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# Solving Bin Packing Problems with Fragmentation

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# **Bin Packing Problems**

Classical Bin Packing Problem (BPP):

- NP-HARD
- well studied in the OR community
- models many problems in logistics ...



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# **Bin Packing Problems**

Classical Bin Packing Problem (BPP):

- NP-HARD
- well studied in the OR community
- models many problems in logistics ...

BPP with item fragmentation (BPP-IF): items can be split at a price.



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# **BPP-IF** in telecommunications



#### Tactical issues in (consolidated) routing:

- channels: (path, frequency, timeslot) tuples  $\Rightarrow$  bin
- data transfer requests of different carriers  $\Rightarrow$  items
- splitting requests consumes energy  $\Rightarrow$  split items as few as possible

Initial attempts with CPLEX: timeout on instances with 10 or 20 items. Spoiler:

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# **BPP-IF** in telecommunications



#### Tactical issues in (consolidated) routing:

- channels: (path, frequency, timeslot) tuples  $\Rightarrow$  bin
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- splitting requests consumes energy  $\Rightarrow$  split items as few as possible

Initial attempts with CPLEX: timeout on instances with 10 or 20 items. Spoiler: branch-and-price could tackle instances with up to 1000 items.

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# **BPP-IF** in transportation

	Split Forbidden	Split Allowed
Routing costs	VRP	Split Delivery VRP
No routing costs	BPP	BPP with Item Fragm.

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# Literature Review

# Main BPP-IF variants

- Bin Minimization; Fragmentations minimization;
- Size Preserving; Size Increasing (weight overhead for each split)

#### Approximation algorithms and applications:

- N. Menakerman, R. Rom., *Bin packing with item fragmentation*. LNCS, proc. of the 7th WADS (2001)
- H. Shachnai, T. Tamir, O. Yehezkely, Approximation schemes for packing with item fragmentation. Theory of Comp. Sys. 43 (2008)
- L. Epstein, A. Levin, R. van Stee, Approximation schemes for packing splittable items with cardinality constraints. Algorithmica 62 (2012).
- B. Lecun, T. Mautor, F. Quessette, M.A. Weisser Bin packing with

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# Literature Review

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- B. Lecun, T. Mautor, F. Quessette, M.A. Weisser Bin packing with fragmentable items: presentation and approximations. Theoretical Computer Science 602 (2015)

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# Results overview:

#### Our approach:

- try to understand which features make the problem so difficult
- design math. prog. algorithms for solving BPPIFs

#### Main results

- A common framework for modeling and solving BPPIFs (bin or fragmentation minimization, size preserving or increasing)
- A characterization of particular subsets of optimal solutions
- Exact algorithms whose computing time scales very well in practice

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# Structure of a solution

**BPP-IF** Graph

Given a BPP-IF solution, build a BPP-IF graph:

- one vertex for each bin
- one edge for each pair of bins with fragments of the same item

Solution



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# Structure of a solution

#### Primitive solutions

Def. primitive solution (MR '01):

- each item is split in at most two fragments
- each bin contains at most two fragmented items
- $\rightarrow$  the BPP-IF graph is a set of paths
- **def:** items beloging to bins of the same path form a *chain*.

#### Solution



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# Structure of a solution

#### Primitive solutions

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# Structure of a BPP-IF solution

# Theorem (MR '02)

There always exists a b.m. BPP-IF optimal solution which is primitive.

# Theorem (CC '13)

There always exists a f.m. BPP-IF optimal solution which is primitive.

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# Structure of a BPP-IF solution

# Theorem (MR '02)

There always exists a b.m. BPP-IF optimal solution which is primitive.

# Theorem (CC '13)

There always exists a f.m. BPP-IF optimal solution which is primitive.

### Theorem (MR '01 - CC '13)

given the set of items belonging to each chain in a primitive solution, a full BPP-IF solution can be found by running Next Fit procedures.

