



Master-Thesis

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

Tobias Heuer

Advisors: Prof. Dr. Peter Sanders
M. Sc. Sebastian Schlag

Institute of Theoretical Informatics, Algorithmics
Department of Informatics
Karlsruhe Institute of Technology

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Abstract

All state-of-the-art multilevel hypergraph partitioner implements the *FM* heuristic [16] to improve a balanced k -way partition. In each step, the *FM* algorithm moves a node with maximum *gain* from its current block to the other block according to an objective function. The *gain* of moving a hypernode mainly depends on the state of all incident hyperedges. Therefore, *FM* only incorporates *local* information about the problem structure and performs a move *greedily*. Consequently, the solution quality heavily depends on the *initial partition* and the quality of the *coarsening* algorithm [14]. Moreover, if we have a large number of moves with equal gain, the quality of the solution is a result of random choices made within the algorithm [28, 33]. Especially for large hyperedges, we often have many moves of vertices which gain is equal to zero if, e.g., the *cut* metric is the objective function. The well-known *max-flow min-cut* theorem [17] establish an analogy between the *global* minimum cut of a network separating two vertices and the maximum flow between them. The technique incorporates *global* information about the problem structure and is not *move-based*. Therefore, utilizing such techniques as *local search* heuristic would overcome the drawbacks of the *FM* algorithm.

In this thesis, we present an alternative *local search* algorithm based on *Max-Flow-Min-Cut* computations for balanced direct k -way hypergraph partitioning. We integrate our framework into the n -level hypergraph partitioner *KaHyPar* [22]. The framework is inspired by the work of Sanders and Schulz [42] who successfully showed that *flow-based local search* in combination with the *FM* algorithm significantly improves the quality of partitions in a multilevel graph partitioner. We generalize many ideas of them such that they are applicable in the multilevel hypergraph partitioning context. We present several techniques to sparsify the state-of-the-art hypergraph flow network representation [30]. The theoretical results are of independent interest because they can also be applied to general flow networks. Our experiments indicate that maximum flow algorithms are up to a factor of 3 faster on our network in practice. Further, we show how to configure a flow problem on a subhypergraph such that a *Max-Flow-Min-Cut* computation improves a balanced k -way partition.

We tested our new approach on a large benchmark set with 3222 instances. In comparison to 5 different systems, our new configuration outperforms the tested state-of-the-art hypergraph partitioner on 70% of the instances. In comparison to the latest version of *KaHyPar*, our new approach produces 2% better quality while only incurring a performance slowdown by a factor of 2. Moreover, our partitioner has a comparable running time to the direct k -way version of *hMetis* and outperforms it on 82% of the benchmarks.

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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 the goal is to simultaneously minimize an objective function.

Classical application areas can be found in *VLSI* design, parallelization of the Sparse Matrix-Vector Product and simplifying *SAT* formulas [26, 33, 37]. 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 [8]. 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 [33].

Hypergraph partitioning is an NP-hard problem [31] and it is even NP-hard to find a good approximation [7]. The most common heuristic used in state-of-the-art hypergraph partitioners is the *multilevel paradigm* [9, 22, 26]. First, a sequence of smaller hypergraphs is generated by contracting a set of matchings between hypernode pairs or clusters in each step (*coarsening phase*). If the hypergraph is small enough, we can use expensive heuristics to *initial 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. One algorithm used in the state-of-the-art multilevel hypergraph partitioners is the *Fiduccia-Mattheyses* heuristic (FM). The FM algorithm maintains gain values (according to a objective function) of moving a node from its current block to another block [16]. A move is performed, if its gain value is maximum among all possible moves. The FM heuristic is generally intuitive, flexible in adapting to different optimization objectives, easy to implement and relatively fast [49].

However, the gain of moving a (hyper)node to another block only depends on the state of the incident (hyper)edges. 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, which quality heavily depends on the initial partition [14]. Therefore, multiple runs are needed to find a solution close to the global optimum. The probability of finding a good approximation of the global optimum significantly drops if we partition large hypergraphs [14]. If we execute FM in the multilevel context, we partially solve the problem. A move of an 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 [37]. The quality of the solution then depends more on the quality of the *coarsening* rather than on the *initial partition*.

Further, 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 remainings 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 contains vertices of more than one block). Especially for large hyperedges, we often have to *move* a sequence of nodes 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 [33]. Krishnamurthy [28] 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 [28]. However, the *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 [15]. The well-known *max-flow min-cut* theorem [17] establish an analogy between the maximum flow from a source s to a sink t and 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, it overcomes the drawbacks of the *FM* algorithm. However, it was overlooked for a long time because it was perceived as computationally expensive and impractical for (hyper)graph partitioning [32].

Sanders and Schulz [42] successfully integrated a *flow*-based refinement algorithm in their multilevel *graph* partitioner. They combine the strength of *flow*-based 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 [32, 38, 48]. A balanced k -way hypergraph partition with such an approach is currently only obtainable by applying the bipartitioning algorithm recursively [48]. The impact of a *flow*-based *local search* algorithm on the solution quality of a multilevel hypergraph partitioner has not been studied yet.

1.1. Problem Statement

Motivated by the successfull integration of a *flow*-based *local search* algorithm in the multilevel graph partitioner *KaFFPa* of Sanders and Schulz [42] to obtain balanced k -way partitions, this thesis investigates the integration of such an approach into the multilevel hypergraph partitioner *KaHyPar* [22].

In the first step, we have to find an appropriate model of a hypergraph as flow network. Afterwards, we want to improve a given bipartition of a hypergraph with a *Max-Flow-Min-Cut* computation by using the flow network of the previous step. This work is the theoretical foundations for developing a *flow*-based *local search* algorithm which works in a multilevel hypergraph partitioner and improves a given balanced k -way partition. The last step is to integrate the framework into the n -level hypergraph partitioner *KaHyPar* [22] 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 is only within a constant factor slower.

1.2. Contributions

We present several techniques to sparsify the state-of-the-art hypergraph flow network modeling approach proposed by Lawler [30]. Our experiments indicate that maximum flow algorithms are up to a factor of 3 faster with our new network. The theoretical results, which leads to the presented sparsification techniques, are of independent interest and can also be applied on general flow networks. Further, we show how to configure a flow problem on a subhypergraph of H such that a maximum (S, T) -flow yields an improved cut of a given bipartition. We choose S and T in a way such that the value of the cut of H after a *Max-Flow-Min-Cut* computation on a subhypergraph can be calculated with the value of a maximum (S, T) -flow. Our *flow*-based *local search* framework is inspired by algorithmic ideas of Sanders and Schulz [42]. However, we generalize many results of their work such that they are applicable on hypergraph partitioning.

Further, we implement several heuristics which might 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 quality of the solutions on average. We integrate our *flow-based local search* algorithm into the n -level hypergraph partitioner *KaHyPar* and show that *flow-based refinement* in combination with the *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 70% of 3222 benchmark instances. In comparison to the latest version of *KaHyPar*, our new approach produces solutions that are 2% better on average, while only incurring a slowdown by a factor of 2. Moreover, our partitioner has a comparable running time to the direct k -way version of *hMetis* and outperforms it on 82% 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 [30] 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

Definition 2.1. 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 $c : V \rightarrow \mathbb{R}_{\geq 0}$ and an edge weight function $\omega : E \rightarrow \mathbb{R}_{\geq 0}$. An edge $e = (u, v)$ is a relation between two nodes $u, v \in V$.

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 2.2. 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* (*SCC*) in a directed graph G with a linear time algorithm proposed by Tarjan [45]. 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 [25]. We can transform a general directed graph G into a *DAG* if we contract each *strongly connected component*. All concepts are illustrated in Figure 1.

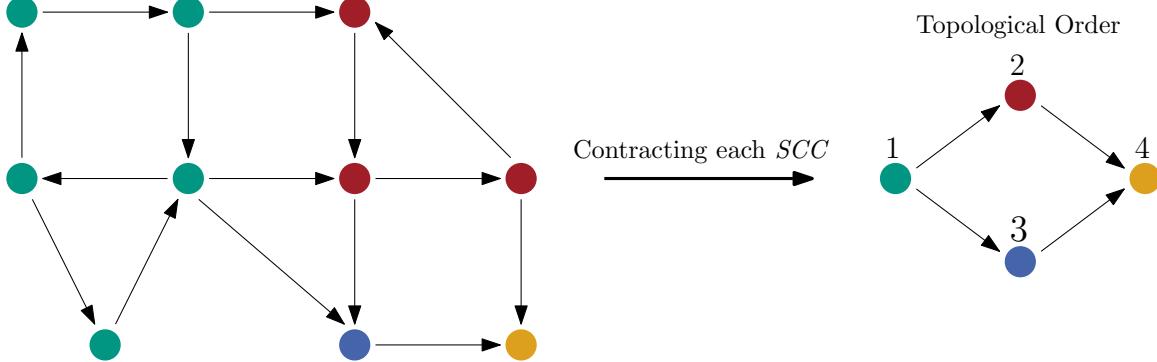


Figure 1: Example of *Strongly Connected Components* in a directed graph and a *Topological Order* of a *Directed Acyclic Graph*. Each *SCC* is marked with the same color.

Definition 2.3. Let $G_{V'} = (V', E_{V'}, c, \omega)$ be the subgraph of a graph G induced by $V' \subseteq V$ with $E_{V'} = \{(u, v) \in E \mid u, v \in V'\}$.

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 amount of flow from s to t in G . A flow is a function $f : E \rightarrow \mathbb{R}_+$, which have 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)

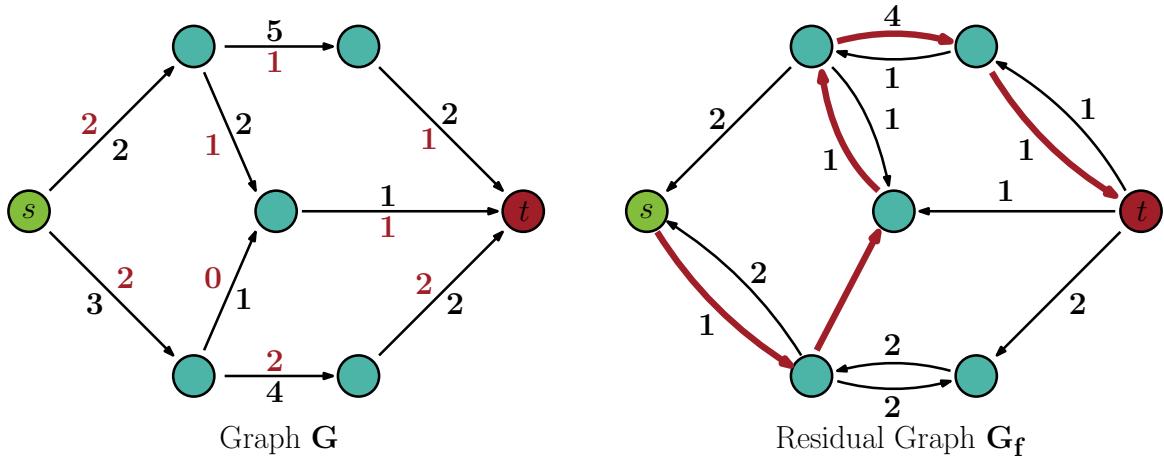


Figure 2: Illustrates concepts related to the maximum flow problem. A flow function f (red values) from s to t of a graph G is shown on the left side. The corresponding *residual graph* G_f with its *residual capacities* (black values) is illustrated on the right side. The red highlighted path is an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

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 $v \in V \setminus \{s, t\}$ is the same as 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 $|f'| > |f|$.

Further, we define the *residual graph* G_f and the *residual capacity* r_f of a flow function f on graph G . The *residual capacity* $r_f : V \times V \rightarrow \mathbb{R}_+$ 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 $v_k = t$ [15]. Figure 2 illustrates all presented concepts.

The *Max-Flow-Min-Cut-Theorem* is fundamental for many applications related to the maximum flow problem [17].

Theorem 2.1. *The value of a maximum (s, t) -flow obtainable in a graph G is equal with the 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 cut edges between the bipartition $(A, V \setminus A)$ is a minimum-weight (s, t) -cutset [18]. A can be calculated with a *BFS* in G_f starting from s .

We can solve with maximum flows many related problems like e.g., maximum bipartite-matching, number of edge- or vertex-disjoint paths in a graph or to find a minimum-weight vertex separator. Solutions for 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 $c : V \rightarrow \mathbb{R}_+$.

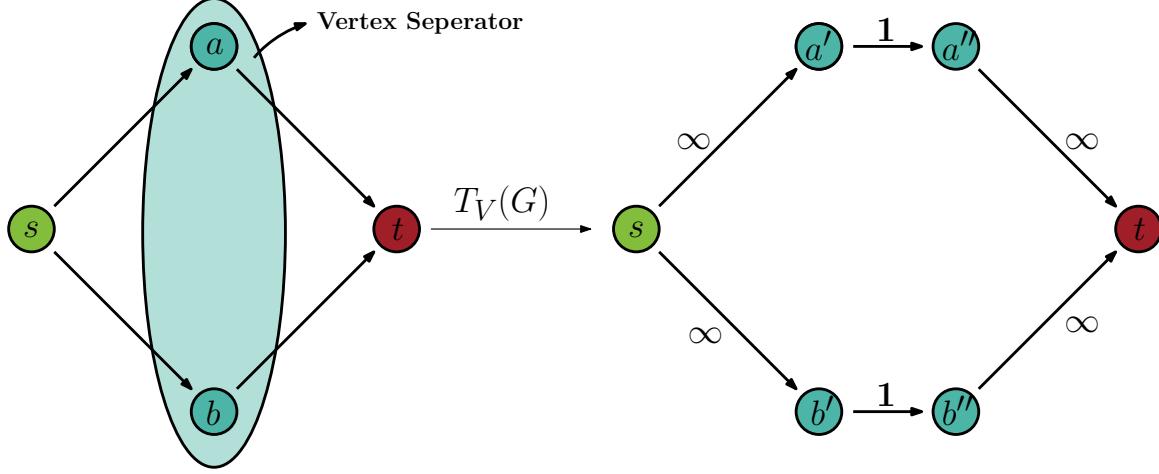


Figure 3: Illustration of the vertex separator problem and the flow network $T_V(G)$ in which we can find a minimum vertex separator.

Definition 2.4. 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 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 $S' \subseteq V$ 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 [47]:

Definition 2.5. 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) $\forall v \in V$ add a directed edge (v', v'') with capacity $u_V(v', v'') = c(v)$
- (iii) $\forall (u, v) \in E$ add two directed edges (u'', v') and (v'', u') with capacity $u_V(u'', v') = u_V(v'', u') = \infty$.

The vertex separator problem and transformation $T_V(G)$ is illustrated in Figure 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 ∞ . 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 [34].

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 2.6. An undirected weighted hypergraph $H = (V, E, c, \omega)$ is a set of hypernodes V and a set of hyperedges E with a hypernode weight function $c : V \rightarrow \mathbb{R}_{\geq 0}$ and a hyperedge weight function $\omega : E \rightarrow \mathbb{R}_{\geq 0}$. A hyperedge e is a subset of V (formally: $\forall e \in E : e \subseteq V$).

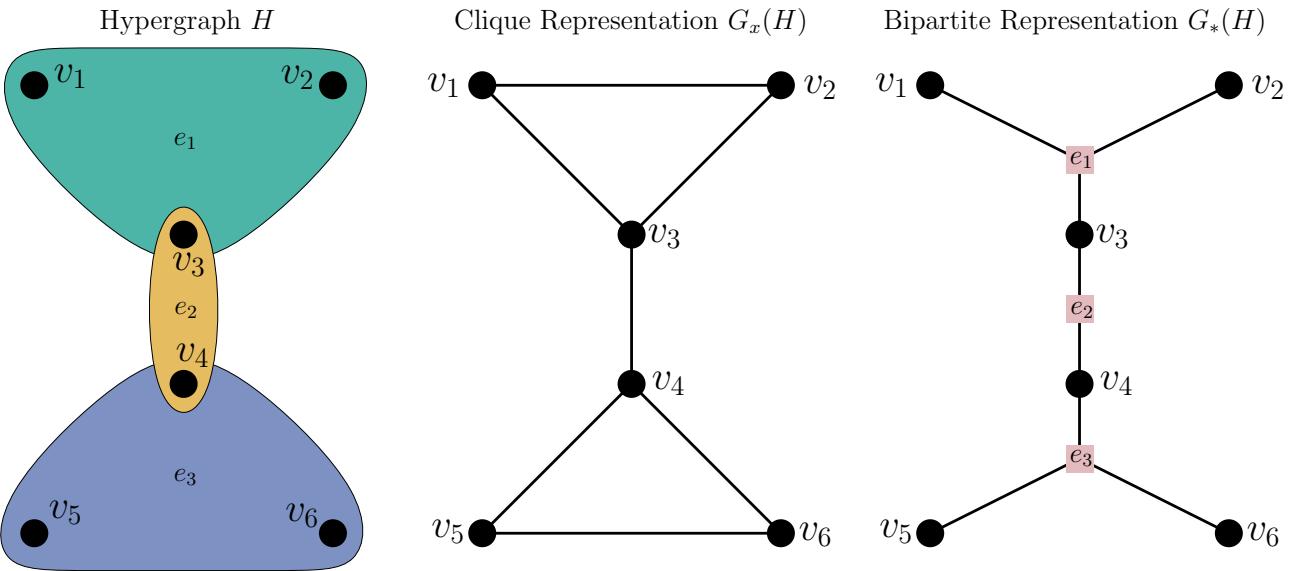


Figure 4: Example of a hypergraph H and its two corresponding graph representations.

