Optimizing Outbound Logistics at a Clinical Laboratory's Patient Service Center

Yang Sun*
California State University, Sacramento, Sacramento, California, USA

Yang Li
California State University, Sacramento, Sacramento, California, USA

We study a stochastic scheduling problem for outbound deliveries of customer jobs at a clinical laboratory's patient service center. Patient specimens are collected at the remote service center throughout the day and are loaded onto a limited number of vehicles, which deliver them to the central laboratory for testing. The problem is to determine vehicle departure times in order to minimize total job waiting time at the service center. We derive optimal scheduling solutions from theoretical developments for both stationary and non-stationary Poisson arrivals under stylized conditions, and further develop heuristics for more general cases. Simulation experiments verify the managerial insight we gain from the theories that a pull-based dispatching policy outperforms the common practice in general cases.

***** Corresponding Author. E-mail address: suny@csus.edu

I. INTRODUCTION AND BACKGROUND

Clinical laboratory testing is central to patient diagnosis and treatment as well as clinical trials and medical research. Every year over 7 billion laboratory tests are performed in the United States and nearly 75% of medical decisions are based on laboratory tests (ACLA, 2014). Laboratory tests enable early detection and prevention of diseases, saving time, costs, and lives. While some hospitals have in-house diagnostic units, many hospitals and smaller clinics today outsource ancillary services like laboratory testing to third-party service providers to avoid heavy capital costs and staffing difficulties. Centralized testing is becoming an increasing trend for quality assurance and consistency reasons (Laczin, 2013). Integration and standardization of laboratory systems can improve efficiency and effectiveness of medical operations (Hernandez et al., 2005). Changes in health care reimbursement policies in the United States have also resulted in significant consolidation of diagnostic units (Sautter and Thomson, 2015).

Consider a large laboratory service provider centrally located in a southwestern state of the United States that has a high-volume production environment. The centralized laboratory receives specimens from all over the state and conducts over 54 million diagnostic laboratory tests per year. Besides the centralized laboratory, the system includes over 70 patient service centers distributed throughout the state in not only metropolitan areas but also rural areas and small towns (Fig.

1). A patient goes to a nearby service center for specimen collection after his or her doctor prescribes the laboratory tests. Collected blood samples and other specimens are then delivered to the central laboratory located in the center of a major metropolitan area. There, the diagnostic tests are performed, and the results are sent back to the doctors and their patients.

Provision of rapid results has been a major concern, since it has a significant impact on patient care. Therefore, fast delivery of the specimens from the patient service center to the central laboratory is necessary. This is especially important for microbiology specimens as optimal analyses require viable organisms (Sautter and Thomson, 2015).

This research focuses on a remotely located patient service center. The site collects a significant amount of patient specimens on a daily basis, but lacks sufficient resources to preserve the samples and therefore a fast delivery is important. However, the site owns only a limited number of vehicles (minivans) to deliver the specimens to the central laboratory. Because of its remote location, the site cannot participate in a transportation system that has vehicles driving around the metropolitan area to collect specimens from various locations and drop them off at the central laboratory. Each vehicle the remote site owns can make only one trip per day to the central laboratory as the round trip takes about 8 hours. While the current schedule has vehicle drivers set out for delivery in an evenly distributed manner throughout the day, the management seeks to improve the scheduling of the outbound deliveries from this patient service site, to reduce the time specimens sit at the site waiting while patients walk in on a random basis. This paper contributes to the operations management literature as well as medical practices by providing theoretical properties and managerial insights for this unique stochastic scheduling problem.

