Multi-Period Technician Scheduling with Experience-based Service Times and Stochastic Customers

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Abstract

This paper introduces the multi-period technician scheduling problem with experience-based service times and stochastic customers. In the problem, a manager must assign tasks of different types that are revealed at the start of each day to technicians who must complete the tasks that same day. As a technician gains experience with a type of task, the time that it takes to serve future tasks of that type is reduced (often referred to as experiential learning). As such, while the problem could be modeled as a single-period problem (i.e. focusing solely on the current day's tasks), we instead choose to model it as a multi-period problem and thus capture that daily decisions should recognize the long-term effects of learning. Specifically, we model the problem as a Markov decision process and introduce an approximate dynamic programming-based solution approach. The model can be adapted to handle cases of worker attrition and new task types. The solution approach relies on an approximation of the cost-to-go that uses forecasts of the next day's assignments for each technician and the resulting estimated time it will take to service those assignments given current period decisions. Using an extensive computational study, we demon-

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strate the value of our approach versus a myopic solution approach that views the problem as a single-period problem.

Keywords: Dynamic Programming, Technician Scheduling, Multi-period, Learning

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1. Introduction

As the global economy recovers, there is growing pressure in the skilled labour markets. According to the Hays Global Skills Index 2014, a statistics-based study designed to assess the dynamics of skilled labour markets across
5 31 countries, this pressure continues to rise, particularly in economies that are returning to pre-crisis levels such as United States, Germany, and the United Kingdom [1]. Maintaining growth in a pressured labor market requires that companies use their expensive and limited labor resources to their greatest potential. One opportunity is for companies to take advantage of the capacity that
10 is gained as employees learn by experience. Matching the right employee with the right job cannot only help a company meet its current needs, but also build capacity for meeting future demand growth as well as build the flexibility needed to buffer against demand uncertainty. Further, the ability to account for each individual employee's ability to learn allows companies to best deploy workers
15 in the face of strategic growth opportunities giving companies the agility that [2] calls essential to surviving in the volatile modern business environment.

In this paper, we explore the issue of how companies can use immediate employee job assignments to meet current demand and build capacity for the future. We focus on service workers, particularly service technicians. The prob-
20 lem discussed in this paper is a variant of the technician and task scheduling problem (TTSP). In the TTSP, a set of technicians serves a set of customer requests. Customers are associated with certain tasks and different tasks have different skills associated with them. In our version of the problem, technicians have different service times depending on their experience in performing a task

25 as well as each technician’s ability to transform that experience into improved productivity. We measure experience in the number of times that the technician has performed the task.

The fact that technician productivity, and really all workers productivity, is linked to experience suggests that what could be modeled as a single-period
30 problem (i.e. focusing solely on making assignments to serve the current day’s tasks) should instead be modeled as a multi-period problem. As such, we consider the multi-period technician scheduling problem that accounts for the fact that productivity increases (or service time decreases) as technicians gain experience. These increases in productivity are often referred to as “learning.” We
35 assume that the time that it takes a technician to complete a task depends on the technician’s experience in the skill associated with the task and how quickly the technician learns. How quickly a technician learns is known as the technician’s learning rate. We assume that we have a set of heterogeneous technicians whose learning rates and initial experience are known. The service time depends
40 on the amount of experience the worker has with the skill required by the task.

We assume that daily demand is not revealed until the day of service. Each day, the technicians serve the day’s demand, . In this work, we seek to minimize the expected sum of each day’s total service times over a finite horizon. Reflecting what are often tight labor market conditions for technicians (a job
45 definition that can span multiple industries, including home appliance repair, lab technician, and home health care), we choose an objective that seeks to maximize the capacity of an existing workforce. We call our problem variant the multi-period technician scheduling problem with experience-based service times and stochastic customers (MTSP-ESTSC).

50 To solve the problem, we propose an approximate dynamic programming (ADP) approach that, at each stage, solves a mixed integer program (MIP) to assign technicians to tasks. In addition to recognizing the resulting service times in the current period, the MIP approximates the impact of those assignments on future technician service times (the “cost-to-go”) with a forecast of each
55 technician’s task assignments in the next period. Assignment decisions in the

next period are partially driven by each technician’s service times on each type of task, which are in turn driven by their experience level on each type of task. To capture this fact, the forecasting model embedded in the MIP is a function of the assignment decisions in the current period.

60 One of the challenges associated with solving optimization models that recognize that humans learn is that the quantitative models of human learning proposed by the psychology community are non-linear. As a result, to solve a MIP at each stage of the ADP, we adapt an exact reformulation method from the literature that relies on the fact that the function we use to map experience
65 to service time has a finite domain.

In this study, we make the following research contributions. First, we present the first model that explicitly models the impact of individualized, experience-based learning on the technician scheduling problem. Such a model will facilitate organizational productivity improvement by allowing for more effective
70 workforce management. Further, we discuss how the presented Markov decision process (MDP) model can be adapted to handle cases of worker attrition and new task types. Second, we introduce a method for approximating the future value of today’s workforce assignments. With the addition of technician learning to the model, decisions today affect tomorrow’s productivity. Thus,
75 the approximation method allows us to do so. Third, using the approximation, we demonstrate how the approximate Bellman equation can be transformed into a linear, mixed integer program. This transformation is significant because the nonlinearity of the learning functions naturally lead to a nonlinear integer programming formulation. Our formulation allows the approximate Bellman
80 equation to be solved by a standard implementation of a commercial integer programming solver.

