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Abstract*—Profitable tour problem (PTP) belongs to the class of vehicle routing problem (VRP) with profits seeking to maximize the difference between the total collected profit and the total cost incurred. Traditionally, PTP involves single vehicle. In this paper, we consider PTP with multiple vehicles. Unlike the classical VRP that seeks to serve all customers, PTP involves the strategic-level customer selection so as to maximize the total collected profit and the operational-level route optimization to minimize the total cost incurred. Therefore, PTP is essentially the knapsack problem at the strategic level with VRP at the operational level. That means the evolutionary bi-level programming would be a suitable choice of methodology for solving the NP-hard PTP. Employing some evolutionary method to solve the bi-level program naively would undoubtedly be prohibitively expensive. We thus present in this paper the notion of *knowledge adoption* to approximate the initial solution to the lower-level optimization problem for a given trial solution of the upper-level decision variables. One may consider the knowledge adoption as a special case of knowledge transfer in which the transfer takes place within the same problem domain. Refining the approximate initial solution with local search causes it to quickly converge to some locally optimal solution. The better the estimation of the initial solution, the closer the local optimum will be to the global one. PTP finds its important application in the fields of transportation and logistics. In addressing last-mile problem using auction at the urban consolidation center (UCC), PTP plays a significant role in the winner determination problem (WDP). Our computational study demonstrates the efficacy of the proposed approach in solving the PTP-based WDP, yielding significantly higher profit, utilization, and service level than when the UCC use the conventional WDP based on multiple knapsack problem (*i.e.* the MKP-based WDP).

I. INTRODUCTION

First proposed by Dantzig and Ramser [1] in 1959, vehicle routing problem (VRP) is an important optimization problem in the fields of transportation and logistics. It seeks to service a number of customers with a fleet of vehicles while incurring the minimum cost possible. Numerous variants of the original problem has been considered to-date [2].

More recent extension to the VRP is the VRP with profits (VRPP) where a profit level is associated with every customer to serve. Unlike the classical VRP, VRPP allows the selection of customers to serve in order to maximize the total collected profits or the difference between the total collected profits and the total costs incurred. In the reality, resources are generally limited. Given a fleet of vehicles, there can only be some finite number of customers served within a time period. Selection of customers to serve is therefore practical. In the e-marketplace or via an e-auction, plenty of requests to deliver spot loads can be found or obtained. Logistics service providers—hereinafter, will be referred to as *carriers*—must determine which requests if served will be most profitable to them while being subjected to the capacity of their fleets of delivery vehicles. Highlighted in some surveys [3][4], VRPP finds its applications in logistics [5][6][7][8], manufacturing [9][10], and tourism industry [11], among others. There exist three generic problems in this class, differing from one another by the objective and the constraint.

- *Orienteering problem* (OP) maximizes the total profit subject to the route duration. Its extension to multiple vehicles is called *team orienteering problem* (TOP).
- *Price-collecting traveling salesman problem* (PCTSP) minimizes the total cost subject to the collected profit.
- *Profitable tour problem* (PTP) aims at maximizing the difference between the total collected profit and the total cost incurred.

Among the three generic problems in the class of VRPP, we focus our work on the multi-vehicle PTP. With an objective of maximizing the difference between the total collected profit and the total cost incurred, PTP represents a realistic scenario in the transportation and logistics businesses. PTP is especially relevant when dealing with the final segment of goods delivery from a freight station or port to their final destinations in some congested urban areas. Congestion has increased the travel cost in urban areas, which is a bad news for fragmented deliveries. In addressing the congestion issue, the local government may set up rules and regulations to provide better living conditions to the residents. However, from the perspective of the carriers, this usually complicates the planning of their last-mile delivery. Often, waiting time becomes inevitable, increasing the delivery cost even further. As the matter of fact, up to 28% of the total delivery cost is contributed by the cost to perform the last-mile delivery. With thinning profit margins due to the ever-growing competition, it is important to include the considerable delivery cost in the objective of the decision makers. Such high cost of the last-mile delivery is commonly referred to as the *last-mile problem* [12].

An urban consolidation center (UCC) provides a potential solution to the last-mile problem. Carriers can engage the UCC to perform the last-mile delivery on their behalf. At the UCC, the deliveries are sorted based on their destinations. Deliveries with the same destination or to destinations within some close proximity are consolidated into truckload. Some cost-saving is thus attainable thanks to the less-fragmented deliveries. Most (if not all) UCCs employ the volume-based fixed-rate charges. Setting the correct rate is crucial for the financial sustainability of the UCC. However, it is not easy to identify the optimal one. Handoko, et al. [13] proposed a profit-maximizing auction to enhance the financial sustainability of the UCC.