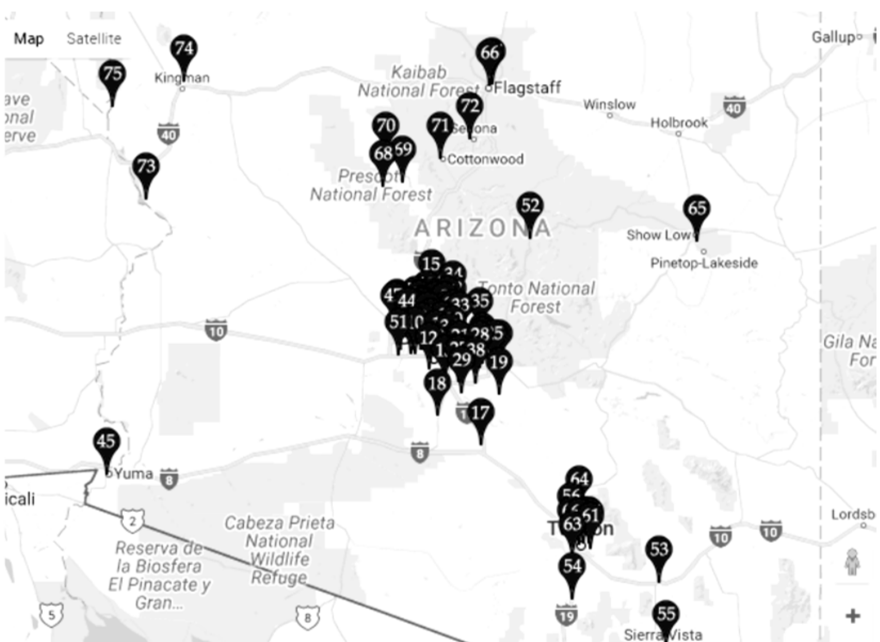

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FIGURE 1. DISTRIBUTION OF PATIENT SERVICE CENTERS.

The rest of the paper is organized as follows. Section II provides a problem definition and literature review for this scheduling issue. Section III derives optimal properties under various conditions. Section IV conducts simulation experiences of several scheduling policies to provide managerial insights, and conclusions are drawn in Section V.

II. PROBLEM DEFINITION AND LITERATURE

Hawkins (2007) reviews the literature on hospital laboratory management and indicates that the completion time from a test request to the delivery of results is a key performance measure; however, this is the measure with which medical professionals are least satisfied (Jones et al., 2006). Operations management principles have been applied to help hospital laboratories improve performance. Such efforts include increasing capacity (Berry 2006), reducing duplicated workload (Beland et al., 2003; May et al., 2006; Georgiou et al., 2007), batching (Persoon et al., 2006), and introducing staffing and processing flexibility (Levandrowski et al., 2004; Steindel and Howanitz, 1993; Winkelman et al., 1994). These studies are done in hospital settings where transportation of specimens happens within the hospital facility. To the best of our knowledge, vehicle-based transportation problems for centralized, third-party laboratory services have not been studied in the literature, whereas transportation (and waiting for transportation) can be the largest part of the turnaround time of centralized laboratory tests.

The vehicle departure scheduling problem we address in this research is a job release control problem in which a physical release constraint exists. The objective is to minimize the total job waiting time at a gate block before stochastically arrived jobs are released for service, delivery, or other processes, as the gate can be opened only for a limited number of times in a certain time period. In this case, a remote patient service site collects blood samples and other specimens from patients throughout a day but has only a few vehicles available to carry the samples to the central clinical laboratory. Job release control is an important operational decision to make in manufacturing environments in order to regulate factory workload or avoid bottleneck starvation (Fowler et al., 2002; Bowman, 2002; Duenyas et al., 1994; Glassey et al., 1988; Gupta et al. 2006; Kim et al, 1998; Choi and Chung, 2013), or to reduce job waiting time or lateness/tardiness (Melnyk and Ragatz, 1989; Ragatz and Mabert, 1988; Zozom et al., 2003; Park and Morrison, 2014). On the other hand, job release problems in service and logistics systems in which physical constraints may exist to limit the number of times jobs can be released for service or delivery in a certain period of time are largely overlooked in the literature. How to allocate the restricted number of releases during the time period has a significant impact on the quality of service measured by the timeliness of the delivery of the service.

In this research, customer jobs are collected specimens ready for delivery from the patient service center to the central laboratory. Job arrivals are random but follow a known stochastic pattern in the given time period T. Specifically, we assume that job arrivals follow a Poisson process, either stationary or nonstationary. In practice, the pattern can be obtained by analyzing historical demand data.

Jobs can be released for exactly m times during the given time period T. Arrived jobs wait at the "gate". Assume process capacity is sufficient so that, as soon as a release occurs, all jobs currently waiting are released for processing and their waiting times at the "gate" are added into the total waiting time. In this study, patient specimens are small packages, and a vehicle always has sufficient space to load all waiting specimens. Job flow times after the release (i.e., driving on the route, sample unloading, sample preparation, and testing at the central laboratory) are considered sunk costs and are not counted in the performance measure. Future jobs will accumulate at the "gate" again and wait for the next release.

The last release always happens at the end of the period. The problem is therefore to allocate or schedule the (m – 1) releases during the period to minimize total waiting time.

III. OPTIMALITY UNDER STYLIZED DEMAND PATTERNS

In this section we present our findings for two kinds of demand arrival patterns: a stationary Poisson process and a nonstationary Poisson process. Let τ_i be the departure time of the ith release, $i = 1,\cdots,m$, where m is the total number of releases within the planning cycle, and $\tau_m = T$.

3.1. Stationary Poisson Arrivals

The customer jobs arrive at the patient service center's outbound area according to a stationary Poisson process with constant rate λ. Theorem 1 shows that evenly distributing the vehicle releases along the planning horizon is the optimal scheduling strategy in terms of minimizing the total waiting time of all specimens.

