

Using Implicit Bidding to Solve Truckload Procurement Auctions

Lead P.I. Amy Cohn

Industrial and Operations Engineering, University of Michigan, Ann Arbor

Co-P.I.'s: Damian Beil, Amitabh Sinha

Ross School of Business, University of Michigan, Ann Arbor

Others: Shervin AhmadBeygi, Richard L. Chen

Industrial and Operations Engineering, University of Michigan, Ann Arbor

Abstract: Studies have shown that the use of combinatorial auctions for truckload procurement consistently leads to more cost effective allocations of loads. Combinatorial bidding allows carriers to minimize cost by leveraging backhaul opportunities in their networks. However, the inherent complexities in solving combinatorial auctions have impeded wide adoption. These complexities are twofold: an exponential number of bids, and consequently, an exponentially-sized winner-determination problem. In this research, we introduce an *implicit bidding mechanism* to address these two complexities. First, we introduce an implicit bidding approach that eliminates exponential bidding. Next, we present a polynomial-sized network model for the winner determination problem. The model is then extended to allow for operational constraints such as carrier limitations and auctioneer preferences. Finally, we present computational results to demonstrate the tractability of our approach.

1. Problem statement: In 2007, US firms spent over \$739 billion in procuring freight transportation services. Of this, \$300 billion was accounted for by the truckload segment (American Trucking Association 2007). Therefore, reducing trucking expenditures can greatly reduce a shipper's cost of goods sold and improve profitability. Typically, shippers estimate the freight to be shipped in an upcoming year based on the prior year's shipments (Foster and Strasser 1991). In procuring truckload services, a shipper puts forth a request for quotes (RFQ) for a network of loads. Prior to the use of combinatorial auctions, carriers submitted quotes for individual loads in the RFQ. This is akin to a *single-item reverse auction*, where each item is awarded independently to the lowest-cost carrier. RFQ continues to be used today in the procurement of trucking services, but combinatorial auctions (in which multiple

loads can be bid on concurrently) are becoming more common, because they enable carriers to take advantage of economies of scale and scope.

In covering a set of loads, carriers must find efficient *continuous moves* to minimize empty mileage and downtime, and to return drivers to their domicile. Truckload carriers have non-additive cost functions: the cost to cover a load from A to B plus the cost to cover a load from B to A is not the same as the cost to cover both loads in one continuous move. We illustrate this example in Figure 1.

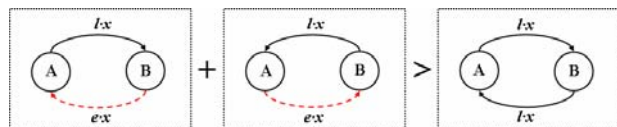


Figure 1: The network shown in this figure includes one load from A to B and one load from B to A. If x is the distance from A to B and l and e are loaded and empty costs per mile respectively, then the cost of serving the two individual loads separately is $2lx + 2ex$, while the cost of serving both loads in a single continuous move is only $2lx$.

In a traditional single-item auction, a carrier has no assurance of winning any combination of loads, so they must bid conservatively to ensure adequate payment for empty movements. In a combinatorial auction, carriers are assured of winning all loads in a given bundle (or none). Therefore, operational expenses can be greatly reduced by forming loads into continuous moves that minimize empty mileage. Combinatorial bidding allows carriers to optimize the usage of their existing load network, capacity, and business preferences.

However, two difficulties remain that impede the wide adoption of combinatorial auctions: *bid expression* and solving the *winner determination problem* (WDP). In bid expression, a carrier must price each bundle of interest by solving a minimum cost flow problem (more

detail in Section 3.3). In order to compute the bid price of a given bundle, a carrier must consider numerous cost components, such as its cost structure, existing load network, capacity, and the availability of the *spot market*. Computational difficulties are further magnified if a carrier is interested in submitting bids for all 2^n-1 combinations of loads, where n is the number of loads in the RFQ. Assuming the carrier is able to compute a bid price for all 2^n-1 bundles, communicating these bids to the auctioneer is also non-trivial. Further, assuming each carrier can communicate all bids efficiently, the auctioneer must still solve an exponentially-sized WDP to award bundles to bidders. Traditionally, WDP is formulated as a set partitioning problem, where each binary variable represents a distinct carrier-bid for a single bundle. This formulation is well known to be intractable for all but the smallest problem instances (Pekec and Rothkopf 2003).