We demonstrate the value of the proposed solution approach with three experiments. In one experiment, the set of technicians and the set of task types remain the same over the problem horizon. In the second, we introduce a work-
85 force disruption in the middle of the horizon in which one technician leaves the workforce and a new technician is added. The third variant adds an additional

task type in the middle of the horizon. For each of the three problem variants, we compare the proposed solution approach to a myopic solution approach that views the problem as a single-period problem, ignoring the impact of current
90 period decisions on future service times. Our comparisons demonstrate that the proposed solution approach leads to higher-quality solutions by better positioning technicians to meet future demands.

The remainder of this paper is organized as follows. Section 2 reviews the literature related to the MTSP-ESTSC. Section 3 presents a model for the
95 problem. Section 4 describes the solution approach. Section 5 discuss the design of the experiments, and Section 6 presents our computational results. Finally, Section 7 concludes this work and suggests areas of future research.

2. Literature Review

We review the literature of technician scheduling and routing problems as
100 well as for experience-based learning.

2.1. Individual Learning and Its Applications

That humans learn as they gain experience, “learning-by-doing” is a well known phenomenon. The learning effect was first examined on a scientific basis by [3], who quantified learning curves with the observation that in the aircraft
105 industry the working costs per unit declined with an increasing production output. Subsequent empirical studies confirmed the existence and importance of learning effects (see for example [4, 5, 6, 7]). In 2016, the concept has become mainstream enough that it is now included in textbooks on operations management ([8, 9]).

The mathematical descriptions of learning are often called learning curves.
110 Reviews of the literature on learning curves can be found in [10], [11], [12], and [13]. Because of the availability of distributions from which to generate workforces, in this research, we use the hyperbolic learning model described in [14]. We note that, while we employ the hyperbolic learning model, most learn-
115 ing curves have similar shapes and would support conclusions similar to those

discussed in Section 6. We note that there also exists an extensive literature focusing on organizational learning. [15] provides an excellent reference.

Work that explicitly models individual learning and the associated heterogeneity of the workforce demonstrates the value of capturing learning. [16] shows that simply modeling worker heterogeneity without considering learning improves system performance versus assuming uniform workforce productivity in flow-line production. [17] extend the analysis of [16] to demonstrate the impact of heterogeneous learning and forgetting curves on system productivity in a assembly-line setting. [18] confirms the results of [17] for technician routing. In addition to flow lines, assembly lines, and technician routing, the value of modeling learning has also been found in call centers ([19]), departmental assignment ([20]), machine scheduling (see [21] for a review), project selection ([22, 23]), and vehicle routing ([24]).

One of the challenges of much of the workforce planning literature that models individual learning is that the nonlinearity of the learning curves creates challenges. For this reason, work such as [19] and [25], simplify the model of individual learning to avoid the nonlinearities. Work such as [26] exploits structural properties of the optimal solution to increase the size of the problem that can be solved. However, such approaches do not generalize. Work such as [27], [28], and [29] are limited to solving small problems. [30] introduce a linear and integer reformulation of the learning curve that takes advantage of the fact that most work is assigned in time intervals. The reformulation allows much larger problems to be solved than had been previously. We take advantage of the reformulation in this work as well. Other examples of the reformulation can be found in [31], [32], and [33]. Additional review of workforce planning models that incorporate learning can be found in [34] and [30].

2.2. Technician Scheduling and Routing

Existing literature contains a variety of technician scheduling and routing problems. A detailed review can be found in [18]. [35] introduce the technician scheduling problem and describe a problem in which technicians are grouped

into teams. Tasks are assigned to teams so that skill requirements and required skill levels can be matched. In 2007, the French Operations Research Society introduced a challenge (<http://challenge.roadef.org/2007/en/>) based on [35]’s work and offered a real-world data set for technician scheduling. The
150 challenge resulted in a stream of papers [36, 37, 38, 39]. All of the papers explore deterministic problems and account for neither learning nor the extended horizon over which learning occurs. The multi-period technician scheduling problem with stochastic customers is discussed in [40], but the solution approach is myopic.

155 A number of papers in the literature consider multi-period scheduling. However, none of these papers incorporates learning effects, and all of the papers study deterministic problems. In contrast, this paper considers that each day’s jobs are revealed over time and that the technicians learn from experience. Examples of deterministic, multi-period scheduling problems include
160 [41, 42, 43, 44, 45, 46, 47, 48].

Other literature incorporates routing in addition to service time aspects of the problem, but again, does not consider learning and a multi-period horizon. A number of papers treat deterministic variants of the problem [49, 50, 51, 52, 53, 54]. A few authors consider stochastic elements of the problem. [55] focuses
165 on uncertainty associated with service times, and [56] on stochastic service travel times. Additional papers incorporate dynamic and stochastic service requests [57, 40, 58, 59]. Unlike in this work, however, all these papers present myopic, reoptimization solution approaches that do not incorporate information about future requests. [60] incorporates information about the future by adapting the
170 sample-scenario approach proposed by [61]. In contrast to the multiple periods studied in this paper, however, [60] focuses serving customers in a one-day period.

We are aware of only one paper in technician routing and scheduling that incorporates learning. [18] consider a multi-period technician routing problem
175 with experience-based learning and stochastic customers. However, unlike in this work, [18] present a myopic solution approach that does not incorporate

information about future requests in daily decision making.

3. Problem Formulation

In this section, we present a formal model for the multi-period technician
180 scheduling problem with experience-based service times and stochastic customers (MTSP-ESTSC). We also discuss how the model can be adapted to a number of problem variants.

