Maximum Profit Facility Location and Dynamic Resource Allocation for Instant Delivery Logistics

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ABSTRACT

- E-commerce usage has become ever-ubiquitous now, especially due to social isolation requirements during COVID-19. E-commerce has experienced 32.1% growth from 2019 Q4 to 2020 Q4, compared to total retail growth of 6.9%.
- Delivery time thresholds for online purchases have become intensive. Options for 2-hour (Walmart, Amazon Prime Now) and 1-hour (Instacart Express, Shipt, Alibaba Fresh Hema) exist, with industry gearing towards an instant (30 minutes or less) delivery goal (Amazon Prime Air, Getir, Wolt).
- Drones or Unmanned Aerial Vehicles (UAVs) are primed for instant delivery with higher operational speed and better cost-effectiveness. Numerous large corporations including Amazon, Walmart, FedEx, UPS, and Kroger are heavily investing in a drone-based technology and infrastructure.
- This work delves into facility location and resource allocation for including instant delivery logistics into a company's operations.
  - Two types of deliveries: instant (30 minutes or less) or regular.
  - Two types of vehicles: drones (can cater both instant and regular requests) and truck (can only cater regular requests).
  - Solution methodology is split in two stages: planning stage and operational stage.
  - Planning stage determines the facilities to be opened, and the amount of product and battery capacity allocated at each opened facility.
  - During operational stage, requests arrive in a stochastic manner, and they need to be fulfilled using drone delivery from a located facility or truck delivery from the central warehouse.
  - Allocation of request results in a profit as well as resource consumption. The goal during the operational stage is maximizing profits subject to resource budget constraints.
  - A novel multi-armed bandits framework is proposed for solving the operational stage problem and is compared with three other heuristics.

STAGE 1: PLANNING STAGE

- Objective function:

$$max_{u,w,x,y,z} \sum_{h\in H}\sum_{g\in G}\sum_{f\in F_g} c^D_{gf} x_{hgf} + \sum_{g\in G}\sum_{f\in F_g} c^T_{gf} w_{gf}$$

- Facility opening constraint:

$$\sum_{h\in H} y_h \le p$$

- Product allocation at facilities:

$$\sum_{h\in H} u_h \le \alpha$$
$$u_h \le \alpha \cdot y_h \qquad \forall\, h\in H$$
$$u_h \ge \alpha_{min} \cdot y_h \qquad \forall\, h\in H$$
$$\sum_{g\in G}\sum_{f\in F_g} o_{gf} x_{hgf} \le u_h \qquad \forall\, h\in H$$

- Truck routing cost constraint:

$$\sum_{g\in G}\sum_{f\in F_g} w_{gf} \le \omega$$

- Battery capacity allocation at facilities:

$$\sum_{h\in H} z_h \le \beta$$
$$z_h \le \beta \cdot y_h \qquad \forall\, h\in H$$
$$z_h \ge \beta_{min} \cdot y_h \qquad \forall\, h\in H$$
$$\sum_{g\in G_h}\sum_{f\in F_g} b_{gh} x_{hgf} \le u_h \qquad \forall\, h\in H$$

- Demand satisfaction logical constraint:

$$w_{gf} + \sum_{h\in H} x_{hgf} \le 1 \qquad \forall\, f\in F_g, g\in G$$

- Variable definitions:

$$x_{hgf}, w_{gf}, y_h \in \{0,1\};\ u_h, z_h \ge 0$$

STAGE 2: OPERATIONAL STAGE

- After Stage 1, opened drone operations sites (set H') with their product (u^*_h) and battery capacity (z^*_h) allocations are known.
- The goal of the operational stage is finding a request allocation policy that maximizes the cumulative rewards subject to resource budget constraints over a horizon of T requests.
- For each request t arriving in an online manner, we know: the demand location g_t placing the request; whether the request requires instant delivery or not, defined by binary variable λ_t; the product consumption $o^t_{g_t}$; and the battery consumption $b^t_{g_t h}$ from each opened facility to demand point and back. Additionally, reward is c^S=0.8 for instant delivery requests, and c^R=0.5 for regular requests.
- The online optimization problem we solve is:

$$\max \sum_{t=1}^{T}\left[\sum\nolimits_{h_t\in H'}\{c^S\lambda_t + c^R(1-\lambda_t)\}I^t_{h_t} + c^R(1-\lambda_t)I^t_{truck}\right]$$

$$\text{s.to.} \sum_{t=1}^{T} o^t_{g_t}\mathbf{1}\{h_t = h\} \le u^*_h \quad \forall\, h\in H';\quad \sum_{t=1}^{T} b^t_{g_t h}\mathbf{1}\{h_t = h\} \le z^*_h \quad \forall\, h\in H';\quad \sum_{t=1}^{T} I^t_{truck} \le \omega$$

Where, binary indicator I^t_{truck} is 1 if truck-based delivery option is chosen, and binary indicator $I^t_{h_t}$ is 1 if facility h_t is chosen for drone delivery.