The main idea of that UCC auction is to let carriers name their prices to get their last-mile deliveries served by the UCC. In the auction, the UCC first invites the interested carriers to participate. The UCC then keeps the auction open for a fixed period of time, during which carriers can submit their bids if they are interested. In each bid, the destination and volume of the goods to deliver is specified. Additionally, the price named by the owner of the goods is stated. This is the price offered to the UCC to serve that particular delivery. Carriers engaging the UCC to serve their last-mile deliveries no longer need to enter the congested urban area. This gives them some amount of cost-savings, based on which the bid prices are determined by the participating carriers. Depending on the willingness of these carriers to share some of their anticipated cost-savings, price offers of various amount may be received by the UCC. At the end of the auction, the UCC determines which and how deliveries can be consolidated to produce the maximum profit, and subsequently, decides the schedule using which deliveries in each individual vehicle are to be served.

To determine the winners of the auction, the UCC assumes zone-based consolidation for the sake of simplicity. This would require the delivery area to be distinguished into a number of non-overlapping zones and each individual destination within the delivery area to be assigned to exactly one zone. With this, consolidation are then restricted to deliveries within the same zone only. Delivery cost to a particular zone is assumed to be representable by a single fixed cost estimate. This is the cost of operating one vehicle to deliver to that zone. Subtracting this cost estimate from the sum of the prices offered earlier to the UCC for serving those deliveries consolidated into that vehicle produces the profit of that particular consolidation. To determine the winners, the UCC then finds the selection that leads to the maximum total consolidation profit. With limited fleet of capacitated delivery vehicles, the winner determination problem (WDP) in this UCC auction resembles the multiple knapsack problem (MKP) in which the "knapsack" is actually one delivery vehicle. Solving the MKP-based WDP facilitates the strategic-level decision-making. For the operational-level decisions, classical VRP is solved for each vehicle dispatched. Given one vehicle with consolidated deliveries, the VRP aims to identify a schedule that serves all of them while incurring the minimum cost. Clearly, this cost is likely to be different from the cost estimate used in the MKP-based WDP.

In the UCC auction discussed above, the concept of VRPP is actually present. Customer selection to maximize the total collected profit and route optimization to minimize the total delivery cost incurred constitute the two components of PTP. Interaction between them is, however, missing. By assuming zone-based consolidation, the delivery cost can be estimated using some constants, one per zone. With this, the UCC does not need to consider routing in order to determine the winning bids. Even though this simplifies the WDP quite considerably, the resulting consolidations are likely to be insufficient to claim the effectiveness of the UCC in solving the last-mile problem. Consider two neighboring zones. Single delivery with small volume is going to one zone. Multiple deliveries are going to the other, but their total volume is yet to make full truckload. Consolidating all of them is possible, but not with zone-based consolidation assumed. Relaxing such assumption, the WDP in the UCC auction is essentially PTP with multiple vehicles. In the PTP-based WDP, the delivery cost is obtained via routing.

From the above discussion, it is clear that PTP is bi-level. At the upper level, a knapsack problem deals with the selection of the customers to serve. The "knapsack" herein represents the entire UCC's fleet. At the lower level, a VRP deals with the optimization of the route given a set of selected customers. In this paper, we propose the use of PTP-based WDP in order to enhance the UCC's effectiveness in addressing the last-mile problem. We formulate the corresponding multi-vehicle PTP as a bi-level program. We then exploit the bi-level structure of the problem and propose the concept of *knowledge adoption* to efficiently solve the bi-level PTP by using the evolutionary bi-level programming. Our contributions, summarized below, are therefore three-fold.

- We propose the use of PTP-based WDP in the UCC auction to improve the effectiveness of the UCC in addressing the last-mile problem
- We formulate the corresponding multi-vehicle PTP as a bi-level prorgram
- We propose the concept of *knowledge adoption* so as to efficiently solve the bi-level PTP using evolutionary bi-level programming

The rest of this paper is organized as follows. In Section II, formulation of the multi-vehicle PTP as a bi-level program is first presented. In Section III, the *knowledge adoption* methodology to solve a bi-level program using evolutionary technique is proposed. Instantiation of the proposed methodology to solve the WDP in the UCC auction based on multi-vehicle PTP then quickly follows. Section IV discusses the various results obtained via computational study. Finally, Section V concludes the paper and provides directions for future works.

II. Problem Formulation

In this section, we shall present the bi-level formulation of the PTP used in determining the winners of the UCC auction. We refer to it as the PTP-based WDP. For simplicity, we only consider the single-period problem in this paper. The proposed formulation can be extended easily to address the multi-period problem in the future.

To begin with, we denote as $\mathcal{B}$ the set of N bids that have been received by the UCC at the end of an auction. Each bid b_i consists of the following pieces of information.

- Delivery destination $\mathbf{d}_i$
- Goods volume v_i
- Bid price p_i offered to the UCC

The UCC has K vehicles available for carrying out last-mile delivery. The capacity of the vehicle k where $k = 1, \ldots, K$ is denoted as Q_k.

