark types. The running time of KaHyPar-MF is within a factor of 2 slower than KaHyPar-CA and is comparable to the running time of hMetis-K and hMetis-R.

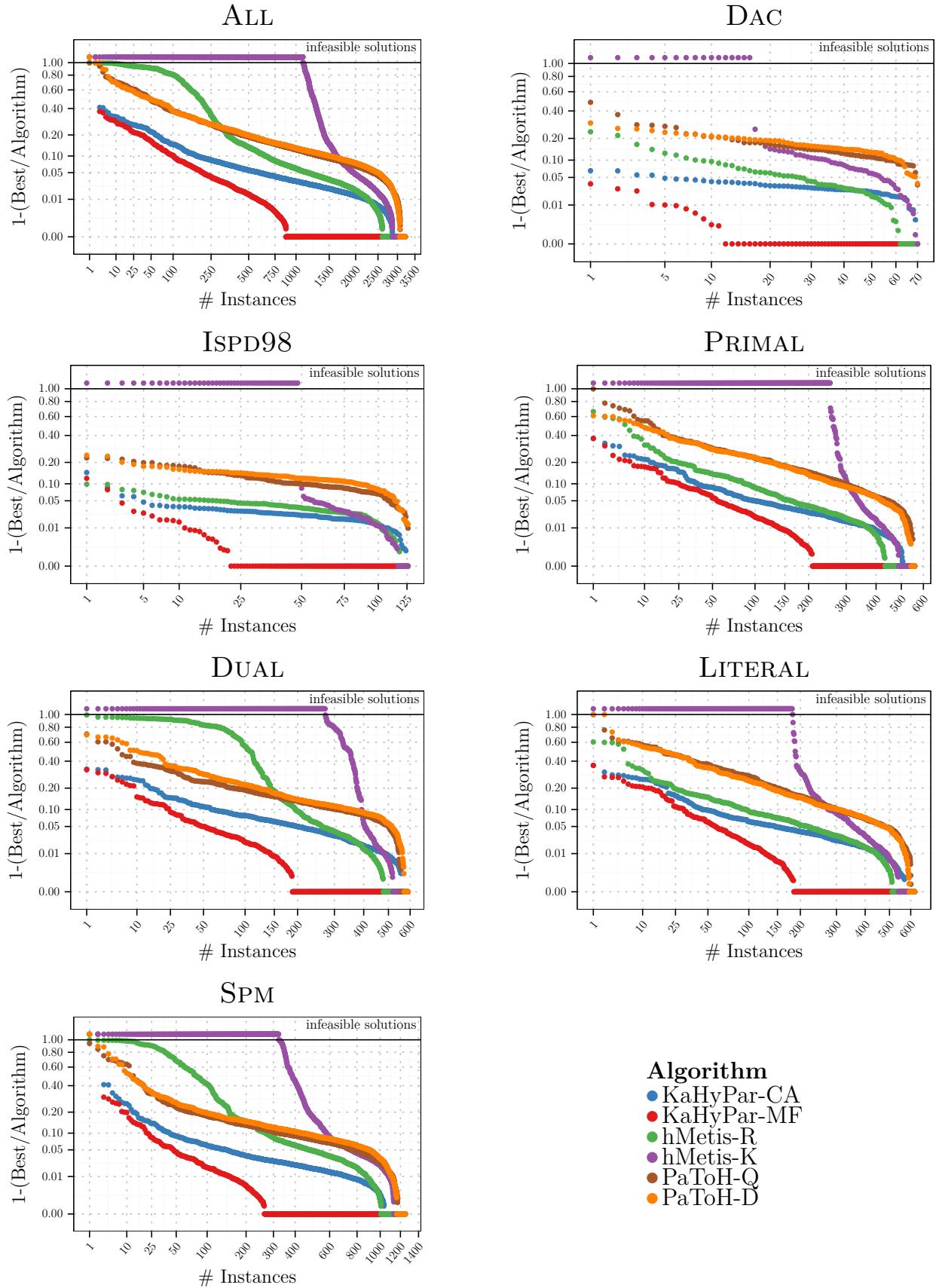


Figure 21: Min-Cut performance plots comparing KaHyPar-MF with KaHyPar-CA and other partitioners. Plots are explained in Section 6.2.

Partitioner	Running Time $t[s]$						
	ALL	DAC	ISPD98	PRIMAL	LITERAL	DUAL	SPM
KaHyPar-MF	63.33	505.75	21.10	71.81	140.53	98.06	32.64
KaHyPar-CA	30.85	368.97	12.35	32.91	64.65	68.27	13.63
hMetis-R	78.47	446.36	29.03	66.25	142.12	200.36	40.64
hMetis-K	57.36	240.92	23.18	44.23	94.89	125.55	35.08
PaToH-Q	5.84	28.34	1.89	6.90	9.24	10.57	3.35
PaToH-D	1.21	6.45	0.35	1.12	1.58	2.87	0.75

Table 5: Comparing the average running time of KaHyPar-MF with KaHyPar-CA and other hypergraph partitioners.

## 7. Conclusion

In this thesis, we present a novel refinement algorithm based on *Max-Flow-Min-Cut* computations for multilevel hypergraph partitioning. We integrate our framework into the  $n$ -level hypergraph partitioner *KaHyPar* and show that in combination with the *FM* algorithm our new approach produces the best partitions for a wide range of applications.

We introduce several techniques to sparsify the standard hypergraph flow network [33], which consists of many edges with *infinite* capacity. We present several theoretical results, which allow us to remove such edges or even to remove nodes. The results are of independent interest, because they are also applicable for min-cuts on hypergraphs and general flow networks with *infinite* capacity edges. The main practical implications are that we can remove any hypernode from the hypergraph flow network and model hyperedges of size 2 more efficiently. Our final flow network combines the two techniques, which reduces the problem size of the resulting flow networks on various benchmark types by up to a factor of 2 compared to the state-of-the-art representation and simultaneously speeds-up the running time of different maximum flow algorithms by the same amount.

Our *flow-based* refinement framework is based on ideas of Sanders and Schulz [44] (developed for multilevel graph partitioning). However, we generalize many results such that they are applicable to hypergraph partitioning. We configure a flow problem on a subhypergraph in such a way that a *Max-Flow-Min-Cut* computation improves a given bipartition of a hypergraph. Further, we show theoretically and practically that with our modeling approach better minimum cuts are achievable compared to the results of Sanders and Schulz. The bipartitioning algorithm is transferred to the direct  $k$ -way partitioning case by executing pairwise *flow-based* refinements on two adjacent blocks according to the *active block scheduling* strategy [26]. The total number of *flow-based* refinements throughout the multilevel hierarchy is controlled by a *flow execution policy*. Additionally, we combine our framework with the *FM* algorithm, which is executed in each level. Furthermore, we develop several heuristics to prevent *unpromising Max-Flow-Min-Cut* computations on two adjacent blocks, which speed-up our framework by a factor of 2.