Let the set $\mathcal{T} = \{1, 2, \dots, T\}$ be the set of T days in the planning horizon. Let $\mathcal{K} = \{1, 2, \dots, K\}$ be the set of technicians, and let $\mathcal{R} = \{1, 2, \dots, R\}$ be
185 the set of all possible task types. In this paper, we assume that the technicians learn independently on each task. However, both our model and our solution approach can easily be modified to account for the transfer of experience on one task to another particularly as described by [62].

Each technician k in $\mathcal{K}$ requires a particular time to complete each task
190 r in $\mathcal{R}$. The service time for a particular task depends on the experience a technician has in performing the task as well as the technician's ability to learn from that experience. We let d_{r0} be the maximum service time for a task r , and D_r^k be the maximum productivity rate for technician k performing task r . The parameter L_r^k defines the learning rate, where the learning rate defines how
195 quickly technician k can learn from experience on task r . In practice, these individual parameters can be estimated from data.

Given these parameters, we can determine technician k 's service times for each task in $\mathcal{R}$ at the start of day t using a learning curve. The learning curve requires a technician's experience on a given task up to day t . We capture this experience in the R -dimensional vector $\mathcal{Q}_t^k = (q_{1t}^k, q_{2t}^k, \dots, q_{Rt}^k)$, where the r^{th} entry q_{rt}^k indicates technician k 's experience with task r^{th} at the start of day t . We let $\mathcal{Q}_0^k$ represent technician k 's experience at the beginning of the horizon. Assuming the hyperbolic learning curve [14], technician k 's service time for task

r on day t is:

$$d_{rt}^k = \left(D_r^k \left(\frac{q_{rt}^k}{q_{rt}^k + L_r^k} \right) \right)^{-1}. \quad (1)$$

Figure 1 is an illustration of the learning curve with $D_r^k = 3.99$ and $L_r^k = 7.65$, showing the negative relationship between technician's experience and service times.

Figure 1: Learning Curve Illustration

On a given day t , we seek to serve a set of tasks $\mathcal{N}_t = \{1, 2, \dots, N_t\}$ by assigning the tasks to individual technicians. We assume that there is a limit or capacity C to the amount of time that a technician can work in a day. We also assume that this set of tasks becomes known only at the beginning of day t . Recalling that we seek to maximize the capacity of an existing workforce, our problem objective is to minimize the expected sum of each day's service times.

We model the optimization problem as a Markov decision process (MDP). A decision is made at the beginning of each day during the planning horizon. Let $t = 1, 2, \dots, T$ be the decision epochs, where day T is the last day in the problem horizon. The state of the system captures all the information that we need to make a scheduling decision. In this case, to make task assignments for the day, we must know the set of tasks that need to be served for the day and the experience of the technicians at the start of the day. Then, the state of the system at the beginning of day t is $s_t = \{\mathcal{N}_t, \mathcal{Q}_t\}$.

Given state s_t , an action is a set of assignments that serves the day t requests.

215 Let action $a_t(s_t) = \{x_{it}^k : i \in \mathcal{N}_t, k \in \mathcal{K}\}$, where binary variables x_{it}^k equals 1 if task i is served by technician k in day t . For notational convenience, let $r(i)$ map a task i into the set of task types $\mathcal{R}$. Then, given a day t , a feasible action satisfies the following constraints:

$$\sum_{k \in \mathcal{K}} x_{it}^k = 1 \quad \forall i \in \mathcal{N}_t, \quad (2)$$

$$\sum_{i \in \mathcal{N}_t} x_{it}^k d_{r(i)t}^k \leq C \quad \forall k \in \mathcal{K} \quad (3)$$

$$x_{it}^k \in \{0, 1\} \quad \forall i \in \mathcal{N}_t, \forall k \in \mathcal{K}. \quad (4)$$

Constraints (2) ensure that a task is assigned to exactly one technician and that
220 the task is assigned only once. Constraints (3) ensure that all technicians finish working by the end of the day, and Constraints (4) ensure integrality.

Let $\mathcal{A}_t(s_t)$ be the set of all actions available on day t given state s_t . We assume that each technician's learning is deterministic and based on accumulated experience. Therefore, given that the state is currently s_t and that action a_t
225 in $\mathcal{A}_t(s_t)$ is selected, a deterministic transition is made to post-decision state $s_t^a = \{\mathcal{N}_t, \mathcal{Q}_t^a\}$ by updating technicians' experience as follows:

$$q_{r,t+1}^k(s_t, a_t) = q_{rt}^k + \sum_{i \in \mathcal{N}_t: r(i)=r} x_{it}^k \quad \forall k \in \mathcal{K}, \forall r \in \mathcal{R} \quad (5)$$

Recalling that experience is measured as the number of times that the technician has performed the task. Equation (5) adds each technician's existing experience the experience gained from the day t assignments.

230 We let $W_{t+1} = (w_{1,t+1}, \dots, w_{\tilde{N}_{t+1},t+1})$ be the random exogenous information for day $t+1$, where $w_{i,t+1}$ is a random variable representing the task type of the i^{th} service request on day $t+1$ and $\tilde{N}_{t+1}$ is a random variable representing the random number of requests on day $t+1$, neither of which is known prior to day $t+1$. Following day t , we observe the exogeneous information for day $t+1$ and transition to decision epoch $t+1$. Decision epoch $t+1$ requires a transition
235

from post-decision state s_t^a to pre-decision state $s_{t+1} = \{\mathcal{N}_{t+1}, \mathcal{Q}_{t+1}\}$, where $\mathcal{N}_{t+1}$ is the realization of the exogenous process for day $t+1$. In this transition, technicians' experience remain unchanged, thus $\mathcal{Q}_{t+1} = \mathcal{Q}_t^a$. The technicians' productivity for day $t+1$ can be calculated according to the learning curve given the technicians' experience levels.

