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Abstract

This paper introduces a bi-objective winner-determination problem and presents a multiobjective genetic algorithm to solve it. The problem examined arises in the procurement of transportation contracts via combinatorial auctions. It is modeled as an extension to the set-covering problem and considers the minimization of the total procurement costs and the maximization of the service-quality level of the execution of all transportation contracts tendered. To solve the problem, a multiobjective genetic algorithm is used. Different operators for population initialization, mutation and repair are applied. Eight variants of the algorithm are tested using a set of 30 new benchmark instances. The results indicate that the quality of a solution depends largely on the initialization heuristic and suggest also that a well-balanced combination of different operators is crucial to obtain good solutions.

Keywords: bi-objective winner-determination problem; multiobjective genetic algorithm; combinatorial auction

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1 Procurement of Transportation Contracts

Retailers as well as industrial enterprises often procure the transportation services they require via reverse auctions, where the objects under auction are *transportation contracts*. Usually, such contracts are designed as framework agreements lasting for a period of one to three years, and defining a pick-up location, a delivery location, and the type and volume of goods that are to be transported between both locations. Additionally, further details such as a contract-execution frequency, e.g. delivery twice a week, and the required quality of service, e.g. an on-time delivery quota, are specified in a transportation contract. A carrier can bid for one or more contracts. In each bid, the carrier states how much he wants to be paid for accepting the contract.

In the scenario presented here there are a number of interesting problems on the carrier's as well as on the shipper's side. This paper focuses on the allocation problem that has to be solved by the shipper after all bids are submitted.

In particular, two characteristics of the given scenario are of interest. *First*, from a carrier's point of view, there are complementarities between some of the contracts. That is, the costs for executing some contracts simultaneously are lower than the sum of the costs of executing each of these contracts in isolation.

Second, allocation of contracts to carriers has to be done taking into account multiple, often conflicting decision criteria. While some of the criteria (e.g. limiting the total number of carriers employed) may be naturally expressed as side constraints, other criteria should be considered explicitly as objectives. In particular, there is usually a trade-off between the classical cost-minimization goal on the one hand and the desire for high service-quality on the other. Both objectives are of almost equal importance to most shippers, cf. Caplice and Sheffi [3] and Sheffi [14].

In order to exploit potential synergies between contracts in the bidding process, the use of so-called combinatorial auctions is increasingly recommended [1], [2], [14]. Combinatorial auctions allow carriers to submit bids on any subset of all tendered contracts ("bundle bids"). Through this, carriers can express their preferences more extensively than in classical auction formats. However, bundle bidding complicates the selection of winning bids. This problem is known as the winner-determination problem (WDP) of combinatorial auctions. In the procurement context, the WDP is usually modeled as a variant of a set-partitioning or set-covering problem, both of which are NP-hard combinatorial optimization problems. For a survey see e.g. [1].

As to the multiple-criteria property of the allocation problem, there are two ways by which most shippers solve the conflict between cost and quality goals:

One way is to restrict participation in the auction to those carriers that comply with the minimum quality standard required to meet the quality demands of any of the contracts. Thus, the quality performance of all remaining carriers is considered equal, and the only objective is to minimize total procurement costs. Unfortunately, unless the contract requirements are fairly homogenous, this approach leads to the quality requirements of many contracts beeing exceeded. The second way is to take into account quality-performance differences between carriers by applying penalties or bonuses to the bundle-bid prices, depending on a carrier's quality performance in previous periods.

This paper focuses on a third alternative, which integrates quality and cost criteria by explicitly modeling the WDP as a bi-objective optimization problem. This model extends a previous model presented in [2], which can be seen as a special case of the model presented in this paper.

Previous work does not generally focus on modeling and solving winner-determination problems under explicit consideration of multiple objectives. Different kinds of winner-determination problems in combinatorial auctions for transportation contracts are treated in [4], [6], [10], [14], [15]. All these studies focus on bundle bidding to exploit complementarities between contracts and consider minimization of total procurement costs to be the only objective.

The structure of the remaining paper is as follows: section two defines the bi-objective winner-determination model that is being studied. To solve instances of this model, a bi-objective evolutionary algorithm based on the algorithm SPEA2 developed by Zitzler et al. [16], [17] is introduced in chapter three and tested on new benchmark instances in chapter four. Finally, section five gives an outlook on planned future work.

2 A Bi-Objective Winner-Determination Problem (2WDP-SC)

The Winner-Determination Problem (WDP) of a combinatorial procurement auction with two objectives is a generalization of the well-known Set-Covering Problem (SC). Hence the problem at hand is called

2WDP-SC. It is formulated as follows:

Given are a set of transport contracts T. Let t denote a transport contract with $t \in T$; a set of bundle bids B where a bundle bid $b \in B$ is defined as 3-tuple $b := (c, \tau, p)$. This means a carrier c is willing to execute the subset of transport contracts τ at a price of p. Given is furthermore a set $Q := \{q_{ct} | \forall c \in C \wedge \forall t \in T\}$ where q_{ct} indicates the quality level by which carrier c fulfills the transport contract t.

