Optimization of Multidisciplinary Staffing Improves Patient Experiences at the Mayo Clinic

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Abstract: We present two new approaches to emergency department (ED) staffing. In the first approach, we use historical patient volumes, which inherently contain existing operational inefficiencies. To address this shortcoming, we use classification and regression trees to identify thresholds for patient-to-staff ratios, which split the patient subpopulations into two groups that have different empirical cumulative distribution functions (ecdfs) for patients' lengths of stay in the ED; one has an extended length, and the other has a shorter length. We apply these thresholds and ecdfs to historical patient volumes to calculate an ideal patient volume. After accounting for arrival patterns of ED patients, ideal patient volumes represent the load on the entire ED if patient-to-staff ratios are always kept under the identified thresholds. We then use a mixed-integer programming model to minimize understaffing with respect to the ideal patient volumes. The ED at Mayo Clinic Saint Marys Hospital in Rochester, Minnesota, a trauma center for both adults and pediatrics, implemented the new shift templates based on this approach in the fourth quarter of 2015. The templates resulted in statistically significant improvements in several patient-centered metrics.

Next, we describe a novel queueing approach that represents ED care delivery process as a queuing network consisting of sequences of treatment and order bundle (i.e., groups of diagnostic workup and treatment) queues. We then capture time-varying patient flow in the ED and estimate its load on treatment stations served by physicians. The treatment queues operate in an efficiency-driven regime but experience negligible abandonment. We describe a new staffing algorithm with a goal of satisfying differentiated tail probability of delay (TPoD) targets for different patient classes based on medical urgency. Rigorous simulation experiments using real-life ED data show that our proposed staffing algorithm can effectively meet TPoD targets when used with carefully designed hybrid routing policies.

Bio: Mustafa Y. Sir, Ph.D., is an Assistant Professor of Health Care Systems Engineering at the Mayo Clinic College of Medicine and co-leads a research program in Information & Decision Engineering at the Mayo Clinic Kern Center for the Science of Health Care Delivery. He graduated with a Ph.D. degree in Industrial and Operations Engineering (IOE) from the University of Michigan in 2007 with a focus on Operations Research. He also holds Bachelor of Science and a Master of Science in Engineering (M.S.E.) degrees in IOE and an M.S.E. degree in Electrical Engineering – Systems, all from the University of Michigan. Through the combination of operations research, machine learning, and informatics, Dr. Sir’s research aims at eliminating waste, improving the safety of patients and providers, and aiding physicians to optimize an individual patient’s treatment plan. For instance, he has developed a novel data-driven patient access management framework, which uses clinical notes and other patient characteristics to determine a patient’s priority and historical appointment data to determine a patient’s willingness-to-wait behavior regarding scheduled appointments. His work on multidisciplinary Emergency Department staffing optimization has been selected as a finalist for the 2016 Daniel H. Wagner Prize for Excellence in Operations Research Practice. Using dynamic & stochastic programming and control theory, he developed adaptive treatment planning strategies for intensity-modulated radiation therapy considering the positional uncertainties caused by daily patient setup procedures and internal organ motion. He is a co-investigator on the AHRQ-funded Improving Diagnosis in Emergency and Acute care – Learning Laboratory (IDEA-LL), a novel program for diagnostic safety surveillance and intervention using actionable, patient-centered data obtained from both frontlines of care and electronic health records (EHRs) as input to a diagnostic error risk prediction tool.