At decision epoch t , given state s_t and action $a_t(s_t)$, a transition from pre-decision state s_k to post-decision state s_k^a results in a contribution

$$C(s_t, a_t) = \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{N}_t} x_{it}^k d_{r(i)t}^k \quad \forall a_t \in \mathcal{A}_t(s_t), \quad (6)$$

which is the total service time to complete all tasks on day t . The problem objective is then $\min_{\pi \in \Pi} E \left[\sum_{t=1}^T C(s_t, \delta_t^\pi(s_t)) \right]$, where π is a policy that determines actions for all days t over the problem horizon T , Π is the set of all policies, and $\delta_t^\pi(s_t)$ is a decision rule specific to policy π that maps the state s_t to an action a_t .

In our experiments, we consider two problem variants: (1) attrition and hiring in the technician pool and (2) a new task type to be serviced. We can accommodate this variants with minor changes to the model. In the attrition and hiring scenario, we assume that a technician k 's decision to leave the workforce is exogenous to our model. As such, we model such a departure as an addition to the exogenous information that is observed the day after a technician's departure. Thus, when technician k leaves the workforce just after day $t-1$ and is replaced by a new technician k' on day t , we update $\mathcal{Q}_t$ by setting $q_{r,t}^k(s_t, a_t) = I_r^{k'}$, where $I_r^{k'}$ is the initial experience level of technician k' on tasks of type r for each task type r .

We handle the second variant similarly. Specifically, for the second variant wherein a new task type (labeled $R+1$) is to be serviced starting on day t , in the transition from day $t-1$ to day t , we expand the state to include the experience levels $q_{R+1,t}^k$, for all k in $\mathcal{K}$. Then, the value of $q_{R+1,t}^k$ is initialized to whatever the appropriate value should be for each technician.

4. Solution Approach

Given our assumptions, an optimal policy can be found by using the well-known Bellman equation. The general form of the Bellman equation and the form sufficient for our problem is given by setting

$$V(s_t) = \min_{a \in \mathcal{A}_t(s_t)} \{C(s_t, a) + E[V(s_{t+1}) \mid s_t, a]\}. \quad (7)$$

While we can easily state the Bellman equation for our problem, because of the need to capture each day's set of requests in the state space, the problem is far too large for an exact solution approach such as backward dynamic programming. Instead, we introduce an approximate dynamic programming (ADP) approach that approximates the cost-to-go, the second term in Equation (7), using a forecast of technician assignments for one day in the future. Using this approximation, we then step forward in time. Analogous to rollout algorithms (see [63]), by stepping forward in time, we need only find actions for states that are realized. In the remainder of this section, we first present our approximation of the cost-to-go. We then demonstrate how to use this approximation to solve an approximate form of the Bellman Equation, Equation (7). Finally, we discuss our forward ADP algorithm.

4.1. Cost-to-Go Approximation and Solving the Approximate Bellman Equation

For each technician, this forecast is based on the technician's previous assignments and a forecast of the next day's tasks. Specifically, for each technician and each task type, we first predict the demand requests for the next period with an exponential smoothing forecasting: $F_{rt}^k = \alpha F_{r,t-1}^k + (1 - \alpha)A_{r,t-1}^k$, where $F_{r,t-1}^k$ and $A_{r,t-1}^k$ are the numbers of predicted and actual type r demand requests assigned to technician k for period $t - 1$, respectively, and F_{rt}^k is the forecasted number of assignments of task type r to technician k on day t . The parameter α is the smoothing factor. Given an assignment of technician k for each task i on day $t - 1$, $x_{i,t-1}^k$, we can compute $A_{r,t-1}^k$ as $\sum_{i \in \mathcal{N}_{t-1}: r(i)=r} x_{i,t-1}^k$.

In addition, given an assignment of technician k for each task i on day $t - 1$, $x_{i,t-1}^k$, we can compute $\hat{d}_{rt}^k$, the forecasted service time on day t for task type r and technician k . For technician k and task type r , $\hat{d}_{rt}^k$ can be calculated using the assignments for day $t - 1$ as:

$$\hat{d}_{rt}^k = \left(D_r^k \left(\frac{q_{r,t-1}^k + \sum_{i \in \mathcal{N}_{t-1}: r(i)=r} x_{i,t-1}^k}{q_{r,t-1}^k + \sum_{i \in \mathcal{N}_{t-1}: r(i)=r} x_{i,t-1}^k + L_r^k} \right) \right)^{-1}. \quad (8)$$

With the forecasted number of assignments for day t , F_{rt}^k and forecasted service times, for each technician k and task type r , we can write an approximate Bellman equation as:

$$\hat{V}(s_{t-1}) = \min_{a \in \mathcal{A}_t(s_{t-1})} \{C(s_{t-1}, a) + \sum_{k \in \mathcal{K}} \sum_{r \in \mathcal{R}} F_{rt}^k \hat{d}_{rt}^k\}. \quad (9)$$