Theorem 1. To minimize the total expected waiting time of all specimens on all vehicles under stationary Poisson arrivals, the optimal departure time of the i^{th} release is $\tau_i^* = \frac{i}{m}T$.

Proof: Prove by sample path. Let N(T) denote the total number of job arrivals before time T. For any given K, that N(T) = K, we prove the optimal departure time for the i^{th} vehicle is $\frac{i}{m}T$.

Given N(T) = K, the total expected waiting time of all K specimens is

$$E[\sum_{i=1}^{K}(\tau_1 - U_{(i)})1_{\{U_{(i)}\le\tau_1\}} + (\tau_2 - U_{(i)})1_{\{\tau_1<U_{(i)}\le\tau_2\}} + \cdots + (T - U_i)1_{\{\tau_{m-1}<U_{(i)}\le T\}}]$$

$$=\int_0^{\tau_1}\sum_{i=1}^{K}(\tau_1 - U_{(i)})K!\frac{1}{T^K}dU_{(1)}\cdots dU_{(K)} + \int_{\tau_1}^{\tau_2}\sum_{i=1}^{K}(\tau_2 - U_{(i)})K!\frac{1}{T^K}dU_{(1)}\cdots dU_{(K)} + \cdots + \int_{\tau_{m-1}}^{T}\sum_{i=1}^{K}(T - U_{(i)})K!\frac{1}{T^K}dU_{(1)}\cdots dU_{(K)}$$

$$= K!\frac{1}{T^K}\sum_{i=1}^{K}[\int_0^{\tau_1}(\tau_1 - U_i)dU_i + \int_{\tau_1}^{\tau_2}(\tau_2 - U_i)dU_i\cdots + \int_{\tau_{m-1}}^{T}(T - U_i)dU_i]$$

$$= K!\frac{1}{T^K}\sum_{i=1}^{K}[\tau_1^2 + \tau_2^2 - \tau_1\tau_2 + \tau_3^2 - \tau_2\tau_3 + \cdots + \tau_{m-1}^2 - \tau_{m-2}\tau_{m-1} + T^2 - T\tau_{m-1} - \frac{T^2}{2}],$$

where $\{U_{(1)},\ldots,U_{(K)}\}$ *is the order statistics of K independent uniform random variables* $\{U_1,\cdots,U_K\}$ *on [0, T], and the joint density function of* $\{U_{(1)},\ldots,U_{(K)}\}$ *is* $K!\frac{1}{T^K}$.

From solving the first order conditions of $\tau_1,\tau_2,\cdots,\tau_{m-1}$:

$$\begin{gathered}2\tau_1 - \tau_2 = 0\\ 2\tau_2 - \tau_1 - \tau_3 = 0\\ 2\tau_3 - \tau_2 - \tau_4 = 0\\ \vdots\\ 2\tau_{m-1} - \tau_{m-2} - T = 0,\end{gathered}$$

We can get the optimal departure time of the i^{th} *vehicle* $\tau_i^* = \frac{i}{m}T$.

3.2. Non-stationary Poisson Arrival

Assume the jobs arrive at the patient service center's outbound area according to a non-stationary Poisson process with arrival rate $\lambda(t)$ at time *t*. $\lambda(t)$ has an upper-bound $\bar{\lambda}$. We first present the result for the general case by constructing the conditions the optimal release schedule should satisfy in Theorem 2. Then we study the optimal scheduling problem for the case of *m* = 2 with specified arrival patterns.

Theorem 2. To minimize the total expected waiting time of all specimens on all vehicles, the optimal departure times τ_1^*, $\tau_2^*, \cdots, \tau_{m-1}^*$ satisfy the following equations:

$$\int_0^{\tau_1} \lambda(t)dt = \tau_2\lambda(\tau_1) - \tau_1\lambda(\tau_1)$$
$$\int_{\tau_1}^{\tau_2} \lambda(t)dt = \tau_3\lambda(\tau_2) - \tau_2\lambda(\tau_2)$$
$$\vdots$$
$$\int_{\tau_{m-2}}^{\tau_{m-1}} \lambda(t)dt = T\lambda(\tau_{m-1}) - \tau_{m-1}\lambda(\tau_{m-1})$$