The task is to find a set of winning bids $W \subseteq B$, such that every transport contract t is covered by at least one bid b. Furthermore the total procurement costs, expressed in objective function f_1, are to be minimized and the total service quality, expressed in objective function f_2, is to be maximized. The 2WDP-SC is modelled as follows:

$$min f_1(W) = \sum_{b \in W} p(b) \tag{1}$$

$$max f_2(W) = \sum_{t \in T} max\{q_{ct} | c \in \{c(b) | b \in W \wedge t \in \tau(b)\}\} \tag{2}$$

$$\text{s.t.} \bigcup_{b \in W} \tau(b) = T \tag{3}$$

Each transport contract t has to be chosen at least once (3). Accordingly, some contracts may be covered by two or more winning bids. In the scenario at hand this is possible, as it appears reasonable to assume free disposal [13]. In the transportation-procurement context, free disposal means that a carrier has no disadvantage if he is asked by the shipper to execute fewer contracts than he was paid for.

The first objective function (1) minimizes the total cost of the winning bids. The second objective function (2) maximizes the total service-quality level of all transport contracts. Note that $\{c(b) | b \in W \wedge t \in \tau(b)\}$ is the set of carriers who have won a bid on transport contract t. Since contracts need to be executed only once, but may be part of more than one winning bid, it is not appropriate to simply add up the respective qualification values of all $b \in W$. Instead, it appears reasonable to assume that the shipper will break ties in favor of the bidder who offers the highest service level for a given contract. Hence, by assumption, for each transport contract t only the maximum qualification values q_{ct} with $c \in \{c(b) | b \in W \wedge t \in \tau(b)\}$ are added up. Note that this rule might introduce an incentive for the carriers towards undesired strategic-bidding behavior. As this paper does not focus on auction-mechanism design, we leave this issue to forthcoming research.

To solve the 2WDP-SC, the next section presents a genetic algorithm.

3 A Bi-Objective Algorithm based on SPEA2

The algorithm introduced follows a Pareto optimization approach, i.e., both objectives are optimized simultaneously and thus there is no need to weight the two objectives. So the shipper does not have to quantify his preferences for both objectives, which can be a challenge [14]. The algorithm finds a set of non-dominated solutions; the shipper finally has to choose a solution from this set according to his subjective preferences. The latter is outside the scope of this study. In the following, for notational convenience, the 2WDP-SC is treated as a pure minimization problem.

To solve the 2WDP-SC a multiobjective genetic algorithm (MOGA) is applied. This approach has been proven suitable for solving hard combinatorial optimization problems. The proposed MOGA follows the Pareto approach and searches for a set of non- dominated solutions. Finally, the shipper has to choose a solution from this set according to his subjective preferences.

At first, the underlying terminology is defined (cf. e.g. [18]): The set of all feasible solutions of an optimization problem is denoted by $\mathbf{X}$, the set of all objective vectors of these solutions is denoted as $\mathbf{Z}$. A solution $\mathbf{x^1} \in \mathbf{X}$ dominates a solution $\mathbf{x^2} \in \mathbf{X}$, if the objective vector $\mathbf{z^1} = \mathbf{f}(\mathbf{x^1})$ dominates the objective vector $\mathbf{z^2} = \mathbf{f}(\mathbf{x^2})$. $\mathbf{z^1}$ dominates $\mathbf{z^2}$ (written $\mathbf{z^1} \prec \mathbf{z^2}$), if and only if no component of $\mathbf{z^1}$ is larger and at least one component of $\mathbf{z^1}$ is smaller than the corresponding component of $\mathbf{z^2}$. A solution $\mathbf{x}^*$ is called *pareto optimal* if there is no $\mathbf{x} \in \mathbf{X}$ that dominates $\mathbf{x}^*$. The set of all pareto optimal solutions is called *pareto set* Ω^*. The goal of a MOGA is to find a close approximation of Ω^* and therefore a set of solutions Ω is called a *(pareto) approximation set*, if every solution in Ω is not dominated by any other solution in Ω.

To find a pareto approximation set, a MOGA controls a set of core heuristics. The core heuristics of a MOGA can be divided into problem-specific and problem-unspecific operators. For the problem-unspecific operators (fitness-assignment strategy, selection of parents and insertion of children in the population), the methods proposed by Zitzler et al. in their Strength Pareto Evolutionary Algorithm 2 (SPEA2) are applied. The decision to use SPEA2 relies on its competitive performance particularly for solving bi-objective combinatorial optimization problems, which is the case for the 2WDP-SC in question [16], [17].

As problem-specific operators, three core heuristics are introduced: *Remove If Feasible*, *Simple Insert* and *Greedy Randomized Construction*. Remove If Feasible is applied as mutation operator, whereas Simple Insert and Greedy Randomized Construction are both used to initialize a population as well as to repair an infeasible solution.

Since all three core heuristics operate on encoded individuals, the chosen encoding is presented first. A binary encoding of a solution seems suitable for set-covering-based problems like the 2WDP-SC. Every gene represents a bundle bid b. If $b \in W$ the gene value is 1, and if $b \notin W$ the gene value is 0.