1.1 Contributions and Outline: In this research, we present an *implicit bidding mechanism* for solving practical-size truckload procurement auctions. Specifically, our contributions are as follows:

- We present an implicit bidding mechanism for solving fully enumerated combinatorial auctions in a single round.
- We apply this implicit bidding mechanism to truckload procurement auctions. Further, we demonstrate the scalability of our approach by presenting computational results for random instances of varying size.
- We use mathematical programming to extend this approach to take into consideration carriers' and shipper's operational constraints.

The rest of the paper is organized as follows: in section 2, we discuss in detail existing methods for solving combinatorial auctions and applications. In section 3, we formally present the carrier's bundle-pricing problem, the implicit bidding mechanism, and an implicit winner determination problem (I-WDP). In section 4, we present computational results and model extensions for operational constraints. In section 5, we present conclusions and directions for future research.

2. Literature Review: There has been a significant amount of research in combinatorial auctions during the last decade, including much research on solution techniques for solving combinatorial truckload procurement auctions. Surveys of combinatorial auctions were presented by de Vries and Vohra (2003) and Pekec and Rothkopf (2003). A recent book by Cramton et al. (2006) presented a comprehensive review of combinatorial auction theory and applications in various domains.

The first obstacle faced by bidders in a combinatorial auction is bid expression, where a bidder must construct, price, and submit bids for all bundles of interest. In truckload procurement, pricing a bundle involves solving a minimum cost flow problem. In a combinatorial auction of n items, a bidder might potentially be interested in submitting bids for all 2^n-1 combinations. Even if a bidder can price each bundle efficiently, submitting bids for all combinations is not possible in most instances due to resource constraints on the part of the bidder and/or the auctioneer.

De Vries and Vohra (2003) suggested the use of an "oracle" to alleviate the bid communication problem. The auctioneer invokes the appropriate oracle at any stage of an auction to determine the bid for a particular bundle. Alternatively, an auctioneer may specify a bidding language (Nisan 2000) to be used by all bidders. These bidding languages specify various ways in which bids must be restricted and their consequences. Finally, the bid communication burden can also be eased by restricting the number of bids and biddable combinations (Rothkopf et al. 1998, Vries and Vohra 2003).

Assuming one can overcome the difficulties of bid expression; the auctioneer is still left with solving an exponentially-sized WDP. In combinatorial auctions, this is equivalent to the set partitioning problem on hypergraphs, a well-known, NP-complete problem (Rothkopf et al. 1998). The auctioneer must solve this set-partitioning problem to award bundles such that the total cost is minimized.

Numerous methods have been developed to cope with the computational difficulties of solving WDP. One strategy is to restrict the number of bids and biddable combinations (Pekec and Rothkopf 2003). Rothkopf et al. (1998) showed that WDP is computationally manageable if the bidding structure is restricted to yield special properties. Further, Rothkopf et al. (1998), Sandholm (2002), and De Vries and Vohra (2003) showed the problem to be solvable in polynomial time under severe bid restrictions. However, such restrictions on the number of bids and biddable combinations are undesirable, as they lead to the same economic inefficiencies as those found in non-combinatorial auctions.

Another strategy is to shift the computational burden to the bidders. Banks et al. (1989) and Bykowsky et al. (1995) proposed using an adaptive user-selection mechanism (AUSM), where non-winning bids are pooled together to form new combinations. Kelly and Steinberg (2000) proposed a Progressive Adaptive User Selection Environment (PAUSE) procedure for discrete-time auctions. PAUSE is a two-stage procedure where bidders evaluate and submit combinatorial bids subject to progressive eligibility and margin improvement requirements.