Let $\mathbf{X}$ be the set of binary decision variables representing the strategic-level decision on which bids are to be accepted. Let $\mathbf{Y}$ be the set of integer decision variables which encodes the operational-level delivery schedule as the permutation of the indices of the bids accepted by the UCC. The PTP-based WDP aims to solve the following bi-level program.

$$\arg\max_{\mathbf{X},\mathbf{Y}} \sum_{i=1}^{N} p_i x_i - cvrp(\mathbf{Y}|\mathbf{Q}) \tag{1}$$

s.t.

$$\sum_{i=1}^{N} v_i x_i \leq \sum_{k=1}^{K} Q_k \tag{2}$$

$$x_i \in \{0, 1\} \tag{3}$$

$$\mathbf{Y} \in \arg\min_{\mathbf{Y}} cvrp(\mathbf{Y}|[\mathbf{Q}, Q_{k+1}, \ldots]) \tag{4}$$

s.t.

$$\forall j, y_j \in \{i : x_i = 1\} \tag{5}$$

$$\forall j \forall j', j \neq j' \Rightarrow y_j \neq y_{j'} \tag{6}$$

where $x_i \in \mathbf{X}$, $y_j \in \mathbf{Y}$, and $Q_k \in \mathbf{Q}$.

Abstracting the lower-level optimization as the capacitated vehicle routing problem CVRP, we reformulate (4) taking into account (5) and (6) as follows.

$$\mathbf{Y} \in \mathrm{CVRP}(\mathcal{C}, [\mathbf{Q}, Q_{k+1}, \ldots]) \tag{7}$$

where

$$\mathcal{C} = \{i : x_i = 1\} \tag{8}$$

In the above reformulation, CVRP receives the following two parameters as inputs.

- The set $\mathcal{C}$ of customer indices whose bids are accepted by the UCC. Having accepted these bids, the UCC is hence committed to serve the corresponding last-mile deliveries. This information is dictated by the value of the vector $\mathbf{X}$ of the upper-level decision variables. This subsequently governs the length of the vector $\mathbf{Y}$ of the lower-level decision variables.
- The vector of vehicle capacities available at the UCC for doing last-mile delivery. The vector $\mathbf{Q}$ quantifies the possibly heterogeneous capacities of the delivery vehicles at the UCC. For a given $\mathcal{C}$, it is possible that there exists no $\mathbf{Y}$ such that all selected customers can be served using the vehicles specified in $\mathbf{Q}$. Indeed, constraint (2) only provides a loose upper bound on the total consolidation volume. To address this issue, $\mathbf{Q}$ must be augmented with some dummy vehicles so as to be able to accommodate serving all the selected customers even when more vehicles than the available fleet are actually required. In the case of homogeneous capacity, a sufficient number of dummy vehicles with the same capacity are introduced to augment $\mathbf{Q}$.

Given the two parameters discussed above, CVRP aims to find the permutation $\mathbf{Y}$ of the indices of the selected customers that minimizes the total delivery cost while taking into account the capacity of each of the available delivery vehicles. This is as depicted in the objective (4) of the lower-level optimization problem. Specifically, the vector $\mathbf{Y}$ contains each element of $\mathcal{C}$ exactly once. As mentioned earlier, the set $\mathcal{C}$ is composed of the indices of all the selected customers, that is $\{i : x_i = 1\}$. As an illustrative example, consider a case where there are 5 customers, each with index i where $i \in \{1, \ldots, 5\}$. Suppose we have $\mathbf{X} = [0, 1, 1, 0, 1]$ at the upper level, implying that there are 3 customers selected. Consequently, $\mathcal{C} = \{2, 3, 5\}$. $\mathbf{Y}$ can thus assume any of the following values.

- $[2, 3, 5]$
- $[2, 5, 3]$
- $[3, 2, 5]$
- $[3, 5, 2]$
- $[5, 2, 3]$
- $[5, 3, 2]$

CVRP then returns in $\mathbf{Y}$ the optimal permutation that incurs the minimum total delivery cost.

The way to interpret $\mathbf{Y}$ is to consider it as the solution to some traveling salesman problem (TSP). $\mathbf{Y}$ can thus be viewed as a giant TSP tour for a vehicle without capacity constraint, that is a tour that visit all customers regardless of the vehicle capacity. A splitting procedure must then be employed to get the best CVRP solution respecting the sequence as dictated by the optimal permutation. Prins proposed two different optimal splitting methods to handle the case of the homogeneous [14] and the heterogeneous [15] fleets of delivery vehicles. In our formulation, the function $cvrp(\cdot)$ first employs the appropriate splitting algorithm in order to come up with the schedule for each individual vehicle and then calculates the total cost of delivery according to the entire schedules. At the lower level, the function $cvrp(\cdot)$ is conditioned on the augmented fleet of delivery vehicles $[\mathbf{Q}, Q_{k+1}, \ldots]$. At the upper level, the same function $cvrp(\cdot)$ is conditioned on the actual fleet of vehicles $\mathbf{Q}$. Shortage of vehicles to serve all the selected deliveries may consequently arise. For every excess of deliveries that cannot be served using the vehicles specified, a sufficiently large cost is imposed and added to the actual cost as penalty. This in turn penalizes the corresponding vector $\mathbf{X}$ of the upper-level decision variables.