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 2.7. Let $H_{V'} = (V', E_{V'}, c, \omega)$ be the subhypergraph of a hypergraph H induced by $V' \subseteq V$ with $E_{V'} = \{e \cap V' \mid e \in E : e \cap V' \neq \emptyset\}$.

A hypergraph $H = (V, E, c, \omega)$ can be represented as an undirected graph. There are two standard transformations, called *clique* and *bipartite* representation [24]. 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 Figure 4.

2.4. Hypergraph Partitioning

Definition 2.8. 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 $V_i \in \Lambda(e, \Pi)$ and $V_j \in \Lambda(e, \Pi)$. A k -way partition is ϵ -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 2.9. *The k -way hypergraph partitioning problem is to find an ϵ -balanced k -way partition Π 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

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

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

Definition 2.10. *We define for a k -way partition $\Pi = \{V_1, \dots, V_k\}$ of a hypergraph H the quotient graph $Q = (\Pi, E')$ which contains an edge between each pair of adjacent blocks of Π . 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 algorithms 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 G_f with $v_1 = s$ and $v_k = t$ [15]. Figure 5 illustrates such a path. Since all $(v_i, v_{i+1}) \in G_f$ it follows that $r_f(v_i, v_{i+1}) > 0$. 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 [15].

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 [17] 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 Δf and decrease the flow on each reverse edge (v_{i+1}, v_i) by Δf . If the capacities are integral, the algorithm always terminates. Since we can find an *augmenting path* in G_f with a simple *DFS* in $\mathcal{O}(|V| + |E|)$ 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 the maximum flow $|f_{max}|$ is exponential in the problem size [15].

Edmond and Karp [15] 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 $\mathcal{O}(|V||E|)$. The running time of Edmond & Karp's maximum flow algorithm is $\mathcal{O}(|V||E|^2)$. A sample execution of the algorithm is presented in Figure 5.

3.1.2. Push-Relabel Algorithm

Goldberg and Tarjan [20] implemented a maximum flow algorithm not based on finding an *augmenting path* in the *residual graph*. 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 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* [20, 44], but this implementation is not practical due to a large hidden constant factor.

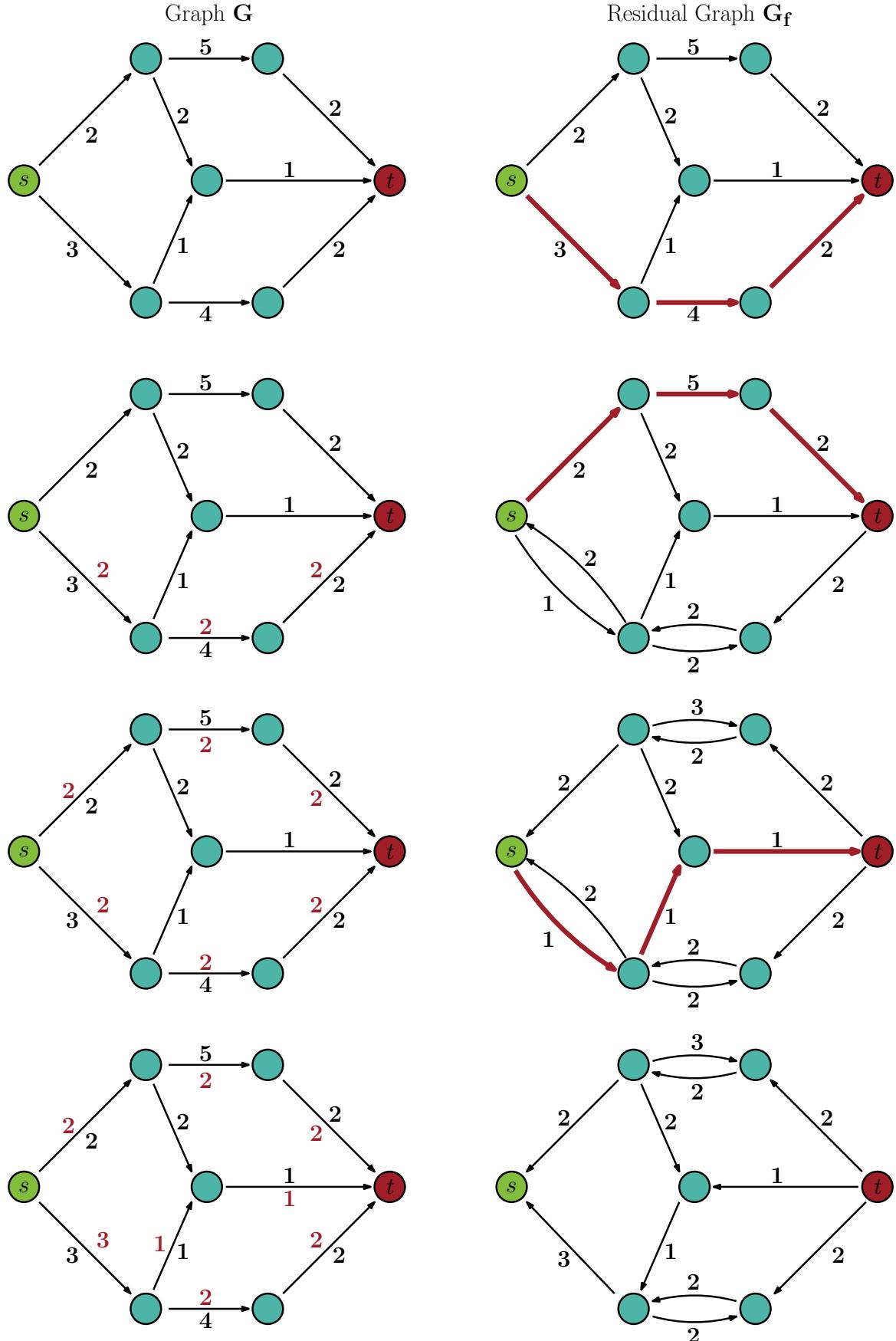


Figure 5: Execution of Edmond & Karps maximum flow algorithm [15]. The network G with its capacities c (black values) and flow f (red values) is illustrated on the left side. The residual graph G_f with its *residual capacities* r_f (black values) is presented on the right side. In each step the current *augmenting path* in G_f is highlighted by a red path.

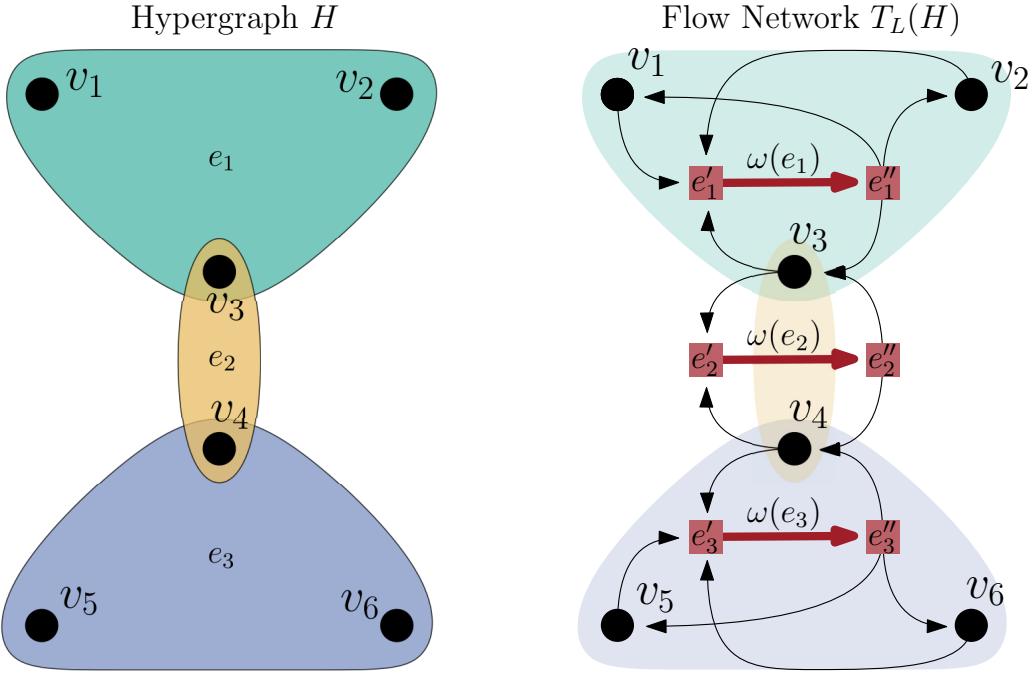


Figure 6: Transformation of a hypergraph into an equivalent flow network by Lawler [30]. Note, capacity of the black edges in the flow network is ∞ .

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 [11]. This can be done with a backward *BFS* in linear time. This technique is performed periodically, e.g., after every n relabeling.

The second heuristic is the *gap heuristic* [10, 13]. 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, we maintain a linked list of nodes with distance label i .

3.2. Modeling Flows on Hypergraphs

Consider the *bipartite graph* representation $G_*(H)$ of a hypergraph H (see Section 2.3). Hu and Moerder [24] 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 with 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 [30]:

Definition 3.1. 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 [30]. $T_L(H)$ 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) $\forall v \in V$ 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 Figure 6. $T_L(H)$ is nearly equivalent to the transformation $T_V(G)$ described in Definition 2.5 except that we do not have to split the hypernodes

$v \in V$. A hypernode cannot be in a minimum-capacity (s, t) -vertex separator because each $v \in V$ has infinity capacity [24]. 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 $|V_L| = 2|V| + |E|$ nodes and $|E_L| = 2(\bar{e} + 1)|E|$ edges, where \bar{e} is the average size of a hyperedge [40]. Using *Edmond-Karps* maximum flow algorithm (see Section 3.1.1) on flow network $T_L(H)$ takes time $\mathcal{O}(|V|^2|E|^2)$ [30].

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 are all vertices $v \in V$ *reachable* from s in the *residual graph* of $T_L(H)$ and the counterpart are all hypernodes not *reachable* from s .

In Figure 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 if you need an illustration of techniques used in the proofs of Section 4.

In this thesis, we often have to mix up nodes and edges of H and $T_L(H)$. If we use $v \in V_L$, there also exists a corresponding $v \in V$. v can be used in both contexts. For all $e \in E$ there exists two corresponding nodes $e', e'' \in V_L$. e' is called *incoming hyperedge node* and e'' is called *outgoing hyperedge node*. In some cases we need to treat $e', e'' \in V_L$ the same way as their corresponding hyperedge $e \in E \Rightarrow e'_1 \cap e''_2$ or $e''_1 \cap e'_2$ should be the same as $e_1 \cap e_2$.

3.3. Flow-based Local Search on Graphs

It seems natural to utilize maximum flow computations to improve the cut metric of a given partition of a graph. Lang and Rao [29] use an approach, called *Max-Flow Quotient-cut Improvement* (MQI), to improve the quality of a graph 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 do not restrict the output of the partition to $S' \subset S$. However, both techniques can not guarantee that the resulting bipartition is balanced and only are applicable for $k = 2$.

Schulz and Sanders [42] integrate flow-based refinement algorithm in their *multilevel graph partitioner KaFFPa*. In general, they build a flow problem a region B around the cut 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 *balanced 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, $P(v) = 1$, if $v \in V_1$ and $P(v) = 2$, otherwise. We will now explain how a given bipartition can be improved with flow computations. This technique can also be applied on a k -way partition by applying the approach on two adjacent blocks [42].

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 all cut nodes δ of G 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 $\delta \cap V_1$ and stops if $c(B_1)$ would exceed $(1 + \epsilon) \frac{c(V)}{2} - c(V_2)$. The second is initialized with all nodes $\delta \cap V_2$ and stops if $c(B_2)$ would exceed $(1 + \epsilon) \frac{c(V)}{2} - c(V_1)$. The two *BFSs* only

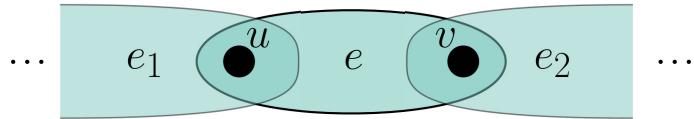
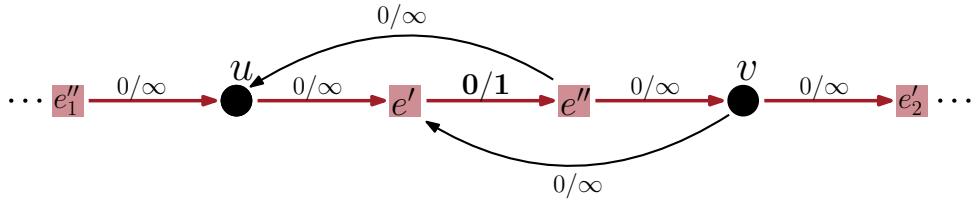
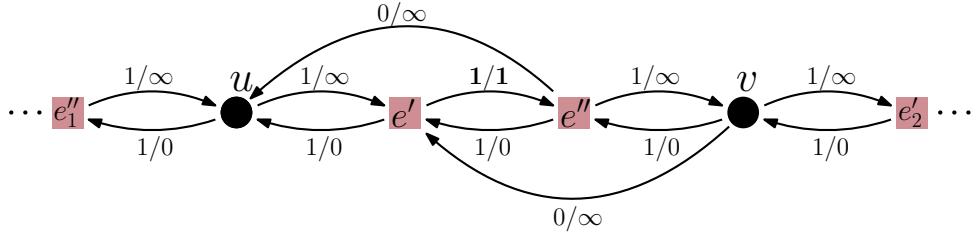
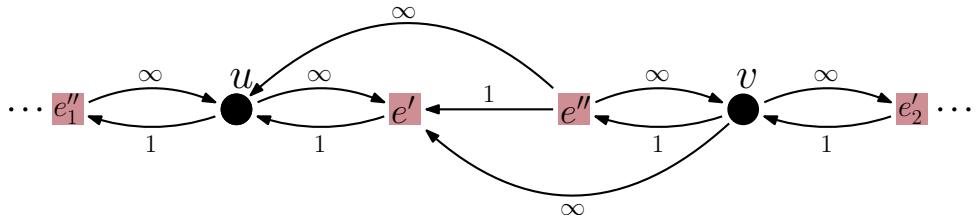
Hypergraph H Flow Network $T_L(H)$ Flow Network $T_L(H)$ after augmentingResidual Graph of $T_L(H)$ after augmenting

Figure 7: Illustration of the structure of a hyperedge e in $T_L(H)$ and the effect of augmenting along a path in this 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 denotes the residual capacity $r_f(x,y)$. The red highlighted path represents an augmenting path.

touches nodes of V_1 resp. $V_2 \Rightarrow B_1 \subseteq V_1$ and $B_2 \subseteq V_2$. The constraints for the weights of B_1 and B_2 guarantees 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 . This also yields the conclusion that 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 Figure 8.

3.3.2. Adaptive Flow Iterations

Sanders and Schulz [42] introduce several techniques to improve their basic approach. If the *Max-Flow-Min-Cut* computation on G_B leads to an improved cut, we can apply the method

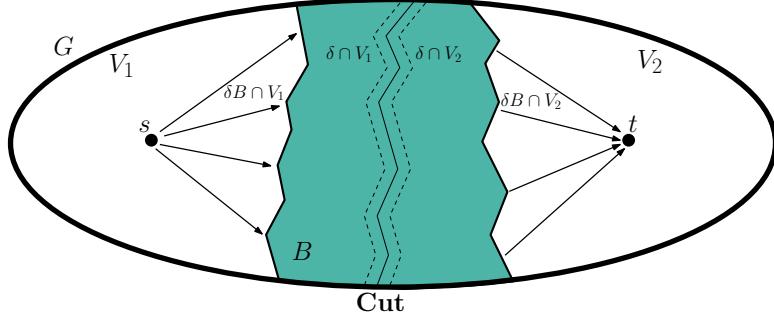


Figure 8: Configuration of a flow problem around the cut of graph G [4].

described in Section 3.3.1 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 ϵ' rather than on ϵ . If we find an improvement on G , we increase α to $\min\{2\alpha, \alpha'\}$ where α' is a predefined upper bound for α . If not, we decrease the size of α to $\max\{\frac{\alpha}{2}, 1\}$. This approach is called *adaptive flow iterations* [42].

3.3.3. Most Balanced Minimum Cut

Picard and Queyranne [39] show that all minimum (s, t) -cutsets are computable with one maximum (s, t) -flow computation. To understand the main theorem and the algorithm to compute all minimum (s, t) -cutsets we need the definition of a *closed node set* $C \subseteq V$ of a graph G .

Definition 3.2. 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 Figure 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 [45] and sweep in reverse topological order over the contracted graph to enumerate all *closed node sets*. Note, if we contract all SCCs of G the resulting graph is a *Directed Acyclic Graph* (DAC). Therefore, a topological order exists.

With the Theorem of Picard and Queyranne [39] 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 having 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 α often leads to cuts in G that violate the balanced constraint. We can enumerate all minimum (s, t) -cutsets 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*.