A third strategy is to use provably fast, but sub-optimal, algorithms and heuristics. Fujishima et al. (1999) presented a market-based approach, Virtual Simultaneous Auction (VSA), to determine an acceptable allocation. VSA generates virtual, simultaneous auction from bids submitted in a real combinatorial auction to find an efficient allocation in the real auction. However, the standard WDP is inapproximable (Sandholm 2002), and therefore, any fast algorithm cannot guarantee a solution even close to optimal. Worse yet, a sub-optimal allocation generally compromises the incentive properties of combinatorial auctions (Nisan and Ronen 2000, Sandholm 2002).

Applications for combinatorial auctions in practice run the gamut of fields, from school meal programs to wireless spectra auctions. Epstein et al. (2002) applied combinatorial auctions assigning catering contracts for school meals. Rassenti et al. (1982) and Ball et al. (2006) examined the use of combinatorial auctions for the allocation of airport landing and take-off time slots. Brewer and Plott (1996) described the use of combinatorial auctions for the allocation of railroad segments. Wireless spectra auctions were studied extensively by McMillan (1994), Cramton (1997, 2002), and Binmore and Klemperer (2002).

Combinatorial truckload auctions were surveyed by Sheffi (2004) and Caplice and Sheffi (2006), while Song and Regan (2003, 2004) as well as Raychaudhuri and Veeramani (2006) addressed carrier bidding strategies at each round of a multi-round transportation service procurement auction. Ledyard et al. (2002) described an early use of combinatorial auctions for the procurement of transportation services. Guo et al. (2005) extends the carrier assignment models used in winner determination to include shipper non-price objectives and carrier transit point costs.

3. Combinatorial Truckload Procurement Auction:

In this research, we consider a single-item, single-round combinatorial truckload procurement auction. The auction is conducted by a single shipper (auctioneer) and $\mathbf{K} = \{1, 2, \dots, K\}$ is the set of prospective carriers.

$\mathbf{L} = \{1, 2, \dots, L\}$ is the set of loads being auctioned. Bundles are subsets of items in $\mathbf{L}$ that carriers are interested in selling to the buyer at specific prices. The buyer's goal is to procure each item in $\mathbf{L}$ at the lowest total cost by selecting a subset of the submitted bundles.

Let carrier k 's bid price for bundle S be given by the solution of a *bid-generating function* (BGF), $f^k(S)$. In theory, a carrier might be interested in submitting bids for all $2^L - 1$ bundles. As such, each carrier must explicitly price all $2^L - 1$ bundles and efficiently communicate them to the auctioneer. Most computational difficulties encountered in combinatorial

auctions are rooted in this combinatorial explosion. In subsequent sections, we show that these difficulties can be avoided by imbedding BGF directly into WDP. In doing so, we avoid the need to explicitly enumerate and price all $2^L - 1$ bundles and, thus, side-step most computational and communication difficulties in a combinatorial auction. Furthermore, as we show in section 3.4, this imbedded winner determination problem (I-WDP) is a multi-commodity flow problem, which is well known to be tractable in practice, even for large instances.

3.1 Basic Combinatorial Auction: As mentioned earlier, the two hurdles of a combinatorial auction are bid expression/communication and solving the winner determination problem. In bid expression, each carrier k constructs, prices, and submits bids for bundles of items. In a fully-enumerated, combinatorial auction, each carrier provides valuations for all $2^L - 1$ items. The valuation for each bundle S is obtained by solving BGF. Carriers communicate all bundle prices to the auctioneer, who must then solve an exponentially-sized WDP to determine the optimal allocation of items in $\mathbf{L}$ such that the total cost is minimized. In a basic combinatorial auction, this is accomplished by solving the following mathematical program, T-WDP. The binary variable x_S^k is 1 if carrier k is awarded bundle S , and 0 otherwise.

$$\min \sum_{k \in \mathbf{K}} \sum_{S \subseteq \mathbf{L}} f^k(S) x_S^k \quad (1)$$

$$\text{s.t.} \sum_{k \in \mathbf{K}} \sum_{S \subseteq \mathbf{L}: l \in S} x_S^k = 1 \quad \forall l \in \mathbf{L} \quad (2)$$

$$x_S^k \in \{0, 1\} \quad \forall k \in \mathbf{K}, S \subseteq \mathbf{L} \quad (3)$$

3.2 An Implicit Bidding Mechanism: The source of computational and communication hurdles in a combinatorial auction is the exponential number of bundles that must be priced and communicated in T-WDP. In this research, we introduce an implicit bidding mechanism to circumvent these hurdles. Specifically, we apply this mechanism to solve fully enumerated truckload procurement auctions.