- Linear Contextual Bandits with Knapsacks (linCBwK):
  - Has K arms which represent fulfillment options (drone delivery from $|H'|$sites + truck-based delivery from central warehouse)
  - Has d=(2K-1) knapsack constraints (product and battery consumption at drone sites and one for truck routing cost).
  - Observes a $K \times K$ context matrix (X_t) for each request t, where the k^{th} diagonal element is 1 if k^{th} arm is available, and 0, otherwise.
  - The reward and resource consumption are linearly dependent on context, i.e., $\mathbb{E}[r_t(a)|X_t(:,a),H_{t-1}] = \mu_*^{\mathrm{T}} X_t(:,a);\quad \mathbb{E}[\boldsymbol{v}_t(a)|X_t(:,a),H_{t-1}] = W_*^{\mathrm{T}} X_t(:,a)$
  - linCBwK allocates the request t to arm a_t such that $a_t = argmax_{a\in[K]} X_t^{\mathrm{T}}(:,a) * (\tilde{\mu}_t(a) - Z\tilde{W}_t(a)\theta_t)$ where, $\tilde{\mu}_t(a)$ and $\tilde{W}_t(a)$ are optimistic estimates of μ_* and W_* at request t. The penalty parameter Z is computed through initial exploration. The online learning parameter θ_t is updated after every request using multiplicative weight update.
- Planning Stage Optimization Allocation (PSOA) Heuristic weighs a delivery option according to its usage for a demand point in the planning stage optimization problem. Different probability distributions are derived for instant delivery requests and regular delivery requests.
- Random Choice (RC) Heuristic chooses drone delivery or truck delivery in a weighted manner according to resource budgets.
- Blind Random Choice (BRC) Heuristic randomly selects one of the available options for order fulfillment.

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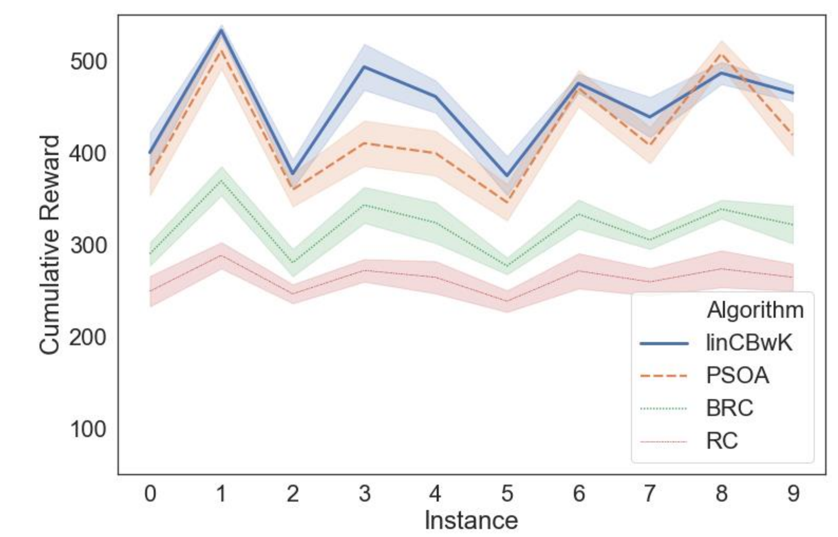
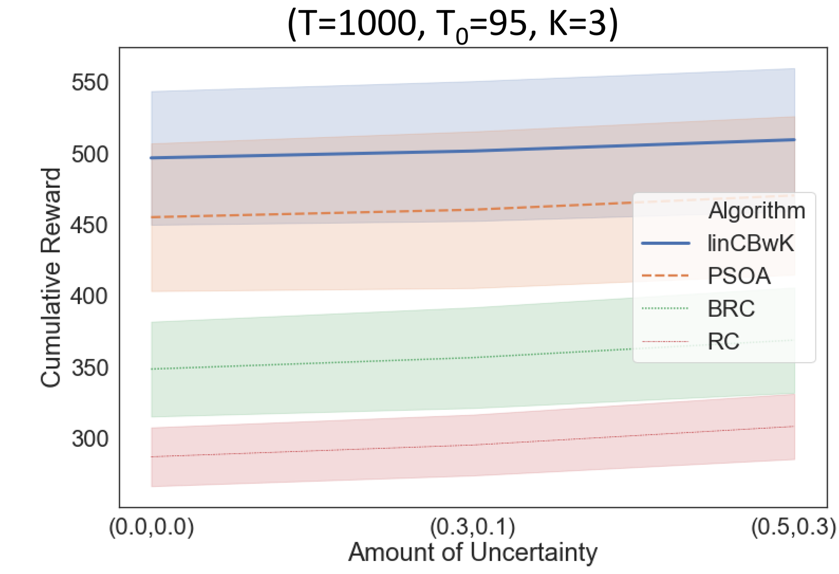
COMPUTATIONAL EXPERIMENTS

- During Stage 1, n^S_g and n^R_g denote estimated number of instant and regular delivery requests from demand point $g \in G$
- During experiments, we assume actual values of n^S_g and n^R_g(denoted by $\tilde{n}^S_g$ and $\tilde{n}^R_g$) are off by at most ρ^S and ρ^R, i.e., $\tilde{n}^S_g \in \left[\frac{1}{1+\rho^S}n^S_g, \frac{1}{1-\rho^S}n^S_g\right]; \tilde{n}^R_g \in \left[\frac{1}{1+\rho^R}n^R_g, \frac{1}{1-\rho^R}n^R_g\right]$
- Experiments on 10 standard p-median instances of size 50 [Osman and Christofides 1994], each instance run 10 times.