The new configuration KaHyPar-MF produces better partitions than our old configuration KaHyPar-CA on 97% of the benchmark instances. On average the solution quality is 2.5% better, while only incurring a slowdown by a factor of 2. In comparison with 5 different state-of-the-art hypergraph partitioners, KaHyPar-MF produces the best partitions on 73% of 3216 benchmark instances. However, our algorithm is still as fast as the direct  $k$ -way version of *hMetis* and outperforms it on 84% of the benchmark instances.

## 7.1. Future Work

The quality of our framework mainly depends on the number of flow executions throughout the multilevel hierarchy. The number of flow executions is a trade-off between time and quality, which depends on the running time of the maximum flow algorithm. Optimizing those two basic building blocks of the framework will allow us to achieve better quality in the same amount of time.

The hypergraph flow network proposed by Lawler [33] has a bipartite structure. Because of this structural regularity, there might be other more specialized flow algorithms which run faster on these types of networks. Further, one could investigate if it is possible to maintain the whole flow network over the multilevel hierarchy instead of explicitly creating the flow network before each flow execution. Also, it would be interesting if information from previous flow calculations can be used to speed-up the current flow calculation. The IBFS maximum flow algorithm [22] supports the functionality to add edges and nodes to the flow network and speed-up the flow computation by using informations of previous runs. This would be an useful extension of the *adaptive flow iteration* strategy, where we solve a sequence of similar flow problems around the cut of two blocks of a partition.

Pistorius [42] describes an algorithm which implicitly executes EDMONDKARP on hypergraphs using labels on the hypernodes. In our first version of the framework, we used a similar technique and implicitly execute a flow algorithm on an implicit representation of the underlying network. During initial experiments, it turned out that the explicit representation was up to a factor of 2-3 faster than the implicit version. This is due to the fact that our flow network represents a subhypergraph of the original hypergraph. Iterating over the edges of a node means to also iterate over hypernodes which are not part of the flow problem and thus have to be ignored. Further, many labels have to be introduced which lead to a large number of main memory accesses. Furthermore, the implicit flow network is not flexible enough. Developing a new technique to sparsify the flow network would require a new implementation of the implicit flow network.

Our current framework optimizes the *connectivity* metric of a  $k$ -way partition. It turned out that it is relatively simple to adapt the algorithm to different objective functions. If we want to improve the *cut* metric of a  $k$ -way partition with a *Max-Flow-Min-Cut* computation on two adjacent blocks  $V_i$  and  $V_j$ , we only have to extend the source and sink set of the resulting flow problem with additional nodes. More precisely, if a hyperedge contains a block  $V_k$  with  $V_k \notin \{V_i, V_j\}$ , we add the *incoming* and *outgoing* hyperedge node to the source and sink set. If we want to optimize *sum of external degree* metric, we can use the same source and sink set as for the *connectivity metric* and double the capacity of each hyperedge  $e$  with  $\lambda(e, \Pi) \leq 2$ . In future versions of the framework, we want to generalize our observations such that it can optimize any objective function, which value depends on the *connectivity* of a hyperedge.

## References

- [1] AKHREMSEV, Y., HEUER, T., SANDERS, P., AND SCHLAG, S. Engineering a direct k-way Hypergraph Partitioning Algorithm. In *Proceedings of 2017 19th Workshop on Algorithm Engineering and Experiments* (2017), SIAM, pp. 28–42.
- [2] ALPERT, C. J. The ISPD98 Circuit Benchmark Suite. In *Proceedings of the 1998 International Symposium on Physical Design* (1998), ACM, pp. 80–85.
- [3] ALPERT, C. J., AND KAHNG, A. B. Recent Directions in Netlist Partitioning: a Survey. *Integration, the VLSI Journal* 19, 1 (1995), 1 – 81.
- [4] ANDERSEN, R., AND LANG, K. J. An Algorithm for Improving Graph Partitions. In *Proceedings of the 19th annual ACM-SIAM Symposium on Discrete Algorithms* (2008), Society for Industrial and Applied Mathematics, pp. 651–660.
- [5] BADER, D. A., MEYERHENKE, H., SANDERS, P., AND WAGNER, D. *Graph Partitioning and Graph Clustering*, vol. 588. 2012.
- [6] BELOV, A., HEULE, M., DIEPOLD, D., AND JÄRVISALO, M. The Application and the Hard Combinatorial Benchmarks in Sat Competition 2014. *Proceedings of SAT Competition* (2014), 81–82.
- [7] BOYKOV, Y., AND KOLMOGOROV, V. An Experimental Comparison of Min-Cut/Max-Flow Algorithms for Energy Minimization in Vision. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 26, 9 (2004), 1124–1137.
- [8] BUI, T. N., AND JONES, C. Finding Good Approximate Vertex and Edge Partitions is NP-Hard. *Information Processing Letters* 42, 3 (1992), 153–159.
- [9] BULUÇ, A., MEYERHENKE, H., SAFRO, I., SANDERS, P., AND SCHULZ, C. Recent Advances in Graph Partitioning. In *Algorithm Engineering: Selected Results and Surveys*. Springer, 2016, pp. 117–158.
- [10] CATALYUREK, U. V., AND AYKANAT, C. Hypergraph-Partitioning-based Decomposition for Parallel Sparse-Matrix Vector Multiplication. *IEEE Transactions on Parallel and Distributed Systems* 10, 7 (1999), 673–693.
- [11] CHERKASSKY, B. V. A Fast Algorithm for Computing Maximum Flow in a Network. *Collected Papers* 3 (1994), 90–96.
- [12] CHERKASSKY, B. V., AND GOLDBERG, A. V. On Implementing the Push-ReLabel Method for the Maximum Flow Problem. *Algorithmica* 19, 4 (1997), 390–410.
- [13] DAVIS, T. A., AND HU, Y. The University of Florida Sparse Matrix Collection. *ACM Transactions on Mathematical Software* 38, 1 (2011), 1.
- [14] DERIGS, U., AND MEIER, W. Implementing Goldberg's Max-Flow-Algorithm – A Computational Investigation. *Mathematical Methods of Operations Research* 33, 6 (1989), 383–403.
- [15] DUTT, S., AND DENG, W. VLSI Circuit Partitioning by Cluster-Removal using Iterative Improvement Techniques. In *Proceedings of the 1996 IEEE/ACM International Conference on Computer-Aided Design* (1996), pp. 194–200.
- [16] EDMONDS, J., AND KARP, R. M. Theoretical Improvements in Algorithmic Efficiency for Network Flow Problems. *Journal of the ACM* 19, 2 (1972), 248–264.
- [17] FIDUCCIA, C. M., AND MATTHEYES, R. M. A Linear-Time Heuristic for improving Network Partitions. In *Papers on 25 Years of Electronic Design Automation* (1988), ACM, pp. 241–247.
- [18] FORD, L. R., AND FULKERSON, D. R. Maximal Flow through a Network. *Canadian Journal of Mathematics* 8, 3 (1956), 399–404.