#### Theorem (CC '13)

There always exists an (optimal) primitive dominant solution, in which the split items of each chain of k bins are the k-1 items of maximum weight belonging to that chain;

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# Overall algorithm (N)

- bounding: compute valid lower bounds
- approximation: compute upper bounds
- branching: (a) fix split / non split items; (b) fix *pairs* of split items for the same bin; (c) assign items to bins whose pairs of split items are fixed
- pruning: cutoff partial solutions, retaining only primitive dominant ones
- feasibility checks: nec. conditions and constraint programming
- acceleration techniques: dual cuts (specialization of Irnich and Gschwind '16)

- residual capacity after chain fixing
- "large bin" capacity check
- multiple-subset-sum chain capacity check

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# Overall algorithm (N)

Branch-and-bound, exploiting:

- bounding: compute valid lower bounds
- approximation: compute upper bounds
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- pruning: cutoff partial solutions, retaining only primitive dominant ones
- feasibility checks: nec. conditions and constraint programming
- acceleration techniques: dual cuts (specialization of Irnich and Gschwind '16)

Feasibility checks:

- residual capacity after chain fixing
- "large bin" capacity check
- multiple-subset-sum chain capacity check
- no split-items subset-sum capacity check

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# Focus: computing valid lower bounds (N)

**Observation:** CC '14 In primitive solutions, minimizing the number of fragments, fragmentations or fragmented items is equivalent.

min $\sum \bar{z}_i^k y^k -  I $
s.t. $\sum_{k \in K} \bar{x}_i^k y^k = 1 \qquad \forall i \in I  \lambda_i$
$\sum_{k\in K} \overline{z}_i^k y^k \leq 2 \qquad \forall i \in I  \mu_i$
$\sum_{\substack{k \in K}} y^k \le  B   \eta$ $y^k \in \mathbb{B} \qquad \forall k \in K$

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# Focus: computing valid lower bounds (N)

**Observation:** CC '14 In primitive solutions, minimizing the number of fragments, fragmentations or fragmented items is equivalent.

Comp	bact model		Exte	nded formulati	ion (MP)	
min	$\sum_{i=1,\dots,n} z_{ij} -  I $		min	$\sum_{i=1}^{k} \bar{z}_{i}^{k} y^{k} -  $	1	
s.t.	$\sum_{j\in B}^{I\in I, j\in B} x_{ij} = 1$	$\forall i \in I$	s.t.	$\sum_{k\in K} \bar{x}_i^k y^k = 1$	$\forall i \in I$	$\lambda_i$
	$\sum_{i\in I} d_i x_{ij} \leq C$	$\forall j \in B$		$\sum_{k\in K} \overline{z}_i^k y^k \leq 2$	$\forall i \in I$	μi
	$egin{aligned} x_{ij} &\leq z_{ij} \ 0 &\leq x_{ij} &\leq 1 \ z_{ij} &\in \{0,1\} \end{aligned}$	$ \begin{aligned} \forall i \in I, \forall j \in B \\ \forall i \in I, \forall j \in B \\ \forall i \in I, \forall j \in B \end{aligned} $		$\sum_{k \in K} y^k \le  B $ $0 \le y^k \le 1$	$oldsymbol{\eta}$ $orall k$ (	∈ <i>K</i>

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# Column generation (N)

The reduced cost of a variable  $y^k$  is:

$$\bar{c}^{k} = \sum_{i \in I} \bar{z}_{i}^{k} - \sum_{i \in I} \lambda_{i} \cdot \bar{x}_{i}^{k} - \sum_{i \in I} \mu_{i} \cdot \bar{z}_{i}^{k} - \eta$$
$$\rightarrow \bar{c}^{k} = \sum_{i \in I} (1 - \mu_{i}) \bar{z}_{i}^{k} - \sum_{i \in I} \lambda_{i} \cdot \bar{x}_{i}^{k} - \eta$$

and a pattern is feasible if

$$\sum_{i \in I} d_i \cdot \bar{x}_i^k \leq C$$

$$0 \leq \bar{x}_i^k \leq z_i^k \qquad \forall i \in I$$

$$\bar{z}_i^k \in \{0, 1\} \qquad \forall i \in I$$

A Fractional Knapsack Problem with Penalties (FKPP)

Theorem (CC '14)

An optimal FKPP solution always exists, containing at most one fragmented item.

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# Pricing Algorithm (N) - Idea

To solve the FKPPs:

- consider 0 fragmented items  $\rightarrow$  a 0–1 KP
- consider 1 fragmented item, and choose it explicitly ightarrow use KP recursion, and then fill optimally.