Equation (9) can be rewritten as a math program as follows:

$$(\mathbf{F}) \quad \min \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{N}_{t-1}} x_{i,t-1}^k d_{r(i),t-1}^k + \sum_{k \in \mathcal{K}} \sum_{r \in \mathcal{R}} F_{rt}^k \hat{d}_{rt}^k$$

subject to (2), (3), (4)

$$F_{rt}^k = \alpha F_{r,t-1}^k + (1 - \alpha) \sum_{i \in \mathcal{N}_t: r(i)=r} x_{i,t-1}^k, \forall k \in \mathcal{K}, \forall r \in \mathcal{R}, \quad (10)$$

$$\hat{d}_{rt}^k = \left(D_r^k \left(\frac{q_{r,t-1}^k + \sum_{i \in \mathcal{N}_{t-1}: r(i)=r} x_{i,t-1}^k}{q_{r,t-1}^k + \sum_{i \in \mathcal{N}_{t-1}: r(i)=r} x_{i,t-1}^k + L_r^k} \right) \right)^{-1}, \forall r \in \mathcal{R}, \forall k \in \mathcal{K}, \quad (11)$$

$$x_{i,t-1}^k \text{ binary}, \forall k \in \mathcal{K}, \forall i \in \mathcal{N}_{t-1}. \quad (12)$$

The objective is to minimize the sum of total service time and the forecasted service time for the next period. As presented earlier, Constraints (2) to (4) define feasible actions. Constraints (10) are replaced with $F_{rt}^k = \sum_{i \in \mathcal{N}_t: r(i)=r} x_{i,t-1}^k$ when $t - 1 = 1$. Constraints (11) determine the service time for the forecasted

assignments.

Model **(F)** is non-linear. We use the reformulation presented by [30] to overcome this challenge. The reformulation takes advantage of the fact that the task assignments and thus experience are discrete and that the maximum number of tasks of each type is known for a given day $t - 1$. Thus, we can enumerate the set of potential forecasted service times for each technician on each task type for day t . We describe the steps of the enumeration in Algorithm 1.

To present the reformulation, we first present some additional notation. We let $z_{r,t-1}^{kj}$ be a binary variable indicating whether technician k did j tasks of type r on day $t - 1$. Let $\bar{d}_{rt}^{kj}$ represent technician k 's estimated service times for serving tasks of type r on day t having done j jobs of task r on day $t - 1$. Then, having completed j tasks of type r on day $t - 1$ and given $\bar{d}_{rt}^{kj}$ for technician k on task type r for day t , the total time required for k to complete the forecasted number of tasks of type r on day t is $\overline{ST}_{rt}^{kj} = \bar{d}_{rt}^{kj} F_{rt}^k$. We introduce ST_{rt}^k as a decision variable that gives the total service time of technician k on tasks of type r for day t . Finally, let $M_{t-1} = (m_{1,t-1}, m_{2,t-1}, \dots, m_{R,t-1})$ be a vector of the number of each task type r for day $t - 1$. Then, the reformulation model is as follows:

$$(\mathbf{R}) \min \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{N}_{t-1}} x_{i,t-1}^k d_{r(i),t-1}^k + \sum_{k \in \mathcal{K}} \sum_{r \in \mathcal{R}} ST_{rt}^k$$

subject to (2), (3), (4), (10) ,

$$ST_{rt}^k = \sum_{j=1}^{m_{r,t-1}} \overline{ST}_{rt}^{kj} z_{r,t-1}^{kj} \quad , \forall r \in \mathcal{R}, \forall k \in \mathcal{K}, \quad (13)$$

$$\sum_{j=1}^{m_{r,t-1}} j z_{r,t-1}^{kj} = \sum_{i \in \mathcal{N}_{t-1}: r(i)=r} x_{i,t-1}^k \quad , \forall r \in \mathcal{R}, \forall k \in \mathcal{K}, \quad (14)$$

$$\sum_{j=1}^{m_{r,t-1}} z_{r,t-1}^{kj} = 1 \quad , \forall r \in \mathcal{R}, \forall k \in \mathcal{K}, \quad (15)$$

$$z_{rt}^{kj} \text{ binary} \quad , \forall r \in \mathcal{R}, \forall k \in \mathcal{K}, j = 1, \dots, m_{rt}. \quad (16)$$

295 Constraints (13) assign one forecasted total service time for each technician on
each task type for day t . Constraints (14) ensure that the next day’s forecasted
total service time of a technician on each task type corresponds to the number
of this type of tasks he/she performed today. Constraints (15) ensure that each
technician is assigned exactly one forecasted total service time for each task
300 type on each day.

4.2. Forward Approximate Dynamic Programming Algorithm

Algorithm 1 presents our forward ADP algorithm for solving instances of
the MTSP-ESTSC. Unlike the traditional backward dynamic programming al-
gorithm, Algorithm 1 steps forward in time. Stepping forward in means offers
305 the advantage that we need only solve the Bellman equation for those states
that are actually visited. However, stepping forward in time also means that
we have not computed values for the cost-to-go in the Bellman equation. We
instead approximate the cost-to-go in the manner described in the previous sec-
tion. Using that approximation and the previously described reformulation, the
310 approximate Bellman equation given in Equation (9) can be solved using the
math program given in **R**.

Algorithm 1 outputs a series of actions, or technician assignments, one for
each state visited over the planning horizon. The algorithm takes as input the
set of technicians, their learning parameters, and the set of task types. Line (3)
315 initializes the state by setting each technicians experience on each task type to
that technician’s given initial experience.