- [19] FORD JR, L. R., AND FULKERSON, D. R. *Flows in Networks*. Princeton University Press, 2015.
- [20] FORTUNATO, S. Community Detection in Graphs. *Physics Reports* 486, 3 (2010), 75–174.
- [21] GOLDBERG, A., HED, S., KAPLAN, H., TARJAN, R., AND WERNECK, R. Maximum Flows by Incremental Breadth-First Search. *Proceedings of 2011 European Symposium on Algorithms* (2011), 457–468.
- [22] GOLDBERG, A. V., HED, S., KAPLAN, H., KOHLI, P., TARJAN, R. E., AND WERNECK, R. F. Faster and more Dynamic Maximum Flow by Incremental Breadth-First Search. 2015, pp. 619–630.
- [23] GOLDBERG, A. V., AND TARJAN, R. E. A New Approach to the Maximum-Flow Problem. *Journal of the ACM* 35, 4 (1988), 921–940.
- [24] HEUER, T. Engineering Initial Partitioning Algorithms for direct k-way Hypergraph Partitioning. Bachelor thesis, Karlsruher Institute of Technology, 2015.
- [25] HEUER, T., AND SCHLAG, S. Improving Coarsening Schemes for Hypergraph Partitioning by Exploiting Community Structure. In *Proceedings of 16th International Symposium on Experimental Algorithms* (2017), vol. 75.
- [26] HOLTGREWE, M., SANDERS, P., AND SCHULZ, C. Engineering a scalable High Quality Graph Partitioner. In *Proceedings of 2010 IEEE International Symposium on Parallel and Distributed Processing* (2010), IEEE, pp. 1–12.
- [27] HU, T. C., AND MOERDER, K. Multiterminal Flows in a Hypergraph. In *VLSI Circuit Layout: Theory and Design*. IEEE Press, 1985, ch. 3, pp. 87–93.
- [28] KAHN, A. B. Topological Sorting of Large Networks. *Communications of the ACM* 5, 11 (1962), 558–562.
- [29] KARYPIS, G., AGGARWAL, R., KUMAR, V., AND SHEKHAR, S. Multilevel Hypergraph Partitioning: Applications in VLSI Domain. *IEEE Transactions on Very Large Scale Integration VLSI Systems* 7, 1 (1999), 69–79.
- [30] KARYPIS, G., AND KUMAR, V. Multilevel k-way Hypergraph Partitioning. *VLSI Design* 11, 3 (2000), 285–300.
- [31] KRISHNAMURTHY, B. An Improved Min-Cut Algorithm for Partitioning VLSI Networks. *IEEE Transactions on Computers*, 5 (1984), 438–446.
- [32] LANG, K., AND RAO, S. A Flow-Based Method for Improving the Expansion or Conductance of Graph Cuts. In *Proceedings of 10th International IPCO Conference* (2004), vol. 4, Springer, pp. 325–337.
- [33] LAWLER, E. L. Cutsets and Partitions of Hypergraphs. *Networks* 3, 3 (1973), 275–285.
- [34] LENGAUER, T. *Combinatorial Algorithms for Integrated Circuit Layout*. Springer Science & Business Media, 2012.
- [35] LIU, H., AND WONG, D. Network Flow Based Multi-way Partitioning with Area and Pin Constraints. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems* 17, 1 (1998), 50–59.
- [36] MANN, Z. Á., AND PAPP, P. A. Formula Partitioning Revisited.
- [37] MENGER, K. Zur Allgemeinen Kurventheorie. *Fundamenta Mathematicae* 10, 1 (1927), 96–115.
- [38] NEWMAN, M. E. Analysis of Weighted Networks. *Physical Rev. E.* 70 (2004), 056131.
- [39] PAPA, D. A., AND MARKOV, I. L. Hypergraph Partitioning and Clustering, 2007.

- [40] PATKAR, S. B., SHARMA, H., AND NARAYANAN, H. Efficient Network Flow Based Ratio-Cut Netlist Hypergraph Partitioning. *WSEAS Transactions on Circuits and Systems* 3, 1 (2004), 47–53.
- [41] PICARD, J.-C., AND QUEYRANNE, M. On the Structure of all Minimum Cuts in a Network and Applications. *Combinatorial Optimization II* (1980), 8–16.
- [42] PISTORIUS, J., AND MINOUX, M. An Improved Direct Labeling Method for the Max-Flow Min-Cut Computation in Large Hypergraphs and Applications. *International Transactions in Operational Research* 10, 1 (2003), 1–11.
- [43] SANCHIS, L. A. Multiple-Way Network Partitioning. *IEEE Transactions on Computers* 38, 1 (1989), 62–81.
- [44] SANDERS, P., AND SCHULZ, C. Engineering Multilevel Graph Partitioning Algorithms. In *Proceedings of 2011 European Symposium on Algorithms* (2011), vol. 6942, Springer, pp. 469–480.
- [45] SCHLAG, S., HENNE, V., HEUER, T., MEYERHENKE, H., SANDERS, P., AND SCHULZ, C. k-way Hypergraph Partitioning via n-Level Recursive Bisection. In *Proceedings of 2016 18th Workshop on Algorithm Engineering and Experiments* (2016), SIAM, pp. 53–67.
- [46] SLEATOR, D. D., AND TARJAN, R. E. A Data Structure for Dynamic Trees. In *Proceedings of the 13th Annual ACM Symposium on Theory of Computing* (1981), ACM, pp. 114–122.
- [47] TARJAN, R. Depth-First Search and Linear Graph Algorithms. *SIAM Journal on Computing* 1, 2 (1972), 146–160.
- [48] VISWANATHAN, N., ALPERT, C., SZE, C., LI, Z., AND WEI, Y. The DAC 2012 Routability-Driven Placement Contest and Benchmark Suite. In *Proceedings of the 49th Annual Design Automation Conference* (2012), ACM, pp. 774–782.
- [49] WEST, D. B., ET AL. *Introduction to Graph Theory*, vol. 2. 2001.
- [50] YANG, H. H., AND WONG, D. Efficient Network Flow Based Min-Cut Balanced Partitioning. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems* 15, 12 (1996), 1533–1540.
- [51] ZHAO, Z., TAO, L., AND ZHAO, Y. An Effective Algorithm for Multiway Hypergraph Partitioning. *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications* 49, 8 (2002), 1079–1092.