III. Proposed Methodology

The naive method to solve bi-level programs is by treating them as nested optimization problems. Taking the reference to the bi-level PTP presented in the previous section, the optimal solution vector $\mathbf{Y}$ to the lower-level optimization problem has to be found for each trial solution vector $\mathbf{X}$ of the upper-level decision variables. Thus, searching for the optimal solutions to bi-level programs involve solving the lower-level optimization problem multiple times. In the case of bi-level PTP formulated in Section II, the NP-hard CVRP at the lower level needs to be solved as many times as the number of the trial solutions generated for the upper-level knapsack problem. Such would undoubtedly be prohibitively expensive. This approach is only practical on small-sized problems. That implies small number of bids in the context of PTP-based WDP.

A plausible workaround for the above-mentioned problem is by applying some kind of approximation to the optimization problem at the lower level. This can be achieved using either surrogate modeling or solution estimation. The earlier has been attempted for real-parameter bi-level programs. In this paper, we shall propose the latter for combinatorial bi-level programs. Specifically, we shall present the notion of *knowledge adoption* in evolutionary bi-level programming to estimate the solution to the lower-level optimization problem and then instantiate it for solving the PTP-based WDP.

Surrogate modeling is very commonly employed in dealing with the computationally-expensive optimization problems in the continuous domain. When dealing with bi-level programs, solving the lower-level optimization problems multiple times constitutes the most resource-intensive component throughout the entire optimization process. Approximating the landscape of the lower-level optimization problem with some polynomial model makes it easier to find its optimal solution given the trial solution of the upper-level decision variables. Intuitively, such landscape approximation changes with the trial solution vector of the upper-level decision variables. With a quadratic model, BLEAQ [16] sets a successful example of this approach. It is, however, only applicable to bi-level programs with continuous parameters.

For the combinatorial bi-level program, we propose herein a methodology to approximate the solution to the lower-level optimization problem. Two phases of the algorithm in Fig. 1 summarizes our proposed methodology. In the first phase, we identify a diverse set $\mathcal{X}$ of the upper-level candidate solution $\mathbf{X}$ for which the corresponding optimal lower-level solutions are sought. At the end of this phase, we thus have a collection $\mathcal{K}$ of optimal lower-level solution vectors that are sufficiently distinct from one another. In the second phase, we focus our search effort on optimizing the upper-level decision variables. For each trial solution to the upper-level decision variables, we estimate the lower-level solution via *knowledge adoption* from the optimal lower-level solutions in $\mathcal{K}$. This consists of *knowledge filtering* to select which knowledge to adopt and *knowledge assimilation* to transform the selected knowledge into a meaningful estimate of the lower-level solution. As with any solution estimates, the approximate solution is likely to be imprecise. Refining the approximate solution with local search quickly makes it converge to a locally optimal solution. With better quality of the approximate solution, the local optimum reached shall be closer to the global one.

assign a number of diverse $\mathbf{X}$'s to $\mathcal{X}$ ▷ Phase 1
for each $\mathbf{X}$ in $\mathcal{X}$ **do**
    find the optimal $\mathbf{Y}$ and assign it to $\mathcal{K}$
end for
initialize a population $\mathcal{P}$ of $\mathbf{X}$ ▷ Phase 2
while no terminating condition is met **do**
    for each $\mathbf{X}$ in $\mathcal{P}$ **do**
        estimate $\mathbf{Y}$ for $\mathbf{X}$ via *knowledge adoption* from $\mathcal{K}$
        refine $\mathbf{Y}$ with local search
        evaluate the quality of $\mathbf{X}$ and the refined $\mathbf{Y}$
    end for
    evolve $\mathcal{P}$ via crossover and mutation
end while

Fig. 1. An evolutionary bi-level programming with solution estimation via knowledge adoption.

assign the optimal $\mathbf{Y}$ for $\mathbf{X} = \mathbf{1}$ to $\mathcal{K}$ ▷ Phase 1
initialize a population $\mathcal{P}$ of $\mathbf{X}$ ▷ Phase 2
while no terminating condition is met **do**
    for each $\mathbf{X}$ in $\mathcal{P}$ **do**
        estimate $\mathbf{Y}$ for $\mathbf{X}$ as subset of permutation in $\mathcal{K}$
        refine $\mathbf{Y}$ with local search
        evaluate the quality of $\mathbf{X}$ and the refined $\mathbf{Y}$
        if $\mathbf{Y}$ requires more vehicles than available **then**
            repair $\mathbf{X}$ in the spirit of Lamarckian learning
    end for
    evolve $\mathcal{P}$ via crossover and mutation
end while

Fig. 2. Solving the bi-level PTP-based WDP using solution estimation via knowledge adoption.

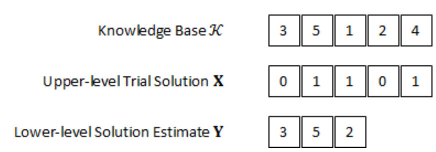

Fig. 3. Knowledge adoption by extracting the subset of the permutation in the knowledge base, which is employed in finding the solution to the bi-level PTP-based WDP using algorithm in Fig. 2. $\mathbf{X}$ selects the 2nd, 3rd, and 5th customers. $\mathbf{Y}$ is thus initialized with their indices in the order found in $\mathcal{K}$.

