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Case duration prediction and estimating time remaining in ongoing cases

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Summary

In this issue of the *British Journal of Anaesthesia*, Jiao and colleagues applied a neural network model for surgical case durations to predict the operating room times remaining for ongoing anaesthetics. We review estimation of case durations before each case starts, showing why their scientific focus is useful. We also describe managerial epidemiology

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studies of historical data by the scheduled procedure or distinct combinations of scheduled procedures included in each surgical case. Most cases have few or no historical data for the scheduled procedures. Generalizability of observational results such as theirs, and automatic computer assisted clinical and managerial decision-making, are both facilitated by using structured vocabularies when analysing surgical procedures.

Keywords: Bayesian methods; case duration; case scheduling; machine learning; neural network; operational research; industrial engineering; operating room management

Jiao and colleagues applied a neural network model for case durations to predict the operating room times remaining for ongoing anaesthetics.[1,2] We review estimation of case durations before the cases start, showing why this focus is useful.[2–19] (Our mini-review excludes many references that can be obtained from those included by citation [e.g., lacking are references to the Bayesian method used by we authors, because it can be found in all of the preceding references].) Jiao and colleagues' statistical application appropriately targets estimation of the longest times cases might take.[2,6,13] We also describe managerial epidemiology studies of historical data by the scheduled procedure or distinct combinations of scheduled procedures included in each case.[14,18,20,21] (Henceforth, all reference to a case's "procedure" means the case's single procedure or distinct combination of scheduled procedures; see Table 1). As context, of the 24–70,000 cases from four hospitals, 9.3% of cases comprised procedures observed only once ("singletons").[21] Of their >70,000 cases, 48% were singletons, as extracted from their electronic health record (EHR) as free text (Table 1).[1,2]

Why were topics other than time remaining in cases appropriately excluded?

What decisions were not modelled by Jiao and colleagues,[12] and why, appropriately, did they not address them? There is negligible potential improvement and, thus, little need for more study. The limiting factor is not lack of scientific knowledge, but implementation.

Staff scheduling occurs months before the surgical date.[17] Therefore, selection of the hours into which cases are scheduled ("allocated time") also happens months in advance.[17] Thus, consideration of case duration prediction is valid only if the preceding chosen staff scheduling and allocated times match actual working hours, at least on average.[17] Given that allocated time and staff schedules are preceding decisions, case durations should be estimated using unbiased estimators of their contributions to those hours.[17,22] That estimator is the expected value of each new case's duration (e.g., estimated using the sample mean).[14] Simply using sample means of historical data by procedure reliably prevents bias. Typically the resulting $(8\ h/day) \times (\sum[Scheduled\ Time - Actual\ Time] / \sum[Actual\ Time])$ is

Table 1 One operating room with four cases performed sequentially on one regular workday at a hospital with Epic Op Time operating room information system.

Case Number	Procedures of Each Case as Listed on the Operating Room Schedule*	Codes Selected by Scheduler**	Descriptions Seen by Scheduler***	"Procedure" Used in Statistical Analyses****
1	GASTROCNEMIUS RELEASE (STRAYER PROCEDURE) (Left); FUSION TOE/TOES (Left Toe); TENOTOMY ACHILLES (Left Ankle)	4332 4328 3590	GASTROCNEMIUS RELEASE (STRAYER PROCEDURE) FUSION TOE/TOES TENOTOMY ACHILLES	3590-4328-4332
2	OSTECTOMY FOOT (Left)	1934	OSTECTOMY FOOT	1934
3	ARTHRODESIS (FUSION) METATARSAL-PHALANYX (Left Foot)	4172	ARTHRODESIS (FUSION) METATARSAL-PHALANYX	4172
4	BONE GRAFT CALCANEOUS (Right); OPEN REDUCTION INTERNAL FIXATION NAVICULAR (FOOT) (Right Foot); OSTECTOMY FOOT (Right Foot)	3589 3367 1934	BONE GRAFT CALCANEOUS OPEN REDUCTION INTERNAL FIXATION NAVICULAR (FOOT)| OSTECTOMY FOOT	1934-3367-3589

* Jiao and colleagues[1,2] treated each procedure as "printed" electronically by Epic OpTime and routinely used (passed) to other systems internally for analytics. For example, the following three were considered different procedures: "ESOPHAGOGASTRODUODENOSCOPY BIOPSY (N/A)", "EGD (N/A)", and "ESOPHAGOGASTRODUODENOSCOPY BIOPSY (Left)".[2]

**The scheduler works by selecting scheduled procedures from the database, multiple procedures per case, each procedure with a distinct code.