Then, the algorithm seeks to determine the set of assignments for each tech-
nician for each day. At the beginning of each day, the day’s service requests
are observed (Line (5)). Then, Lines (6) to (13) enumerate the possible total
320 forecasted service times for day $t + 1$. With these enumerated values, Line (14)
solves the resulting instance of math program **R**.

Algorithm 1 Forward Approximate Dynamic Programming Algorithm

- 1: Output: Assignments of technicians over the planning horizon
 - 2: Input: Technician $\mathcal{K}$, task type $\mathcal{R}$, parameters of learning functions L_r^k , D_r^k , I_r^k for each technician k and each task type r
 - 3: $q_{r1}^k = I_r^k, \forall r \in \mathcal{R}, \forall k \in \mathcal{K}$
 - 4: **for** $t = 1$ **to** T **do**
 - 5: Observe $\mathcal{N}_t$
 - 6: **for** $r = 1$ **to** R **do**
 - 7: **for** $j = 1$ **to** m_{rt} **do**
 - 8: $\bar{q}_{r,t+1}^{kj} \leftarrow q_{rt}^k + j$
 - 9: $\bar{d}_{r,t+1}^{kjj} \leftarrow \left(D_r^k \left(\frac{\bar{q}_{r,t+1}^{kj}}{\bar{q}_{r,t+1}^{kj} + L_r^k} \right) \right)^{-1}$
 - 10: $\bar{F}_{r,t+1}^{kj} = \alpha F_{r,t}^k + (1 - \alpha)j$
 - 11: $\bar{ST}_{r,t+1}^{kj} = \bar{F}_{r,t+1}^{kj} \bar{d}_{r,t+1}^{kjj}$
 - 12: **end for**
 - 13: **end for**
 - 14: Solve Model **(R)** resulting in the action a_t
 - 15: Update technician productivity based on experience gained on day t according to Equations (1) and (5)
 - 16: **end for**
-

5. Experimental design

In this section, we describe the instances that we create to computationally test the value of our solution approach. Our instances all involve one of 30 workforces of five technicians with heterogeneous learning parameters. In particular, the learning rate and steady state productivity rate are sampled from a multivariate normal distribution with the mean and covariance matrix derived from empirical data by [14], given in Table 1.

$$\mu^T = \begin{pmatrix} \log D & \log I & \log L & F \\ 1.448 & 1.963 & 2.0446 & 2.269 \end{pmatrix}$$

$$\Sigma = \begin{pmatrix} \log D & \log I & \log L & F \\ \log D & 0.0045 & 0.0167 & 0.0191 & -0.0214 \\ \log I & 0.0167 & 0.4621 & 0.2443 & 0.2380 \\ \log L & 0.0191 & 0.2443 & 0.1905 & 0.2326 \\ F & -0.0214 & -0.2380 & -0.2326 & 0.3638 \end{pmatrix}$$

Table 1: Mean and covariance of workforce parameters

For each workforce, we consider four levels of capacity (C). These levels are 7, 8, 9 and 10, where 7 is the tightest capacity that ensures feasibility. These levels represent the maximum amount of time that a technician can work in a day. We also assume four different cardinalities for the set of task types $\mathcal{R}$. We refer to these levels as task diversity. We consider four levels of task diversity (R): 5, 10, 15, and 20. With 30 workforces, four levels of workforce capacity, and four levels of task diversity we have 480 instances in total.

We test the 480 instances on 120-day horizons. To limit the number of factors in our experimental design, we assume 50 task requests per day. For each of the 480 instances, we generate 100 trials of the 120-day horizon. To generate a trial, for each day, each of the 50 requests is randomly assigned a task type using a discrete uniform distribution.

We also conduct experiments regarding the two problem variants discussed in Section 3. For the first, we model a disruption in the workforce wherein one technician leaves the workforce and a new technician is hired as a replacement in the middle of the planning horizon. Specifically, Technician 1 is replaced with a new technician with initial experience level on all types of tasks on day 61. Specifically, on day 61, the transition function for Technician 1 is $q_{r,61}^1(s_{60}, a_{60}) = I_r^1$ for every r in $\mathcal{R}$.

For the second variant, we consider the situation in which a new task type is

introduced in the middle of the planning horizon. We assume that all technicians
 350 are inexperienced on this new task type, and we set their experience levels on
 the new task type to be one on the day of the introduction (day 61). Specifically,
 on day 61, the transition function for the new task type is $q_{R+1,61}^k(s_{60}, a_{60}) =$
 $1 \quad \forall k \in \mathcal{K}$. In both the case of workforce disruption and the new task type, we
 use capacity levels of 9, 10, 11, and 12 to ensure the feasibility.

355 With these instances, we consider three separate experiments. In all three
 experiments, we seek to demonstrate the value of our method for approximating
 the future value of current decisions. In the first set of experiments, we con-
 sider the 480 instances described above and solve each with the proposed ADP
 approach. As a benchmark, we present solutions from a myopic approach that
 360 approximates the Bellman equation by setting the second term of Equation (7)
 to 0. The resulting daily optimization problem can then be solved by solving
 a simplified version of the math program **R**. Our choice of benchmark is mo-
 tivated by the work in [18] that demonstrated that the difference between the
 quality of solutions from models that incorporate learning and those that do
 365 not are significant. The second and third experiments are analogous to those
 just described except that we solve the workforce disruption and new product
 variants, respectively.

All computations are performed by Gurobi 5.6 with Python 2.7 interface on
 Intel Xeon processor running at CentOS 6.3. In addition, for all experiments, we
 370 set the smoothing factor (α) to $\alpha = 0.9$. This value was chosen after examining
 the results of various choices of α over many different instances.