## A. Benchmark Instances

### A.1. Parameter Tuning Benchmark Set

Type	Num	min  V	Avg.  V	max  V	min  E	Avg.  E
ISPD98	5	32498	49049	69429	34826	52202
PRIMAL	5	53919	90467	163622	245440	414577
LITERAL	5	96430	141622	283720	140968	323388
DUAL	5	100384	297768	1070757	34317	85669
SPM	5	12328	34129	74104	12328	34129
Type	max  E	Avg.  e	Med.  e	Avg. $d(v)$	Med. $d(v)$	Avg. $\frac{ E }{ V }$
ISPD98	75196	3.79	2.00	4.04	3.57	1.06
PRIMAL	629461	2.56	2.30	11.74	6.54	4.58
LITERAL	629461	2.56	2.30	5.85	3.25	2.28
DUAL	229544	8.05	6.03	2.32	2.00	0.29
SPM	74104	20.91	19.92	20.91	17.87	1.00

Table 6: Summary of the parameter tuning instances.

### A.2. Benchmark Subset

Type	Num	min  V	Avg.  V	max  V	min  E	Avg.  E
DAC	5	522482	708389	917944	511685	697951
ISPD98	10	53395	110344	210613	60902	119535
PRIMAL	30	7729	141143	1613160	29194	632173
LITERAL	30	15458	281238	3226318	29194	632173
DUAL	30	29194	632173	6429816	7729	141143
SPM	60	11028	64765	1000005	4371	59589
Type	max  E	Avg.  e	Med.  e	Avg. $d(v)$	Med. $d(v)$	Avg. $\frac{ E }{ V }$
DAC	898001	3.37	2.00	3.32	3.18	0.99
ISPD98	201920	3.87	2.08	4.20	3.67	1.08
PRIMAL	6429816	2.58	2.20	11.54	7.39	4.48
LITERAL	6429816	2.58	2.20	5.79	3.78	2.25
DUAL	1613160	11.54	7.39	2.58	2.20	0.22
SPM	1000005	16.25	12.95	14.95	12.58	0.92

Table 7: Summary of the benchmark subset instances.

### A.3. Full Benchmark Set

Type	Num	min  V	Avg. V	max  V	min  E	Avg. E
DAC	10	522482	888090	1360217	511685	876629
ISPD98	18	12752	59801	210613	14111	64240
PRIMAL	92	7502	111371	1621762	28770	649991
LITERAL	92	15004	221981	3226318	28770	649991
DUAL	92	28770	649991	13378617	7502	111371
SPM	184	10000	56930	9845725	163	52709
Type	max  E	Avg. e	Med. e	Avg. $d(v)$	Med. $d(v)$	Avg. $\frac{ E }{ V }$
DAC	1340418	3.41	2.00	3.37	3.27	0.99
ISPD98	201920	3.83	2.05	4.11	3.52	1.07
PRIMAL	13378617	2.74	2.31	16.01	8.12	5.84
LITERAL	13378617	2.74	2.31	8.03	3.65	2.93
DUAL	1621762	16.01	8.12	2.74	2.31	0.17
SPM	6920306	15.72	12.15	14.56	10.99	0.93

Table 8: Summary of the full benchmark set instances.

### A.4. Excluded Test Instances

Hypergraph	2	4	8	16	32	64	128
10pipe-q0-k.dual				△	△	△	○△
10pipe-q0-k.primal	□	□	□	□	□	□	□
11pipe-k.dual	△	○△	○△	○△	○△	○△	○△
11pipe-k				○	○	○	○
11pipe-k.primal	□	□	□	□	□	□	○□
11pipe-q0-k.dual					△	○△	○△
11pipe-q0-k.primal	□	□	□	□	□	□	□
9dlx-vliw-at-b-iq3.dual							△
9dlx-vliw-at-b-iq3.primal	□	□	□	□	□	□	□
9vliw-m-9stages-iq3-C1-bug7.dual	△	●○△	●○△	●○△	●○△	●○△	●○△
9vliw-m-9stages-iq3-C1-bug7	△	△	●○△	●○△	●○△	●○□△	●○□△
9vliw-m-9stages-iq3-C1-bug7.primal	△	△		△	○△	○△	○△
9vliw-m-9stages-iq3-C1-bug8.dual	△	●○△	●○△	●○△	●○△	●○△	●○△
9vliw-m-9stages-iq3-C1-bug8	△	△	●○△	●○△	●○△	●○□△	●○□△
9vliw-m-9stages-iq3-C1-bug8.primal	△	△		△	○△	○△	○△
blocks-blocks-37-1.130-NOTKNOWN.dual	○	●○	●○	●○	●○	●○	●○△
blocks-blocks-37-1.130-NOTKNOWN	□		□	□	□	□	□
blocks-blocks-37-1.130-NOTKNOWN.primal	□	□	□	□	□	□	□
E02F20.dual							○
E02F22.dual						○	○
openstacks-p30-3.085-SAT.primal	□	□	□	□	□	□	□
openstacks-sequencedstrips-nonadl-	□	□	□	□	□	□	□
nonnegated-os-sequencedstrips-p30-3.025-							
NOTKNOWN.primal							
openstacks-sequencedstrips-nonadl-	□	□	□	□	□	□	□
nonnegated-os-sequencedstrips-p30-3.085-							
SAT.primal							