Cumulative revenue obtained through successful allocations (T=1000, T_0=95, K=3, ρ^S=0.3, ρ^R=0.1)

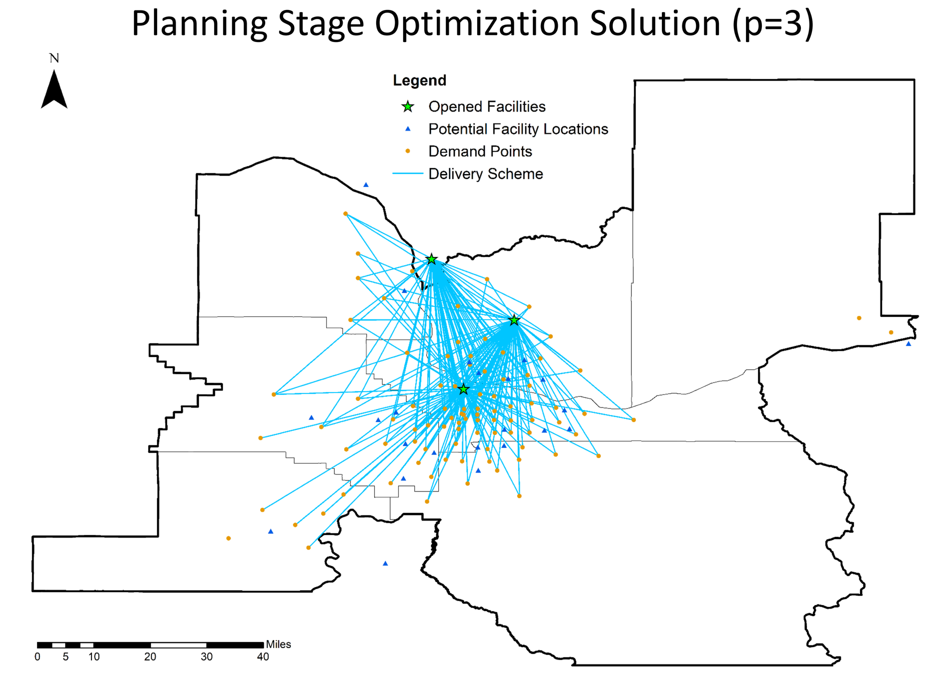


Cumulative revenue with varying amount of estimation uncertainty (ρ^S,ρ^R) (T=1000, T_0=95, K=3)

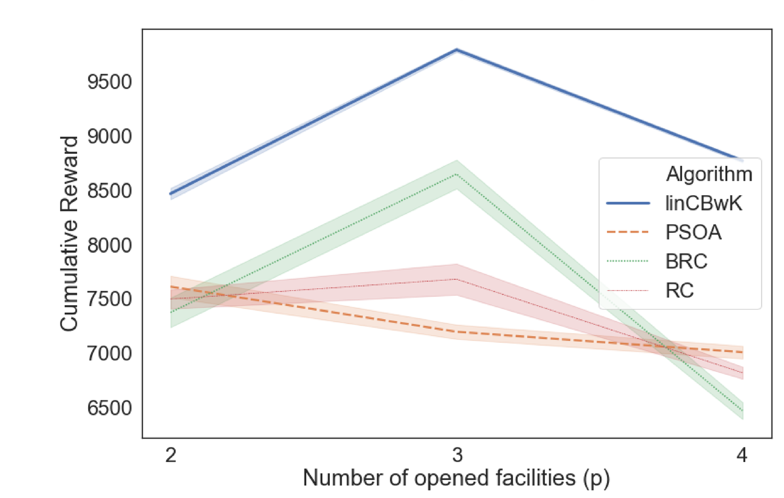


- Portland Metro Area Case Study: Walmart considering to expand its delivery options to include instant delivery. 26 Walmart stores as potential drone operation locations, and 90 ZIP Code centroids as demand points.

Planning Stage Optimization Solution (p=3)



Cumulative revenue with varying number of opened facilities (T=15,000, K=p+1, ρ^S=0.3, ρ^R=0.1)



RESULTS AND CONCLUSIONS

- The study investigated a facility location and online resource allocation problem applicable to a logistics company expanding to offer instant delivery using drones/UAVs and proposed a novel two-stage approach for the same.
- A multi-armed bandit framework (named linCBwK) is proposed that explicitly accounts for global knapsack constraints arising in our application. The linCBwK framework outperforms the second-best PSOA by providing 7% more rewards, on average. For a case-study application in Portland Metro Area with longer planning horizon, linCBwK outperformed the second-best approach by at least 11.2%.
- The current work does not accommodate the non-fulfillment option for a request, as well as does not consider congestion effects at facilities. These represent important considerations that should be tackled in future research.