6. Computational Analysis

In this section, we present the results of our computational experiments. We
 do not report runtimes as the math program **R** solves nearly instantaneously
 375 and is thus capable of providing daily technician assignments in a timely fashion.

Figure 2: Average daily gaps by task diversity (%)

6.1. The Value of Incorporating Information about Future Requests

In this first experiment, we solve the 120-day MTSP-ESTSC with the ADP algorithm and the previously described myopic approach. Figures 2 and 3 present the results of the experiment. The figures present the average daily differences between the two solution approaches, averaged over all capacity and diversity levels, respectively. Specifically, for both ADP and myopic approaches, we record the total service time for each day of the 120-day horizon for each trial (using common trials between the two approaches). We record these values as Obj_m^t and Obj_p^t for the myopic and ADP approaches, respectively. We then compute the objective gap on day t as $gap_{m-p}^t = \frac{obj_m^t - obj_p^t}{obj_p^t} \times 100\%$ for each trial. For Figure 2, for each diversity level, the results are presented for each diversity level averaged over all capacity levels. Analogously, for Figure 3, the results are presented for each capacity level averaged over all diversity levels.

For all task diversities and all capacity levels, the average daily gap follows a similar trend. From Figures 2 and 3, we see a sharp increase from negative to positive gaps for the first three to eight days depending on the diversity levels.

Figure 3: Average daily gaps by capacity (%)

The myopic approach focuses on optimizing only current period service times while the ADP algorithm balances current and next periods so as to achieve the best assignment over both current and next periods. Then, the objective value on day one is not optimal with the ADP algorithm. In addition, there is no history information on day one, so the ADP approach has no advantage over the myopic approach. The above two reasons explain the negative gap on day one. As it accumulates more information over time, the ADP approach shows an increasing advantage, which is reflected by the sharp increase of the positive gaps between the two approaches. According to learning curves, most learning effects occur during the early periods, which corresponds to the larger gaps between the myopic and ADP earlier in the horizon. Then, as the technicians accumulate more experience and approach the plateau of the learning curves, the average daily gaps decrease slowly to a relatively stable level.

Comparing the performance of the ADP algorithm and the myopic approach across task diversity levels (Figure 2), we see that the benefits associated with

looking into the future when performing task assignments are negatively correlated with diversity level; the lower the diversity level, the greater the benefit. We hypothesize that there are two reasons for this behavior: (1) with a lower task diversity level our forecasting model is more accurate as there is more historical data for each task type, and, (2) with a lower task diversity level, as there are many tasks of each type, we are able to fully leverage the benefits of learning more quickly by looking into the future.

Comparing the performance of the ADP algorithm and the myopic approach across capacities (Figure 3), we see that the benefits associated with looking into the future when performing task assignments are negatively correlated with capacity; the lower the capacity level, the greater the benefit. An examination of the results suggests that the myopic approach seeks to assign each task to the technician that can perform it the quickest. However, the ability of the approach to do so is especially limited when capacity is tight. We hypothesize that, by looking into the future, the ADP algorithm recognizes the value of developing the proficiency level of multiple technicians so that many of them are able to perform each task quickly. As a result, as it positions the workforce so that it can assign tasks to different technicians that have the same proficiency, the ADP algorithm outperforms the myopic approach the most at lower capacity levels.

We also study the distribution of the average daily gap among instances. Table 2 shows the number of instances with positive, negative and zero average daily gap for all diversities and capacities, respectively. Results indicate that there are more instances with positive gap than those with negative gap and two approaches are more likely to perform the same in terms of the gap with loose capacity. This result is not surprising as, when technicians are allowed to serve more tasks per day, the faster learners and more experienced technicians are assigned to more tasks.

	Positive gap				Negative gap				Zero gap			
	R=5	R=10	R=15	R=20	R=5	R=10	R=15	R=20	R=5	R=10	R=15	R=20
C=7	1074	1055	926	1237	455	518	599	365	1471	1427	1475	1398
C=8	1104	907	793	1112	306	517	586	385	1590	1576	1621	1503
C=9	977	836	761	1065	348	511	572	352	1675	1653	1667	1583
C=10	773	792	760	1064	401	501	573	361	1826	1707	1703	1575

Table 2: Distribution of the average daily gaps

6.2. Responding to a Disruption in the Workforce

In this subsection, we present the results of the experiments designed to identify the impact of a disruption in the workforce. Figure 4 illustrates the changes of average daily gap by diversity level. The gaps are computed analogously to those presented in Figures 2 and 3. The general trends of the average daily gap changes are similar to those in the previous experiments, except for the temporary fluctuations on and after the day in which one technician departs and a new technician joins the workforce (day 61-70). The performance of the ADP approach after the disruption mimics its performance at the beginning of the planning horizon, where we see a transition from a negative to a positive daily gap as it positions this new technician for future demands by accepting longer service times in the near-term.

Figure 4: Average daily gaps by task diversity (%) with workforce fluctuation

Next, we study the new technician's workload (i.e. Technician 1 in our experiment). Figures 5a and 5b present the average workload of the new technician (as a percentage of the 50 tasks served) over the horizon (days 61-120) and on the day of disruption (day 61). We see that in both cases the ADP algorithm assigns more work to the new technician than the myopic approach does. Just as at the beginning of the planning horizon, the ADP algorithm is positioning the new technician to have sufficient experience for task requests on future days, something the myopic approach ignores. In fact, in some cases the new technician does more than the average (20%) of the work. We hypothesize that in these cases the ADP approach is aggressively building up the experience level of the new technician.