Simple Insert (SI) randomly determines in each iteration a bundle bid b on a till-now uncovered transportation contract as a winning bid. The transport contracts τ_b in bid b are marked as covered. These steps are repeated until all contracts T are covered and SI terminates.

Greedy Randomized Construction (GRC) is inspired by the construction phase of the metaheuristic GRASP [8] and is slightly adapted for the bi-objective case (see Algorithm 1). During each iteration, a winning bid is selected randomly from the restricted-candidate list (RCL).

Algorithm 1 GreedyRandomizedConstruction (GRC)

input: infeasible solution W
while W infeasible **do**
  best bundle approximation set $RCL \leftarrow \{\}$
  for all $b \in B \backslash W$ **do**
    if b not dominated by any $b' \in RCL$ **then**
      $RCL \leftarrow RCL \cup \{b\}$
    end if
  end for
  randomly chose a b from RCL
  $W \leftarrow W \cup \{b\}$
end while
output: feasible solution W

Note that the RCL is an approximation set of best bundles, which holds only non-dominated bundles with respect to the rating function $g := (g^p, g^q)$ with

$$g^p(b,W) = p(b)/|\tau(b) \setminus \tau(W)| \text{ for } |\tau(b) \setminus \tau(W)| > 0, \text{ else } g^p(b,W) := \infty,$$
$$g^q(b,W) = (f_2(W) - f_2(W \cup b))/\sum_{b' \in W \cup b} |\tau(b')|.$$

Both functions assign smaller values to better bundles. g^p divides the costs $p(b)$ of bundle bid b by the number of new contracts in b. g^q divides the decrease of f_2 with an additional bid by the total number of procured contracts.

Remove If Feasible (RIF) randomly chooses a winning bid $b' \in W$, labels b' as visited and removes b'

from W. If after this the solution W is still feasible, then another randomly chosen winning bid (which is also labeled as visited) is removed etc. If W becomes infeasible by removing b', then b' is reinserted in W. RIF terminates if all winning bids are labeled as visited.

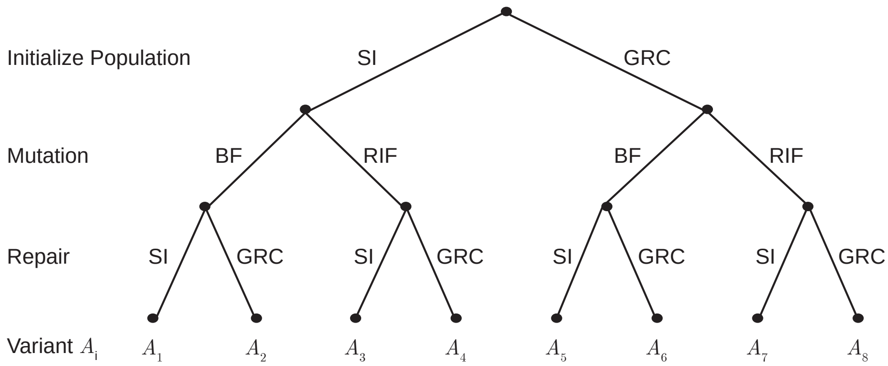


Figure 1: Eight possible combinations of core heuristics to form an algorithm $\mathscr{A}_i$

Via combination of the core heuristics a set of different algorithms $\mathscr{A}$ is obtained (see Fig. 1). Each algorithm $\mathscr{A}_i \in \mathscr{A}, i = 1...8$ is denoted as a 3-tuple, e.g. $\mathscr{A}_2$ is represented by (SI/BF/GRC) which reads as follows: $\mathscr{A}_2$ uses SI to construct solutions, BF as mutation operator and GRC as repair operator. In order to refer to a set of algorithms, the wildcard $*$ is used at one or more positions, e.g. (*/BF/GRC) identifies $\mathscr{A}_2$ and $\mathscr{A}_6$.

4 Evaluation

The eight proposed MOGA variants are tested on a set of 30 benchmark instances. Before the results are presented, the generation of these instances is described.

4.1 Generating Test Instances

To the best of our knowledge, no benchmark instances exist for a multiobjective WDP like the proposed 2WDP-SC. However, there are several approaches for generating problem instances for single-objective winner-determination problems with various economical backgrounds, e.g. the combinatorial auction test suite "CATS" of Leyton-Brown and Shoham [11] or the bidgraph algorithm introduced by Hudson and Sandholm [9]. To generate test instances for the 2WDP-SC, some ideas of the literatur are extended to incorporate features specific to the procurement of transportation contracts.

First of all, it is assumed that carriers reveal their true preferences. Then no strategic bidding behaviour has to be taken into account and the terms ”price” and ”valuation” of a contract combination can be used synonymical. General requirements of artificial instances for combinatorial auctions are stated by Leyton-Brown and Shoham. Both postulations seem self-evident, but have not allways be accounted for in the past [11]:

- Some combinations of contracts are more frequently bid on than other combinations. This is due to usually different synergies between contracts.
- The charged price of a bundle-bid depends on the contracts in this bundle-bid. Simple random prices, e.g. drawn from [0,1] are unrealistic and can lead to computational easy instances.