Fig. 2 presents the instantiation of the above methodology for solving the bi-level PTP-based WDP formulated in Section II. The UCC is setup to address the last-mile problem. Thus, it must wish to accept as many bids as possible to be effective. Inspired by this, the lower-level VRP is first solved with $\mathbf{X} = \mathbf{1}$ as if all bids are accepted. A memetic algorithm [14][15] can be employed to search for the optimal $\mathbf{Y}$ to form the knowledge base $\mathcal{K}$. A genetic algorithm with binary chromosomes is then invoked to search for the optimal $\mathbf{X}$ that solves the upper-level knapsack problem with the PTP objective. Each individual in the population represents a trial solution $\mathbf{X}$ of the upper-level decision variables. For each of them, a solution estimate for $\mathbf{Y}$ is generated via knowledge adoption by extracting the subset of the permutation in $\mathcal{K}$ as illustrated in Fig. 3. The estimate is first refined via local search before evaluating the quality of the individual. In this instantiation, $\mathbf{X}$ is repaired to match the deliveries in $\mathbf{Y}$ that can be served using the available fleet. Evolution then continues until the terminating condition is met.

IV. Computational Study

A. Data Generation

To assess the efficacy of our proposed solution technique, we generate synthetic datasets by following the steps outlined below.

//Generating destinations
randomize L delivery points in 2D Cartesian coordinates $[0, 100] \times [0, 100]$
//Generating datasets
for $j = 1$ to M **do**
  for $i = 1$ to N **do**
    select destination $\mathbf{d}_i$ randomly from the L locations
    randomize volume $v_i \in [v_{\min}, v_{\max}]$
    randomize $\omega \in [\omega_{\min}, \omega_{\max}]$
    compute bid price $p_i = \omega(v_i/\overline{Q})cost(\mathbf{d}_0, \mathbf{d}_i)$
  end for
end for

Specifically, we generate L delivery locations and M datasets, each with N bids. In the above, $\mathbf{d}_0$ is the location of the UCC and $\overline{Q}$ represents the average capacity of the last-mile delivery vehicles available at the UCC, that is

$$\overline{Q} = \frac{1}{K}\sum_{k=1}^{K} Q_k \tag{9}$$

B. Experimental Setup

In our computational study, we set the relevant parameters as follows.

- $L = 100$ (see Fig. 4)
- $M = 10$
- $N = 100$
- $v_{\min} = 5$
- $v_{\max} = 20$
- $\omega_{\min} = 1.5$
- $\omega_{\max} = 2.0$

Additionally, we set the following UCC-related parameters in our experiments.

- $\mathbf{d}_0 = (0, 0)$
- $K = 10$
- $Q_k = 100, \forall k = 1, \ldots, K$

For simplicity, we have assumed that a homogeneous fleet of vehicles are available at the UCC for carrying out the last-mile delivery. As such, it is also assumed that all the vehicles incur the same cost to travel between two fixed locations. Herein, we consider the Euclidean distance between the two locations as the travel cost. The function $cost(\cdot)$ thus calculates the cost of traveling from location $\mathbf{d}_i$ to location $\mathbf{d}_j$ as

$$cost(\mathbf{d}_i, \mathbf{d}_j) = \|\mathbf{d}_j - \mathbf{d}_i\| \tag{10}$$

where $\|\cdot\|$ denotes the L2-norm.

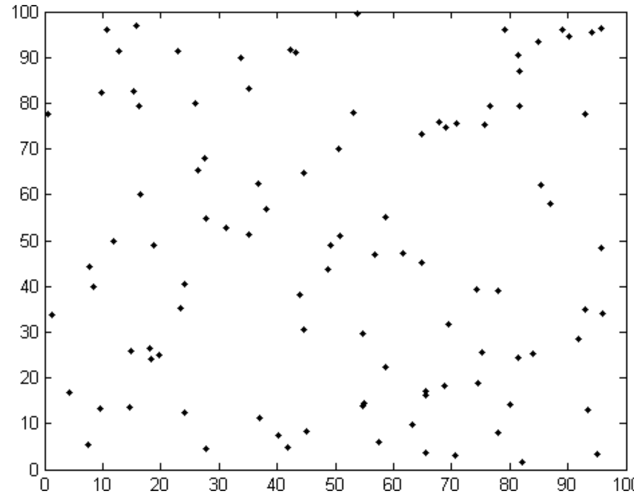

Fig. 4. 100 uniformly randomized destinations in 2D Cartesian coordinates.