## A BENCHMARK INSTANCES

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q-query-3-L100-coli.sat.dual							△
q-query-3-L150-coli.sat.dual							△
q-query-3-L200-coli.sat.dual							△
q-query-3-L80-coli.sat.dual							△
transport-transport-city-sequential-25nodes-							△
1000size-3degree-100mindistance-3trucks-							△
10packages-2008seed.030-NOTKNOWN.dual							△
transport-transport-city-sequential-	□						□
25nodes-1000size-3degree-100mindistance-							□
3trucks-10packages-2008seed.050-							□
NOTKNOWN.primal							□
velev-vliw-uns-2.0-uq5.dual			△	△	△	△	△
velev-vliw-uns-2.0-uq5.primal	□	□	□	□	□	□	□
velev-vliw-uns-4.0-9.dual				△	△	△	△
velev-vliw-uns-4.0-9.primal	□	□	□	□	□	□	□
192bit	□		□				
appu					○	○	
ESOC	□	□		□	○□	□	
human-gene2				○△	○△	○△	
IMDB			△	△	△	△	△
kron-g500-logn16	△	△	△	△	○△	○△	
nlpkkt120	△	△	△	△	△	△	○△
Rucci1				□			
sls	□	□	□	○□	○□	○□	○□
Trec14							○

△ : KaHyPar-CA/KaHyPar-MF exceeded time limit
● : hMetis-R exceeded time limit
○ : hMetis-K exceeded time limit
□ : PaToH-Q memory allocation error

Table 10: Instances excluded from the full benchmark set evaluation.

## B. Removing Infinite Weight Nodes of the Vertex Separator Problem

Finding a minimum-weight  $(s, t)$ -cutset of a hypergraph can be reduced to the problem of finding a minimum-weight  $(s, t)$ -vertex separator of the bipartite graph representation  $G_*(H)$  of the hypergraph [27, 33]. The weight of the hyperedge nodes is the weight of the corresponding hyperedge and the weight of all hypernodes is *infinity*. We can calculate a minimum-weight  $(s, t)$ -vertex separator of  $G_*(H)$  with a maximum  $(s, t)$ -flow calculation on the Lawler-Transformation  $T_L(H)$ . In Section 4.1 we have shown how to remove a hypernode  $v$  from  $T_L(H)$  by adding *shortcut* edges between all outgoing hyperedges  $e''$  and all incoming hyperedges  $e'$  with  $e \in I(v)$ . The correctness of the transformation follows with Lemma 4.1. The total number of inserted edges is  $d(v)^2$  where  $d(v)$  is the degree of hypernode  $v$ . Since the underlying problem is to find a minimum-weight  $(s, t)$ -vertex separator, we can prove that  $d(v)(d(v) - 1)$  edges are sufficient to model the problem equivalently. The problem is illustrated in Fig. 22. In the following, we show that we can remove the red edges, which are exactly the edges between two equivalent hyperedge nodes.

**Lemma B.1.** *Let  $G = (V, E, c)$  be an undirected graph and  $v \in V$  with  $c(v) = \infty$ . We can find a minimum-weight  $(s, t)$ -vertex separator of  $G$  with graph  $G'$  which is the graph without node  $v$  and having a clique between all adjacent nodes of  $v$ .*

*Proof.* We will show that each  $(s, t)$ -vertex separator of  $G$  is also a  $(s, t)$ -vertex separator of  $G'$  and vice versa. Since the weight of each node in both network is the same, a minimum-weight  $(s, t)$ -vertex separator of  $G$  is also a minimum-weight  $(s, t)$ -vertex separator of  $G'$  and vice versa. We call an edge of  $G'$ , which is part of the inserted clique, a *shortcut* edge.

Let  $V' \subseteq V$  be a  $(s, t)$ -vertex separator of  $G$  with  $c(V') < \infty$ . Assume after removing all  $u \in V'$  from  $G'$  there still exists a path from  $s$  to  $t$ . If the path does not contain any *shortcut* edge, the same path must connect  $s$  and  $t$  in  $G$  because we have removed all  $u \in V'$  from  $G'$ . This is a contradiction that  $V'$  is a vertex separator of  $G$ . Assume the path contains a *shortcut* edge  $(u, w)$  of  $G'$ . Because  $c(V') < \infty$  and  $c(v) = \infty$ , it follows that  $v \notin V'$ . We can replace  $(u, w)$  with two edges  $(u, v)$  and  $(v, w)$  and obtain a path connecting  $s$  and  $t$  in  $G$ . This is also a contradiction that  $V'$  is a vertex separator of  $G$ .

The same argumentation holds, if we want to show that each  $(s, t)$ -vertex separator of  $G'$  is a  $(s, t)$ -vertex separator of  $G$ . If the path  $P$  connecting  $s$  and  $t$  in  $G$  contains the removed node  $v$  with edges  $(u, v) \in P$  and  $(v, w) \in P$  we can replace the two edges with the *shortcut* edge  $(u, w)$  of  $G'$ . The resulting path connects  $s$  and  $t$  in  $G'$ . This is a contradiction due to the fact that  $V'$  is a vertex separator of  $G'$ .  $\square$

Lemma B.1 can be used to remove the *infinity* capacity edges between the same hyperedge nodes (see red edges in Fig. 22). Instead of removing a hypernode  $v$  of  $T_L(H)$  with Lemma 4.1, we can apply Lemma B.1 on a hypernode  $v$  of the bipartite graph representation of the hypergraph. Afterwards, we can use the vertex separator transformation (see Defintion 2.3) to obtain a flow network in which the value of a maximum  $(s, t)$ -flow is equal to the weight of a minimum-weight  $(s, t)$ -vertex separator. Both networks on the right side of Fig. 22 are equivalent, but the removal of a hypernode now induces  $d(v)(d(v) - 1)$  edges instead of  $d(v)^2$  edges in the new network.