In addtion to those general requirements, it seems reasonable to demand that the following assumptions specific to transportation procurement auctions are valid:

- All submitted bids are mandatory and exhibit additive valuations (OR-bids, cf. [12]). Hence, a carrier is supposed to be able to execute any combination of his submitted bids at expenses which do not exceed the sum of the corresponding bid prices. Extra costs do not arise. Due to the medium-term contract period of one to three years in the scenario at hand capacity adjustments are possible in order to avoid capacity bottlenecks. Furthermore, the carrier has the opportunity to resell some contracts to other carriers who guarantee the same quality of service.
- From the previous assumption it follows that a rational carrier c does only bid on combinations of contracts which exhibit a *strictly subadditive valuation*. The valuation of a set of contracts τ is called strictly subadditive, if for each partition of set τ the valuation of τ is strictly lower than the sum of the valuations of all parts of the respective set partition. Formally this is expressed in (4), in which $\mathbf{P}(\tau)$ denotes the powerset of τ:

$$\forall \mathscr{T} \subseteq \mathbf{P}(\tau) : \bigcup_{\tau' \in \mathscr{T}} \tau' = \tau \wedge \bigcap_{\tau' \in \mathscr{T}} \tau' = \emptyset \wedge p^c(\tau) < \sum_{\tau' \in \mathscr{T}} p^c(\tau'). \tag{4}$$

  Strict subadditivity of a single bid is due to synergies between contracts. Bids composed of contracts which exhibit strict subadditive valuations are refered to as *essential* bids. Since all submitted bids are supposed to be OR-bids, any non-essential bid could always be replaced by an equivalent combination of two or more essential bids. Therefore, bidding on non-essential bids is redundant.

- The 2WDP-SC was modelled as a set covering problem, as it appeared reasonable to assume *free disposal*. Free disposal means, that the price charged by carrier c for a set of contracts τ is at least as high as the price carrier c would charge for any subset of τ. Formally this is expressed in (5), in which B^c denotes the set of bundle-bids submited by carrier c:

$$p(b') \leq p(b) \;\mid\; \forall \tau(b') \subseteq \tau(b) \wedge b, b' \in B^c. \tag{5}$$

  To be an appropriate instance of the 2WDP-SC, the bundle-bids of each carrier should also feature the free disposal property.

- Finally, it is assumed that the carrier-specific costs of a transport contract depend on both the contract's resource requirements and the service quality level at which the carrier is able to perform the contract.

The bids are generated using Algorithm 2, which takes four values as input: the number of bids to generate, b_max, the index sets C and T which represent carriers and transport contracts respectively, and the density of a synergy matrix ρ. The synergy matrix indicates the pairwise synergies between contracts. Synergies between contracts imply, that the respective contract combination is cost subadditive. A higher density tends to result in more and larger contract combinations a carrier has to consider.

Algorithm 2 BidGeneration

input: b_max, $T = \{1, \dots, t\_max\}$, $C = \{1, \dots, c\_max\}$, density of synergy matrix ρ
$\forall c \in C$: randomly set relevant contracts $T^c \subset T$, such that $\bigcup T^c = T$
$\forall c \in C$ and $\forall t \in T^c$: randomly set resource demand $r_{ct} \in [0.1, 0.5]$
for all carriers $c \in C$ **do**
    $\forall t \in T^c$: randomly set contract quality $q_{ct} \in \{1, 2, 3, 4, 5\}$
    $\forall i, j \in T^c$: set $s^c_{ij} \leftarrow 1$ with probability ρ, indicating that between contracts i and j exist synergies
    determine essential contract combinations Π
    subadditiveBidGraphAlgorithm(Π) to calculate prices $p(\tau), \tau \in \Pi$.
    $B^c \leftarrow select(\Pi)$
end for
output: all carrier bids $B = \bigcup_{c \in C} B^c$

First of all, *BidGeneration* (Algorithm 2) initializes and calculates some variables. For each carrier a subset of contracts T^c is determined as the set of contracts which the carrier is supposed to be willing to bid for. The service quality q_{ct} at which carrier c is able to execute contract t is chosen randomly from the integer values one to five, with higher values indicating a higher service level. Furthermore, to each contract a resource demand r_{ct} is assigned. This is an abstract indicator for the resources required by a carrier c to execute the contract t. The resource demand of a given contract may vary from carrier to carrier, as carriers might have, e.g. different locations of their depots, different types of vehicles or existing transportation commitments which influence the required ressources. The values r_{ct} are chosen randomly between 0.1 and 0.5. It is assumed that any number of contracts can be combined in a single bid, as long as the sum of the corresponding resource demands does not exceed a maximum total resource demand of 1.

To obtain the set of essential contract combinations in line 7, assume for each carrier c a synergy graph $SG^c = (T^c, E^c)$. Let the vertices be the contracts T^c carrier c is interested in. If two contracts $i \in T^c$ and $j \in T^c$ feature synergies, that is $s^c_{ij} = 1$, then both contracts are connected via an edge, that is $E^c = \{(i, j) | s^c_{ij} = 1 \wedge i, j \in T^c\}$. The resource demand of each contract $t \in T^c$ is given by r_{ct}. Then the set of feasible essential combinations of contracts equals the set of all possible induced subgraphs of SG^c with $\sum_t r_{ct} \leq 1$.