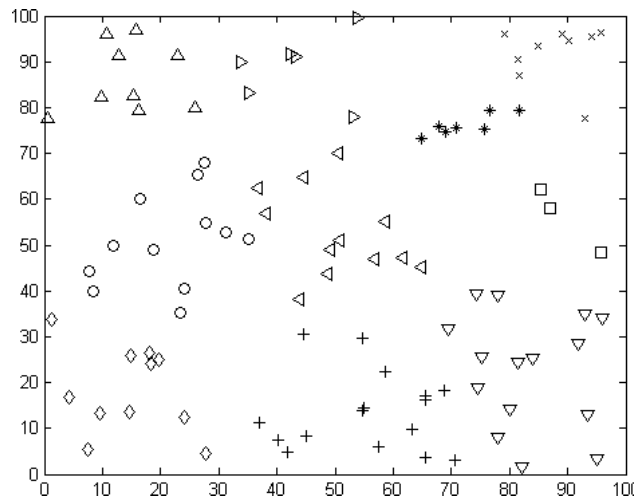

Fig. 5. 10 delivery zones as the results of applying k-means clustering with $k = 10$ to the 100 uniformly randomized destinations in Fig. 4. Destinations in each zone are depicted using a unique legend. These zones are used for zone-based consolidations in the MKP-based WDP.

For our baseline, we are going to use the MKP-based WDP that facilitates zone-based consolidations [13]. For that reason, we simulate the zoning of the 100 randomized destinations via the use of k-means clustering. Fig. 5 shows the resulting zones with $k = 10$ by means of 10 different legends. Delivery costs to these zones are tabulated in Table I. They are composed of two components. The first is the average cost to travel between the UCC and the destinations in a particular zone. The second is the average cost of traveling between any two destinations in the zone. With the volume of individual deliveries ranging from 5 to 20 with uniform distribution and with homogenous vehicle capacity of 100, a vehicle is expected to deliver to 8 destinations, performing 7 inter-destination travels. The second cost component must thus be multiplied by 7 or one less than the number of destinations in the zone, whichever is smaller. Summing up the two cost components yields the approximate cost of operating a delivery vehicle to the zone. In our study, we solve the MKP-based WDP to optimality using CPLEX's exact algorithm.

TABLE I. ZONE-BASED DELIVERY COST FOR THE MKP-BASED WDP

Zone	Cost
1	234.40
2	331.17
3	239.50
4	257.39
5	234.66
6	161.21
7	310.83
8	272.78
9	263.85
10	272.00

Lastly, the specifications listed below are adhered to when employing the evolutionary methods to solve the bi-level PTP to determine the winners of the UCC auction.

- For the first-phase memetic algorithm,
  - Chromosomes: ordered (permutation-based)
  - Population size: 36
  - Evolutionary operators:
    - order crossover with probability of 0.8
    - substring-reshuffling mutation with probability of 0.2
  - Evolution length: 10 generations
- For the second-phase genetic algorithm,
  - Chromosomes: binary
  - Population size: 50
  - Evolutionary operators:
    - uniform crossover with probability of 0.9
    - flip-bit mutation with probability of 0.1
  - Evolution length: 100 generations
- For refining the lower-level solution estimates, we use Prins' local search [14]

Note that we have purposely utilized quite different settings for the first- and second-phase algorithms. While the second-phase genetic algorithm is a general-purpose evolutionary technique, the first-phase memetic algorithm is a specialized evolutionary procedure for solving the VRP [14]. As will subsequently be witnessed, the settings have been effective in producing good results for the PTP-based WDP.

C. Results and Discussions

First of all, we shall investigate the UCC's earned profits. Herein, the UCC's earned profit refers to the total collected bid payments subtracted by the total actual delivery costs incurred. In the context of MKP-based WDP, the highest objective value identified by solving the corresponding mixed-integer program does not directly constitute the earned profit. Routing must be performed for each "knapsack" (that is, vehicle) to determine the actual cost of deliveries. Intuitively, the PTP-based WDP brings the UCC higher profit than does the MKP-based WDP. With PTP, consolidating small delivery with those that are yet to reach full truckload from two neighboring zones is possible. Fig. 6 summarizes the statistics of the UCC's earned profits in boxplot. Paired t-test on the data yields a p-value of 2.6×10^{-6}, showing the superiority of the PTP- over the MKP-based WDP. The individual datasets representing unique UCC scenarios in Table II shows consistent enhancements to the earned profits, hence the statistical significance.

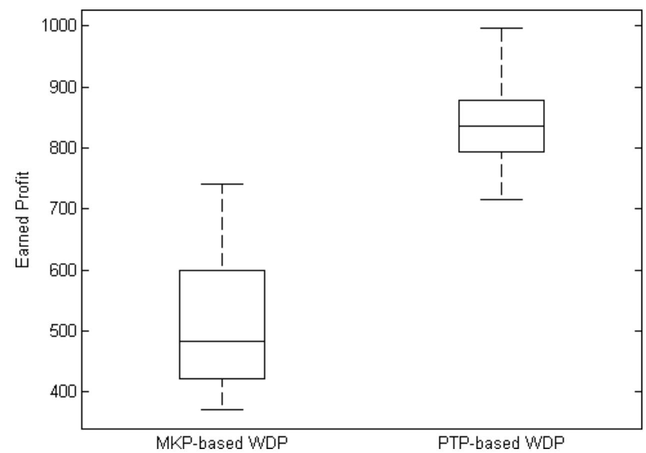

Fig. 6. Statistics of the UCC's earned profit over 10 different scenarios. The UCC's earned profit refers to the total collected bid payments subtracted by the total actual delivery costs incurred.