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# Pricing Algorithm (N) - Details

$$\begin{split} \min \bar{c}^k &= \sum_{i \in I} (1 - \mu_i) \bar{z}_i^k - \sum_{i \in I} \lambda_i \cdot \bar{x}_i^k - \eta \\ s.t. \sum_{i \in I} d_i \cdot \bar{x}_i^k &\leq C \\ 0 &\leq \bar{x}_i^k \leq \bar{z}_i^k \\ \bar{z}_i^k \in \{0, 1\} & \forall i \in \end{split}$$

Pricing algorithm:

(a) no fragmented items:  $\bar{x}_i^k = \bar{z}_i^k$ 

$$egin{aligned} \minar{c}^k &= \sum_{i\in I} (1-\mu_i-\lambda_i)ar{z}^k_i - \eta \ s.t.\sum_{i\in I} d_i\cdotar{z}^k_i &\leq C \ ar{z}^k_i &\in \{0,1\} \ &orall i\in I \end{aligned}$$

(b) one fragmented item: for each  $i \in I$ 

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# Pricing Algorithm (N) - Details

$$\begin{split} \min \bar{c}^k &= \sum_{i \in I} (1 - \mu_i) \bar{z}_i^k - \sum_{i \in I} \lambda_i \cdot \bar{x}_i^k - \eta \\ s.t. \sum_{i \in I} d_i \cdot \bar{x}_i^k &\leq C \\ 0 &\leq \bar{x}_i^k \leq \bar{z}_i^k \\ \bar{z}_i^k \in \{0, 1\} & \forall i \in I \end{split}$$

Pricing algorithm:

- (a) no fragmented items:  $\bar{x}_i^k = \bar{z}_i^k \rightarrow \bar{c}^k = \sum_{i \in I} (1 \mu_i \lambda_i) \bar{z}_i^k \eta$ (b) one fragmented item: for each  $i \in I$ 
  - assume *i* is the (unique) fragmented item  $(\bar{x}_i^k = \bar{z}_i^k \quad \forall j \in I : j \neq i)$
  - solve a binary KP using traditional DP recursion, skipping i, and obtain  $f_c \forall c = 0 \dots C$

take

$$\min_{c=1...d_i-1}\left\{f_{C-c}-\lambda_i\cdot c\cdot\frac{1}{d_i}\right\}$$

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### Structure of a solution

#### Solution



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**Observation:** CC '15 Once items are organized in chains, a feasible fm-BPP-IF solution (if any exists) can be found by solving a Bin Packing feasibility problem  $\Rightarrow$  search for optimal packing in *chains* instead of optimal packing in *bins*.

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# **BPP-IF** models

### Compact model

min	$\sum_{i\in I,j\in B} z_{ij} -  I $	
s.t.	$\sum_{j\in B} x_{ij} = 1$	$\forall i \in I$
	$\sum_{i\in I} d_i x_{ij} \leq C$	$\forall j \in B$
	$x_{ij} \leq z_{ij}$	$\forall i \in I, \forall j \in B$
	$0 \le x_{ij} \le 1$	$\forall i \in I, \forall j \in B$
	$z_{ii} \in \{0, 1\}$	$\forall i \in I, \forall j \in B$

#### Chain based model

nin	$\sum_{k\in K} l_k - b_k$	
s.t.	$\sum_{k\in \mathcal{K}} z_{ik} = 1$	$\forall i \in I$
	$\sum_{i \in I} d_i z_{ik} \leq C \cdot I_k$	$\forall k \in K$
	$\sum_{k\in \mathcal{K}} l_k \leq  \mathcal{B} $	
	$b_k \leq l_k$	$\forall k \in K$
	$b_k \in \{0,1\}, l_k \in \mathbb{Z}_+$	$\forall k \in K$
	$z_{ij} \in \{0,1\}  \forall i \in I,$	$\forall k \in K$

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			BPP-IF	mod	els		
Cha	in-based n	nodel		Chai form	n-based exter ulation (MP)	nded	
min	$\sum_{k\in K} l_k - b_k$			min	$\sum_{p\in\Omega,i\in I} (\bar{l}^p - 1)$	· y <sup>p</sup>	
s.t.	$\sum_{k\in K} z_{ik} = 1$		$\forall i \in I$	s.t.	$\sum_{p\in\Omega}\bar{z}_i^p\cdot y^p=1$	$\forall i \in I \ \lambda_i$	
	$\sum_{i\in I} d_i z_{ik} \leq$	$C \cdot I_k$	$\forall k \in K$				
	$\sum_{k\in K} l_k \le  B $	'			$\sum_{p\in\Omega}\overline{l}^p\cdot y^p\leq  E $	3  <i>η</i>	
	$b_k \leq l_k$ $b_k, l_k \in \mathbb{Z}_+$		$orall k \in K$ $orall k \in K$		$y^{p} \in \mathbb{B}$	$orall p\in \Omega$	
	$z_{ij} \in \{0,1\}$	$\forall i \in I$	$,\forall k\in K$				