The main idea of implicit bidding stems from the insight that for combinatorial auctions, in certain domains, the price of a bundle is not exogenously endowed. We show that if BGF can be formulated as a computationally-tractable optimization problem then BGF can be imbedded directly into T-WDP, thus, avoiding the need for bidders to explicitly compute the price for each bundle and communicate these bids to the auctioneer. The resulting imbedded combinatorial

auction is often dramatically more tractable than a T-WDP.

In the following sections, we formalize BGF for truckload procurement auctions and the corresponding implicit winner determination problem (I-WDP).

3.3 Carrier's Bundle Pricing Problem: The crux of the implicit bidding mechanism relies on the existence of computationally efficient bid generating functions that can be directly embedded into T-WDP. In a combinatorial truckload procurement auction, given a bundle S , how does a carrier determine the bid for this bundle? The cost for servicing this bundle is the minimum-cost set of tours that covers all loads in the bundle. The cost to cover these loads depends on, among other things, the carrier's cost structure, domicile, existing loads, and the probability of finding connecting loads in the spot market.

In pricing bundle S , the carrier must account for two sets of service costs, direct and indirect. Given a load ($l \in S$), the direct cost of this load, d_l^k , is the cost of transporting load l from its origin to its destination. The indirect cost e_{ij}^k is the expected connection cost incurred for movement from the destination of current load l to the origin of the next load. Let $\mathbf{N}$ be the set of nodes, where a node is a load origin, a load destination, or both. Let the set O_n denotes the set of all loads with origin city n , where $n \in \mathbf{N}$. Similarly, let the set D_n denotes the set of all loads with destination city n , where $n \in \mathbf{N}$. Then the bid price for bundle S is the solution to the following minimum cost flow problem.

$$\min \sum_{l \in S} d_l^k x_l^k + \sum_{i \in \mathbf{N}} \sum_{j \in \mathbf{N}} e_{ij}^k y_{ij}^k \quad (4)$$

$$\text{s.t. } \sum_{l \in O_j} x_l^k + \sum_{i \in \mathbf{N}} y_{ji}^k + \sum_{i \in \mathbf{N}} z_{ji}^k = \sum_{l \in D_j} x_l^k + \sum_{i \in \mathbf{N}} y_{ij}^k + \sum_{i \in \mathbf{N}} z_{ij}^k \quad \forall j \in \mathbf{N} \quad (5)$$

$$0 \leq z_{ij}^k \leq c_{ij}^k \quad \forall i, j \in \mathbf{N} \quad (6)$$

$$0 \leq y_{ij}^k \leq \infty \quad \forall i, j \in \mathbf{N} \quad (7)$$

Here x_l^k is a parameter with value 1 if $l \in S$ and 0 otherwise. Variable y_{ij}^k represents the number of times carrier k moves empty from city i to city j as part of a continuous move. Variable z_{ij}^k represents the number of existing loads from city i to city j used as part of a

continuous move. The objective function (4) states that carrier k 's bid price for bundle S is the sum of direct and indirect costs of transporting loads in S . Constraint (5) states that for each city j in $\mathbf{N}$ the amount of flow into city j must be equal to the flow out of city j . Constraint (6) states that the number of existing load movements from city i to city j must not exceed the existing load capacity from city i to city j . We refer to the minimum cost flow problem described by (4)-(7) as BGF.

In T-WDP, each carrier must solve a separate instance of BGF for each bundle of interest. In an auction of $\mathbf{L}$ loads there are potentially $2^L - 1$ distinct bundles that a carrier might want to price. In practice, carriers price a limited number of bundles due to resource and time constraints. Because of these limitations, auctions in practice often result in sub-optimal allocation of loads. We next show that this limitation can be mitigated by directly embedding BGF into T-WDP.