Proof: By the thinning theory, the non-stationary Poisson Process with rate $\lambda(t)$ at time t can be constructed as a process split from the stationary Poisson process with constant arrival rate $\bar{\lambda}$ by performing a Bernoulli trial at any time t with success probability $\lambda(t)/\bar{\lambda}$.
Then we first construct the stationary Poisson process with rate $\bar{\lambda}$ by generating the order statistics $\{U_{(1)}, \ldots, U_{(k)}\}$ of K independent uniform random variables $\{U_1, \cdots, U_K\}$ on [0, T] given N(T) = K, where N(T) is the total number of arrivals by time T for the stationary Poisson process with rate $\bar{\lambda}$. Among these K arrivals, with probability $\frac{\lambda(t)}{\bar{\lambda}}$, an arrival is considered as a specimen arrival accepted by the service center, i.e., an arrival from the non-stationary Poisson Process with rate $\lambda(t)$.
Prove by sample path. Denote $p_i = \lambda(U_i)/\bar{\lambda}$. Given N(T) = K, the total expected waiting time of all specimens is

$$E[\textstyle\sum_{i=1}^{K}(\tau_1 - U_{(i)})1_{\{U_{(i)}\le\tau_1\}} + (\tau_2 - U_{(i)})1_{\{\tau_1<U_{(i)}\le\tau_2\}} + \cdots + (T - U_i)1_{\{\tau_{m-1}<U_{(i)}\le T\}}]$$
$$= \int_0^{\tau_1}\textstyle\sum_{i=1}^{K}(\tau_1 - U_{(i)})\frac{\lambda(U_{(i)})}{\bar{\lambda}}K!\frac{1}{T^K}dU_{(1)}\cdots dU_{(K)} + \int_{\tau_1}^{\tau_2}\sum_{i=1}^{K}(\tau_2 - U_{(i)})\frac{\lambda(U_{(i)})}{\bar{\lambda}}K!\frac{1}{T^K}dU_{(1)}\cdots dU_{(K)} + \cdots + \int_{\tau_{m-1}}^{T}\sum_{i=1}^{K}(T - U_{(i)})\frac{\lambda(U_{(i)})}{\bar{\lambda}}K!\frac{1}{T^K}dU_{(1)}\cdots dU_{(K)}$$
$$= K!\frac{1}{T^K\bar{\lambda}}\textstyle\sum_{i=1}^{K}[\int_0^{\tau_1}(\tau_1 - U_i)\lambda(U_i)dU_i + \int_{\tau_1}^{\tau_2}(\tau_2 - U_i)\lambda(U_i)dU_i \cdots + \int_{\tau_{m-1}}^{T}(T - U_i)\lambda(U_i)dU_i]$$
$$= K!\frac{1}{T^K\bar{\lambda}}\textstyle\sum_{i=1}^{K}[\int_o^{\tau_1}\tau_1\lambda(U_i)dU_i + \int_{\tau_1}^{\tau_2}\tau_2\lambda(U_i)dU_i \cdots + \int_{\tau_{m-1}}^{T}T\,\lambda(U_i)dU_i - \int_0^T U_i\lambda(U_i)dU_i]$$

We only need to find $\tau_1, \tau_2, \cdots, \tau_{m-1}$ to minimize $\int_o^{\tau_1}\tau_1\lambda(t)dt + \int_{\tau_1}^{\tau_2}\tau_2\lambda(t)dt \cdots + \int_{\tau_{m-1}}^{T}T\,\lambda(t)dt$.
The optimal departure time τ_1^*, $\tau_2^*, \cdots, \tau_{m-1}^*$ should satisfy the following first order conditions:

$$\int_0^{\tau_1} \lambda(t)dt = \tau_2\lambda(\tau_1) - \tau_1\lambda(\tau_1)$$
$$\int_{\tau_1}^{\tau_2} \lambda(t)dt = \tau_3\lambda(\tau_2) - \tau_2\lambda(\tau_2)$$
$$\vdots$$
$$\int_{\tau_{m-2}}^{\tau_{m-1}} \lambda(t)dt = T\lambda(\tau_{m-1}) - \tau_{m-1}\lambda(\tau_{m-1})$$