3.3.4. Active Block Scheduling

Active Block Scheduling is a *quotient graph style refinement* technique for k -way partitions [23, 42]. The algorithm is organized in rounds and executes a two-way local improvement

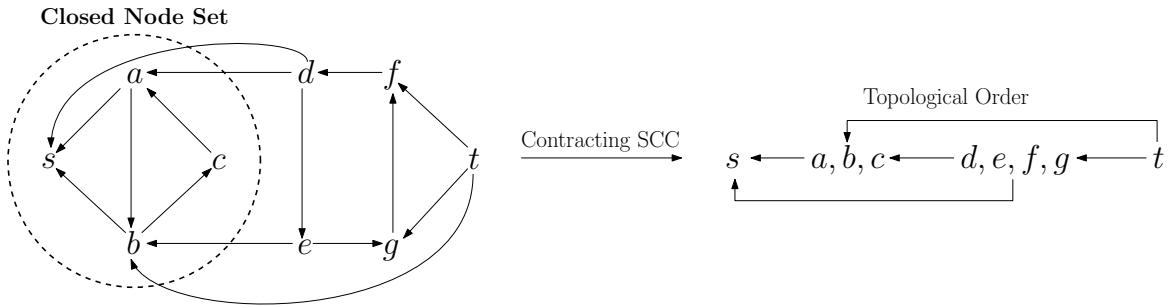


Figure 9: $C = \{s, a, b, c\}$ is a *closed node set* of graph G (left side). After contracting all *Strongly Connected Components*, we can enumerate all *closed node sets* of G by sweeping in reverse topological order over the contracted graph (right side).

algorithm on each adjacent pair of 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 [16] 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 an 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 [42].

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, 37] which we describe in Section 3.4.1. The results of this thesis is integrated into n -level hypergraph partitioner *KaHyPar*. Therefore, we give a brief overview of implementation details of this framework (see Section 3.4.2).

3.4.1. Multilevel Paradigm

The *multilevel paradigm* is a three phase algorithm to solve the *hypergraph partitioning problem* (see Figure 10). In the first stage, called *coarsening phase*, vertex matchings or clusterings are calculated which we contract. 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, we can use expensive algorithms 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 [16].

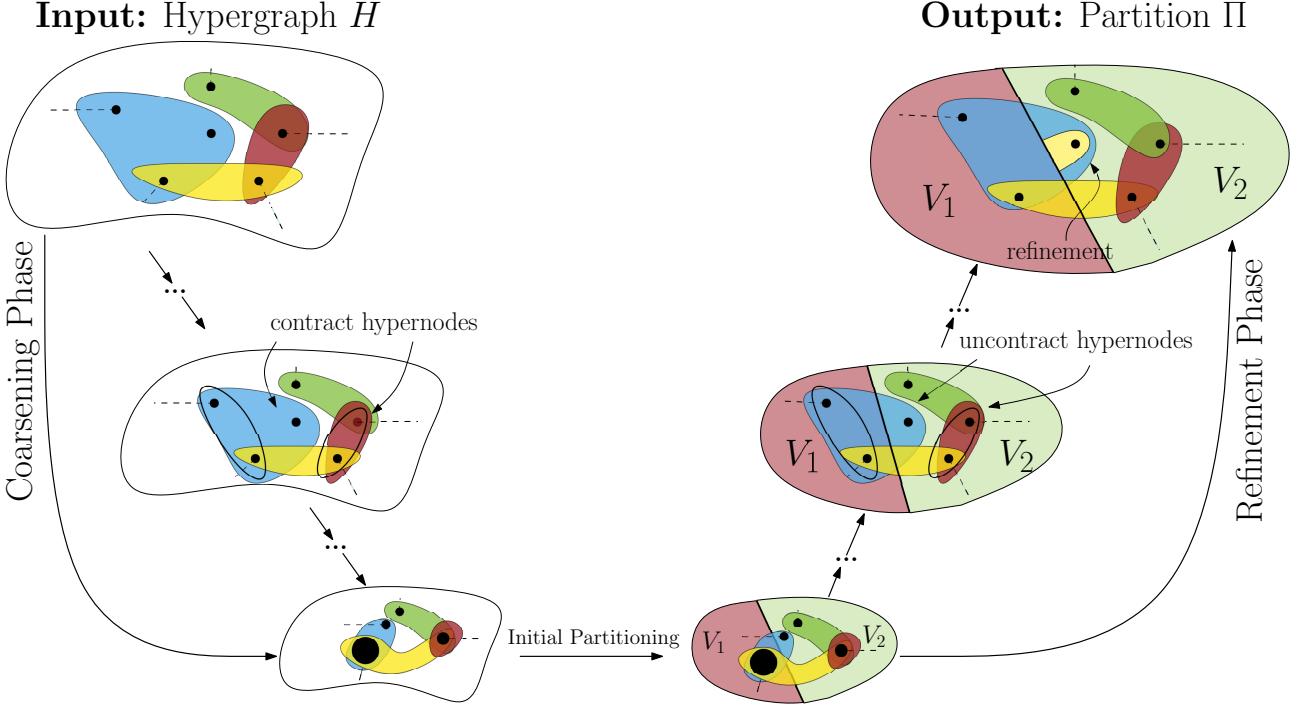


Figure 10: Multilevel Hypergraph Partitioning

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 [22]. 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 [43]. *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* [19, 22]. 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 $r(u, v) := \sum_{e \in I(u) \cap I(v)} \frac{\omega(e)}{|e|-1}$ [26]. 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 , we determine the contraction partner v according to the *heavy-edge* rating function [43]. A pass ends if each vertex is either considered as representative or contraction partner. The passes are repeated until only $t = 160k$ hypernodes remains. The *initial partitioning* uses the *recursive bisection* approach to calculate a k -way partition in combination with a portfolio of initial partitioning techniques [21]. In the *refinement phase*, a localized *FM* search is started [16], initialized with the current uncontracted vertices. The *local search* maintains k *priority queues* (PQ) for each block V_i exactly one [1]. A hypernode v contained in the i -th PQ with gain g means that moving vertex v to block V_i has gain g . After a move, the gains of all adjacent hypernodes are updated with a *delta-gain* update strategy [37]. The recalculation of all gain values at the beginning of a *FM* pass is one of the main bottlenecks of the algorithm [37]. Therefore, Schlag et al. [1, 43] 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, when an

improvement during an *FM* pass becomes unlikely. This model is called *adaptive stopping rule* [1]. Sanders and Osipov [36] shows that it is unlikely that *local search* gives an improvement if $p > \frac{\sigma^2}{4\mu^2}$, where p is the number of moves in the current *FM* pass, μ is the average gain, and σ^2 the corresponding variance.

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-weight (S, T) -cutset of H is a minimum-capacity (S, T) -cutset of $T_L(H)$ [30]. However, the resulting flow network has significantly more nodes and edges than the original hypergraph. The running time of a maximum (S, T) -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* could 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).

4.1. Removing Hypernodes via Clique-Expansion

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 induce 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, either e' or e'' . Further, for all $e \in I(v)$ the capacity $u_L(v, e')$ is ∞ . Therefore, if we push flow over a hypernode v , coming from a hyperedge, we can redirect the flow to any hyperedge node $e' \in I(v)$ during the whole maximum flow calculation because $u_L(v, e') = \infty$. The following lemma is central to our first sparsifying technique and is illustrated in Figure 11. 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 $u \in V$.

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 equal to ∞ . 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 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 ∞ , f' also satisfies the capacity constraint $\Rightarrow f'$ 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:

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

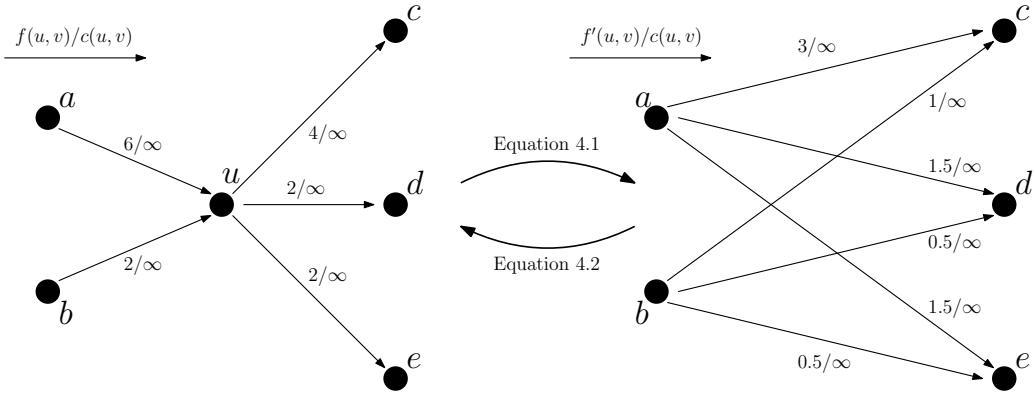


Figure 11: Illustration of Lemma 4.1 and Equation 4.1 and 4.2.

The amount of flow from each $v \in \text{in}(u)$ to each $w \in \text{out}(u)$ 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

The structure we add between all *incoming* and *outgoing* edges is called *maximum bipartite graph* or *biclique*. In $T_L(H)$ all incoming and outgoing edges of a hypernode v have capacities equal to ∞ . For all $e \in I(v)$ there is an edge from v to e' and from e'' to v . Consequently, $\text{in}(v) = \bigcup_{e \in I(v)} e''$ and $\text{out}(v) = \bigcup_{e \in I(v)} e'$. Therefore, we can remove v and add a *biclique* between $\text{in}(v)$ and $\text{out}(v)$. A removal of a hypernode induce $d(v)^2$ 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 equivalent. In Appendix B we proof that we can remove a *infinite* weight node v 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 2.5) results in a flow network where a removal of a hypernode induce $d(v)(d(v) - 1)$ instead of $d(v)^2$ edges. The technique is illustrated in Figure 23. The removed edges are exactly the edges between the same hyperedge nodes. More formally, $\forall e \in I(v)$ we can remove edge (e'', e') from the *biclique* 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 $H' = (V \setminus V', E', c, \omega)$ be the hypergraph with $E' = \{e \setminus V' \mid e \in E \wedge e \setminus V' \neq \emptyset\}$, then we add all edges of $T_L(H')$ to E_H with their corresponding capacities.

An example of the transformation is shown in Figure 12. We have to proof that a minimum-capacity (S, T) -cutset of $T_H(H, V')$ is equal with a minimum-weight (S, T) -cutset of H . However, 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 with the amount 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 [15] show that we can find a maximum

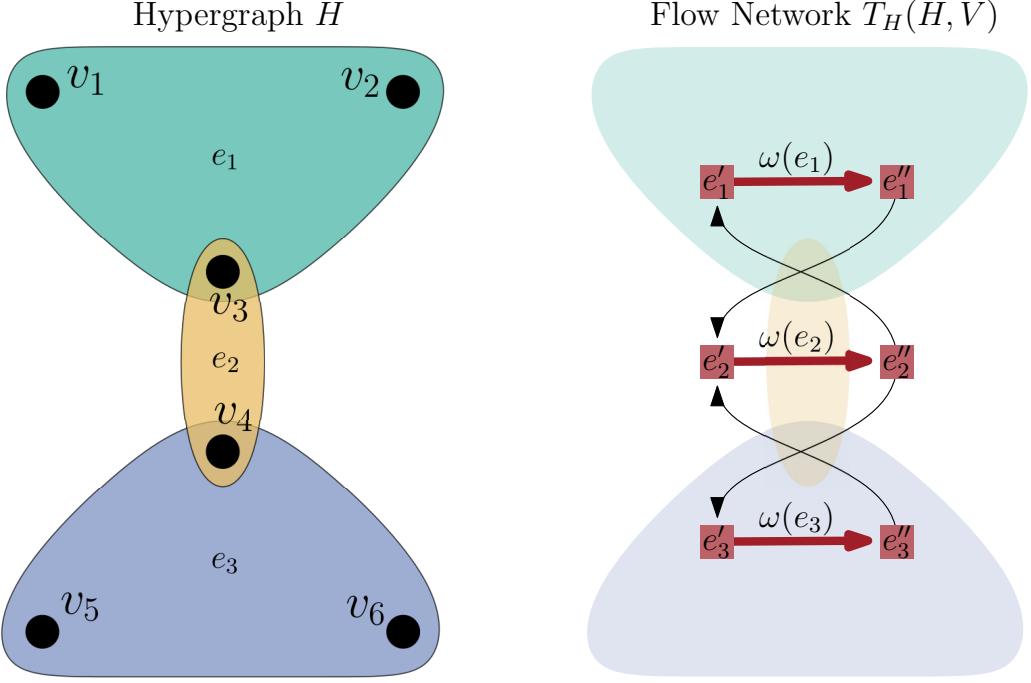


Figure 12: Transformation of a hypergraph H into an equivalent flow network $T_H(H, V)$ by removing all hypernodes of $T_L(H)$. Note, capacity of the black edges in the flow network is ∞ .

(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 and connect a with all sources $s' \in S$ and all sinks $t' \in T$ with b . $\forall s' \in S : u(a, s') = \infty$ and $\forall t' \in T : u(t', b) = \infty$. 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 ∞ .

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 with a minimum-capacity (S', T') -cutset of the flow network $T_H(H, V')$ ($V' \subseteq V$) with $S' = S \setminus V' \cup \bigcup_{e \in N(V' \cap S)} \{e'\}$ and $T' = T \setminus V' \cup \bigcup_{e \in N(V' \cap T)} \{e''\}$.

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 with 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 with 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 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 $T_L(H)$. Assume, if $v \in A$, then $\forall e \in I(v)$ the *outgoing hyperedge node* e'' is not contained in A which implies that 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 $T_H(H, V')$. Regardless of the flow network, we can calculate a maximum flow on it and define the set E'' , which contains all *outgoing hyperedge nodes* e'' reachable from a source node $s \in S$ in the *residual graph* of the flow network. Further, $(A := \bigcup_{e \in E''} e, V \setminus A)$ 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 could be much larger.

Consider a hypernode $v \in V$. We replace v in $T_L(H)$ with a biclique 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 to the network and add one additional node. 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. Removing Graph 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 $e \in E$ [17]. Hypergraphs are a generalization of graphs, where an edge can consist of more than two nodes. However, a hyperedge e of size 2 can still be interpreted as a graph edge. Instead of modeling those edges as described by Lawler [30] (see hyperedge e_2 in Figure 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 have the same structure as 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 with 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 Mengers Theorem [34], a maximum (s, t) -flow is then equal with 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 Figure 13) [34]. 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 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 Figure 13). 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 [35] 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

As a consequence of the construction of the proof of Lemma 4.4 the weighted directed graph illustrated on the right side of Figure 13 can be transformed into a single undirected edge with 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) $V_G = V \cup \bigcup_{e \in E : |e| \neq 2} \{e', e''\}$
- (ii) $\forall e \in E$ with $|e| = 2$ and $v_1, v_2 \in e$ ($v_1 \neq v_2$) we add two directed edges (v_1, v_2) and (v_2, v_1) to E_G with capacity $u_G(v_1, v_2) = \omega(e)$ 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 Figure 14. A hyperedge e of size 2 consists exactly of 4 nodes and 5 edges in $T_L(H)$ (see Figure 6). The same hyperedge induces 2 nodes and 2 edges in $T_G(H)$ (see Figure 15).

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 with a minimum-capacity (S, T) -cutset of the flow network $T_G(H) = (V_G, E_G, u_G)$.*

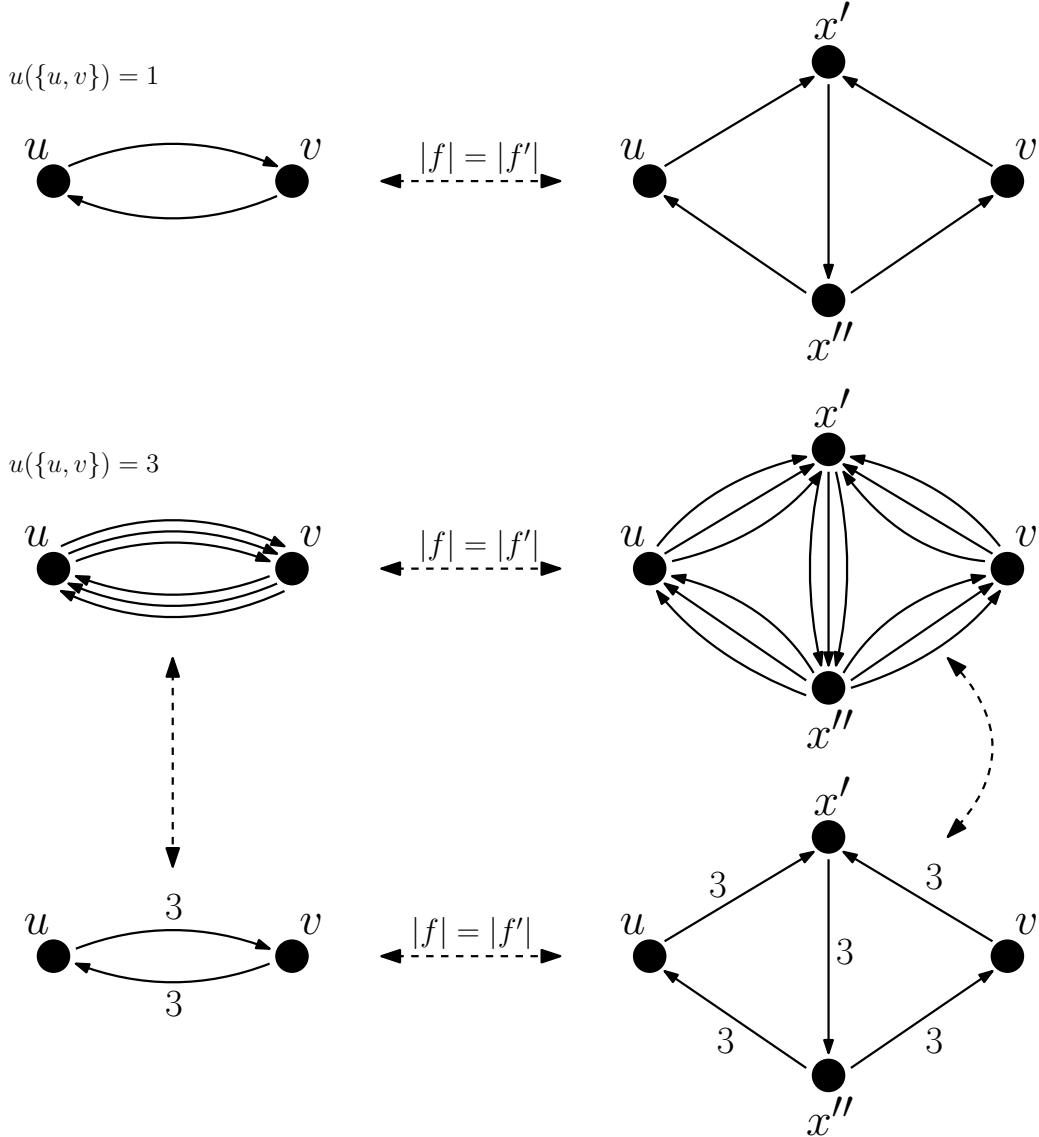


Figure 13: Illustration of the transformation of an unweighted or weighted undirected graph into an unweighted or weighted directed graph. The equivalence of a maximum (s, t) -flow of a unweighted multigraph and their corresponding weighted graph is a result of a work by Newman [35].