3.4 Combinatorial Truckload Procurement Auction: In an implicit combinatorial truckload procurement auction, carriers submit their BGF, instead of submitting $2^L - 1$ bundle-price pairs. The auctioneer embeds these BGFs directly into T-WDP to obtain I-WDP.

I-WDP is based on the following notation. I-WDP has three sets of variables, x_l^k , y_{ij}^k and z_{ij}^k that generalize BGF as defined by (4)-(7). Whereas x_l^k is a parameter in BGF, in I-WDP, x_l^k is a binary variable with a value of 1 if load l in $\mathbf{L}$ is assigned to carrier k , and 0 otherwise. The variables z_{ij}^k and y_{ij}^k are as defined previously.

$$\min \sum_{k \in \mathbf{K}} \sum_{l \in \mathbf{L}} d_l^k x_l^k + \sum_{k \in \mathbf{K}} \sum_{i \in \mathbf{N}} \sum_{j \in \mathbf{N}} e_{ij}^k y_{ij}^k \quad (8)$$

$$\text{s.t. } \sum_{k \in \mathbf{K}} x_l^k = 1 \quad \forall l \in \mathbf{L} \quad (9)$$

$$\sum_{l \in O_j} x_l^k + \sum_{i \in \mathbf{N}} y_{ji}^k + \sum_{i \in \mathbf{N}} z_{ji}^k = \sum_{l \in D_j} x_l^k + \sum_{i \in \mathbf{N}} y_{ij}^k + \sum_{i \in \mathbf{N}} z_{ij}^k \quad \forall j \in \mathbf{N}, k \in \mathbf{K} \quad (10)$$

$$z_{ij}^k \leq c_{ij}^k \quad \forall i, j \in \mathbf{N}, k \in \mathbf{K} \quad (11)$$

$$y_{ij}^k, z_{ij}^k \in \mathbf{Z}^+ \quad \forall i, j \in \mathbf{N}, k \in \mathbf{K} \quad (12)$$

The objective function (8) minimizes the total load assignment cost. The first set of terms accounts for all loaded movement costs and the second set of terms

accounts for all connection costs between loads. This model leverages carriers' existing loads to find the minimum cost set of tours that cover all loads in $\mathbf{L}$. Constraint (9) states that each load must be assigned to exactly one carrier. Constraint (10) states that the amount of flow into and flow out city j ($j \in \mathbf{N}$) must be balanced. Constraint (10) also ensures that the solution is a set of tours. Note that I-WDP is a multi-commodity flow problem (Ahuja et al. 1993) with network structures that permit efficient solution.

4. Computational Experiments and Results: In the next two sections, we present computational results to quantify the performance of I-WDP.

4.1 Computational Setup: In this section, we demonstrate the tractability of I-WDP. All of the experiments were run on a Sun x4600-M2 with 8 AMD Opteron 8218 processors and 64 GB of RAM running Red Hat Enterprise Linux 4. Models and algorithms were coded using C++ and ILOG Concert Technology and solved using ILOG CPLEX 10.0.

We provide results for auctions of size 1000, 2000, and 5000 loads. For the nominal I-WDP, computation times reported for each set of auctions are averages of 100 randomly-generated instances. For each instance, the number of carriers is fixed at 50. Loads were generated across a network consisting of the 100 biggest cities in the United States. Each carrier's cost structure was also randomly generated. Line-haul movement cost was based on a randomly-generated loaded cost per mile using a Normal $(1.10, 0.05^2)$ random variate. A carrier's cost to service a given load is equal to the distance from load origin to load destination times the carrier's loaded cost per mile. Indirect movement is comprised of empty moves and existing load movements. While the cost of using an existing load in a continuous move is zero, the cost of an empty move is equal to the distance traveled times the carrier's empty cost per mile, which is randomly generated using a Normal $(0.80, 0.05^2)$ random variate. The number of existing loads for a carrier was uniformly generated to be between 5%-15% of the number of loads in the auction. Existing loads for each carrier were constructed by randomly selecting origin-destination pairs for the network of 100 cities.