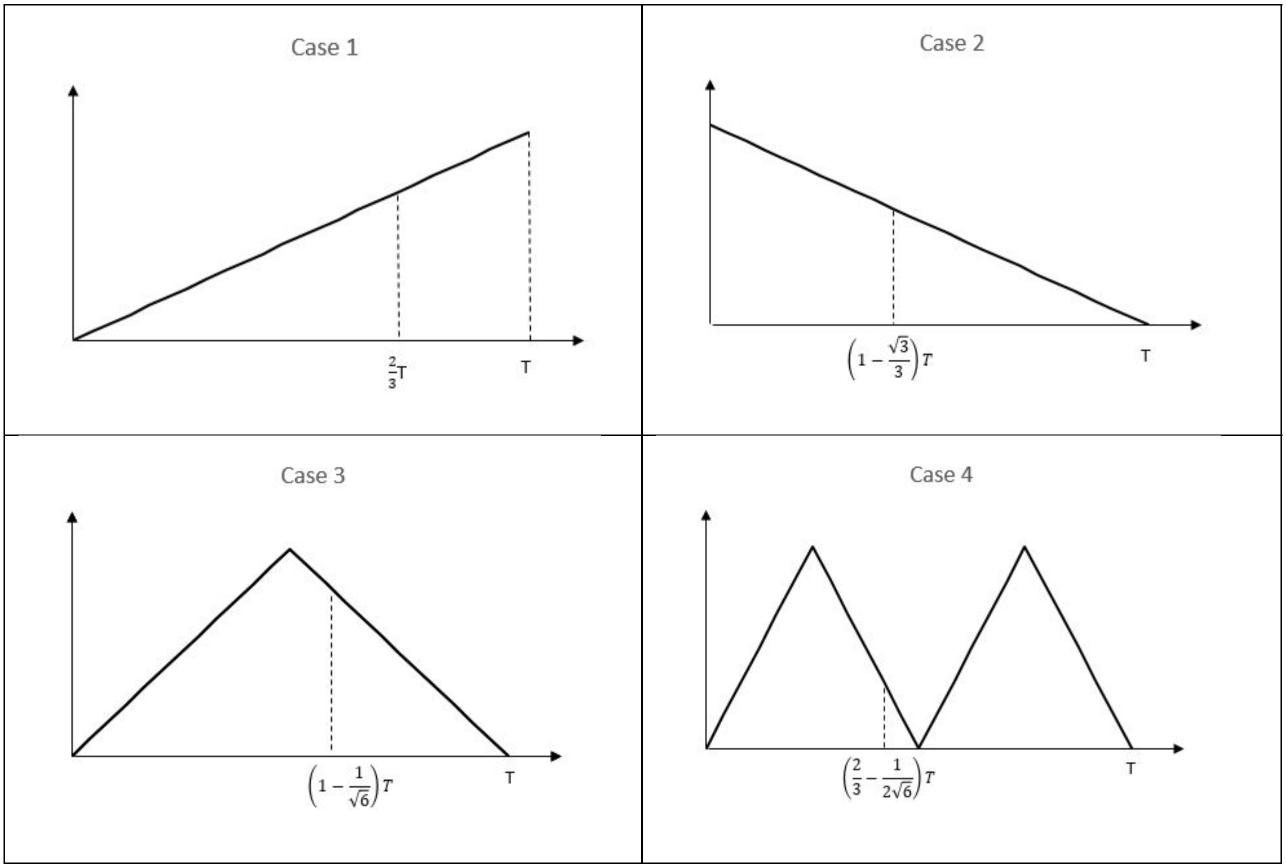

FIGURE 2. FOUR STYLIZED CASES.

Note that the integral on the left hand side of each first order condition above is the work-in-process (WIP) inventory of the vehicle release. Solving the optimal release time for each vehicle is to determine the best threshold for the WIP of each release.

Examples of Non-Stationary Poisson Arrivals with *m* = 2

When there is a total of two vehicle releases, i.e., m = 2, according to Theorem 2, the optimal release time of the first vehicle τ^* satisfies $\int_o^\tau \lambda(t)dt = (T-\tau)\lambda(\tau)$. Below we solve the optimal scheduling problem for 4 special cases as illustrated in Fig. 2.

Cases 1 and 2 assume a linear trend in the arrival rate. We find that as long as the arrival rate linearly changes during the planning horizon, the optimal release time of the first vehicle only depends on the sign of the arrival rate curve. It is independent of the specific slope of the arrival rate.

***Case 1:** Work flow arrival rate linearly increases from zero to λT within the planning horizon:*

$\lambda(t) = \lambda t.$

Optimal departure time of the first release $\tau^* = \frac{2}{3}T$.

Case 2: *Work flow arrival rate linearly decreases from* λT *to zero within the planning horizon:*

$$\lambda(t) = \lambda(T - t).$$

Optimal departure time of the first release $\tau^* = \left(1 - \frac{\sqrt{3}}{3}\right)T < \frac{T}{2}$.

Cases 3 and 4 assume the arrivals achieve peak(s) during the planning horizon. In both cases, the arrival rate exhibits a symmetric pattern during the planning horizon. Interestingly, we find that the optimal release times of the two vehicles are not evenly distributed.

Case 3: *Work flow linearly increases from zero during the first half of the planning horizon, then linearly decreases to zero during the second half of the planning horizon:*

$$\lambda(t) = \lambda t,$$
$$if\ t \le \frac{T}{2};\ \lambda(t) = \lambda(T - t),$$
$$if\ \frac{T}{2} < t \le T.$$

Optimal departure time of the first release $\tau^* = \left(1 - \frac{1}{\sqrt{6}}\right)T > \frac{T}{2}$.