In the next step, a price for each combination of contracts is determined using the *SubadditiveBidGraph* algorithm, which is explained below. After that the *select* operator choses among all feasible contract combinations those combinations on which each carrier is supposed to place his bids. For this, all contract combinations in Π are rated according to two criteria: cost per contract $p(b)/|\tau(b)|$ and quality per contract $\sum_{t \in \tau(b)} q_{c(b)t} / |\tau(b)|$. Then, the best contract combinations with respect to these criteria are selected according to the dominance concept. In doing so, *select* makes sure that on the one hand, the total number of bids submitted by all bidders is *b_max*, and on the other hand, each $t \in T_c$ is covered by at least one bundle bid to obtain a solvable instance.

The *SubadditiveBidGraph* algorithm (cf. Algoirthms 3, 5 and 6) is applied to determine prices for the essential contract combinations which comply with the assumptions of free disposal and strict subadditivity. The SubadditiveBidGraph algorithm applied here is based on the approach of Hudson and Sandholm [9] which generates bids with free disposal. The approach is extended, so that it generates bids with strictly subadditive valuations, too.

The idea of the original bidgraph algorithm as proposed by Hudson and Sandholm is to define lower bounds $LB(\tau)$ and upper bounds $UB(\tau)$ for each considered contract combination τ such that free disposal holds. Then the procedure successively draws a price for each contract combination between its lower and upper bounds; this price is propagated through the bidgraph to sharp the lower and upper bounds of the

Algorithm 3 SubadditiveBidGraph

```
1: input: set of essential contract combinations Π, service quality Q
2: A^sup ← {(i, j)|i, j ∈ Π and i ⊂ j}
3: A^sub ← {(i, j)|i, j ∈ Π and i ⊃ j}
4: initialize bidgraph BG ← (Π,A^sup,A^sub)
5: ∀τ ∈ Π with |τ| > 1: UB(τ) ← LB(τ) ← p(τ) ← ∅
6: ∀τ ∈ Π with |τ| = 1: UB(τ) ← LB(τ) ← p(τ) ← RandomBasePrice(τ, Q)
7: initialize lower bounds: ∀τ ∈ Π with |τ| = 1: UpdateLowerBounds(BG, τ)
8: initialize upper bounds: ∀τ ∈ Π with |τ| > 1: UB(τ) = ∑_{t∈τ} p(t)
9: k ← 2
10: while k ≤ |Π| do
11:    for all τ ∈ {τ ∈ Π|p(τ) = ∅ and |τ| = k} do
12:       set price randomly LB(τ)←UB(τ)← p(τ) ∈ ]LB(τ), UB(τ)[
13:       UpdateLowerBounds(BG, τ)
14:       UpdateUpperBounds(BG, τ)
15:    end for
16:    k ← k + 1
17: end while
18: output: prices p(τ) for each τ ∈ Π consistent to the free disposal and the subadditivity assumption
```

remaining contract combinations.

In order to extend this approach to support contract combinations which exhibit free disposal as well as strictly subadditive valuations, the bidgraph is initialized as follows. The vertices of the bidgraph BG represent all essential contract combinations Π. There are two sets of arcs, A^{sup} and A^{sub}. The arcs in A^{sup} indicate a superset relation, i.e., an arc from vertex i to j means that the contracts in j are a superset of the contracts in i. Similarly, the arcs in A^{sub} represent all subset relationships.

In line 5 through 8 of Algorithm 3, the lower and upper bounds of all k-combinations of contracts are initialized. For a given $k \in \mathbb{N}$, let the set of all k-combinations of contracts be defined as $\{\tau \in \Pi : |\tau| = k\}$. The lower bounds LB of the 1-combinations of contracts are initialized by Algorithm 4. The price $p(t)$of a single contract t is a random variable which is normal distributed with mean *my* and variance $sigma^2$. The values of $p(t)$ are forced into the intervall $[minPrice, maxPrice]$ with $minPrice = 0.5$ and $maxPrice = 1.5$. As stated above, higher resource requirements and a higher service level should tend to result in a higher price. Thus, *mu* depends on the resource demand r_{ct} and the service quality q_{ct} of contract t. *Sigma* is defined as 1.0.

After *RandomBasePrice* (Algorithm 4) has initilized the *LB* of a 1-combination, Algorithm 5 propagates this price recursively through the bidgraph and updates the lower bounds of all superset contract combina-

Algorithm 4 RandomBasePrice

input: t, r_{ct}, q_{ct}
minPrice $\leftarrow 0.5$
maxPrice $\leftarrow 1.5$
ressources_multiplier $\leftarrow r_{ct}/0.3$
qualification_multiplier $\leftarrow q_{ct}/3$
my $\leftarrow$ 1.0 * ressources_multiplier * qualification_multiplier
sigma $\leftarrow 1.0$
$p(t) \leftarrow$ normal distributed random variable with mean *my* and variance $sigma^2$
if $p(t) > maxPrice$ OR $p(t) < minPrice$ **then**
    RandomBasePrice(t, r_{ct}, q_{ct})
end if
output: p

tions, if necesseray. By now, the upper bounds for the k-combinations, $k > 1$, can be calculated as the sum of the prices of all respective 1-combination contracts.

