Increasing the Robustness of Surgery Schedules against Emergency Break-ins

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Rising healthcare costs and an aging population are placing ever higher stress and demands on European healthcare systems. As the surgery department is one of the largest cost categories in hospitals (estimated as high as 40%; Macario et al, 1995), it is a frequent target in the search for efficiency gains. Creating robust schedules is a key component here, as the planning for elective (scheduled) patients is often disarrayed once emergency patients arrive.

To address the problem of operating room scheduling, we expand on the Break-In-Moment (BIM) problem first proposed in Essen et al, 2011. It relates to a common procedure in hospitals: as all operating rooms are often being utilized when emergency patients arrive, they must be treated in the first room that becomes available after the emergency patients arrives; “breaking into” the elective schedule. Each surgery end time is thus a potential break-in-moment (BIM), and the distance between two consecutive end times is referred to as the break-in-interval (BII).
As time is of the essence for emergency patients, it makes sense to spread these BIMs over the schedule in such a way as to minimize their expected waiting time. In the case where arrivals are time-independent, this means seeking to spread the BIMs as uniformly as possible. This leads to the basic BIM problem statement: how should one schedule a certain set of surgeries, so that the maximum BII in the schedule is minimized.

Previous work focused on a deterministic ILP formulation of the problem and proposed a variety of heuristics and local search methods; a validation of these results in a stochastic environment (with uncertain surgery times) was also shown. In contrast, we fully reformulate the problem in stochastic terms (yielding the Stochastic BIM problem; SBIM), taking into account the uncertainty of surgery times from the start. This increases the complexity of the problem, but it also makes it more robust by analyzing a variety of scenarios. As surgery times tend to show significant variance (often following lognormal distributions), this can be a strong advantage.

To solve the computationally more involved SBIM, we employ the Sample Average Approximation (SAA), a two-stage optimization technique. Rather than drawing a large amount of samples from distributions of surgery lengths and solving to optimality for this large set (infeasible in our case), SAA first solves M smaller replications of the problem, and then estimates the true optimal solution based on the M candidate solutions.
In addition, we propose heuristics to solve the SBIM problem in an acceptable timeframe.