Case 4: *Work flow arrival achieves the first peak in the middle of the first half of the planning horizon, then achieves the second peak in the middle of the second half of the planning horizon:*

$$(t) = \lambda t,$$
$$if\ t \le \frac{T}{4};\ \lambda(t) = \lambda\left(\frac{T}{2} - t\right),$$
$$if\ \frac{T}{4} < t \le \frac{T}{2};\ \lambda(t) = \lambda\left(t - \frac{T}{2}\right),$$
$$if\ \frac{T}{2} < t \le \frac{3T}{4};\ \lambda(t) = \lambda(T - t),$$
$$if\ \frac{3T}{4} < t \le T.$$

Optimal departure time of the first release $\tau^* = \left(\frac{2}{3} - \frac{1}{2\sqrt{6}}\right)T < \frac{T}{2}$.

IV. HEURISTICS AND SIMULATION STUDIES FOR GENERAL CASES

The optimality development in Section III under stylized cases provides insights for developing decision heuristics for general cases. It is shown that the optimal schedule does not have an even time-between-departure distribution in general cases with nonstationary Poisson arrival rates. However, it is straightforward to show that the distribution of the departure times should be more even when the case becomes more approximate to the stationary case; i.e., if the arrival rate has a larger positive intercept and smaller slope (in absolute value). A number of vehicle release heuristics are proposed for general cases where the nonstationary Poisson arrival rate does not follow a stylized pattern. The arrival rate's pattern can be estimated using historical data in practice. As an example, Fig. 3 summarizes the estimated arrival rates at the patient service center's outbound area across 30-minute time buckets on a common day. Each 30-minute sub-period has a different expected number of arrivals. In this example, the expected number of arrivals is 6 between t = 0 and t = 30 (min), and 20 between t = 30 (min) and t = 60 (min), etc.

We keep the decision rule that the m^{th} vehicle must depart at the end of the time period T so that all specimens collected within the planning horizon will be released. The proposed departure scheduling heuristics are as follows.

1) **Uniform (UN)**: the m releases are performed with equal time intervals between them. This is the common practice adopted by patient service centers.

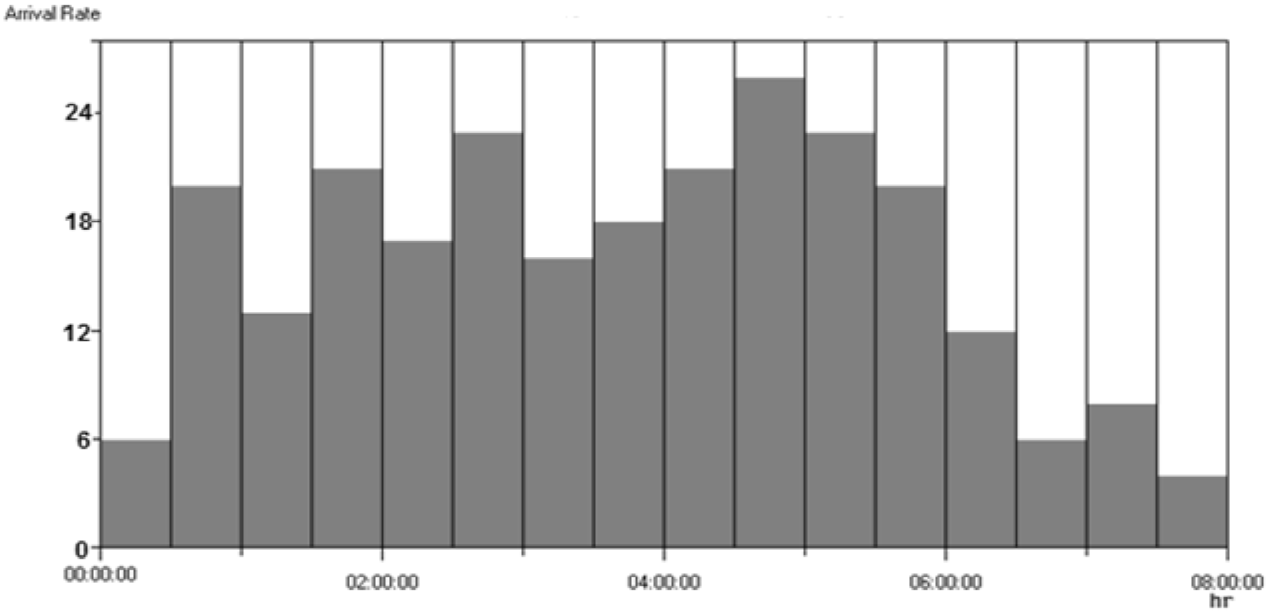

FIGURE 3. SAMPLE JOB ARRIVAL RATE PATTERN (SEMI-HOURLY RATES).