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			BPP-IF	mod	els		
Cha	in-based n	nodel		Chai form	n-based exter ulation (MP)	nded	
min	$\sum_{k\in K} l_k - b_k$			min	$\sum_{p\in\Omega,i\in I} (\bar{l}^p - 1)$	• <i>y</i> <sup><i>p</i></sup>	
s.t.	$\sum_{k\in K} z_{ik} = 1$		$\forall i \in I$	s.t.	$\sum_{p\in\Omega}\bar{z}_i^p\cdot y^p=1$	$\forall i \in I \ \lambda_i$	
	$\sum_{i\in I} d_i z_{ik} \leq$	$C \cdot l_k$	$\forall k \in K$				
	$\sum_{k\in K} l_k \le  B $	8			$\sum_{p \in \Omega} \bar{l}^p \cdot y^p \le  B $	3  η	
	$b_k \leq l_k$ $b_k, l_k \in \mathbb{Z}_+$		$orall k \in K$ $orall k \in K$		$0 \le y^p \le 1$	$orall p\in \Omega$	
	$z_{ij} \in \{0,1\}$	$\forall i \in I$	$\forall k \in K$				

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# Column generation (C)

The reduced cost of a variable  $y^p$  is:

$$\bar{c}^{p} = (\bar{l}^{p} - 1) - \sum_{i \in l} \lambda_{i} \cdot \bar{z}_{i}^{p} + \bar{l}^{p} \cdot \eta$$
$$\rightarrow \bar{c}^{p} = -1 + (1 + \eta) \cdot \bar{l}^{p} - \sum \lambda_{i} \cdot \bar{z}_{i}^{p}$$

and a pattern is feasible if

$$egin{aligned} &\sum_{i\in I} d_i\cdotar{z}_i^p \leq C\cdotar{l}^p\ &ar{z}_i^p\in\{0,1\} &orall i\in I\ &ar{l}^p\in\mathbb{Z}_+ \end{aligned}$$

#### Observation

When  $\overline{I}^p$  is fixed, the pricing problem is a 0–1 Knapsack Problem (KP)

 $\rightarrow$  a Variable Size 0–1 Knapsack Problem (VSKP)



# Pricing algorithm

#### Observation

The VSKP can be solved in pseudo-linear time.

#### Exact algorithm:

- let *U* (resp. *L*) be an upper (resp. lower) bound on the length of a chain;
- sort *I* ;
- let f(n, c) be opt. KP subproblem solution;
- compute  $f(|I|, U \cdot C)$  using KP Dynamic Programming recursion;
- for  $\ell = L \dots U$  set  $\pi_\ell = (1 + \eta) \cdot \overline{I}^p f(|I|, C \cdot \ell);$
- select  $\overline{I}^p = \operatorname{argmin}_{\ell=L...U} \pi_{\ell}$ ;
- select  $\bar{z}_i^p$  accordingly.

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# Exact Algortihm (C)

Tree search simplifies as well:

- elect *leading items*, one for each chain;
- fix/forbid assignments to specific chains;
- leading items make chains asymmetric.

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# Experimental setting

Implementation:

- Algorithms coded in C++
- SCIP 3 as framework for branch-and-price
- IBM ILOG CPLEX 12.3 for LP subproblems
- Hardware: 3.0GHz CPU, 4GB RAM

Dataset 0: industrial instances. Competitors:

- IBM ILOG CPLEX 12.3 ILP Solver
- Exact Algo (Nat)
- Exact Algo (Chain)



# Overall comparison

- Dataset 1 (180 instances, different size distrib., different available cap.)
- Number of inst. solved to proven optimality within 1h CPU time (fm):

11	CPLEX (N)	CPLEX (C)	Exact Algo (N)	Exact Algo (C)
10	56	60	60	60
50	37	58	57	60
100	20	33	36	60

• Number of inst. solved to proven optimality within 1h CPU time (bm):

I	CPLEX (N)	CPLEX (C)	Exact Algo (C)
10	11	15	60
50	10	10	60
100	0	4	60

• Exact Algo (C) computing time: always less than 1 minute.



#### Stress test

Dataset 2 (360 instances, different size distrib., different available cap.) Bin Minimization





Main conclusions:

- branch-and-price much more effective than CPLEX
- fragmentation minimization harder than bin minimization
- 1%C size increasing yields up to 4% cost increase in our (bm) instances (and scales linearly)
- for branch-and-price size increasing is not substantially harder to handle

In BPPIFs, be ready to pay an additional computing effort at a pricing stage, but avoid fractional decisions at a master stage.



# Follow-up

#### Lately we:

- extended to variable size and cost packing
- applied similar ideas to bike sharing systems

#### Currently

Research on shortest path problems for hybrid vehicles.