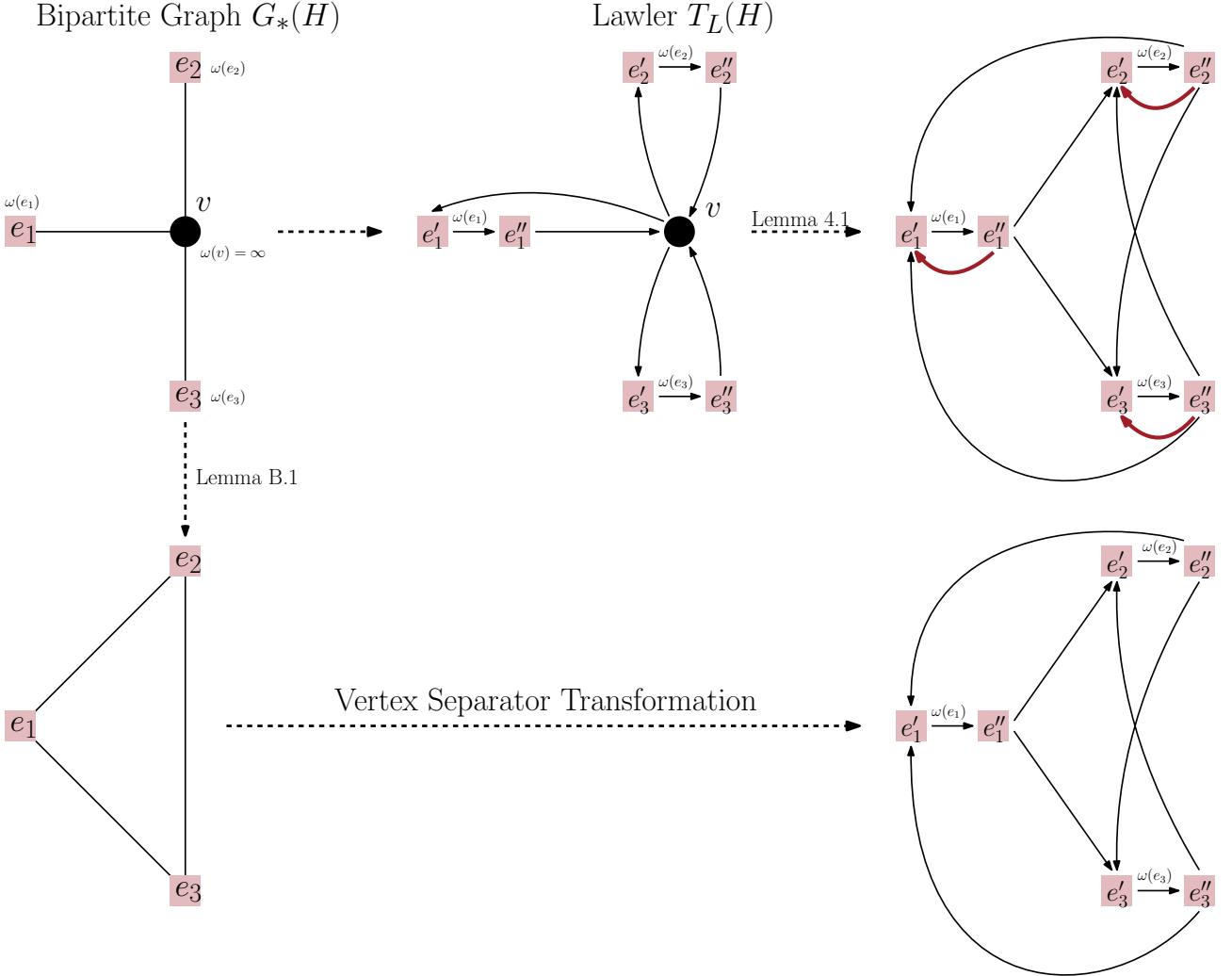


Figure 22: Illustration of the technique to remove a hypernode such that the removal induce  $d(v)(d(v) - 1)$  edges instead of  $d(v)^2$  edges in the corresponding flow network. The edges without an explicit capacity are *infinite* capacity edges. The transformation on the top of the figure illustrates the technique presented in Section 4.1. Using Lemma B.1 and the vertex separator transformation (see Defintion 2.3) results in a equivalent flow network without the red highlighted edges.

## C. Detailed Flow Network and Algorithm Evaluation

Instance	$ V' $	IBFS $t[ms]$	BOYKOV-KOLMOGOROV $t[%]$	GOLDBERG-TARJAN $t[%]$	EDMOND-KARP $t[%]$
ALL	500	0.81	1.79	24.56	<b>-7.36</b>
	1000	<b>1.91</b>	12.92	26.88	13.90
	5000	<b>13.52</b>	38.11	63.68	108.43
	10000	<b>28.40</b>	53.52	92.56	182.79
	25000	<b>64.18</b>	50.19	95.25	157.03
DAC	500	0.29	-10.46	11.79	<b>-34.02</b>
	1000	0.71	-9.51	18.18	<b>-35.86</b>
	5000	5.16	-5.94	12.21	<b>-17.03</b>
	10000	10.23	<b>-1.30</b>	33.46	32.26
	25000	<b>26.05</b>	2.14	112.29	67.77
ISPD98	500	0.42	-11.77	23.10	<b>-13.55</b>
	1000	0.98	-11.76	14.61	<b>-12.01</b>
	5000	7.33	<b>-1.06</b>	65.21	41.04
	10000	<b>15.19</b>	5.27	209.29	164.02
	25000	<b>41.50</b>	15.04	782.45	525.31
DUAL	500	0.24	-12.17	1.24	<b>-42.11</b>
	1000	0.51	-11.40	3.32	<b>-43.34</b>
	5000	3.41	-7.46	7.30	<b>-43.50</b>
	10000	6.65	-2.56	21.99	<b>-37.53</b>
	25000	15.63	3.86	65.81	<b>-17.12</b>
PRIMAL	500	<b>1.45</b>	24.48	58.97	143.23
	1000	<b>3.51</b>	22.79	66.63	200.62
	5000	<b>26.34</b>	23.07	122.09	589.46
	10000	<b>48.87</b>	14.37	110.18	484.42
	25000	<b>102.32</b>	17.38	237.90	852.30
LITERAL	500	<b>0.66</b>	0.55	61.36	38.80
	1000	<b>1.63</b>	8.06	51.86	84.71
	5000	<b>11.55</b>	13.41	94.09	227.94
	10000	<b>25.28</b>	14.81	130.87	375.89
	25000	<b>55.67</b>	7.27	125.34	367.70
SPM	500	1.60	3.50	8.07	<b>-39.46</b>
	1000	3.79	34.29	14.28	<b>-14.95</b>
	5000	<b>26.30</b>	121.86	65.34	105.19
	10000	<b>60.57</b>	196.95	103.28	256.18
	25000	<b>140.35</b>	169.78	14.70	62.44

Table 11: Average running times of our maximum flow algorithms on flow network  $T_{\text{Hybrid}}$ . Note, all values in the table are in percentage relative to the running time of the IBFS algorithm. In each line the fastest variant is marked bold.