Figure 5: Workload of new technician

We also note that the lower the task diversity the larger the negative gaps when introducing the new technician (see the deep plunge on day 61). With a lower task diversity, there are more tasks for each task type, which in turn leads to technicians rapidly accumulating enough experience to operate at their maximum productivity. As such, there is a greater difference in the service times between the new technician and the existing workforce on the day the new technician begins. Yet, as discussed above, the ADP approach assigns more work to the new technician than the myopic approach to better prepare the new technician for future task requests. This impact of diversity is most apparent at the lowest level ($R=5$). Here, we see the greatest difference in the workload assigned to the new technician as the myopic approach is focused solely on leveraging the productivity of the existing, highly-experienced technicians.

6.3. Responding to a New Task Type

We next present results for the experiments that examine the impact of introducing a new task. Figure 6 illustrates average daily gaps by day and diversity. The gaps are computed analogously to those in Section 6.1. We notice that the general trends of the average daily gap remain the same as those seen in Section 6.2. As with attrition, after a new task type is introduced the ADP algorithm accepts longer service times to better position the workforce to handle task requests for the new task type in the future.

Figure 6: Average daily gaps by task diversity (%) with a new task type

Next, for each approach (the myopic and the ADP), we examine the distribution of experience in the new task type. Specifically, for each workforce and each instance, we calculate the percentage of times that the tasks of the new type are performed by the technician who performs them the most often (who we will call the most frequent technician). Similarly, we calculate the percentage of times that the tasks of the new type are performed by the technician who performs them the second most often (and third most, fourth most, fifth most). We report in Figure 7 the percentage of times for each approach and diversity level tasks of the new type are performed by the most frequent technician. As these new type tasks are very rarely (e.g. $< .65\%$ of the time) performed by the technician who performs it the third (or fourth or fifth) most often, one can reasonably conclude that, when the most frequent technician does not perform the task type, it is performed by the second most frequent technician.

Figure 7: How often most frequent technician performs tasks of new type

What we observe in Figure 7 is that both approaches favor having one individual specialized on tasks of the new type and that specialization is directly correlated to the diversity of the instance (i.e. the number of different task types). However, the ADP approach also builds proficiency in the new task type in a second technician and does so more often when diversity is low. Similar to the discussion above, we hypothesize that this is because, at lower diversity levels, technicians can quickly develop proficiency, due to the number of opportunities, in the original task types. Thus, it is less impactful to divert two of them towards building proficiency in the new task type.

7. Conclusions and Future Work

In this paper, we study the scheduling problem of assigning tasks to technicians wherein the tasks to perform each day are not known until the day they are to be done. Such a problem can be modeled as a daily, task assignment problem. However, we also model that technicians learn. That is, technicians' service times decrease as technicians gain experience performing tasks. As such, we model the problem as a multi-period problem in which each day's decisions are made with an eye to building capacity (via experience accumulation) for the future. This problem, which we call the multi-period technician scheduling problem with experience-based service times and stochastic tasks, is new to the

510 literature. We present a Markov decision process model for the problem and discuss how it can be adapted to disruptions in the workforce and the introduction of new task types to service.

We present an approximate dynamic programming-based solution approach for this model that repeatedly solves optimization problems to make daily assignments that recognize the impact of technicians gaining experience on future service times. The optimization problem approximates the cost-to-go with forecasts of the next day’s assignments for each technician and the resulting estimated time it will take to service those assignments given the current day’s decisions. As quantitative models of human learning are non-linear, we use
520 a technique from the literature to reformulate these optimization problems to mixed integer programs which can then be solved (nearly) instantaneously.

We demonstrate the value of both the model and the solution approach with an extensive computational study. We benchmark the performance of the model and ADP-based solution approach against a myopic approach that models the problem as a single-period problem, ignoring the impact of experience gained today on service times on later days. We see that across all variants (the baseline problem, disruption in workforce, and introduction of new task types) the ADP-based approach outperforms the myopic approach by sacrificing solution quality in a few near-term periods to better position the workforce for future task service
530 requests.

There are a number of avenues for future work. First, as noted in Section 3, there are a number of factors other than experience that can affect an individual’s ability to perform a task. Such considerations include learning from similar task [62], learning by transfer from other technicians [64], the training received
535 [65, 66], and even the technician’s workload [67, 68]. While industrial psychologists have not completely identified how to measure all of these effects, including elements such as these in the formulation could offer additional insights into the problem. Second, the currently proposed cost-to-go approximation estimates the value of experience accumulation through today’s assignments only one day
540 into the future. Future work could explore alternate methods that approximate

that value farther into the future. Also, many technician-related scheduling problems include a routing component. It would be interesting to test the value of the proposed (or a similar) approach on such a problem. Finally, an analysis of the structure of solutions produced by an ADP-based solution approach could
545 yield interesting insights into how schedulers should make these assignment decisions on a daily basis.

Appendix

We have examined the results of various choices of α over many different instances with our base experiment. We test α values of 0.1, 0.3, 0.5, 0.7, and 0.9.
550 Figures 8 and 11 present the average daily differences between the approximate dynamic programming and myopic approaches with different values of α .

Figure 8: Average daily gaps (%) for diversity=5

Figure 9: Average daily gaps (%) for diversity=10

Figure 10: Average daily gaps (%) for diversity=15

Figure 11: Average daily gaps (%) for diversity=20

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