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The technician routing problem with experience-based service times ☆

Xi Chen [a], Barrett W. Thomas [a,*], Mike Hewitt [b,1]

[a] Department of Management Sciences, Tippie College of Business, University of Iowa, Iowa City, IA 52242, USA
[b] Information Systems and Operations Management, Quinlan School of Business, Loyola University Chicago, Chicago, IL 60611, USA

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ABSTRACT

While home services are a fast growing industry, little attention has been given to the management of its workforce. In particular, the productivity of home-service technicians depends not only on efficiently routing from customer-to-customer, but also the management of their skillsets. This paper introduces a model of technician routing that explicitly models individualized, experience-based learning. The results demonstrate that explicit modeling and the resulting ability to capture changes in productivity over time due to learning lead to significantly better and different solutions than those found when learning and workforce heterogeneity is ignored. We show that these differences result from the levels of specialization that occur in the workforce.

1. Introduction

Home services are one of the fastest growing industries in the US. For example, revenue from heating, ventilation and air conditioning service is expected to rise at an average annual rate of 5.9% between 2012 and 2017, reaching $2.5 billion by 2017 [29]. To maintain growth, a key challenge for home-service companies is managing their expensive and limited labor resources. In particular, the time an employee needs to provide high quality service often depends on his/her experience. Importantly, experience increases over time, thus gradually decreasing the time required to provide service. By accounting for employee experience and the accompanying learning, managers can take advantage of capacity increases that result from experience, improving efficiency and enabling further growth.

While home service workers have many job titles, we will generically refer to them as technicians throughout this paper. As such, it is easy to see that the problem discussed in this paper is a variant of the technician routing and scheduling problem (TRSP), a problem first introduced by Dutot et al. [13]. In the TRSP, a set of technicians serves a set of customer requests. The key difference between the TRSP and traditional routing problems is that, in the TRSP, customers are associated with certain tasks and different tasks can have different service times associated with them. In our version of the problem, in addition to the task, technicians can have different service times depending on their experience with the skill required for the task. These differences in service times are a reflection of each technician's experience.

In this paper, we consider the TRSP over multiple periods or days and account 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 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. For this problem, the experience of a technician with a skill depends on the number of times the technician has performed the task.

We assume that daily demand is not revealed until the day of service. Each day, the technicians serve the day's known demand, starting and ending each day at the depot. In this work, we seek to minimize the sum of each day's makespan over a finite horizon, accounting for both travel and service times on each individual day. The objective accounts for the desire to increase the capacity available to grow the business. We call our problem variant the technician routing problem with experience-based service times (TRSP-EST).

To solve the problem, we implement a rolling-horizon procedure, creating routes for each day's known demand without regard for future demand. In the rolling-horizon framework, the objective becomes simply the minimization of the makespan for a given day. To solve the daily routing problem, we use a variant of the record-to-record travel algorithm (RTR), a heuristic first introduced by Li et al. [27]. At the end of each day, we update each technician's accumulated experience.

As the first to explicitly model the impact of experience-based learning on technician productivity, this paper makes several

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* Corresponding author. Tel.: +1 319 335 0938, fax: +1 319 335 0297.
E-mail addresses: xichen3@uiowa.edu (X. Chen), barrett-thomas@uiowa.edu (B.W. Thomas), mhewitt3@luc.edu (M. Hewitt).
[1] Tel.: +1 312 915 7394.

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contributions to the literature. First, we introduce to the literature a Markov decision process model of the problem and introduce a myopic solution approach. In addition, this paper presents several important insights. These are

1. Explicitly modeling workforce heterogeneity and learning offers better solutions in comparison to assuming homogeneous learning curves and/or static productivity.
2. Importantly, modeling workforce heterogeneity and learning captures that fast learners have more capacity that can be used to improve solution quality.
3. Regardless of the learning rate, inexperienced technicians specialize more than more experienced technicians.

Further, we show that, in the presence of workforce heterogeneity and human learning, technician routing solutions trade-off routing and scheduling. We introduce “rules of thumb” that demonstrate which aspect is more important based on the individual characteristics of a technician.

The remainder of this paper is organized as follows. Section 2 reviews the literature on problems related to the TRSP-EST. Section 3 presents a model for the problem. Section 4 describes the solution approach. Section 5 introduces the datasets used in this paper, and Section 6 presents our computational results. Finally, Section 7 concludes this work and suggests areas of future research.

2. Literature review

Two major fields of literature are related to the problem studied in this paper: the technician routing and scheduling problem (TRSP) and learning.