Proof. Consider a hyperedge e with $|e| = 2$ and $u, v \in e$ ($u \neq v$). The capacity of (u, e') , (v, e') , (e'', u) and (e'', v) is infinity 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 with 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 with a minimum-weight (S, T) -cutset of H .

□

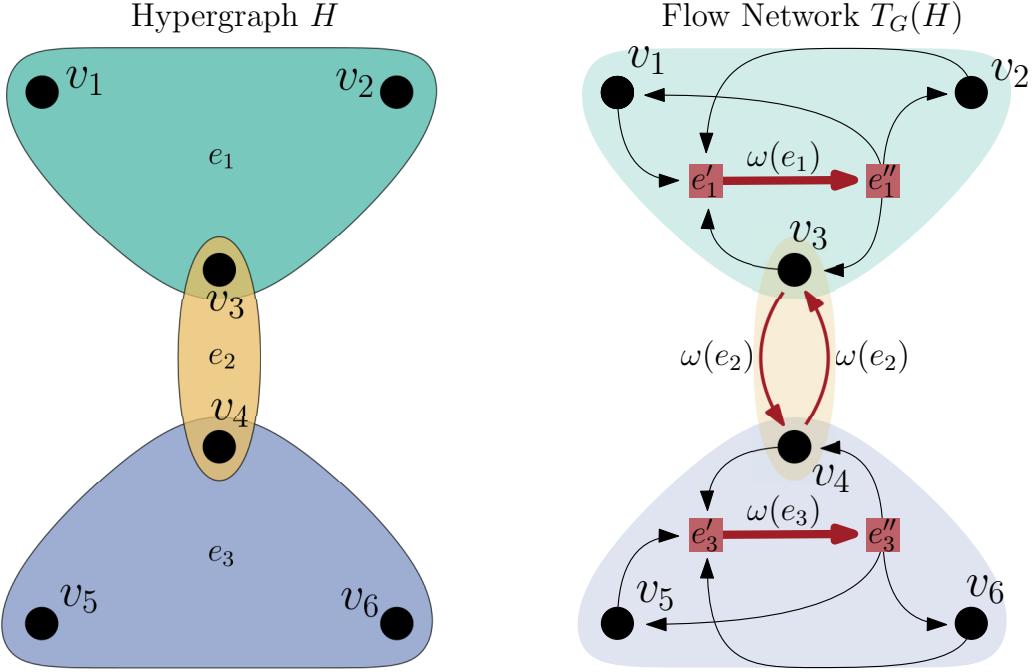


Figure 14: Transformation of a hypergraph into an equivalent flow network by inserting an undirected edge with capacity $\omega(e)$ for each hyperedge of size 2. Note, capacity of the black edges in the flow network is ∞ .

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 their corresponding hyperedge. Since there exists a one-one correspondence between the hypernodes of $T_L(H)$ and $T_G(H)$ the corresponding bipartition are all hypernodes *reachable* from all nodes in S and all 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:

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

where $\overline{d(v)}$ is the average hypernode degree, $\overline{|e|}$ is the average hyperedge size and $|P|$ are the number of pins. Many real world benchmark instances have either a low or high density. For an example, consider the statistical summary of our benchmark set in Table 7. Hypergraphs with a large density have usually a average hypernode degree significantly greater than the average hyperedge size. Whereas, the opposite behavior can be observed on instances with a low density. High density hypergraphs often have a structure similiar to a graph and low density hypergraphs often have large hyperedges with low degree hypernodes. Of course, there exists instances which are counterexamples to this observation, but for a large majority of real world benchmarks we often find the described behavior.

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 $T_G(H)$ performs significantly better 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 which performs best on most instances.

Definition 4.3. Let T_{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) $V_{\text{Hybrid}} = V \setminus V' \bigcup_{\substack{e \in E \\ |e| \neq 2}} \{e', e''\}$
- (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 $v_1, v_2 \in e$ 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 $T_L(H)$).

Figure 15 summarizes all explained transformations of this section. We can prove the correctness of $T_{\text{Hybrid}}(H, V')$ with Lemma 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 with 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).

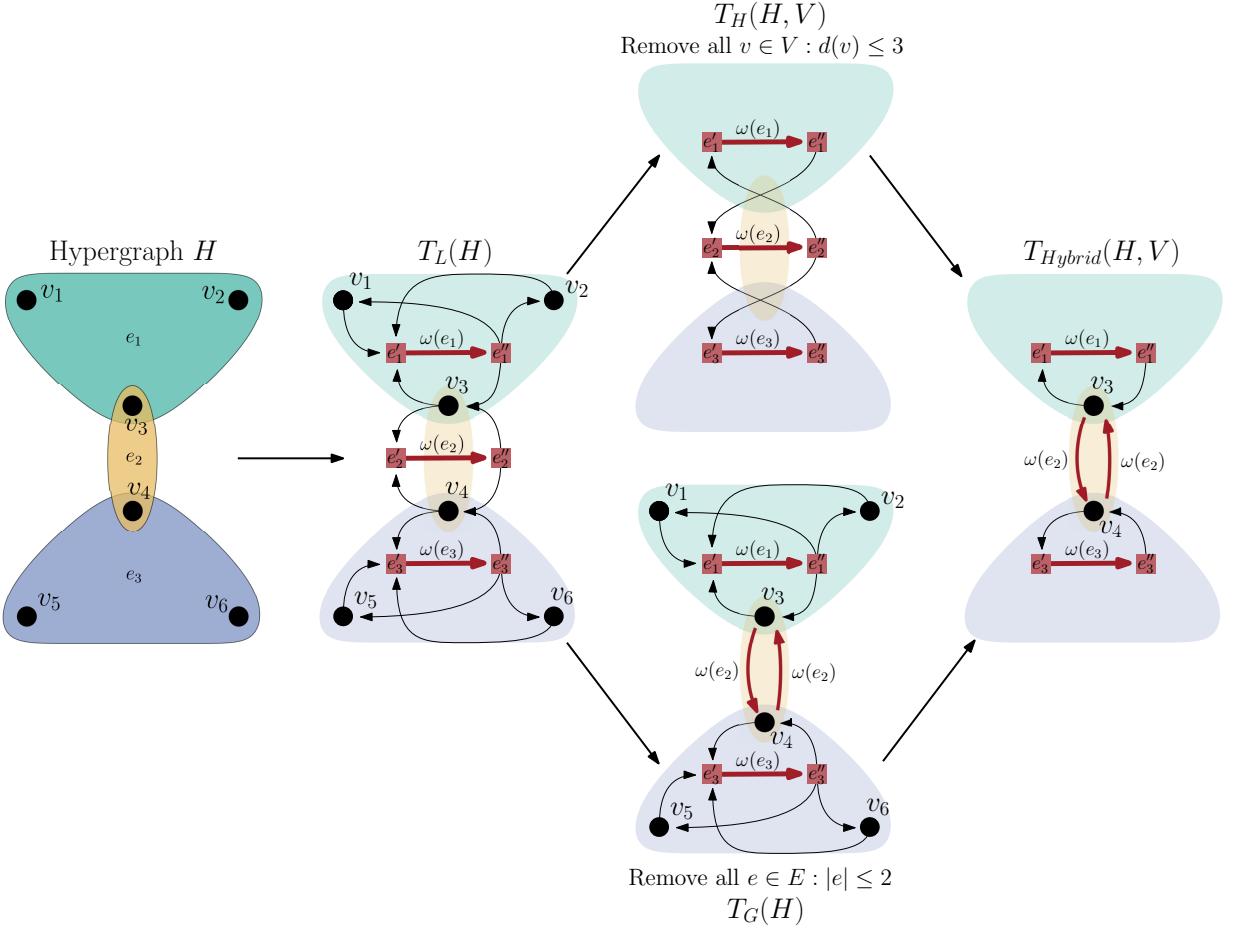


Figure 15: Illustration of all presented techniques to sparsify the flow network of a hypergraph. Transformation from $T_L(H)$ to $T_H(H, V)$ follows with Lemma 4.1. Transformation from $T_L(H)$ to $T_G(H)$ follows with Lemma 4.4.

5. Max-Flow-Min-Cut Refinement Framework

We will now give a detailed overview of our *flow-based refinement framework*. The main idea is to extract a subhypergraph $H_{V'}$ from an already partitioned hypergraph H . V' is chosen in such way that it is a subset of two adjacent blocks V_i and V_j . Afterwards, we transform the subhypergraph $H_{V'}$ into one of the flow networks proposed in Section 4. We will show how to configure the sources S and sinks T of the corresponding flow network such that a minimum (S, T) -bipartition of $H_{V'}$ can be used to improve the connectivity metric of H (see Section 5.1). Further, we describe how the ideas of Sanders and Schulz [42] presented in Section 3.3 can be adapted to work in the n -level hypergraph partitioner *KaHyPar*.

5.1. Source and Sink Configuration

Let $H = (V, E, c, \omega)$ be a hypergraph and Π_1 be a bipartition of H . 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 a bipartition Π_1 of H with a maximum (S, T) -flow calculation on $T_L(H_{V'})$ (with f as maximum flow) such that after applying the minimum (S, T) -bipartition of $H_{V'}$ on H the resulting bipartition Π_2 of H has a cut less than or equal to the cut of Π_1 . However, an important concept of this Section will be the definition of the *extension* of a subhypergraph (see Figure 16).

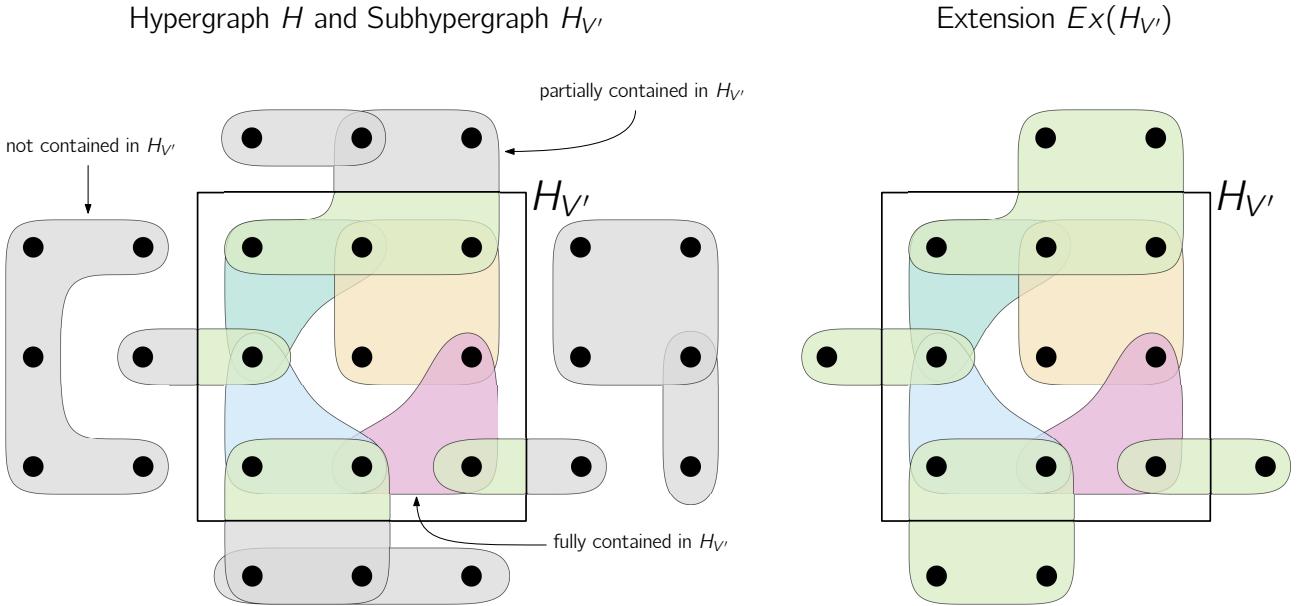


Figure 16: Illustration of an *extension* of a subhypergraph. Each hyperedge of the hypergraph H which is fully or partially contained in $H_{V'}$ is fully contained in $Ex(H_{V'})$. The nodes not contained in the rectangle of the right figure are part of V'' .

Definition 5.1 (Extension of a Subhypergraph). *We define the extension $Ex(H_{V'})$ of a subhypergraph $H_{V'}$ such that each hyperedge of $H = (V, E, c, \omega)$ which is partially contained in $H_{V'}$ is fully contained in $Ex(H_{V'})$. More formally, $Ex(H_{V'}) = (V' \cup V'', E', c, \omega)$ with $V'' = \bigcup_{e \in E, e \setminus V' \neq \emptyset} e \setminus V'$ and $E' = \{e \in E \mid e \subseteq (V' \cup V'')\}$.*

In the following, we will first define our source and sink set on flow network $T_L(Ex(H_{V'}))$ such that each hypernode $v \in V''$ is either a source or sink node. We can show, that a maximum (S, T) -flow on $T_L(Ex(H_{V'}))$ then improves a given bipartition Π_1 of H . Afterwards, we will remove all hypernodes $v \in V''$ of $T_L(Ex(H_{V'}))$ with Theorem 4.1 which will result in a source set S' and sink set T' for $T_L(H_{V'})$. Moreover, the value of a maximum (S, T) -flow of $T_L(Ex(H_{V'}))$ and a maximum (S', T') -flow of $T_L(H_{V'})$ will be the same.

We introduce the extension of subhypergraph $H_{V'}$ because we have to redefine the definition of the cut of $H_{V'}$ related to a bipartition Π of H as follows:

$$\omega_{H_{V'}}(\Pi) := \omega_{Ex(H_{V'})}(\Pi) \quad (5.1)$$

Note, that the cut $\omega_{H_{V'}}$ is defined over the cut nets of H (which are equal to the cut nets of $Ex(H_{V'})$). A cut hyperedge e of H is not necessarily a cut hyperedge of $H_{V'}$. For example, if $e = \{v_1, v_2\}$ is a hyperedge with $v_1 \in V_1$ and $v_2 \in V_2$ and $v_1 \in V'$ and $v_2 \notin V'$, then e is cut in H , but not in $H_{V'}$, because v_2 is not contained in $H_{V'}$. The reason that we still define e as cut hyperedge of $H_{V'}$ has to do with our problem statement, which we will define as follows:

Problem 5.1. *Given a subhypergraph $H_{V'}$ ($V' \subseteq V$) and bipartition Π_1 of hypergraph H . How should S and T be defined such that after a maximum (S, T) -flow calculation (with f as maximum flow) the resulting minimum (S, T) -bipartition Π_2 of H satisfy the following conditions:*

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

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 $\omega_H(\Pi_2) = w_H(\Pi_1) - \Delta_{H_{V'}}$, 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 $\omega_{H_{V'}}(\Pi_1)$.

Note, that the equality

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

holds only if we define the cut of subhypergraph $H_{V'}$ over the cut hyperedges of H (see Equation 5.1). For example, if a *Max-Flow-Min-Cut* computation on $H_{V'}$ removes a hyperedge e from the cut of $H_{V'}$, but e is still cut on H , then the equality did not hold if we define the cut of $H_{V'}$ over the cut hyperedges of $H_{V'}$. Because $\Delta_{H_{V'}}$ is then equal to 1 and Δ_H is equal to 0. Further, if we can show that $|f| = \omega_{H_{V'}}(\Pi_2)$, we simultaneously show that our source and sink set modeling approach satisfies condition (ii) $\Delta_H = \Delta_{H_{V'}}$.