TABLE II. DETAILS OF THE UCC'S EARNED PROFIT

Scenario	MKP-based WDP	PTP-based WDP	Improvement Ratio
1	412.00	817.30	1.98
2	654.86	752.12	1.15
3	371.27	715.04	1.93
4	429.80	878.02	2.04
5	600.01	876.75	1.46
6	741.53	995.88	1.34
7	442.73	793.76	1.79
8	421.74	810.04	1.92
9	533.82	855.61	1.60
10	522.49	896.43	1.72

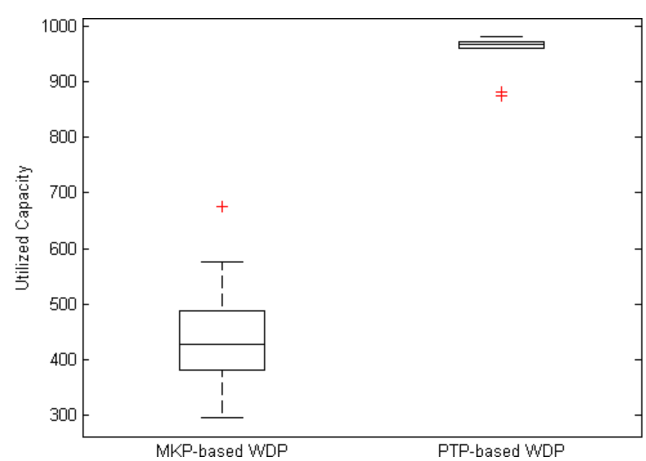

Fig. 7. Statistics of the UCC's utilized capacity over 10 different scenarios.

TABLE III. DETAILS OF THE UCC'S UTILIZED CAPACITY

Scenario	MKP-based WDP	PTP-based WDP	Improvement Ratio
1	381	960	2.52
2	577	875	1.52
3	297	976	3.29
4	300	980	3.27
5	489	970	1.98
6	676	960	1.42
7	459	971	2.12
8	386	972	2.52
9	475	964	2.03
10	397	882	2.22

For the understanding on what causes the enhanced profit, we would now investigate the utilization of the UCC's fleet of last-mile delivery vehicles. The zone-based consolidations in MKP-based WDP have, as the matter of fact, rendered many of the vehicles unutilized. This is mainly due to the lack of deliveries to consolidate within the same zone. The UCC will simply not profit from the zone-based consolidations of such deliveries. Instead, it will suffer from losses if these deliveries were to be forcibly consolidated based on their zones. Though there may be sufficient deliveries to consolidate within a zone, non-profitable consolidation can still occur. Dispatching every vehicle incurs a considerable cost. Utilization of every vehicle needs to generally be maximized to achieve the most profitable consolidation. This often leaves behind several deliveries with low bid prices, which are not sufficient to produce a profitable consolidation. In contrast, nearly full utilization of the UCC's fleet of last-mile delivery vehicles is obtained with PTP-based WDP. This is achieved as consolidations of various deliveries to different zones are allowed. Such significant difference on the utilization of the UCC's fleet of last-mile delivery vehicles is summarized in Fig. 7 and detailed in Table III. The paired t-test on the results yield a p-value of 8.8×10^{-7}, signifying considerable improvement on the utilization of the UCC's fleet. From the individual scenarios detailed in the table, it is clear that improvement ratio between 2 to 3 is generally attainable. Exceptions are noted when deliveries are sufficiently clustered, resulting in the MKP-based WDP producing reasonably high utilization of the UCC's fleet.

Comparing the improvement ratio of the utilized capacity with that of the earned profit of the UCC in Table III and II, respectively, we observe that large improvement in the utilized capacity does not necessarily translate into an improvement as large in the earned profit. The deliveries not served in the case of MKP-based WDP are generally those with lower bid prices. Although PTP-based WDP manages to form several profitable consolidations for some of these deliveries, serving them will not bring as much profit to the UCC. This explains the lower improvement ratio in the earned profit. Despite this, nearly full utilization of the UCC's fleet signifies the UCC's effectiveness in addressing the last-mile problem. At the same time, higher earned profit means better financial sustainability to the UCC. With this, the UCC's dependence on the government's subsidy is reduced. Handoko, et al. [13] suggested that the UCC's profit can be enhanced by conducting auction rather than employing the fixed-rate mechanism. While this is true, considering PTP instead of MKP in the WDP further increases the profit.

Finally, we will now examine the service level of the UCC. The service level is defined as the ratio of the number of bids accepted by to the total number of bids submitted to the UCC, expressed in term of percentage. Intuitively, higher utilization of the UCC's fleet can be linked to more bids being accepted by the UCC, hence higher service level. In Fig. 8, the statistics of the UCC's service level over 10 different datasets is shown via boxplots. In Table IV, details of the UCC's service level are tabulated. Subjecting the results to paired t-test, a p-value of 5.6×10^{-7} is obtained. This is quite close to the p-value of the UCC's utilized capacity. As the matter of fact, comparing improvement ratio of the service level with that of the utilized capacity of the UCC, one shall notice their similarity with one another. Indeed, they are very highly correlated with Pearson's correlation coefficient of 0.9869.