4.2 Computational Results for Nominal I-WDP: In this section we report computation time characteristics for auctions with 1000, 2000, and 5000 bid loads. Note, that using T-WDP to solve fully enumerated instances of these sizes is not practical nor even possible. Solving a fully-enumerated truckload combinatorial auction with 1000 loads would require each carrier to submit approximately 10^{300} bundle-price pairs to the auctioneer. The auctioneer must in turn solve a T-WDP with

approximately $10^{300} \times 50$ binary variables, which is clearly intractable.

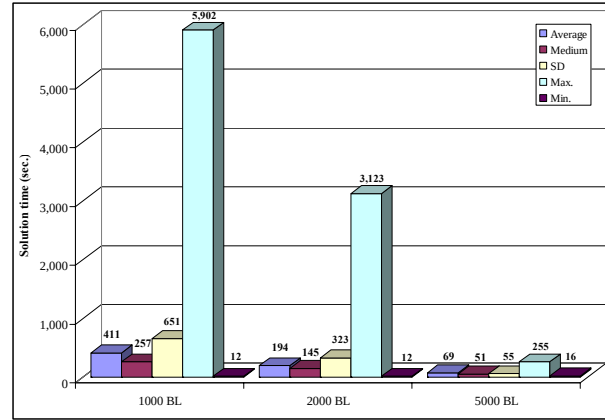


Figure 2: Computation time characteristics of the nominal I-WDP.

Our results show that using an implicit bidding approach to solve a 1000 load instance requires on average 411 seconds. Furthermore increasing the number of loads in the auction increases the tractability of the I-WDP. Average computation time decreases from 411 to 69 seconds as the number of loads in the auction is increased from 1000 to 5000 loads. The intuition is this: given a fixed-size network, an increase in the number of loads also increases the probability of finding cost-effective connections between loads. In this case, the problem becomes easier to solve as a greater proportion of the loads are trivially assigned to the lowest cost carrier.

4.3 Operational Constraints: In practice, it is often not sufficient to simply find the minimum cost set of tours such that all loads ($l \in \mathbf{L}$) are covered. Carriers and shippers may have other constraints and business preferences they would like to consider in such auctions. Below, we extend I-WDP to consider two of these operational constraints.

Number of winners: The shipper might want to award loads to no fewer than $i_{\min}$ carriers and to no more than $i_{\max}$ carriers, thus ensuring a manageable number of vendor relationships and an adequate spreading of risk. We can model such restrictions as follows, where the value of w^k is 1 if carrier k is awarded at least one load and 0 otherwise and $l_{\max}^k$ is the maximum number of loads carrier k can win. If the number of loads carrier k can win is unrestricted then $l_{\max}^k$ is equal to the number of bid loads.

$$w^k \leq \sum_{l \in L} x_l^k \leq l_{\max}^k w^k \quad \forall k \in \mathbf{K} \quad (13)$$

$$i_{\min} \leq \sum_{l \in L} w^k \leq i_{\max} \quad \forall k \in \mathbf{K} \quad (14)$$

Number of loads: The shipper and carrier can specify minimum and maximum numbers of loads that a carrier can be awarded. From a shipper's perspective, a minimum ensures that each carrier wins enough business to justify the cost of maintaining a shipper-carrier relationship. A maximum ensures that the risk of transporting loads is spread across many carriers. From carriers' perspectives, a minimum ensures they win at least a threshold volume, and a maximum ensures they win at most a number of load that they can manage. This can be modeled as follows, where $l_{\min}^k$ is the minimum number of loads carrier k must win (or nothing), and $l_{\max}^k$ is the maximum number of loads carrier k can win.

$$w^k \leq \sum_{l \in L} x_l^k \leq l_{\max}^k w^k \quad \forall k \in \mathbf{K} \quad (15)$$

$$l_{\min}^k w^k \leq \sum_{l \in L} x_l^k \leq l_{\max}^k w^k \quad \forall k \in \mathbf{K} \quad (16)$$

4.4 Computational Results for Constraint I-WDP:

Parameters for the constrained I-WDP experiments are generated similarly to those for the nominal I-WDP. We performed three sets of experiments corresponding to 1000, 2000, and 5000 bid loads. Each set of experiments consists of ten randomly generated instances. We perform four computational experiments on each of these instances. The four experiments are defined as follows: unconstrained (nominal instance), number of winners (nominal instance with constraints on the number of winners), number of loads (nominal instance with constraints on the number of loads) and both (nominal instance with constraints on both the number of winners and the number of loads). The number of winners is constraint to be between 10 (min) and 15 (max) inclusive. We limit the number of loads to be between 5 (min) and 40 (max) percent of the number of bid loads.