We will first define S and T for flow network $T_L(Ex(H_{V'}))$, because for each maximum (S, T) -flow f of $T_L(Ex(H_{V'}))$ and its corresponding minimum (S, T) -bipartition Π_2 the equality $|f| = \omega_{Ex(H_{V'})}(\Pi_2) = \omega_{H_{V'}}(\Pi_2)$ holds per Equation 5.1 and due to the *max-flow-min-cut* theorem [17]. 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 $T_L(Ex(H_{V'}))$, because such hypernodes cannot move if we solve a flow problem on subhypergraph $H_{V'}$. Therefore, we define all hypernodes $V'' \cap V_1$ as sources and all hypernodes $V'' \cap V_2$ as sinks (V'' is defined in Definition 5.1). More formally:

$$S = V'' \cap V_1 \tag{5.2}$$

$$T = V'' \cap V_2 \tag{5.3}$$

The pins of a hyperedge which is partially contained in the extension of the subhypergraph are not able to change its block after a *Max-Flow-Min-Cut* computation, because we define them either as source or sink. Consequently, no hyperedge partially contained in $Ex(H_{V'})$ can change its state from non-cut to cut and therefore it follows with the *max-flow-min-cut* theorem [17] that the inequality $\omega_H(\Pi_2) \leq \omega_H(\Pi_1)$ holds. Since, only nets fully contained in $Ex(H_{V'})$ can change its state and $|f| = \omega_{Ex(H_{V'})}(\Pi_2) = \omega_{H_{V'}}(\Pi_2)$, it holds that $\Delta_H = \Delta_{H_{V'}}$.

We will now define the source and sink set of $T_L(H_{V'})$, which will be a consequence of the proof of Theorem 5.1.

$$S' = \{e' \mid e \in I(S)\} \tag{5.4}$$

$$T' = \{e'' \mid e \in I(T)\} \tag{5.5}$$

For a source node $s \in S$ resp. sink node $t \in T$ of $T_L(Ex(H_{V'}))$ we define the corresponding *incoming* resp. *outgoing* hyperedge nodes of all incident hyperedges $e \in I(s)$ resp. $e \in I(t)$ as source resp. sink nodes of $T_L(H_{V'})$.

Theorem 5.1. *The value of a maximum (S, T) -flow of $T_L(Ex(H_{V'}))$ is equal with a maximum (S', T') -flow of $T_L(H_{V'})$.*

Proof. The value of a maximum (S, T) -flow of $T_L(Ex(H_{V'}))$ is equal with a maximum (S', T') -flow of $T_H(Ex(H_{V'}), V'')$ according to Theorem 4.1. Since each $v \in V''$ is either a source or sink node of $T_L(Ex(H_{V'}))$, the removal of v does not induce any additional edges in $T_H(Ex(H_{V'}), V'')$ (see Lemma 4.2). Therefore, $T_H(Ex(H_{V'}), V'') = T_L(H_{V'})$. \square

We are now able to extract a subhypergraph $H_{V'}$ out of an already bipartitioned hypergraph H and calculate a minimum (S, T) -bipartition of $H_{V'}$ with S and T as defined in Equation 5.2

and 5.3. The resulting bipartition induce a new cut on H smaller or equal than the old cut. Further, we show with our modeling technique of S and T that Δ_H can be calculated with the help of the amount of a maximum (S, T) -flow computation on $T_L(H_{V'})$.

In Section 4.3 we described how to remove hyperedges of size $|e| = 2$ by adding an undirected

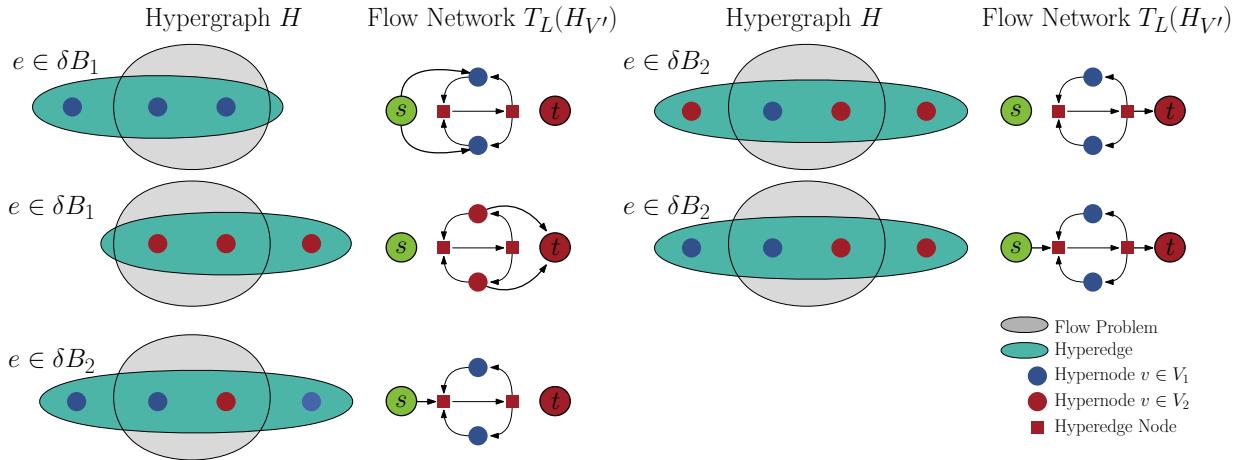


Figure 17: Illustration of modeling sources and sinks defined in Equation 5.2 and 5.3.

flow edge between the corresponding vertices $u, v \in e$. However, if the incoming or outgoing hyperedge node is a source or a sink node, we can not directly remove the hyperedge nodes. There are two special cases which are illustrated in Figure 18. This situation occurs if one of the two vertices is part of the flow problem and one not. In case, if the incoming hyperedge node e' is a source node, we only remove the outgoing hyperedge node e'' and add a directed flow edge from e' to v with capacity $\omega(e)$. In the second case, if the outgoing hyperedge node e'' is a sink node, we only remove the incoming hyperedge node e' and add a directed flow edge from v to e'' with capacity $\omega(e)$.

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 a k -way partition $\Pi = (V_1, \dots, V_k)$ if the objective is the connectivity metric. 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 .

5.2. Most Balanced Minimum Cuts on Hypergraphs

Picard and Queyranne [39] 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 . The corresponding algorithm is presented in Section 3.3.3.

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-capacities (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. Note, we can use Lemma 4.3 to find all minimum (s, t) -cutsets with one maximum (s, t) -flow calculation. However, the algorithm would become a lot more complicated. Since the algorithm has a linear running time, we decided to use simple trick.

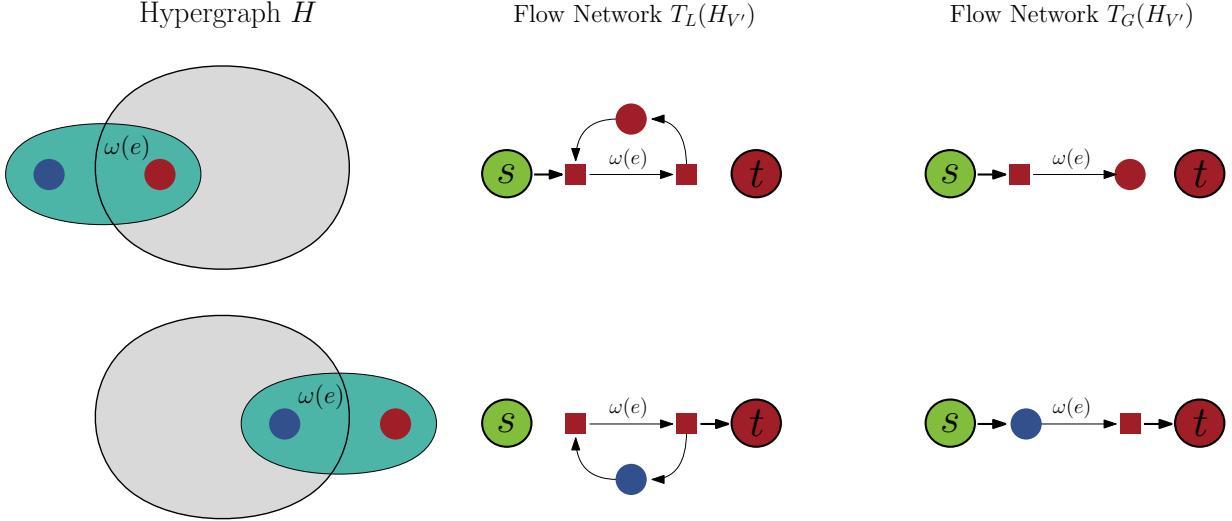


Figure 18: Illustration of modeling hyperedges of size two if the incoming or outgoing hyperedge node is a source or a sink node of the flow problem.

After a maximum (s, t) -flow calculation (with f as maximum flow) on one of the two mentioned networks we insert all removed hypernodes with their corresponding edges again into the residual graph of our flow network. If we remove a hypernode, we insert a biclique between all *incoming* and *outgoing* edges with *infinite* capacity. Since $|f| < \infty$, there cannot be any inserted edge which is the minimum-capacity (s, t) -cutset regarding to maximum (s, t) -flow f . Otherwise, an edge of the biclique would be in the minimum-capacity (s, t) -cutset, too and this would imply that $|f| = \infty$. Further, the maximum (s, t) -flow f is still maximal. If we find an *augmenting* path in the network with the inserted hypernodes, we can map the path to an *augmenting* path in the network without them by simply using the shortcut edges instead of the inserted edges. Note, that the mapping is valid because all edges involve in the transformation have *infinite* capacity. This is a contradiction that f is a maximum (s, t) -flow.

5.3. A direct k -way Flow-Based Refinement Framework

We have described 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 (see Section 3.2). Additionally, we present techniques to sparsify the flow network $T_L(H)$ [30] to reduce the complexity of the flow problem (see Section 4). Further, we show how to configure the source and sink sets of the flow network of a subhypergraph $H_{V'}$ (with $V' \subseteq V$) such that a *Max-Flow-Min-Cut* computation improves a given bipartition of H (see Section 5.1). Finally, we can enumerate all minimum-weight (S, T) -cutsets of a subhypergraph $H_{V'}$ with one maximum (S, T) -flow calculation [39].

We will now present our direct k -way *flow-based* refinement framework which we integrate into the n -level hypergraph partitioner *KaHyPar* [22] (see Section 3.4.2). Our framework optimizes the *connectivity* metric. We use a similiar architecture as proposed by Sanders and Schulz [42] (see Section 3.3). The basic concepts of the framework are illustrated in Figure 19.

We perform a *flow-based local search* on two adjacent blocks of the partition Π . We embed our *Max-Flow-Min-Cut* computations into an *active block scheduling* refinement strategy [23] (see Section 3.3.4). The algorithm starts by constructing the quotient graph Q of Π (see definition 2.10). 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 . We use two *BFSs*, one only touches hypernodes of V_i and the second only touches hypernodes of V_j . The

BFS is initialized with all hypernodes contained in a cut hyperedge of the bipartition (V_i, V_j) . We embed the pairwise *flow-based refinement* into an *adaptive flow iterations* strategy [42] (see Section 3.3.2) which also determines the size of the flow problem.

After we define the subhypergraph $H_{V'}$, which we use to improve the bipartition (V_i, V_j) , we construct one of the flow networks proposed in Section 4 with sources S and sinks T defined in Section 5.1. We implement two maximum flow algorithms. One is a slightly modified *augmenting path* algorithm of Edmond & Karp [15] (see Section 3.1.1) and the second is the *Push-Relabel* algorithm of Goldberg & Tarjan [11, 20] (see Section 3.1.2). 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 as possible edge-disjoint paths 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 [11]. After we determine a maximum (S, T) -flow on our flow network, we iterate over all minimum (S, T) -bipartitions of $H_{V'}$ [39] and choose the *Most Balanced Minimum Cut* (see Section 3.3.3 and 5.2) according to our *balanced constraint*.

KaHyPar is an n -level hypergraph partitioner ($|V| = n$) taking the multilevel paradigm to its extreme by removing only a single vertex in each level of the hierarchy [1] (see Section 3.4.2). During the refinement step n local searches are instantiated. Therefore, using our *flow-based refinement* as local search algorithm on each level is not applicable, because the performance slowdown would be tremendous. Therefore, we introduce *Flow Execution Policies*. One is to execute our *flow-based refinement* on each level i where $i = \beta \cdot j$ with $j \in \mathbb{N}_+$ and β as a predefined tunning 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 an *FM* algorithm [1, 16, 41] (see Section 3.3.4).

An observation during the implementation of this framework was that only a minority of the pairwise refinements based on flows yields an improvement on hypergraph H . Thus, we introduce several rules which might prevent *unpromising* flow executions to improve the effectiveness ratio by simultaneously speeding up the running time.

- (R1) If a *flow-based refinement* did not lead to an improvement on two blocks in all previous runs, we use the *Max-Flow-Min-Cut* computations only in the first iteration of *active block scheduling*.
- (R2) If the cut between two adjacent blocks in the quotient graph is small (e.g. ≤ 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.

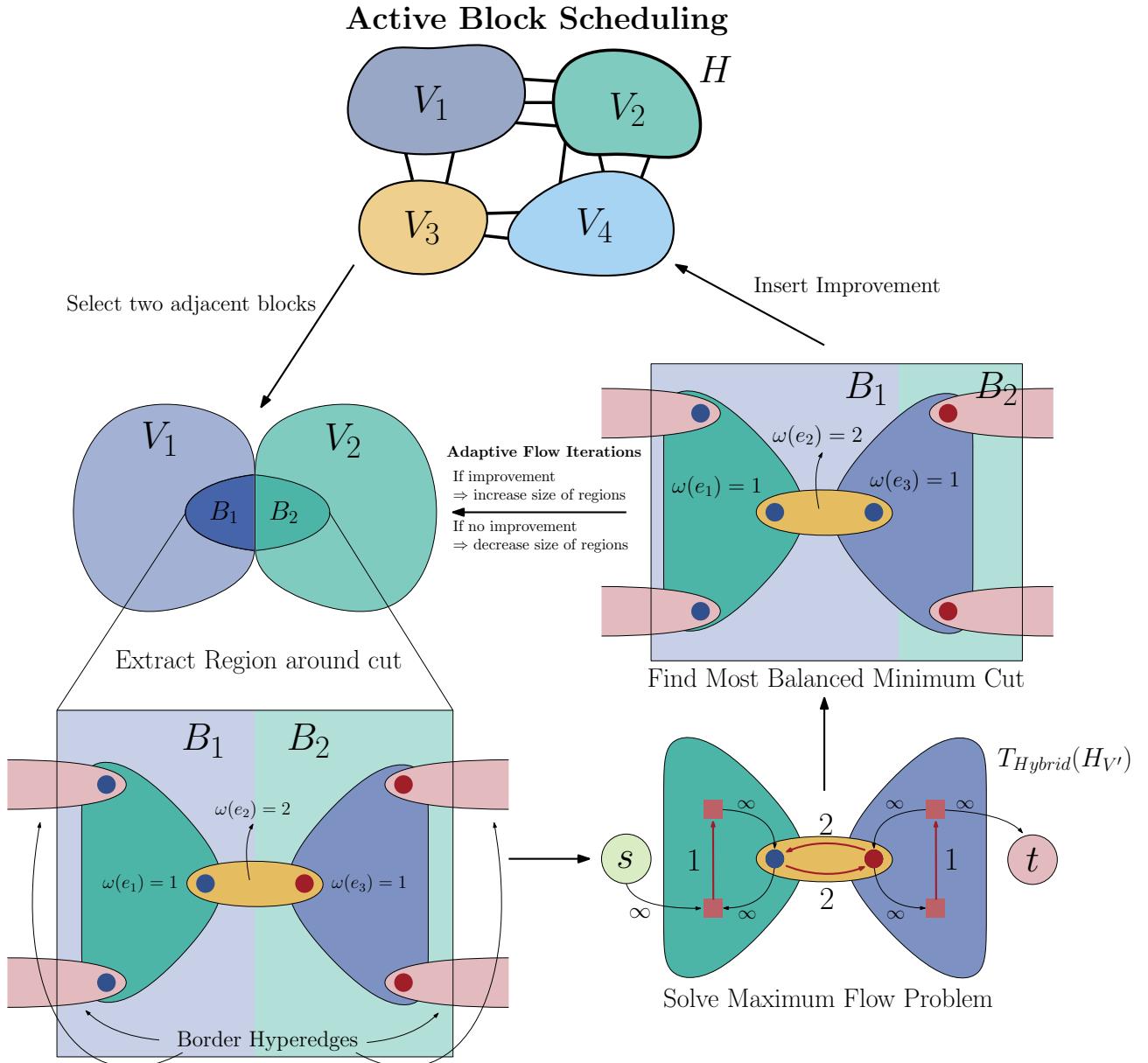


Figure 19: Illustration of our *flow-based* refinement framework for direct k -way hypergraph partitioning.

6. Experimental Results

In this Section, we evaluate the performance of our flow-based refinement framework proposed in Section 4 and 5. First, we show the effect of the techniques to sparsify the Lawler-Network [30] on the performance of our maximum flow algorithms. Afterwards, we analyze how the maximum flow problem size influence the solution quality of different configurations of our framework. Finally, we compare the new version of *KaHyPar* with *Max-Flow-Min-Cut* computations against other state-of-the-art hypergraph partitioners on our full benchmark set.

6.1. Instances

Our full benchmark set consists of 488 hypergraphs. We choose our benchmarks from three different research 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) [46]. Further, we interpret the Sparse Matrix instances of the *Florida Sparse Matrix collection* (SPM) [12] as hypergraphs using the row-net model [9]. 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 interpretation of a SAT formula as hypergraph is to interpret the literals as vertices and each clause as a net (LITERAL) [37]. Mann and Papp [33] suggested two other hypergraph representation of SAT formulas, 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 induced nets containing all clauses where the corresponding variable occurs. A statistical summary of the different instance types is presented in Table 7.