2.1. Technician routing and scheduling

The existing literature contains a variety of technician routing and scheduling problems. A limited review can be found in Castillo-Salazar et al. [8]. The TRSP was first introduced by Dutot et al. [13] based on a real problem in the telecommunications industry. In problem as introduced in Dutot et al. [13], technicians are grouped into teams, and tasks are assigned to teams so that skill requirements and the skill level can be matched. However, neither learning nor the extended horizon over which learning occurs is considered. In 2007, the French Operations Research Society introduced a challenge (http://challenge.roadef.org/2007/en/) based on Dutot's work and offered a real-world data set for technician scheduling. The challenge resulted in a stream of papers. The papers are largely algorithmic, and none of the papers resulting from the challenge consider routing. Hurkens [19] uses mixed integer programming to construct a day schedule and demonstrates the effectiveness of the linear programming techniques in solving scheduling problems. Firat and Hurkens [14] propose a solution methodology that uses a flexible match model for a special multi-skill workforce scheduling problem, in which a set of combined technicians stays together for the duration of a work day. Cordeau et al. [9] propose a construction heuristic and an adaptive large neighborhood search heuristic for the technician and task scheduling problem arising in a large telecommunications company. The objective is to minimize a weighted combination of makespans of each priority class. Hashimoto et al. [17] present a variant of the Greedy Randomized Adaptive Search Procedure (GRASP) for solving the technician and interventions scheduling problem for telecommunications. The authors also introduce a lower bounding procedure for the problem.

Other literature has considered both the travel and service time aspects of the problem, but again, does not consider learning and a multi-period horizon. Kovacs et al. [23] define the service technician routing and scheduling problem with and without team building. The objective is to minimize the sum of total routing and outsourcing costs. Tsang and Voudouris [38] and Pillac et al. [30] propose heuristics for related problems. Alsheddy and Tsang [1] consider a bi-objective optimization problem in which both the technician routing costs and the employees' interests are considered. Cortés et al. [10] introduce constraint programming and branch-and-price approaches for a multi-objective single-day technician routing problem where the objectives seek to reduce deviation from target response times as well as travel and service costs.

Additional papers incorporate dynamic and stochastic service requests. Similar to the work in this paper, Bostel et al. [7] consider a multi-period planning and routing problem of technicians in the field. However, Bostel et al. [7] do not consider learning that takes place over time. Also similar to this work, the problem is solved without incorporating information about future information. Other work considers single-day problems. Inspired by British Telecommunications plc, Lesaint et al. [26] describe a dynamic scheduler based on a combination of heuristic search and constraint-based reasoning for dynamic workforce scheduling problem. Weintraub et al. [39] address the routing and scheduling of service technicians for energy providers in Chile. Customers service requests are considered to be stochastic and priorities of different tasks are taken into consideration. The objective is to minimize the response time to these requests. Binart et al. [5] introduce a technician routing problem with stochastic service and travel times and solve the problem with a two-stage stochastic programming method. Pillac et al. [31] study the Dynamic TRSP in which new requests appear over time by proposing a fast reoptimization approach based on a parallel Adaptive Large Neighborhood Search and a Multiple Plan Approach.

Home healthcare scheduling and routing is a special case of the technician routing problem. Shao et al. [36] solve for weekly schedules in the scheduling and routing of heterogeneously skilled therapists to jobs. A key feature of the home healthcare literature is the need to respect patient preferences for particular healthcare workers. These preferences usually result from a patient's prior experience with a particular worker. In a sense, these preferences capture the fact that the home healthcare problems are multi-period, even if they are not explicitly modeled as such. Examples include Bertels and Fahle [4], Rasmussen et al. [33], Mısır et al. [28], and Bard et al. [3].

The authors are aware of only limited work that incorporates learning in a routing context. Zhong et al. [41] explicitly models driver learning, but in the context of familiarity with a particular geographic area and the customers found in that area. Unlike this work, the heterogeneity of tasks at the individual customers is ignored. While learning is not explicitly modeled, work on consistency in multi-day vehicle routing often cites advantages of repeat visits to the same region or same customers. For example, Smilowitz et al. [37] suggest that repeated visits may allow a delivery driver to “more efficiently serve her customer base”.

2.2. Models of learning

The impact of experience on service or production times is often called “learning” in the literature. There exists an extensive body of literature that develops mathematical representations for the improvement in service and production times as experience increases. These representations are often called learning curves. Detailed discussions of various learning curves and their applications are available in [11,21,20,2,35]. A review of learning curves in optimization models for manufacturing and project scheduling can be found in [18]. Reviews of literature and recent results related to learning in machine scheduling problems can be found