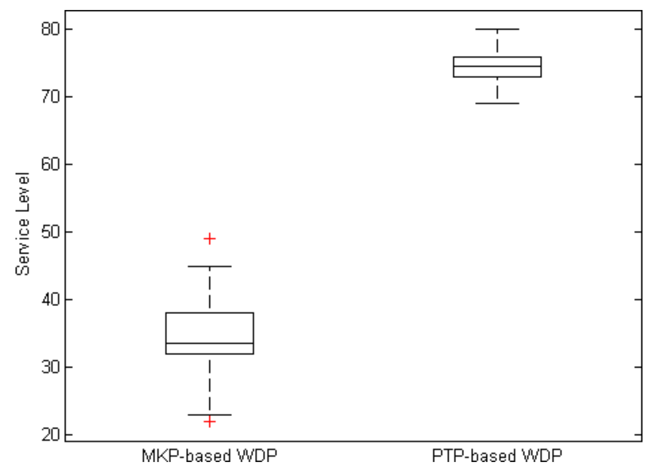

Fig. 8. Statistics of the UCC's service level over 10 different scenarios. The service level is the percentage of the bids accepted with respect to the total number of bids. With 100 bids in each scenario, the service level is the same as the number of bids accepted by the UCC.

TABLE IV. DETAILS OF THE UCC'S SERVICE LEVEL

Scenario	MKP-based WDP	PTP-based WDP	Improvement Ratio
1	33	76	2.30
2	45	69	1.53
3	23	75	3.26
4	22	74	3.36
5	38	77	2.03
6	49	73	1.49
7	34	76	2.24
8	32	80	2.50
9	38	73	1.92
10	32	69	2.16

A collection of 100 deliveries with uniformly randomized volume between 5 to 20 has an expected total volume of 1250. The total capacity of the UCC's fleet is 1000. The UCC is thus expected to be able to serve approximately 80 deliveries. With service level ranging from 69% to 80%, the PTP-based WDP virtually makes the UCC run at full capacity most of the time. This demonstrates, in particular, the efficacy of the algorithm outlined in Fig. 2 for solving the bi-level PTP-based WDP. In general, this proves the effectiveness of the proposed solution methodology for solving any bi-level programs via *knowledge adoption* in evolutionary bi-level programming. With most bids rejected due to capacity constraint, the PTP-based WDP will undoubtedly be hailed as a fair competition by the participating carriers. This provides the incentives for the carriers to keep participating in the UCC auction and to adjust their bid prices strategically. Note that the purpose of a carrier participating in the UCC auction is primarily to reduce cost. This is realized when the UCC delivers on behalf of the carrier. As the result, the carrier no longer needs to enter the city center where there may be traffic congestion and numerous rules and regulations set by the government, which in turn complicates the planning of the carrier. To avoid these hassles, the carrier must be willing to strategically adjust the bid prices offered to the UCC so long as cost-saving is attainable. In MKP-based WDP, lots of bids are rejected due to lack of deliveries to consolidate with, unless the deliveries are nicely clustered. This issue can be addressed by offering the UCC ridiculously high prices, hence attaining no cost-saving. As such, this will drive the carriers away from participating in the UCC auction.

V. Conclusion

In this paper, we present a winner determination problem (WDP) for the UCC auction based on multi-vehicle profitable tour problem (PTP). The PTP-based WDP is a more realistic yet more complex alternative to the conventional WDP based on multiple knapsack problem (MKP). First, we re-formulate the PTP as a bi-level program. Then, we propose the notion of *knowledge adoption* as a means to approximate the solution to the lower-level optimization problem, given a trial solution to the upper-level decision variables. Subsequently, we instantiate the proposed solution methodology so as to effectively identify the solution to the PTP-based WDP. Via computational study, we show the efficacy of our solution methodology empirically in solving the multi-vehicle PTP, producing all of the time an almost full utilization of the UCC's fleet of last-mile delivery vehicles. We also demonstrate the superiority of the PTP-based over the MKP-based WDP by bringing the UCC higher profit. This suggests the importance of combining the strategic-level with the operational-level decision-making. Since the resulting optimization problem easily becomes intractable, evolutionary bi-level programming sooner or later shall become the method of choice for solving the problem.

Moving forward, we shall consider different options of data generation, such as the non-uniform randomization, to simulate an even more diverse set of scenarios possibly encountered at the UCC. We shall also consider the multi-period problem in which deliveries cannot be served before their arrival periods at the UCC or beyond their deadline periods. Additionally, we shall consider a fleet of delivery vehicles with heterogeneous capacities. Algorithmically, we shall instantiate the proposed *knowledge adoption* methodology to solve more problems that can be re-formulated as bi-level programs and then compare these instantiations' performance with that of the conventional methods commonly-used to solve them.

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