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

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 8×256 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)o mmunity-(A)ware* coarsening as *KaHyPar-CA*.

We compare *KaHyPar-MF* against the state-of-the-art hypergraph partitioner *hMetis* [26, 27] and *PaToH* [9]. *hMetis* provides a direct k -way (*hMetis-K*) and recursive bisection (*hMetis-R*) implementation. Further, we also use the default configuration (*PaToH-D*) and quality preset (*PaToH-Q*) of *PaToH*. We configure *hMetis* to optimize the *sum-of-external-degree-metric* (SOED) and calculate $(\lambda - 1)(\Pi) = \text{SOED}(\Pi) - \text{cut}(\Pi)$. This is also suggested by the authors of *hMetis* [27]. Further, 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 ϵ -balanced partition after $\log_2(k)$

bisections we have to adapt ϵ 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 our hypergraph partitioner, we first summarize the results by calculating the average (or minimum) of a specific metric for the different *seeds* of a hypergraph instance 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 more detailed we use performance plots introduced in [43] (see Figure 22). In the following, we will call a hypergraph partitioned into k blocks an *instance*. For each partitioner resp. algorithm we determine the instance with the minimum cut (of the 10 different *seeds*). Each color in the plot corresponds to one algorithm. The x -axis represents an instance and the y -axis represents the quality produced by an algorithm for an instance relative to best partition of an algorithm produced for the instance. 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 $1 - \frac{105}{100} = 0.05$ and for partitioner P_1 is $1 - \frac{100}{100} = 0$ which means that the partition of partitioner P_2 for instance X is 5% 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 insert the points in 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 techniques to sparsify the state-of-the-art hypergraph flow network representation (see Section 4) on the performance of our maximum flow algorithms GOLDBERG-TARJAN and EDMOND-KARP. We refer to our different flow networks as T_L (see Section 3.2), T_H (see Section 4.2), T_G (see Section 4.3) and T_{Hybrid} (see Section 4.4).

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 6) for $k = 2$ and five different seeds. After an instance is bipartitioned, we generate flow problem instances with the above-mentioned sizes and execute each possible combination of flow algorithm and flow network on it.

The benchmark instances can be split into 6 different benchmark types. The properties of the instances regarding the average hypernode degree and average hyperedge size is shown in Table 6. Remember, T_G should perform best on instances with a small average hyperedge size and T_H should perform best on instances with a low average hypernode degree. Based on Table 6, T_G should significantly reduce the number of nodes and edges on PRIMAL and LITERAL instances and T_H on DUAL instances in comparison to our baseline T_L . Also both should sparsify the resulting flow network of ISPD98 and DAC instances. Further, we expect that T_{Hybrid} combines the advantages of both networks and performs best on all benchmark types.

Figure 20 shows the the number of nodes and edges of the resulting flow networks for flow

problems with 25000 hypernodes. T_{Hybrid} reduces the number of nodes of nearly each benchmark type by at least a factor of 2, except on SPM instances. Moreover, instances with a large average hypernode degree, like PRIMAL or LITERAL, yields large flow problem instances and instances with a small average hypernode degree yields small flow problem instances (see DUAL instances).

In Figure 21 we compare the performance of our maximum flow algorithms on the differ-

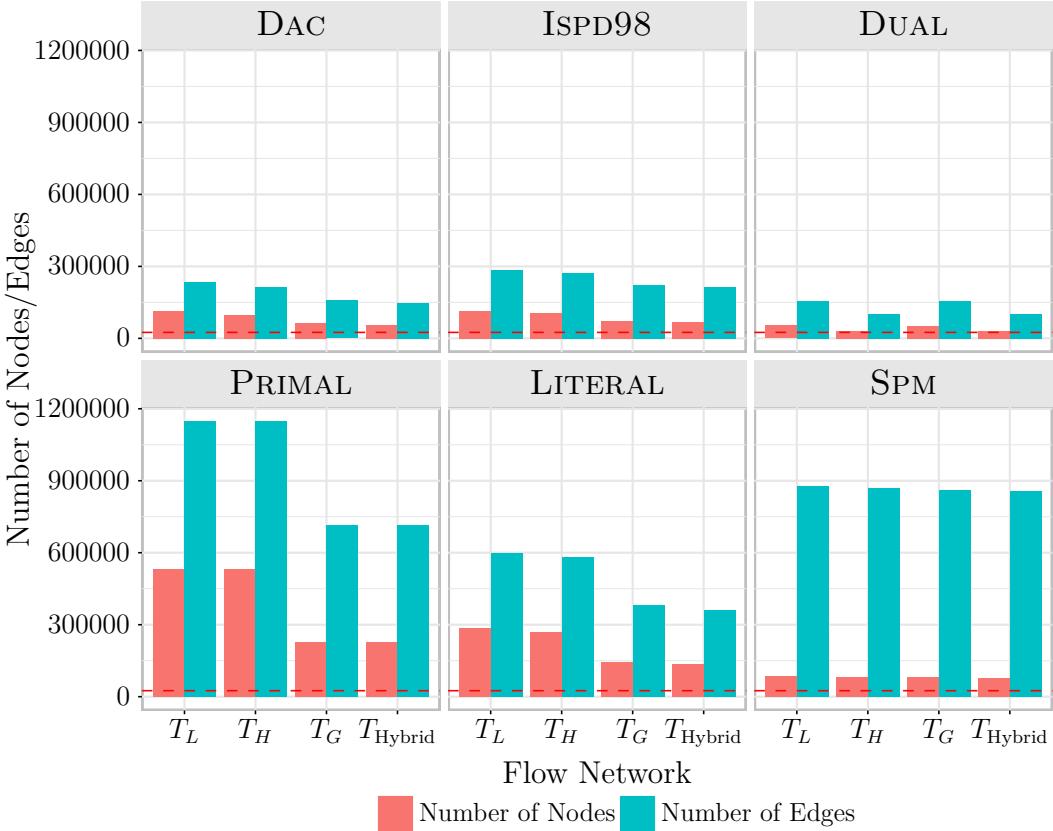


Figure 20: Comparison of the number of nodes and edges induced by flow problems of size $|V'| = 25000$ on our flow network for different benchmark types. The red dashed lines indicates 25000 nodes.

ent flow networks. The bars in the plot indicates speed-ups relative to the flow algorithm EDMONDKARP on flow network T_L . The main observation is that EDMONDKARP performs best on small flow network instances and GOLDBERG-TARJAN on large flow network instances. For $|V'| \leq 1000$ EDMONDKARP is faster than GOLDBERG-TARJAN on most of the different benchmark types. For $|V'| > 1000$ we can observe the opposite behavior except for DAC and DUAL instances. But the resulting flow problems of these instances induce still the small flow problems compared to e.g., PRIMAL or LITERAL. (see Figure 20). On the largest flow network instances PRIMAL and LITERAL for $|V'| = 25000$ GOLDBERG-TARJAN is up to a factor of 4-7 faster than EDMONDKARP. Further, both algorithms perform best on T_{Hybrid} .

Table 1 shows the summary of our flow algorithm and flow network experiment. It proofs our assumption that EDMONDKARP works best on small instances and GOLDBERG-TARJAN on large instances. However, the flow problem sizes in our *flow-based refinement* algorithm are chosen adaptively and depend on the *adaptive flow iteration* parameter α (see Section 3.3.2). Therefore, the running time of flow instances generated with a large α will dominate the ones with small α . Thus, we choose GOLDBERG-TARJAN in combination with our flow network T_{Hybrid} in the following experiments.

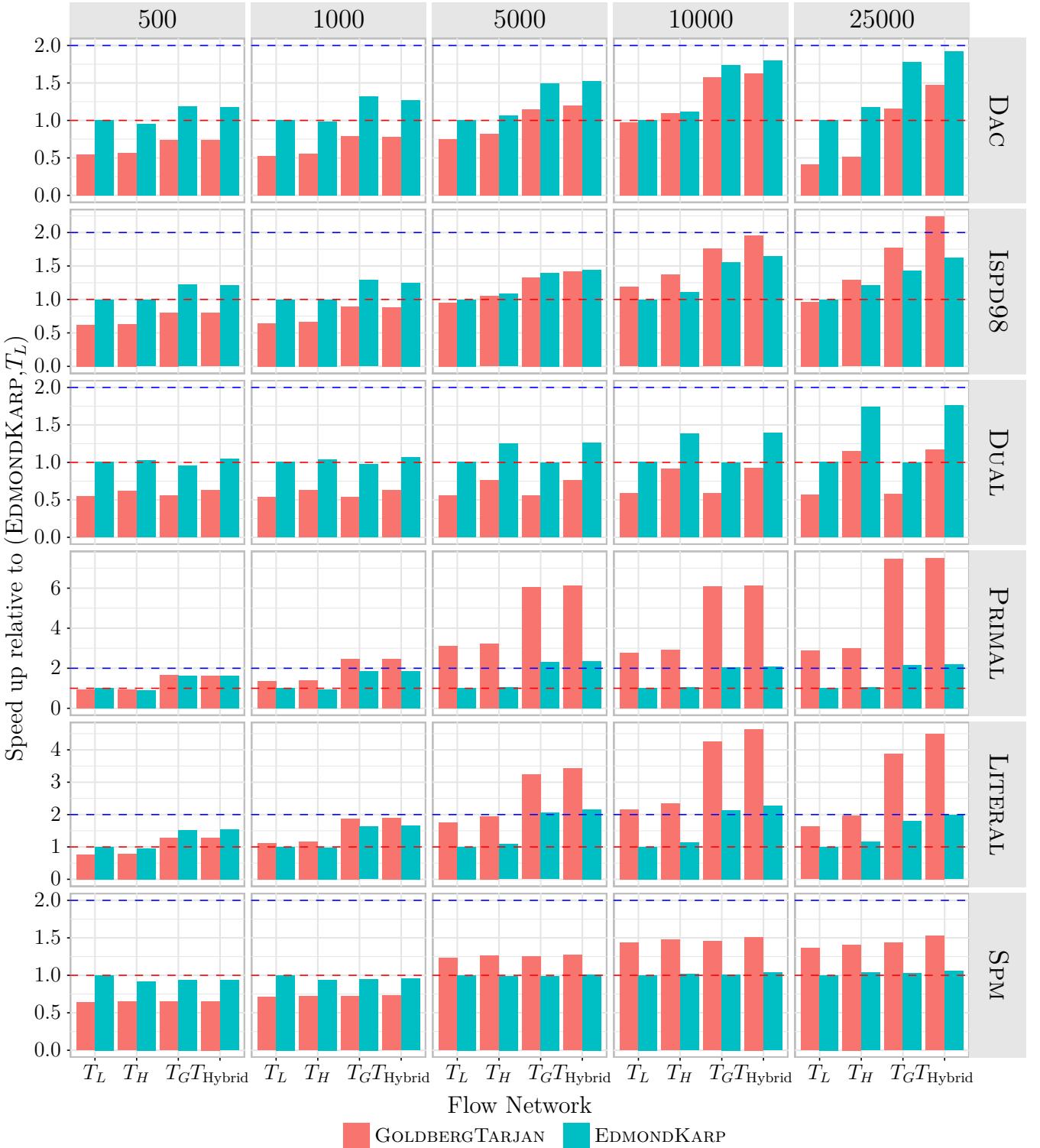


Figure 21: Speedup of our flow algorithms and networks relative to EDMONDKARP on T_L for different instance sizes and types. The red dashed line indicates the $(\text{EDMONDKARP}, T_L)$ implementation and the blue dashed line indicates a speedup by a factor of 2.

Instance	GOLDBERG-TARJAN				EDMOND-KARP				
	T_{Hybrid}	T_G	T_H	T_L	T_{Hybrid}	T_G	T_H	T_L	
$ V' $	$t[ms]$	$t[\%]$	$t[\%]$	$t[\%]$	$t[\%]$	$t[\%]$	$t[\%]$	$t[\%]$	
ALL	500	0.91	+2.24	+24.93	+29.35	-25.39	-24.3	-6.68	-11.53
	1000	1.95	+3.65	+26.19	+32.95	-13.99	-12.36	+10.81	+7.51
	5000	13.71	+8.63	+29.39	+43.11	+27.03	+35.33	+73.97	+86.31
	10000	30.54	+12.57	+36.15	+54.62	+47.93	+61.72	+100.41	+123.31
	25000	67.96	+23.36	+52.12	+87.8	+53.25	+77.85	+100.95	+138.8

Table 1: Running time comparison of maximum flow algorithms on different flow networks.

Note, all values in the table are in percentage relative to GOLDBERG-TARJAN on flow network T_{Hybrid} . In each line the fastest variant is marked bold.

6.4. Setup of the 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 (see Table 5). There are several configurations and tuning parameters which we have to evaluate:

- *Max-(F)low-Min-Cut* computations as refinement algorithm (see Section 5.3)
- *Adaptive Flow Iteration* parameter α' (see Section 3.3.2)
- *(M)ost Balanced Minimum Cut* heuristic (see Section 5.2)
- Combining *Max-(F)low-Min-Cut* computations with *(FM)* refinement

In the following, we will denote a configuration e.g. with (+F,-M,-FM) which 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 a configuration for $k \in \{2, 4, 8, 16, 32, 64, 128\}$, $\alpha' \in \{1, 2, 4, 8, 16\}$ and 10 different seeds on our parameter tuning benchmark subset ($\epsilon = 3\%$). We execute a *flow-based local search* on each level i with $i = 2^j$ ($j \in \mathbb{N}_+$) (see Section 5.3). Additionally, we add configuration (+F,+M,+FM) with *flow execution policy* $i = 128j$ ($j \in \mathbb{N}_+$). This configuration has an impracticable running time, but should provide a lower bound of the solution quality achievable with *Max-Flow-Min-Cut* computations in combination with *FM* refinement. We refer to this variant as CONSTANT128. Further, we use the latest version of *KaHyPar* as reference [22]. We refer to this variant as (-F,-M,+FM).

The results are summarized in Table 2. The values in the column *Avg* are improvements of the connectivity metric relative to our baseline configuration (-F,-M,+FM). The running time are absolute values in seconds. The first observation is that flows on its own as refinement strategy are not strong enough to outperform the *FM* heuristic. Our strongest configuration with $\alpha' = 16$ is 2.58% worse than our *FM* baseline. But the result is still remarkable because we only execute flows on $\log n$ levels instead of n as the *FM* algorithm is executed. The running time scales nearly linear with parameter α' .

Enabling the *Most Balanced Minimum Cut* heuristic significantly improves the quality compared to the configuration (+F,-M,-FM). But the quality improvements are more significant for large α' . The 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 according to our balanced constraint. Also it outperforms our baseline *FM* configuration for $\alpha' = 16$ by 0.51%.

If we enable *FM* refinement in all levels where no flow is executed, we improve the solution

Config.	(+F,-M,-FM)		(+F,+M,-FM)		(+F,+M,+FM)		CONSTANT128	
α'	Avg.[%]	$t[s]$	Avg.[%]	$t[s]$	Avg.[%]	$t[s]$	Avg.[%]	$t[s]$
1	-15.48	12.94	-15.26	13.29	0.14	14.99	0.32	67.38
2	-10.5	16.07	-10.12	16.93	0.36	16.93	0.62	139.21
4	-5.98	21.22	-5.08	23.01	0.67	20.76	1.03	274.6
8	-3.22	30.73	-1.64	33.72	1.25	28.65	1.67	558.81
16	-1.52	50.89	0.51	56.39	1.87	46.17	2.44	1220.92
Ref.	(-F,-M,+FM)	6373.88	13.73					

Table 2: Table contains results for different configurations of our flow-based refinement framework for increasing α' . The quality in column *Avg.* is relative to our baseline configuration without the usage of flows.

quality by nearly 2% (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. It has as a consequence that a block becomes faster *inactive* during the *active block scheduling* algorithm and this decreases the number of rounds of complete pairwise flow-based refinements.

Finally, CONSTANT128 gives us a lower 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 2.44% better than our baseline configuration, but ≈ 100 times slower. Compared to (+F,+M,+FM) for $\alpha = 16$, CONSTANT128 is only 0.57% better and around ≈ 25 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.

6.5. Speed-Up Heuristics

At the end of Section 5.3, we have presented several heuristics to prevent *unpromising* flow executions during the *active block scheduling* refinement ((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 6).

Table 3 summarizes the results of the experiment. KaHyPar-CA is the current version of *KaHyPar* and KaHyPar-MF is our current flow configuration of Section 6.4. The indices of the different variants of KaHyPar-MF describes which speed-up heuristic is enabled (see Section 5.3). On average, enabling all speed-up heuristics worsen the quality of KaHyPar-MF only by 0.09%. On the other hand, the framework is significantly faster by a factor of ≈ 2 . In its final configuration KaHyPar-MF_(R1,R2,R3) computes partitions with 2% better quality ($(\lambda - 1)$ -metric) than KaHyPar-CA, while only incurring a slowdown of a factor of 2. In the following, we will denote our final configuration KaHyPar-MF_(R1,R2,R3) with KaHyPar-MF.