Now the bidgraph is initialzied properly. The drawing of random prices between the upper and lower bounds as well as the price propagation can start. To ensure strictly subadditive valuations, the while-loop of Algorithm 3 processes in each iteration the k-combinations of contracts starting with $k = 2$ and increasing k in each iteration. For all k-combinations with an $LB(\tau) \neq UB(\tau)$ a price is drawn randomly between $LB(\tau)$ and $UB(\tau)$. The price is propagated through the bidgraph to adjust the lower and upper bounds of the other contract combinations. To ensure the stict subadditivy property and to find a tighter upper bound, Algorithm 6 has to solve a set partioining problem to optimality. Without this, the UB(τ) might be higher than the costs of the optimal set partitioning solution which may lead to inconsistency of the prices according to the assumption of strictly subadditive valuations. The instance of the set partitioning problem is given by the sets $\{j|(\tau, j) \in A^{sub}\}$ and the associated costs $UB(j)$.

Algorithm 5 UpdateLowerBounds

input: BG, τ
for all $\tau' \in BG.\Pi|(\tau, \tau') \in BG.A^{sup}$ **do**
    if $LB(\tau') < p(\tau)$ **then**
        $LB(\tau') \leftarrow p(\tau)$
        UpdateLowerBounds(BG, τ')
    end if
end for

The *BidGraphAlgorithm* continues until all prices of all contract combinations are initialized. After that, the *select*-Operator of Algorithm 2 is applied as described above. The procedure keeps generating bids for

Algorithm 6 UpdateUpperBounds

```
input: BG, τ
for all τ' ∈ BG.Π|(τ, τ') ∈ BG.A^sup do
    p* ← price of optimal set partitioning solution to {τ'|(τ, τ') ∈ BG.A^sub} and associated UB(τ')
    if p* < UB(τ') then
        UB(τ') ← p*
        UpdateUpperBounds(BG, τ')
    end if
end for
```

for all carriers, until the test instance is complete.

The size of an instance depends on the number of bids (500 to 2000), the number of contracts (125 to 500) and the number of carriers (25 to 100). In addition, the density ρ of the synergy matrix was varied (25% to 75%). With respect to the observation that auctions with fewer transport contracts usually tend to attract fewer bidders, it appeared reasonable to restrict the combinations of instance parameter values to those shown in Tab. 2.

4.2 Results and Discussion

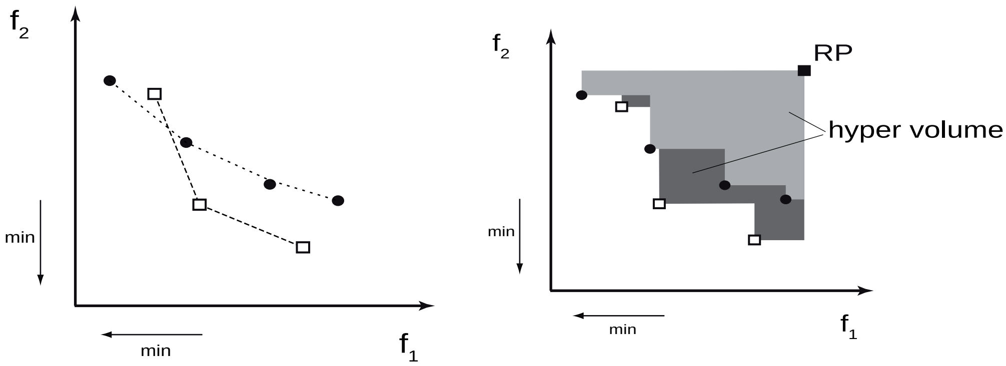
The algorithms were tested on an Intel Pentium 4 650 (3,4 GHz). The problem-specific heuristics were coded in Java 6; for the problem-independent parts the SPEA2 distribution coded in C was used [7].

The parameter-values were derived by some preliminary testing. Two to five alternative values for each parameter were tested on three randomly selected instances. The values that gave the best results in manageable time are those presented in Tab. 1. These values were constant for all runs on all test instances.