## D. Effectiveness Tests for Flow Configurations

To evaluate the effectiveness of our configurations presented in Section 6.4 we give each configuration the same amount of time to produce as many as possible partitions of a hypergraph  $H$  for a given  $k$ . We define  $t_{H,k}$  which is the maximum partition time of a configuration to partition  $H$  in  $k$  blocks. If we execute a configuration on a hypergraph  $H$  for a given  $k$  and  $\alpha'$  the time to produce as many as possible partitions is restricted by  $3t_{H,k}$ . We sum up the partition times during execution and if that sum plus the current average partition time would exceed  $3t_{H,k}$  we perform the next run with a certain probability such that the expected running time is  $3t_{H,k}$ . The effectiveness tests were proposed by Sanders and Schulz [44]. The results of the tests mirrors our results of Section 6.4.

Config.	(+F,-M,-FM)	(+F,+M,-FM)	(+F,+M,+FM)
$\alpha'$	Avg[%]	Avg[%]	Avg[%]
1	-6.08	-5.57	0.23
2	-3.22	-2.10	0.72
4	-1.90	-0.26	1.18
8	-0.91	0.92	1.67
16	-0.29	1.65	2.15
Ref.	(-F,-M,+FM)	6376.03	

Table 12: Table contains results of the effectiveness test for different configurations of our flow-based refinement framework for increasing  $\alpha'$ . The quality in column *Avg.* is relative to our baseline configuration (-F,-M,+FM).

## E. Detailed Speed-Up Heuristic Evaluation

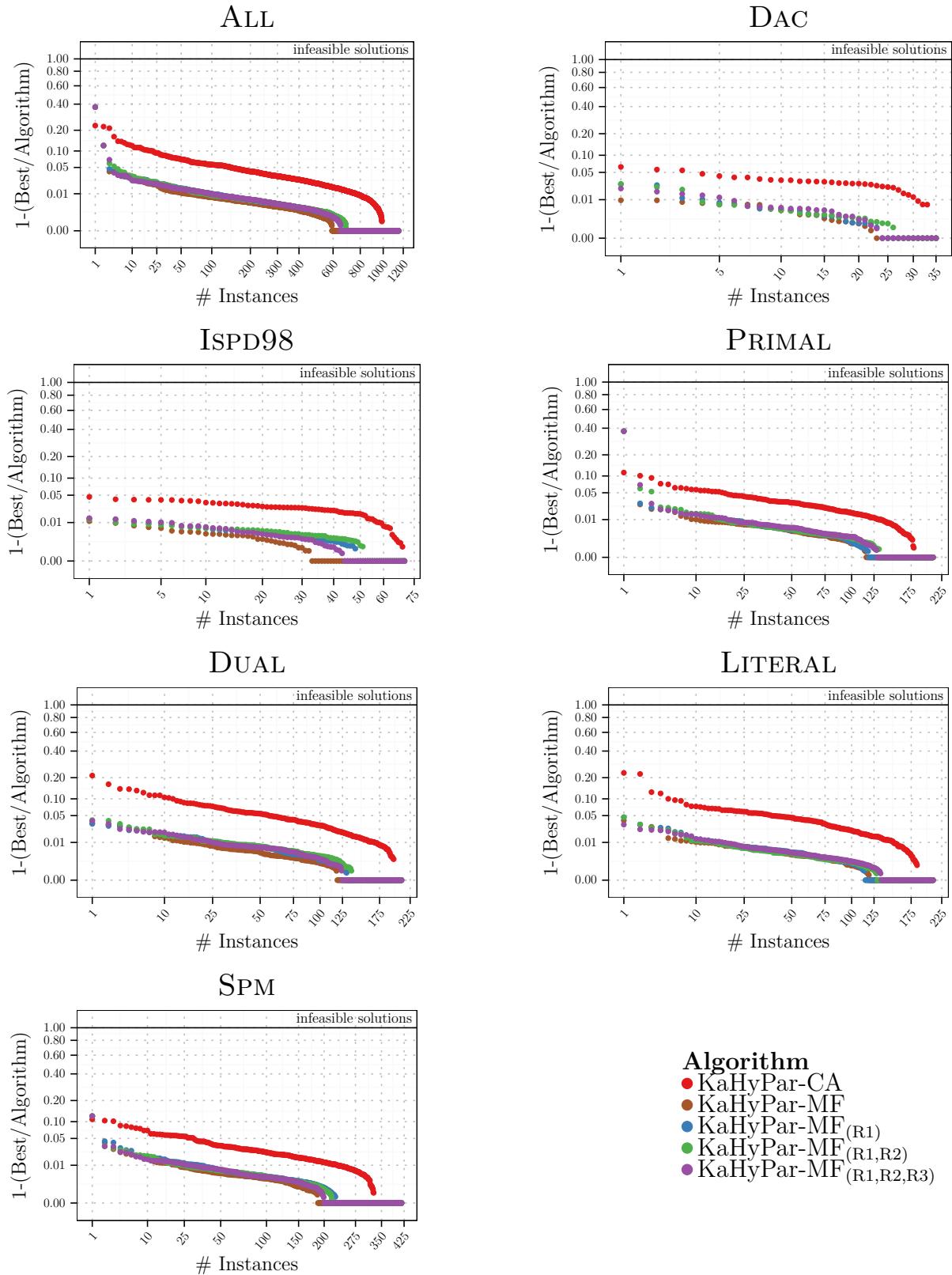


Figure 23: Min-Cut performance plots comparing KaHyPar-MF with KaHyPar-CA. The plots are explained in Section 6.2.

Partitioner	Running Time $t[s]$						
	ALL	DAC	ISPD98	PRIMAL	LITERAL	DUAL	SPM
KaHyPar-CA	29.26	343.40	21.57	36.44	56.49	58.75	11.31
KaHyPar-MF	81.02	610.48	69.84	107.72	164.68	127.09	33.81
KaHyPar-MF <sub>(R1)</sub>	70.47	526.26	55.56	91.10	136.17	113.87	30.62
KaHyPar-MF <sub>(R1,R2)</sub>	64.82	503.04	47.31	84.65	123.63	101.41	28.95
KaHyPar-MF <sub>(R1,R2,R3)</sub>	55.90	452.27	39.03	71.64	105.20	89.07	25.24

Table 13: Comparing the average running time of KaHyPar-MF with KaHyPar-CA.