2) **Random (RN)**: the first (m – 1) releases are randomly scheduled during the time period with a uniformly distributed inter-release time.
3) **Workload Regulation (WR)**: the m releases are scheduled such that each release will carry the same expected number of jobs based on forecasted job arrivals.
4) **Peak Time Releases (PT)**: the first (m – 1) releases are scheduled at the end of the (m – 1) sub-periods with the (m – 1) highest expected number of job arrivals among all sub-periods except for the last sub-period.
5) **WIP Cap (WIPC)**: a WIP limit is set at the "gate" and as soon as the number of waiting jobs hit this limit, all waiting jobs are released. Future jobs then need to pile up and wait for the next time this limit is hit. This is done for the first (m – 1) releases while all remaining jobs will be released by the last release. The WIP cap can be chosen using optimization-via-simulation for a given demand pattern.
6) **Longest Waiting Time Cap (LWTC)**: as soon as the waiting time for the earliest job currently waiting at the "gate" exceeds a given threshold, all waiting jobs are released. The waiting time is measured when a new job arrives and therefore at each release the last arrived job has a waiting time of zero. Future jobs then need to pile up and wait for the next time this threshold is hit. This is done for the first (m – 1) releases while all remaining jobs will be released by the last release. The cap can be chosen using optimization-via-simulation for a given demand pattern.
7) **Cumulated Waiting Time Cap (CWTC)**: as soon as the cumulated

waiting time for jobs currently waiting at the "gate" exceeds a given threshold, these jobs are released. The cumulated waiting time is measured when a new job arrives and therefore at each release the last arrived job has a waiting time of zero. Future jobs then need to pile up and wait for the next time this threshold is hit. This is done for the first $(m - 1)$ releases while all remaining jobs will be released by the last release. The cap can be chosen using optimization-via-simulation for a given demand pattern.

Policies 5~7 are dispatching policies under which releases are triggered by the arrival of a job, whereas Policies 1~4 are scheduling policies under which releases are scheduled in advance. While none of the above policies guarantees optimality in a general stochastic case, it is straightforward to show that in a dispatching operation the $(m - 1)$ release times in any optimal solution must coincide with certain job arrival times. Note that in this vehicle departure problem, a job arrival is defined as a collected patient specimen package that is ready for delivery.

Theorem 3. To minimize the total waiting time of all specimens on all vehicles, the optimal departure times $\tau_1^*, \tau_2^*, \cdots, \tau_{m-1}^*$ must equal certain job arrival times.

Proof: Prove by contradiction. Assume that there exists an optimal solution such that the j^{th} release time τ_j is different from any job arrival time. Assume that τ_j is between the arrival times of job i and job (i + 1). A feasible solution can always be constructed by bringing forward τ_j to the arrival time of job i, which has a known arrival time as it has arrived before τ_j. This operation will strictly decrease the total waiting time of the j^{th} release. However, the total waiting times of other releases will not be changed.

Theorem 3 indicates that a dispatching approach needs to be incorporated into the departure schedules in order to minimize total waiting time. However, this may create implementation difficulties in common practice as vehicle drivers need instructions as simple as setting out at a given time. Nonetheless, we keep the dispatching policies in our comparative study and assume that in practice it is feasible to ask a driver to get ready earlier with a sufficient buffer time and set out as soon as a given job arrival signals the departure.

Discrete event simulation models are coded on Matlab and simulation experiments are performed with the following parameters:

- Time Period: $T = 480$ minutes
- Release Constraint: $m = 4$

Note that it is not necessarily to let the first three vehicles carry the same thresholds (WIP, LWT, or CWT Caps) for Policies 5 ~ 7. The threshold parameters are optimized using a response surface method with designed simulation experiments under the given demand pattern (Fig. 3). Let $\widehat{TWIP}$ be the expected total number of job arrivals in *T*. Table 1 lists the design points for data collection in a factorial 2^3 design of experiments for the example of parameterizing the WIP Caps. At each design point, 10 replicates are simulated to collect the total waiting time performance data. A second-order polynomial response surface model is fitted with a significant curvature and the best WIP Cap setting is derived from the fitted model. The same procedure is implemented to parameterize the LWTC and CWTC policies under the same given demand pattern as shown in Fig. 3.

The parameterized heuristics (Policies 5 ~ 7) are then put into comparison among all policies. A two-stage Ranking and Selection procedure (Dudewicz and Dalal, 1975) is followed to select the best of the 7 systems (policies) without running too many replications. In the first stage, 30 replicates are performed for each of the 7 systems. Total sample size needed for each system is calculated and additional replications are made in the second stage. The overall weighted sample mean of a system is calculated as a linear combination of the first-stage sample mean and the second-stage sample mean. Simulation results are presented in Table 2. UN is a common practice and can be used as the baseline for comparison purposes. Since the Ranking and Selection procedure guarantees that the performance differences between UN, WIPC, LWTC, and CWTC are statistically significant, we conclude that WIPC should be selected for the given demand pattern. The results verify the managerial insight we gain from the theories that pull-based dispatching policies outperform the common practice in general cases.