Table 1: Chosen parametervalues for the test

Parameter	**Value**
size of population	50 individuals
uniform crossover-probability	15%
bit-exchange-probability in uniform-crossover	50%
mutation-probability	100%
bitflip-probability	10%
runtime	300 seconds
no. of parents μ for creating λ offsprings	4
no. of offsprings λ generated by μ parents	4

To evaluate the solution quality of the algorithms, the respective approximation sets are compared. Often there are no clear dominance relations between approximation sets, see e.g. Fig. 2. Therefore the quality of an approximation set Ω is measured by the *hypervolume indicator* I_{HV} (cf. [18] for an intensive discussion of I_{HV} and other quality indicators). I_{HV} measures the dominated subspace of an approximation set, bounded by a reference point *RP*. *RP* must be chosen such that it is dominated by all solutions of the approximation sets. For each instance, *RP* is defined as $(f_1^{max}; f_2^{max}) = (f_1(B); 0)$ (note: $-f_2$ has to be minimized). Furthermore, the objective values of all solutions in the approximation sets are normalized according to $f_i = (\overline{f}_i - f_i^{min})/(f_i^{max} - f_i^{min})$ with $i = 1, 2, f_1^{max} = f_1(B), f_2^{min} = f_2(B) - 1, f_2^{max} = 0$. Thus values of I_{HV} range from zero to one, and larger values indicate better approximation sets. However, as *RP* can be chosen freely to a large degree, I_{HV} is a interval-based measure.



(a) Solutions of two approximation sets found by two algorithms.

(b) The shaded areas of each algorithm depict the dominated subspace respectively. Note that the light-shaded area is overlapping the dark-shaded area in part.

Figure 2: Illustration of hypervolume indicator I_{HV}

The results for the hypervolume indicator are presented in Tab. 2. The last column indicates the best value of the reference approximation set $\overline{\Omega} = \bigcup_{A \in \mathscr{A}} \Omega^A$ found in each of five runs.

The results in Tab. 2 and Tab. 3 were statistically evaluated with the Kruskal-Wallis and the Mann-Whitney test. All statistical conclusions are stated at a significance level of 5%. With respect to the given test instances, the compared heuristics and the applied quality indicator, the following conclusions may be drawn.

– The probability distributions of the I_{HV} values of the eight algorithms differ significantly. The ranks given in Tab. 2 are derived by a systematic pairwise comparison of the hypervolume values using the the Kruskal-Wallis rank test.

– A_8 performs very well, as could be expected, since it incorporates three problem-specific heuristics.

Table 2: Comparison of I_{HV} for eight MOGA variants applied to the set of all 30 test instances (specified by columns 1 to 4). Stated is the best I_{HV} value obtained in five runs for each of the eight MOGA variants A_1 to A_8. All runs were terminated after 5 minutes (300 seconds).

$\|B\|$	$\|T\|$	$\|C\|$	ρ	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	$\overline{\Omega}$
500	125	25	.25	.8477	.8475	.8394	.8241	.8622	.8622	**.8886**	.8886	.9479
			.50	.8622	8617.	.8636	.8573	.8777	.8777	**.9032**	.9018	.9519
			.75	.8607	.8607	.8609	.8669	.8802	.8802	.8915	**.8937**	.9546
1000	125	25	.25	.9170	.9170	.8768	.8660	.9401	.9401	.9459	**.9462**	.9479
			.50	.9220	.9214	.8742	.8779	.9493	.9493	**.9519**	.9519	.9519
			.75	.9339	.9340	.9203	.9117	.9441	.9441	.9518	**.9546**	.9546
	250	25	.25	.8631	.8634	.8633	.8631	.8855	.8855	**.8967**	.8961	.8967
			.50	.8631	.8630	.8633	.8573	.8748	.8748	.8960	**.8966**	.8966
			.75	.8555	.8553	.8569	.8557	.8754	.8754	.8961	**.8964**	.8964
		50	.25	.8453	.8469	.8214	.8137	.8868	.8848	.8914	**.8914**	.8934
			.50	.8473	.8484	.8397	.8351	.8781	.8781	.8935	**.8940**	.8940
			.75	.8487	.8489	.8441	.8476	.8783	.8783	.8922	**.8949**	.8949
2000	125	25	.25	.9534	.9538	.8750	.8653	**.9714**	.9714	.9488	.9488	.9742
			.50	.9582	.9579	.8985	.8775	.9761	.9761	.9781	**.9781**	.9781
			.75	.9614	.9613	.9310	.9334	.9755	**.9754**	.9707	.9707	.9761
	250	25	.25	.9265	.9263	.9091	.8970	.9493	.9493	.9534	**.9538**	.9538
			.50	.9276	.9275	.9133	.9136	.9466	.9466	.9523	**.9524**	.9524
			.75	.9261	.9261	.9278	.9288	.9417	.9417	.9490	**.9513**	.9513
		50	.25	.9126	.9139	.8419	.8413	**.9457**	.9442	.9319	.9320	.9494
			.50	.9219	.9216	.8864	.8722	.9476	.9483	.9477	**.9484**	.9531
			.75	.9218	.9212	.8987	.8927	.9454	.9447	**.9505**	.9504	.9512
	500	25	.25	.8700	.8700	.8913	.8960	.8919	.8919	.9000	**.9000**	.9000
			.50	.8601	.8601	.8783	.8863	.8822	.8822	.8924	**.8924**	.8924
			.75	.8587	.8587	.8802	.8851	.8774	.8774	.8884	**.8917**	.8917
		50	.25	.8496	.8496	.8464	.8515	.8784	.8784	**.8886**	.8886	.8886
			.50	.8595	.8594	.8587	.8646	.8801	.8801	.8923	**.8940**	.8940
			.75	.8523	.8528	.8576	.8714	.8732	.8732	.8874	**.8891**	.8907
		100	.25	.8336	.8319	.8166	.8164	.8707	.8707	.8805	**.8805**	.8805
			.50	.8395	.8394	.8232	.8205	.8787	.8776	**.8814**	.8813	.8893
			.75	.8455	.8445	.8423	.8381	.8780	.8772	**.8892**	.8891	.8900
			rank	5.5	5.5	7.5	7.5	3.5	3.5	1.5	1.5	
			mean	.8848	.8848	.8699	.8676	.9081	.9079	.9160	.9166	
			standard dev.	.0405	.0405	.0308	.0310	.0378	.0378	.0311	.0311	
			10% quantile	.8455	.8466	.8372	.8237	.8747	.8747	.8883	.8886	
			25% quantile	.8496	.8496	.8441	.8476	.8780	.8776	.8914	.8917	
			75% quantile	.9219	.9216	.8913	.8863	.9457	.9447	.9490	.9504	
			90% quantile	.9359	.9360	.9138	.9117	.9515	.9515	.9524	.9539	