6.6. Comparison with other Hypergraph Partitioner

Finally, we compare our new approach KaHyPar-MF with different state-of-the-art hypergraph partitioner on our full benchmark set. We excluded 194 instances of 3416 either because PaToH-

Variant	Avg.[%]	Min.[%]	$t_{\text{flow}}[s]$	$t[s]$
KaHyPar-CA	7077.2	6820.17	-	29.26
KaHyPar-MF	-2.13	-1.8	52.28	81.54
KaHyPar-MF _(R1)	-2.05	-1.74	41.48	70.74
KaHyPar-MF _(R1,R2)	-2.05	-1.73	35.27	64.54
KaHyPar-MF _(R1,R2,R3)	-2.04	-1.75	27.62	56.88

Table 3: Results of our flow-based refinement framework with different speedup heuristics.

Q could not allocate enough memory or other partitioners did not finish in time. The excluded instances are shown in Table 9.

Figure 22 summarizes the results of the experiment. KaHyPar-MF produce on $\approx 70\%$ of all benchmark instances the best partitions. It is followed by hMetis-R (14%), hMetis-K (11%), KaHyPar-CA (2.4%), PaToH-Q (1.9%) and PaToH-D (1.4%). Comparing KaHyPar-MF individually with each partitioner, KaHyPar-MF produces better partitions than KaHyPar-CA, hMetis-R, hMetis-K, PaToH-Q, PaToH-Q on 96%, 80%, 82%, 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 Figure 22).

Table 12 shows the running time of all partitioner 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.

Partitioner	Running Time $t[s]$						
	ALL	DAC	ISPD98	PRIMAL	LITERAL	DUAL	SPM
KaHyPar-MF	62.24	637.58	22.29	71.63	140.84	106.24	29.61
KaHyPar-CA	31.05	368.97	12.35	32.91	64.65	68.27	13.91
hMetis-R	79.23	446.36	29.03	66.25	142.12	200.36	41.79
hMetis-K	57.86	240.92	23.18	44.23	94.89	125.55	35.95
PaToH-Q	5.89	28.34	1.89	6.9	9.24	10.57	3.42
PaToH-D	1.22	6.45	0.35	1.12	1.58	2.87	0.77

Table 4: Comparing the average running time of KaHyPar-MF with KaHyPar-CA and other hypergraph partitioners.

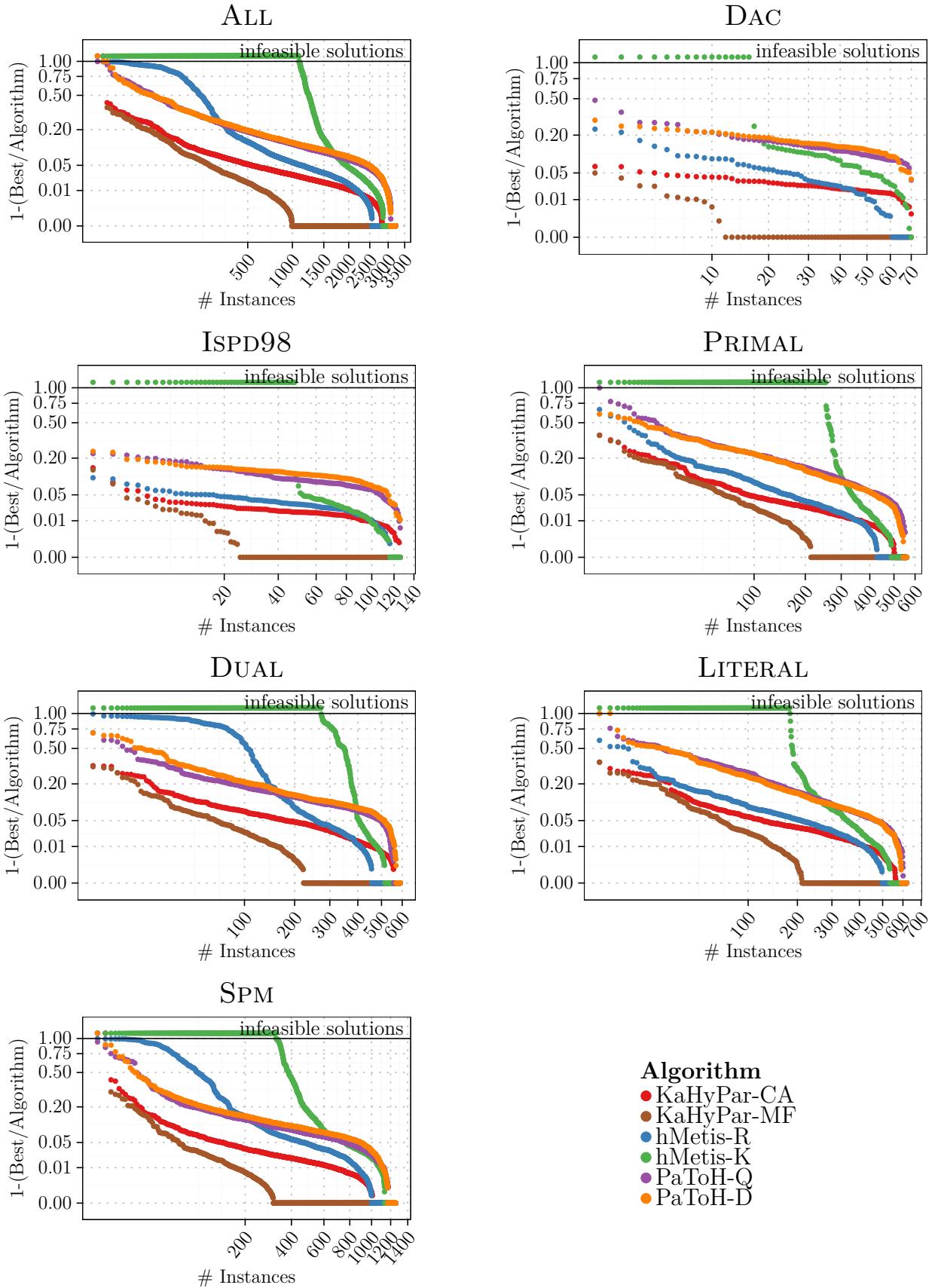


Figure 22: Min-Cut performance plots comparing KaHyPar-MF with KaHyPar-CA and other systems. Plots are explained in Section 6.2.

7. Conclusion

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

On the road to a practical implementation, we introduce several techniques to sparsify the state-of-the-art hypergraph flow network representation [30]. The network consists of many edges with *infinite* capacity. We present several theoretical results, which allows us to remove such edges or even to remove nodes, if all *incoming* and *outgoing* edges have a capacity equal to *infinity*. The results are of independent interest, because they are also applicable on general flow networks with *infinite* capacity edges. As a consequence, we can remove all hypernodes from the flow network of a hypergraph, because all *incoming* and *outgoing* edges have *infinite* capacity in the corresponding flow network [30]. However, the removal of a hypernode in the flow network introduce new edges between all incident nodes, which number depends on the degree of a vertex. We show that we can minimize the number of edges, if the degree of a hypernode is smaller than or equal to 3. Further, we show that each weighted undirected graph can be modeled as a weighted directed graph with the same *min-cut* property. The transformation introduces new nodes and edges in the corresponding weighted directed graph. However, we have shown that the transformation of an undirected edge results in the same structure as the transformation of hyperedges of size 2 in the hypergraph flow network. As a consequence, we can model each hyperedge e with $|e| = 2$ as a undirected flow edge. We combine both techniques in a *Hybrid-Network* and show that maximum flow algorithms are up to a factor of 3 faster compared to the execution on the *Lawler-Network* [30] on real-world hypergraph benchmarks.

Our *flow-based* refinement framework is based on the ideas of Sanders and Schulz [42] (developed for multilevel graph partitioning). However, we generalize many results such that they are applicable on hypergraph partitioning. We show how one can improve a given bipartition of a hypergraph by executing a *Max-Flow-Min-Cut* computation only on a subhypergraph. Further, if we use the *FM* heuristic, the value of the cut after moving a node from one block to another can be calculated with the gain value of the move and the cut before. We show how the source and sink set of the corresponding flow problem can be modeled such that the value of the cut of the improved bipartition can be calculated with the value of a maximum (S, T) -flow. Additionally, we explain how one can find all minimum (s, t) -cutsets with one maximum (s, t) -flow calculation on hypergraphs.

We integrated our framework into the n -level hypergraph partitioner *KaHyPar*. We embed our *flow-based local search* algorithm into an *active block scheduling* refinement strategy. The algorithm works in rounds and in each round we start a *flow-based* refinement between each adjacent block. The algorithm terminates if no hypernode changed its block in a round. The flow problem is build around the cut of two adjacent blocks. The sizes of the flow problems are chosen adaptively. If a *flow* computation on two blocks yields an improvement, we increase the flow problem size, otherwise we decrease it. Additionally, we try to automatically balance the partition after *Max-Flow-Min-Cut* computation by using the *Most Balanced Minimum Cut* heuristic. The *active block scheduling* refinement is executed in $\log n$ levels of the multilevel hierarchy. In the remaining levels, where no flow is performed, the classical *FM* heuristic is used to improve the quality of a partition. An observation during implementation was that only a minority of the *Max-Flow-Min-Cut* computations leads to an improvement in quality. Therefore, we implement several speed-up heuristics which prevents the execution of unpromis-

ing pairwise *flow* refinements.

The new configuration KaHyPar-MF produces on 95% of our benchmark instances better partitions than our old configuration KaHyPar-CA. On average the solution quality is 2% 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 on 70% of 3222 benchmark instances the best partitions. Moreover, our partitioner has a comparable running time to the direct k -way version of *hMetis* and outperforms it on 82% of the benchmark instances.

7.1. Future Work

Due to the novelty of the approach, there is a lot of potential in optimizing our basic framework. We made a trade-off between time and quality to obtain a *High-Quality n-level Hypergraph Partitioner* which runs in reasonable time. The quality mainly depends on the number of flow executions throughout the multilevel hierarchy. The number of flow executions, which we can do in reasonable time, depends on the running time of the flow algorithm and the size of the flow problem. Optimizing those two basic building blocks of the framework will allow us to achieve better quality in the same amount of time.

The flow network of a hypergraph proposed by Lawler [30] 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. Therefore, a useful work would be to evaluate many different maximum flow algorithms on our benchmark set. Further, one could investigate if it is possible to maintain the whole flow network over the multilevel hierarchy without explicitly setting up 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. Pistorius [40] described an algorithm which implicitly executes EDMOND-KARP on a hypergraph using labels on the hypernodes. In our first version of the framework, we also used a similar technique and implicitly executes a flow algorithm on an implicit representation of the underlying network. During experiments, it turned out that the explicit representation was up to a factor of 2-3 faster than the implicit version. We encountered several reasons for that behavior:

- (i) Our flow network represents a subhypergraph of the original hypergraph. Iterating over the edges of a node means to iterate also over hypernodes which are not part of the flow problem and therefore have to be ignored.
- (ii) There are many different cases when we want to increase the flow along an *augmenting path*.
- (iii) Many labels have to be introduced which lead to a large number of main memory accesses.
- (iv) Also 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.

In Section 5.3 and 6.5 we show that with three simple speed up heuristics our *flow-based* refinement framework is up to a factor of 2 faster with comparable quality. Therefore, it would be beneficial to further increase the effectiveness ratio of the flow computation by introducing more heuristics.

It is also possible to further sparsify the flow network. Assume there exists two hypernodes v_1 and v_2 with $d(v_1) = 3$ and $d(v_2) = 4$. Further, $|I(v_1) \cap I(v_2)| = 3$ which means that in each hyperedge e where $v_1 \in e$ also $v_2 \in e$ except for one hyperedge e' where $v_2 \in e'$ and $v_1 \notin e'$. We remove all hypernodes with $d(v) \leq 3$ in our *hybrid* flow network. Consequently, we would remove v_1 and insert a clique between all incident hyperedges. However, v_2 is part of the flow network and induce $2d(v_2) = 8$ edges because $d(v_2) > 3$. Alternatively, we can remove v_2 and expand the clique between all hyperedges of $I(v_1)$ with e' . In that case, we have to insert

an edge from each hyperedge in $I(v_1)$ to e' and vice versa. Since $|I(v_1)| = d(v_1) = 3$ only $2|I(v_1)| = 6$ edges are inserted and we can remove one hypernode. In general, an expansion of a k -clique to a $(k+i)$ -clique induced ik edges from the k nodes already contained in the clique to the i new nodes and $i(k+1-1)$ edges from the i new nodes to the k nodes in the clique. If we can remove a hypernode from the flow network by expanding a k -clique between hyperedge nodes to a $(k+i)$ -clique, it is beneficial if the following inequality holds

$$ik + i(k+i-1) = i^2 + 2ki - i \leq 2(k+i)$$

The inequality is only satisfied for $i = 1$. In this case, we can exactly remove 2 edges and 1 node from the flow network. A possible algorithm could be to sort the hypernodes according to the degree and for each hypernode store a clique label which indicates between how many incident hyperedges already exist a clique. Afterwards, we iterate over the hypernodes and if we remove a hypernode, we have to update the clique label of all hypernodes in the intersection of the currently inserted clique. We iterate over the hypernodes until none of the hypernodes could be removed anymore. However, we didn't find an efficient implementation of the above-described algorithm. The algorithm requires a fast calculation between the intersection of several hyperedges. An explicit construction of the intersection hypergraph would occupy too much memory.

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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	4.04	3.57	1.06
PRIMAL	629461	2.56	2.3	11.74	6.54	4.58
LITERAL	629461	2.56	2.3	5.85	3.25	2.28
DUAL	229544	8.05	6.03	2.32	2	0.29
SPM	74104	20.91	19.92	20.91	17.87	1

Table 5: Statistical 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	3.32	3.18	0.99
ISPD98	201920	3.87	2.08	4.2	3.67	1.08
PRIMAL	6429816	2.58	2.2	11.54	7.39	4.48
LITERAL	6429816	2.58	2.2	5.79	3.78	2.25
DUAL	1613160	11.54	7.39	2.58	2.2	0.22
SPM	1000005	16.25	12.95	14.95	12.58	0.92

Table 6: Statistical 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	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 7: Statistical 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							

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	△	△	△	△	△	○△	○△
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 9: 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 of the hypergraph. 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 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 a biclique 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 inserted biclique induce exactly $d(v)^2$ edges 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 equivalent. The problem is illustrated in Figure 23. 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 where a node v exists with $c(v) = \infty$. We can find a minimum-weight (s, t) -vertex separator of G (weight must be smaller than ∞) 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 will 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 exists still a path from s to t . If the path not contains 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 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 Figure 23). 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 Definition 2.5) to obtain a flow network in which the value of a maximum (s, t) -flow is equal with the weight of a minimum-weight (s, t) -vertex separator. Both networks on the right side of Figure 23 are equivalent, but a removal of a hypernode now induce $d(v)(d(v) - 1)$ edges instead of $d(v)^2$ edges in the new network.

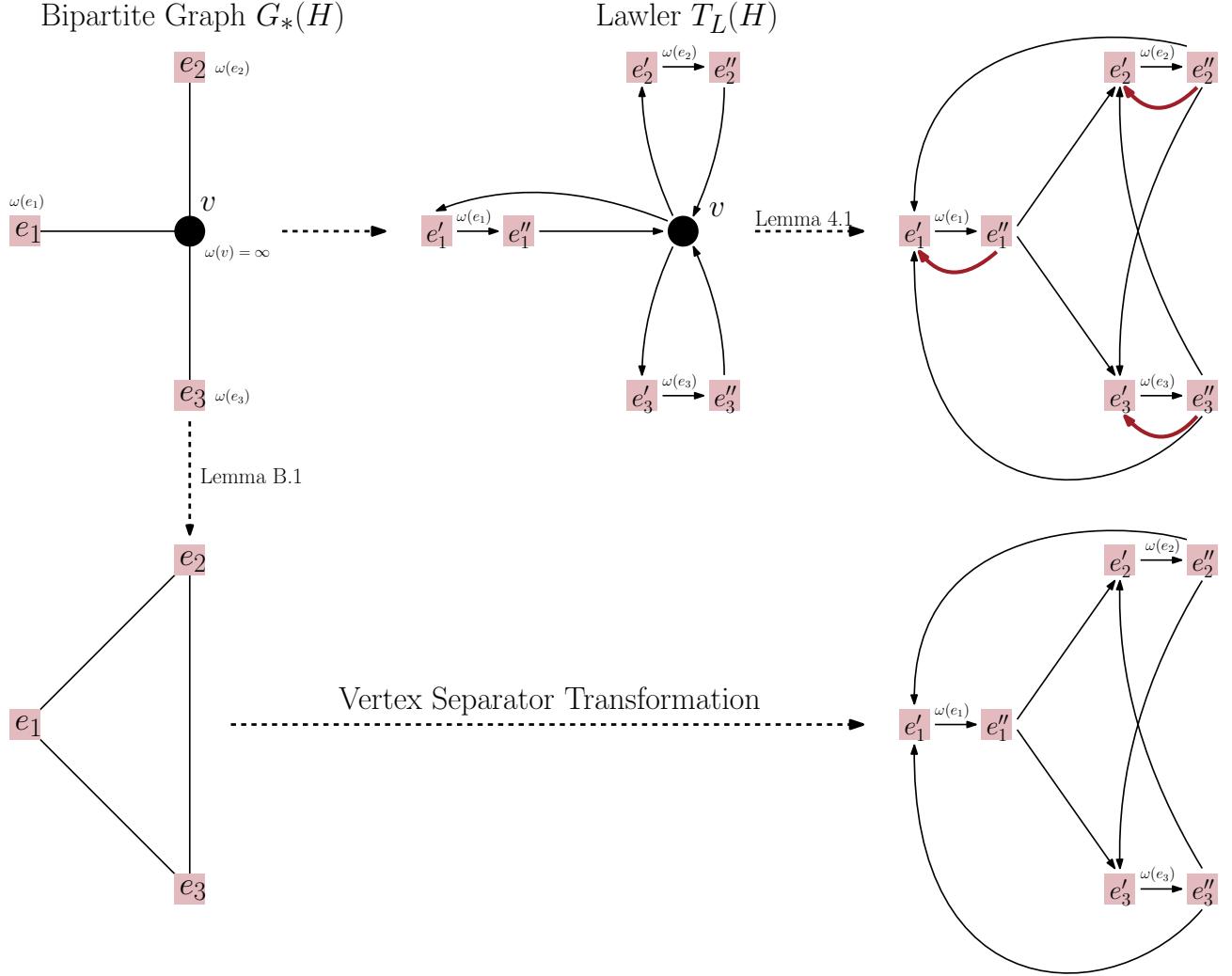


Figure 23: Illustration of the technique to remove a hypernode such that the removal induce $d(v)(d(v) - 1)$ edges instead of $d(v)^2$ edges in the corresponding flow network. The edges without an explicit capacity are *infinite* capacity edges. The transformation on the top of the figure illustrates the technique presented in Section 4.1. Using Lemma B.1 and the vertex separator transformation (see Defintion 2.5) results in a equivalent flow network without the red highlighted edges.