TABLE 1. DESIGN POINTS FOR PARAMETERIZING THE WIPC POLICY USING DESIGNED SIMULATION EXPERIMENTS UNDER THE GIVEN DEMAND PATTERN.

Design Points	Vehicle 1 WIP Cap	Vehicle 2 WIP Cap	Vehicle 3 WIP Cap
-1, -1, -1	0.8 $\widehat{TWIP}$ / 4	0.8 $\widehat{TWIP}$ / 4	0.8 $\widehat{TWIP}$ / 4
-1, -1, +1	0.8 $\widehat{TWIP}$ / 4	0.8 $\widehat{TWIP}$ / 4	1.2 $\widehat{TWIP}$ / 4
-1, +1, -1	0.8 $\widehat{TWIP}$ / 4	1.2 $\widehat{TWIP}$ / 4	0.8 $\widehat{TWIP}$ / 4
-1, +1, +1	0.8 $\widehat{TWIP}$ / 4	1.2 $\widehat{TWIP}$ / 4	1.2 $\widehat{TWIP}$ / 4
+1, -1, -1	1.2 $\widehat{TWIP}$ / 4	0.8 $\widehat{TWIP}$ / 4	0.8 $\widehat{TWIP}$ / 4
+1, -1, +1	1.2 $\widehat{TWIP}$ / 4	0.8 $\widehat{TWIP}$ / 4	1.2 $\widehat{TWIP}$ / 4
+1, +1, -1	1.2 $\widehat{TWIP}$ / 4	1.2 $\widehat{TWIP}$ / 4	0.8 $\widehat{TWIP}$ / 4
+1, +1, +1	1.2 $\widehat{TWIP}$ / 4	1.2 $\widehat{TWIP}$ / 4	1.2 $\widehat{TWIP}$ / 4
Center point (0,0,0)	$\widehat{TWIP}$ / 4	$\widehat{TWIP}$ / 4	$\widehat{TWIP}$ / 4

TABLE 2. TOTAL WAITING TIME PERFORMANCES (IN MINUTES) FROM THE SIMULATION STUDIES.

	UN	**RN**	**WR**	**PT**	**WIPC**	**LWTC**	**CWTC**
First-stage mean	14602.387	27601.56	20786.293	16017.733	14360.893	14368.613	14403.653
Total replications	31	164	342	62	93	78	52
Second-stage mean	14930.24	27707.253	20501.387	16476.827	14245.373	14374.827	14261.64
Overall mean	**14641.933**	**27693.12**	**20520.68**	**16320.333**	**14273.067**	**14373.107**	**14324.973**
Benchmarking	**(vs. UN)**	13051.19	5878.747	1678.4	**-368.866**	**-268.826**	**-316.96**

V. CONCLUSION REMARKS

The outbound vehicle departure scheduling problem in this research is modeled as a job release control problem with physical release constraints. The objective is to minimize total job waiting time before they are released. Theoretical developments in Section III by using the thinning theory hint that the optimal solution for a general case has a WIP cap for each release. This is illustrated in Section IV that a parameterized WIPC policy outperforms the other heuristic decision policies in a general case. The LWTC and CWTC policies also perform well since they set an upper bound (worst-case scenario) on the performance measure. The simulation-based procedure can be easily automatized in a software package to assist operational decisions.

In practice, stochastic job arrival patterns can be estimated by analyzing historical data. If the job arrival rate is stationary throughout the day, the UN policy is optimal; whereas this is unlikely to be the case in practice. Meanwhile, UN is the *de facto* common practice and the simulation results in Section IV show that UN is a reasonable scheduling policy with an acceptable performance. To further improve the operational performance of total job waiting time, dispatching policies such as the WIPC need to be implemented. The dispatching policies are "pull" strategies that release jobs based on system status and their implementation is not as easy as scheduling policies such as UN. A future research direction is to develop a way to streamline the implementation of a dispatching policy in practice so that a good buffer can be provided for vehicle drivers to get ready for departure ahead of time. This logistics problem can be extended to the case of optimizing the entire looped supply chain in which patients provide jobs and receive final results from the central laboratory. We also suggest future research to explore the use of supervised machine learning to dynamically forecast demands and select the best job release solutions in various business applications. For example, push notification scheduling on mobile devices has a similar job release scheduling/dispatching problem with release constraints due to energy concerns and user requirements. In this case, both the stochastic demand pattern (message arrivals) and user behaviors need to be studied in a dynamic manner.

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