Similar to the results for nominal I-WDP, computation time decreases as the number of loads in the auction increases. In fact, results of our experiments show that auctions with 5000 bid loads and both sets of constraints active can be solve in approximately twenty minutes. This is in sharp contrast to the computation time (approximately seventeen hours) needed to solve auctions with 1000 bid loads and both sets of constraints active. Constraints on the number of carriers appear to

have limited impact on computation time. However, this result might be specific to the upper and lower bounds we have chosen. We are currently conducting additional experiments to assess the impact of these bounds on computation times. On the contrary, constraints on the number of loads per winner significantly increase computation time.

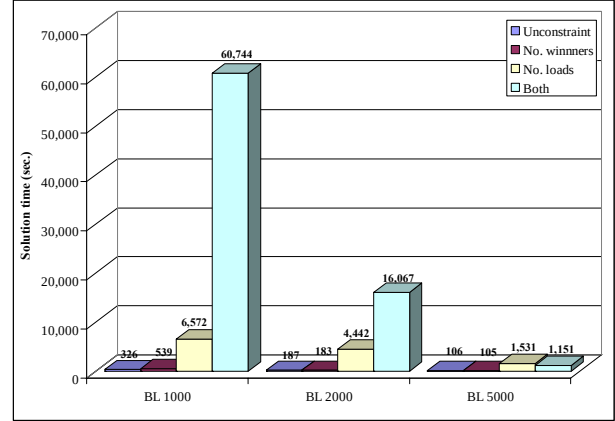


Figure 3: Comparison of computation times for constraint I-WDP.

Finally, adding constraints on both the number of winners and the number of loads dramatically increases computation time. However, despite these additional constraints, I-WDP remains tractable for practical-size problems. The most computationally difficult experiment, auctions with 1000 bid loads and both sets of constraints active, on average solved in less than twenty hours using default CPLEX solver settings and no preprocessing algorithms.

5. Concluding Remarks and Future Research: In this research, we introduce the implicit bidding mechanism to address limitations of combinatorial truckload procurement auctions (specifically, overcoming the challenges of exponential bid expression and winner determination). We show that these two problems can be addressed simultaneously by embedding the carriers' BGF directly into WDP. Using this mechanism, carriers convey BGFs directly to the auctioneer, thus avoiding the need to price and communicate an exponential number of bids and sidestepping the difficulties of bid expression.

We show that the carrier's BGF is a minimum flow cost problem, with parameters corresponding to both the direct cost of transporting loads and the indirect connection cost incurred during movements between loads. Next, we show that by embedding carriers' BGFs directly, the WDP can be posed as a multicommodity flow problem (I-WDP), which is known to be tractable in practice even for large instances. We extend the model to include practical constraints such as the

number of winners and the number of loads. We present computational results demonstrating the tractability of I-WDP for auctions with up to 5000 bid loads.

Future research includes addressing additional operational constraints, such as regional coverage, backup carrier bids, service requirements for alternatives, etc. Although I-WDP is extremely tractable, length of tours cannot be modeled with this formulation. We believe an alternative *tour-based approach* using *column generation* would give us high scalability and allow for the inclusion of all operational constraints. Additionally, we have assumed that carriers' cost parameters are deterministic; however, in practice these cost parameters are not known with certainty. Consequences of variability due to spot market changes, uncertainties in carriers' existing and future load networks, fuel cost, and timing effects should be incorporated into the model to achieve greater realism.

Finally, in addition to truckload procurement, there are other applications where the bid generating functions appear amenable to the implicit bidding mechanism. A sample of these includes wireless spectrum auctions, energy auctions, and procurement auctions with capacity-constrained suppliers.

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