C. Detailed Flow Network and Algorithm Evaluation

Instance	$ V' $	GOLDBERG-TARJAN				EDMOND-KARP			
		T_{Hybrid} $t[\text{ms}]$	T_G $t[\%]$	T_H $t[\%]$	T_L $t[\%]$	T_{Hybrid} $t[\%]$	T_G $t[\%]$	T_H $t[\%]$	T_L $t[\%]$
ALL	500	0.91	+2.24	+24.93	+29.35	-25.39	-24.3	-6.68	-11.53
	1000	1.95	+3.65	+26.19	+32.95	-13.99	-12.36	+10.81	+7.51
	5000	13.71	+8.63	+29.39	+43.11	+27.03	+35.33	+73.97	+86.31
	10000	30.54	+12.57	+36.15	+54.62	+47.93	+61.72	+100.41	+123.31
	25000	67.96	+23.36	+52.12	+87.8	+53.25	+77.85	+100.95	+138.8
DAC	500	0.34	-0.36	+30.14	+34.98	-37.61	-38.08	-23.12	-26.56
	1000	0.8	-1.7	+41.18	+47.43	-38.94	-41.19	-20.88	-22.17
	5000	5.2	+4.11	+46.02	+58.5	-21.35	-19.79	+12.55	+19.6
	10000	10.67	+3.2	+48.92	+66.83	-9.41	-6.44	+46.23	+63
	25000	31.43	+26.81	+186.2	+255.32	-23.53	-17.16	+25.16	+47.29
ISP98	500	0.48	-0.58	+26.23	+28.54	-33.85	-34.5	-19.55	-20.14
	1000	1.11	-0.8	+32.35	+37.47	-29.32	-31.59	-11.91	-11.88
	5000	7.06	+6.65	+35.1	+49.35	-1.67	+1.64	+31.03	+41.91
	10000	16.33	+10.97	+42.54	+64.68	+18.38	+25.84	+75.19	+95.09
	25000	75.01	+26.26	+73.85	+132.06	+37.85	+56.79	+85.28	+124.01
DUAL	500	0.3	+12.37	+0.99	+13.6	-40.36	-34.35	-39.13	-37.67
	1000	0.6	+16.87	+0.83	+18.38	-40.93	-35.35	-39.47	-37.18
	5000	3.2	+37.54	+0.21	+37.78	-39.66	-23.77	-39.17	-24.01
	10000	5.78	+55.72	+1.21	+55.86	-34.01	-7.81	-33.3	-8
	25000	14.71	+105.19	+2.15	+105.88	-33.35	+17.43	-32.59	+17.28
PRIMAL	500	1.85	-0.73	+73.92	+76.03	+0.86	+0.17	+79.92	+63.57
	1000	3.9	+0.15	+77.48	+81.23	+33.02	+33.57	+160.43	+145.98
	5000	29.8	+0.84	+88.23	+96.71	+160	+162.28	+481.91	+510.71
	10000	45.94	+0.69	+109.75	+120.04	+195.68	+197.69	+487.6	+511.93
	25000	174.32	+0.21	+151.07	+159.04	+243.77	+248.81	+609.44	+648.46
LITERAL	500	0.86	+0.72	+63.65	+67.45	-16.1	-15.41	+35.63	+29.41
	1000	1.92	+1.64	+64.51	+71.46	+15.13	+17.07	+95.07	+90.72
	5000	12.31	+6.15	+76.65	+94.2	+59.04	+66.99	+216.7	+243.13
	10000	29.75	+8.55	+97.28	+115.37	+102.47	+117.45	+302.93	+363.17
	25000	64.4	+15.75	+128.34	+175.78	+126.59	+148.78	+286.31	+349.43
SPM	500	1.46	+0.35	+1.22	+2.47	-29.92	-30.42	-28.84	-34.57
	1000	3.09	+1.45	+1.14	+3.28	-23.32	-22.94	-22.17	-26.89
	5000	25.81	+1.79	+1.09	+3.26	+26.02	+28.55	+28.61	+27.43
	10000	74.81	+3.78	+2.48	+5.38	+45.86	+49.36	+48.77	+51.06
	25000	107.6	+6.67	+8.56	+12.07	+44.39	+48.88	+47.68	+52.96

Table 10: Running time comparison of maximum flow algorithms on different flow networks.

Note, all values in the table are in percentage relative to Goldberg-Tarjan on flow network T_{Hybrid} . 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 α' 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 [42]. The results of the tests mirrors our results of Section 6.4.

Config.	(+F,-M,-FM)	(+F,+M,-FM)	(+F,+M,+FM)
α'	Avg.[%]	Avg.[%]	Avg.[%]
1	-15.48	-15.22	0.14
2	-10.53	-10.11	0.36
4	-6	-5.13	0.66
8	-3.24	-1.68	1.24
16	-1.7	0.44	1.82
Ref.	(-F,-M,+FM)	6374.42	

Table 11: Table contains results of the effectiveness test for different configurations of our flow-based refinement framework for increasing α' . The quality in column *Avg.* is relative to our baseline configuration without the usage of flows.

E. Detailed Speedup Heuristic Evaluation

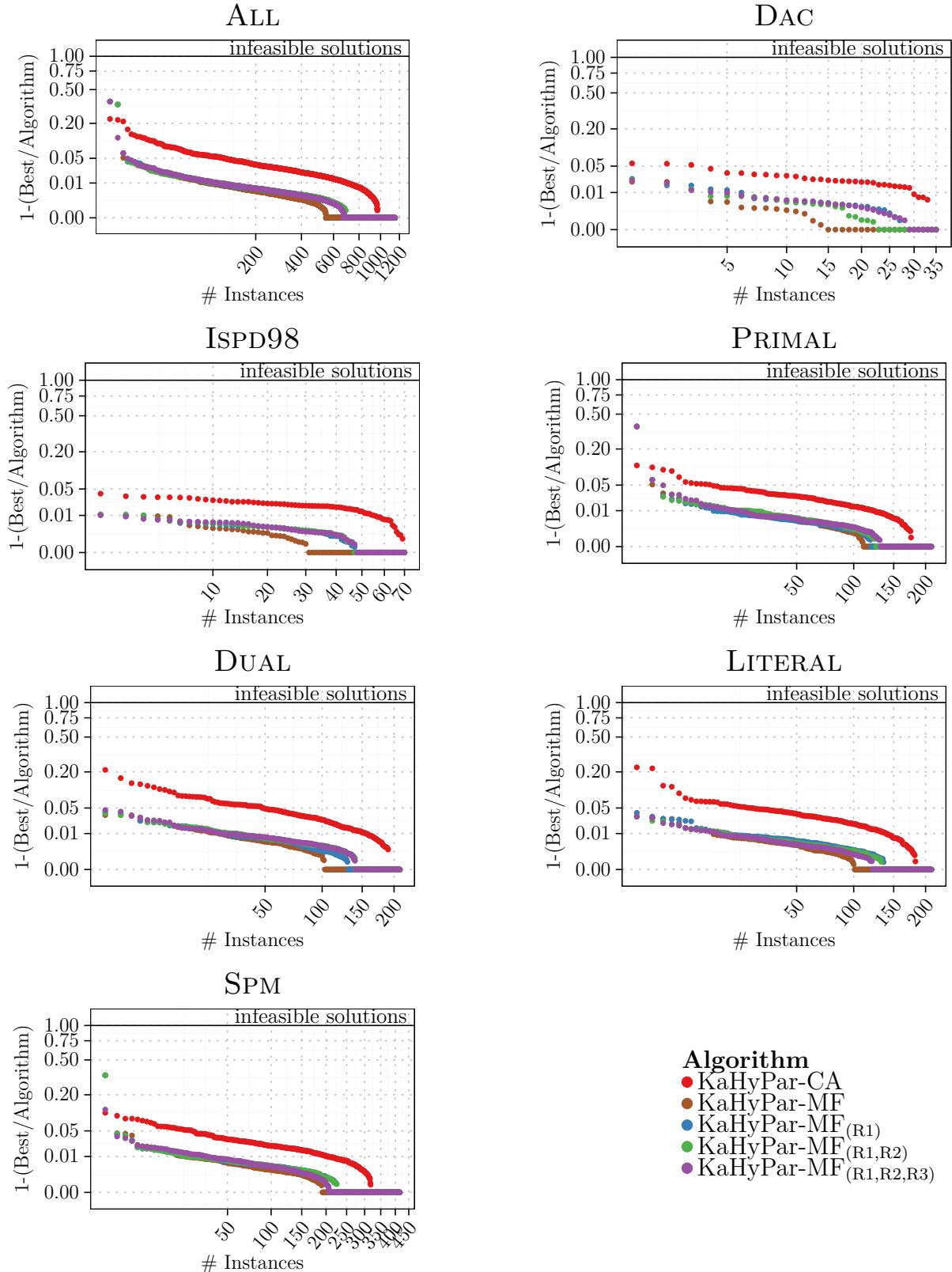


Figure 24: Min-Cut performance plots comparing KaHyPar-MF with KaHyPar-CA. The plots are explained in Section 6.2.

Partitioner	Running Time $t[s]$						
	ALL	DAC	ISPD98	PRIMAL	LITERAL	DUAL	SPM
KaHyPar-CA	29.26	343.4	21.57	36.44	56.49	58.75	11.31
KaHyPar-MF	81.54	699.18	75.97	114.67	185.56	143.93	28.74
KaHyPar-MF _(R1)	70.74	600.87	59.69	94.9	150.56	128.67	26.47
KaHyPar-MF _(R1,R2)	64.54	573.41	50.28	88.11	134.84	113.59	24.8
KaHyPar-MF _(R1,R2,R3)	56.88	526.86	43.32	74.76	116.79	101.76	22.31

Table 12: Comparing the average running time of KaHyPar-MF with KaHyPar-CA.

F. Detailed Comparison with other Systems

Partitioner	Average $\lambda - 1$						
	ALL	DAC	ISPD98	PRIMAL	LITERAL	DUAL	SPM
KaHyPar-MF	7819.11	17590.1	5671.37	15923.74	15844.61	3061.94	6165.74
KaHyPar-CA	2.03	2.47	1.72	1.69	2.25	2.71	1.75
hMetis-R	15.21	2.99	1.14	1.69	2.31	42.33	19.22
hMetis-K	14.71	7.78	0.9	3.66	8.77	27.66	19.09
PaToH-Q	8.98	12.86	7.41	11.72	12.81	7.96	6.37
PaToH-D	16.21	22.98	14.54	17.83	20.97	17.4	12.5

Table 13: Comparison of average ($\lambda - 1$) metric of KaHyPar-MF with KaHyPar-CA and other systems 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	1064.06	3147.96	6062.8	9406	14756.03	21978.89	31820.94
KaHyPar-CA	1.73	2.06	2.36	2.28	2.11	1.9	1.73
hMetis-R	26.46	18.26	16.34	15.25	12.33	10.23	8.08
hMetis-K	26.86	17.19	15.18	15.06	11.29	9.83	8.1
PaToH-Q	11.1	8.5	8.57	9.49	8.87	8.6	7.7
PaToH-D	14.62	15.94	18.55	19.34	15.62	15.31	14.09

Table 14: Comparison of average ($\lambda - 1$) metric of KaHyPar-MF with KaHyPar-CA and other systems for different values of k . The results are in percentage relative to KaHyPar-MF.

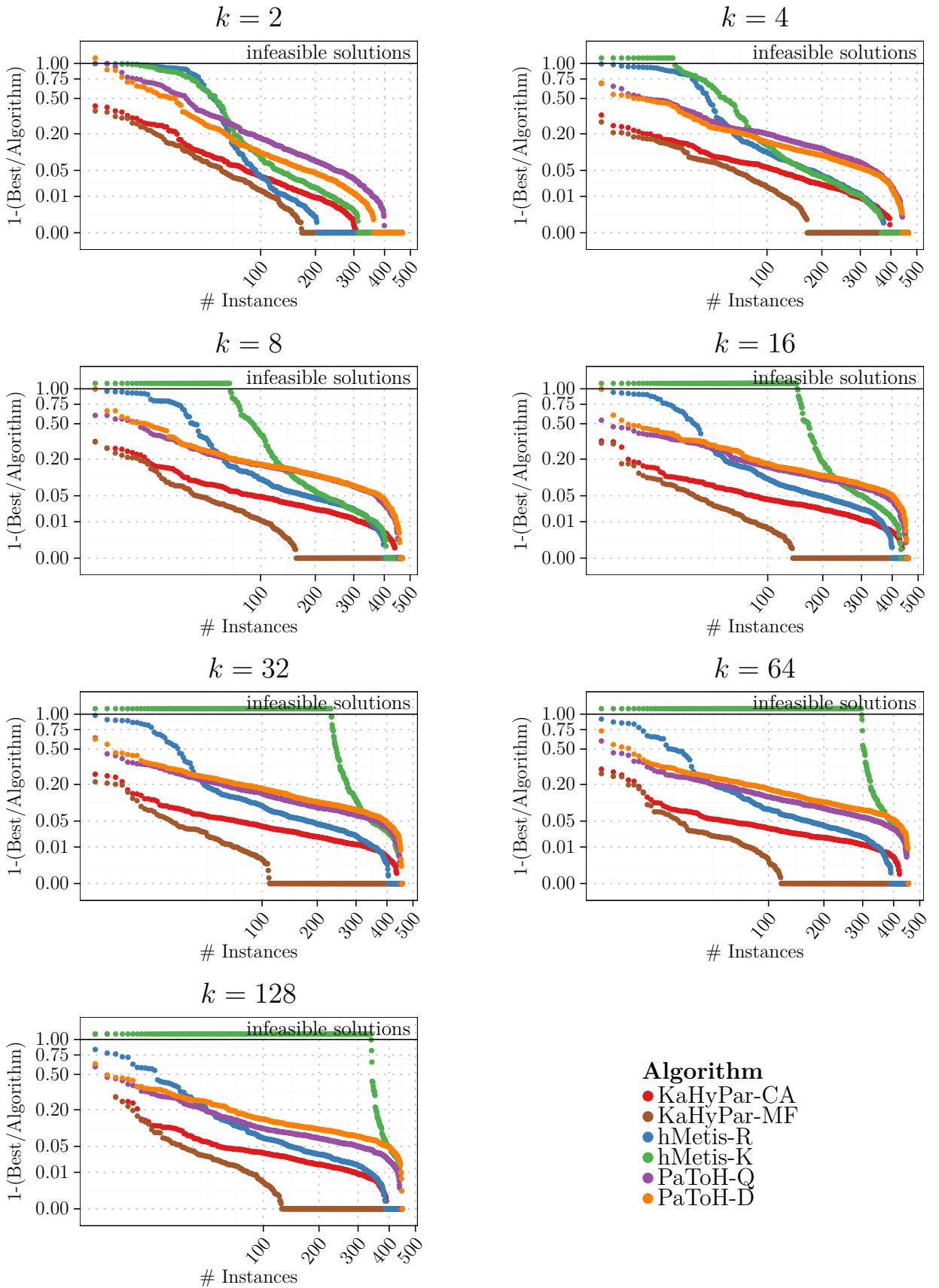


Figure 25: Min-Cut performance plots comparing KaHyPar-MF with KaHyPar-CA and other systems for different values of k .

Partitioner	Running Time $t[s]$						
	$k = 2$	$k = 4$	$k = 8$	$k = 16$	$k = 32$	$k = 64$	$k = 128$
KaHyPar-MF	22.13	38.51	55.04	67.83	85.75	108.97	128.04
KaHyPar-CA	12.68	17.16	23.88	31.01	41.69	57.35	76.61
hMetis-R	27.87	51.59	74.74	91.09	109.13	128.66	149.34
hMetis-K	25.47	32.27	42.5	53.41	74	109.12	152.92
PaToH-Q	1.93	3.61	5.44	7.01	8.4	10.06	11.44
PaToH-D	0.43	0.77	1.12	1.42	1.71	2.02	2.29

Table 15: Comparing the average running time of KaHyPar-MF with KaHyPar-CA and other systems for different values of k .