## F. Detailed Comparison with other Hypergraph Partitioners

Partitioner	Average $\lambda - 1$						
	ALL	DAC	ISPD98	PRIMAL	LITERAL	DUAL	SPM
KaHyPar-MF	7727.97	17 480.70	5644.61	15 863.61	15 769.49	3038.31	6027.03
KaHyPar-CA	2.49	3.11	2.20	2.08	2.74	3.51	2.08
hMetis-R	15.79	3.64	1.62	2.07	2.80	43.44	19.77
hMetis-K	15.25	8.46	1.38	4.05	9.29	28.65	19.54
PaToH-Q	9.51	13.57	7.92	12.14	13.35	8.80	6.79
PaToH-D	16.77	23.75	15.08	18.27	21.54	18.31	12.92

Table 14: Comparison of average ( $\lambda - 1$ ) metric of KaHyPar-MF with KaHyPar-CA and other partitioners on different benchmark types. The results are in percentage relative to KaHyPar-MF.

Partitioner	Average $\lambda - 1$						
	$k = 2$	$k = 4$	$k = 8$	$k = 16$	$k = 32$	$k = 64$	$k = 128$
KaHyPar-MF	1057.94	3105.80	5988.27	9292.89	14 582.34	21 735.78	31 477.02
KaHyPar-CA	2.32	2.62	2.86	2.73	2.55	2.28	2.08
hMetis-R	27.19	18.98	16.97	15.81	12.86	10.70	8.49
hMetis-K	27.59	17.84	15.75	15.58	11.78	10.25	8.48
PaToH-Q	11.74	9.14	9.14	10.01	9.38	9.05	8.10
PaToH-D	15.29	16.60	19.17	19.91	16.15	15.78	14.52

Table 15: Comparison of average ( $\lambda - 1$ ) metric of KaHyPar-MF with KaHyPar-CA and other partitioners for different values of  $k$ . The results are in percentage relative to KaHyPar-MF.

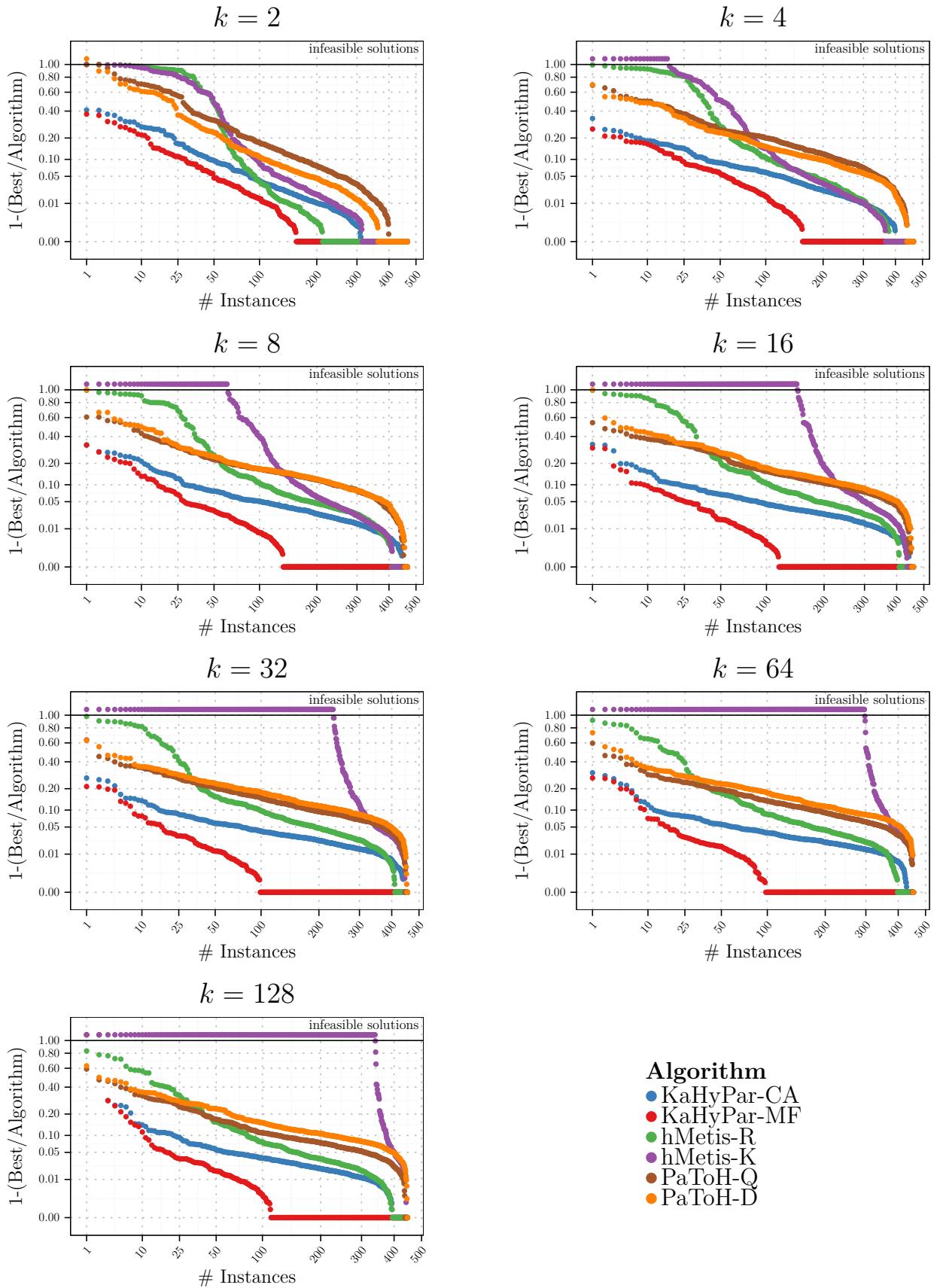


Figure 24: Min-Cut performance plots comparing KaHyPar-MF with KaHyPar-CA and other partitioners for different values of  $k$ .

Partitioner	Running Time $t[s]$						
	$k = 2$	$k = 4$	$k = 8$	$k = 16$	$k = 32$	$k = 64$	$k = 128$
KaHyPar-MF	23.56	39.84	56.44	68.69	86.73	108.35	125.74
KaHyPar-CA	12.68	17.02	23.70	30.78	41.38	56.95	76.05
hMetis-R	27.87	51.03	73.94	90.09	107.94	127.26	147.72
hMetis-K	25.47	31.92	42.06	52.87	73.30	108.15	151.63
PaToH-Q	1.93	3.58	5.39	6.95	8.32	9.97	11.34
PaToH-D	0.43	0.76	1.11	1.40	1.69	2.00	2.27

Table 16: Comparing the average running time of KaHyPar-MF with KaHyPar-CA and other partitioners for different values of  $k$ .