Table 3: Statistical comparision of selected sets of algorithms. The null hypothesis H_0 says that the hypervolume indicators of the approximation sets obtained by A_i and A_j have the same distribution. The significance level α of all rejections is 0.05. The Power is the probability of rejecting H_0 when H_1 is true.

No.	$\mathbf{A}_i$ **vs.**$\mathbf{A}_j$	$\mathbf{H}_0$	**Power(%)**
1	$(GRC/*/*)$ vs. $(SI/*/*)$	**reject**	$\leq$0.01
2	$(*/RIF/*)$ vs. $(*/BF/*)$	-	50.55
3	$(*/*/GRC)$ vs. $(*/*/SI)$	-	90.99
4	$(SI/BF/*)$ vs. $(SI/RIF/*)$	**reject**	$\leq$0.01
5	$(GRC/RIF/*)$ vs. $(GRC/BF/*)$	**reject**	$\leq$0.01
6	$(*/RIF/SI)$ vs. $(*/BF/SI)$	-	60.13
7	$(*/RIF/GRC)$ vs. $(*/BF/GRC)$	-	64.02
8	$(SI/*/GRC)$ vs. $(SI/*/SI))$	-	85.63
9	$(GRC/*/GRC)$ vs. $(GRC/*/SI)$	-	84.34
10	$(*/BF/GRC)$ vs. $(*/BF/SI)$	-	84.32
11	$(*/RIF/SI)$ vs. $(*/RIF/GRC)$	-	96.73

A_8 dominates all other algorithms but A_7. A_8 computes the best results for 18 out of 30 test instances, followed by A_7 which achieves the highest value 9 times (A_5 and A_6 score two and one best value, respectively).

- The variants A_1, A_2, A_3, A_4 which belong to the class (SI/*/*), never achieve a best value in any one of the instances (cf. Tab. 2).

- The impression that a weak initial population significantly compromises final solution quality even if more elaborate mutation and repair operators are used intensifies by considering test no. 1 in Tab. 3. The approximation sets derived by the class of algorithms which use GRC as initialization heuristic clearly outperform the class of algorithms which use SI as initialization heuristic. This is true even on a significance level of 0.001.

- From the fact that the overall performance strongly depends on the initialization heuristic, one can assume that any effort invested here will be rewarded.

- Tests 2 and 3 give no hints that the more intelligent operators RIF and GRC (applied in the repair phase) promise better results than BF and SI in the general case. On the contrary, in some cases the intelligent operator RIF even shows inferior results to BF (test 4). However, the performance of RIF significantly improves if it is applied to an intelligently initialized population (test 5).

– Tests 6 and 7 give evidence that the mutation operators BF and RIF do not show different behavior, even if the repair operator is changed. However, if RIF is applied successfully to an individual, then there is no need to apply any repair operator, as the operator leaves the individual feasible by definition.

– Interestingly, an influence of the repair heuristic on the performance of all algorithms is not observable (test 8-11). This result gets emphasized as we could not prove a significant performance advantage of A_8 over A_7 (both differ only in the applied repair operator). This followed from the Kruskal-Wallis-Test, which takes into account all 1200 observations (30 instances, 8 algo-rithms, 5 runs). However, statistics paint a different picture if only the 300 observations resulting from A_7 and A_8 are compared with a sign test. Then, A_8 clearly outperforms A_7. Hence, in well-balanced algorithms the repair operator may be of importance.

5 Conclusions and Outlook

A model for a bi-objective winner-determination problem based on a set-covering problem (2WDP-SC) was presented. To solve this model, the evolutionary algorithm SPEA2 was extended by a set of problem-specific evolutionary operators. The performance of these operators was evaluated on a set of new test instances. The results show a strong dependence on the performance of the algorithm to the quality of the initial population, the intelligent operators do not result in better solutions, in all cases: a well balanced composition of operators is crucial. As the performance depends strongly on a well-initialized population, we intend to test other evolutionary operators and compare the evolutionary approach for solving the 2WDP-SC to a neighborhood search approach.

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