

SIMULATION-BASED OPTIMIZATION OF DYNAMIC SCHEDULING OF OUTPATIENT APPOINTMENTS WITH PATIENT NO-SHOWS AND PROVIDER LATENESS

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ABSTRACT

Hospitals would like to improve efficiency due to an aging population and increasing expenditures. This research is designed to address the dynamic and stochastic appointment scheduling problem with patient unpunctuality and provider lateness. Our model considers a single provider with whom patients seek to schedule appointments dynamically on a first-come, first-serve basis. The problem setting captures the uncertainty for the number of patients request appointments, service time durations, patient unpunctuality, provider lateness, patient no-show, unscheduled emergency walk-ins. The aim is to find the optimal schedule start times for the patients in a cost effective manner. We propose a discrete-event framework model to evaluate the sample path gradient of the total cost. We use sample average approximation and stochastic approximation algorithms based on unbiased gradient estimators to achieve computational efficiency. We also present the stochastic linear formulation. Our numerical experiments suggest that these approximation algorithms converge to a global optimum.

1 INTRODUCTION

Due to increasing healthcare expenditures and an increasing demand for healthcare services, hospitals are under growing pressure to improve the efficiency of their operations. As a result, governments and healthcare decision makers are constantly seeking to develop more efficient healthcare systems. A popular field for such development is operations research, which provides numerous methodologies and solution techniques to simultaneously reduce costs and improve access to healthcare services.

In recent years, outpatient clinics have become more central in healthcare systems due to an emphasis on preventive medical practices, shorter hospital stays, and service provision on an outpatient basis. Appointment system is an important component for efficient care delivery in outpatient systems.

The proposed work focuses on one particular problem in healthcare systems, which is dynamic appointment scheduling problem with patient unpunctuality and provider lateness (**D-ASPUPL**) in the presence of a single server. Our aim is to determine the optimal Scheduled Start Times of each patient. The patients call in advance over time to schedule appointments with a single server on a given day. The stochasticity originates from the the number of patients requesting appointments, service duration, patient unpunctuality and provider lateness, patient no show, and emergency walk-ins. We assume that the probability distribution associated with those terms follow some known random distributions.

2 METHODOLOGY

We develop a stochastic linear model for the finite scenario conversion of (**D-ASPUPL**) that is adopted from (Denton and Gupta 2003). We have added the dynamic number of calls, provider lateness and patient unpunctuality, patient no show and emergency patient features to their model.

Our problem is computationally difficult due to its stochastic and dynamic nature. Therefore, we use approximation techniques for solving our formulation in an effective and near-optimal manner.

There are two well known and common approaches for solving a stochastic problem: **(i)** Sample average approximation (SAA) **(ii)** Stochastic approximation (SA). Both methods use Monte Carlo simulation.

The SAA method is an approach for solving stochastic optimization problems by converting the stochastic problem into a deterministic counterpart by taking a finite sample of scenarios. The resulting deterministic SAA problem is then solved by deterministic optimization techniques. The process can be repeated with different samples to obtain candidate solutions along with statistical estimates of their optimality gaps. The details about the methodology and empirical behavior of SAA are presented in (Linderoth et al. 2006). SAA is shown to be most effective if the expected cost function is continuous (Kim et al. 2015).

SA methods, on the other hand, search for optimal solutions by using one or a few sample paths to determine improving directions in each iteration. In SA, at each iteration, one or a few new scenarios are generated, a gradient is estimated from these new samples, and a step is taken. The step size is slowly reduced at each iteration until some stopping criterion is met. SA has been shown to have good convergence properties as long as the problem exhibits certain properties. An important difference between SA and SAA is that, SA solves the true stochastic problem whereas SAA solves the deterministic finite scenario approximation. The sample gradient is calculated analytically based on perturbation analysis. We develop both SAA and SA based gradient descent algorithms that utilizes perturbation-based gradients.

3 NUMERICAL RESULTS

Our aim in this experiment is to compare the performance of SAA Algorithm with multiple initial solutions. Since SAA is an adaptive stepsize algorithm based on objective improvement, starting from a bad initial solution does not necessarily hurt the chances of getting a near optimal solution.

The efficiency and the convergence of our SAA algorithm with multiple initial scheduled start times is depicted in the following figure. We see the objective value change over the iterations where we use multiple initial scheduled start times, (which we call “restarts”).

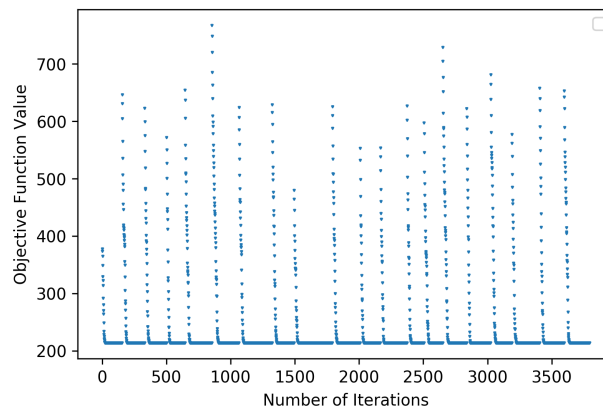


Figure 1: SAA objective values over iterations with multiple restarts.

REFERENCES

- Denton, B., and D. Gupta. 2003. “A Sequential Bounding Approach for Optimal Appointment Scheduling”. *IIE Transactions* 35(11):1003–1016.
- Kim, S., R. Pasupathy, and S. G. Henderson. 2015. “A Guide to Sample Average Approximation”. In *Handbook of Simulation Optimization*, edited by M. C. Fu, 207–243. New York: Springer.
- Linderoth, J., A. Shapiro, and S. Wright. 2006. “The Empirical Behavior of Sampling Methods for Stochastic Programming”. *Annals of Operations Research* 142(1):215–241.