***When the scheduler selects each procedure, the scheduler sees a description of each procedure, those listed in the third column.

****For purposes of statistical analyses, laterality is ignored. The concatenated procedure codes are sorted in ascending sequence. Each distinct combination (e.g., "1934" or "3590-4328-4332") is treated as the case's scheduled "procedure."

small, only a few minutes per day.[4,10,15,22] The result essentially is guaranteed just by using the sample mean of historical data by procedure.[10,14,15,22] That simple method is sufficient. Fancier methods that downweight outliers generally have no less bias or mean absolute error.[23] Alternatively, one can simply check plausibility of surgeon/scheduler estimates and adjust if systematically biased.[3,8–12]

Obviously, if a case is taking longer than estimated, the surgeon should not truncate the debriefing or review of pathology specimens to reduce operating room time toward the mean. Similarly, if surgery will finish earlier than expected, the anaesthesia team should not delay emergence to reduce mean absolute error. Likewise, if a surgeon is performing one case and will follow with a long case that will result in overutilised time, assigning the fastest first assistant to the surgeon would be ideal (assuming there was no suitable scheduling alternative).[17] The implications are not obvious. Good clinical and managerial decision-making increases mean absolute errors in case durations.[14,17,24] Therefore, one should anticipate imprecision (but not bias),[14,17] and implement staff schedules that are modestly (30 to 60 min) longer than allocated time.[17]

When predicting durations for procedures performed many times (>30) within the past few years, the sample mean alone can be used for estimating operating room time.[12,14] When there are few previous cases (<10),[12,19] combining estimates from historical data and the surgeon reduces mean absolute error.[10–12,25] This has been recognised for >25 yr.[25] The weighted combination can include adjustment for small scheduling bias of individual surgeons or services.[8,10] For example, if general surgeons systematically underestimate by 5 min, add 5 min to their estimates, or if they consistently overestimate by 10%, reduce proportionately.[8–12] Sometimes the benefit from this simple adjustment is large, sometimes small.[8–10,12] What is most important is to use both surgeon/scheduler estimates and historical case durations.[12] Disregarding this issue results in avoidable waiting of the to-follow surgeon in the room and causes operating room nurses and anaesthesia practitioners to work unnecessarily late.[9,17] There sometimes are case duration outliers. These can be trimmed[11] or least absolute values linear regression applied,[8,10,12,25] both implemented easily for each service using spreadsheet formulas.[12,19]

When there are increasing (>3)[12,19] historical data by procedure, choosing the combination of estimates from historical data, surgeon/scheduler estimate, or their combination can be done several ways.[15] Different Bayesian methods variably weight the historical data versus surgeon/scheduler under different assumptions.[6,8,10,15,16] For example, instead of using a single estimate from the surgeon/scheduler,[6,14] for each case scheduled and with few (<10) historical data for the procedure, the surgeon can be requested to give more information, specifically, expected percentiles of duration.[8] What matters most is not which method is used, but, rather, that one of them is implemented. When there are some historical data by procedure, but not so many historical cases for the procedure to discount the surgeon's estimate, considerable reduction in mean absolute errors and overutilised time ensues.[8,10,12,15] Again, the benefits are to reduce surgeon waiting and the extra hours that nursing and anaesthesia teams work unnecessarily.[9,17]

When these methods are applied, excess overutilised operating room time from inaccuracy in case duration prediction is small, averaging 1.0 min per room per workday at an ambulatory surgery centre and 5.4 min per hospital operating room per day.[24] In other words, even if there were magical improvements in prediction accuracy, we know the maximum possible reduction in overutilised time because the best possible predictions are the actual case durations, known once the cases have ended (i.e., perfect retrospective knowledge). The reasons for small potential additional improvement are two-fold. First, errors in case duration prediction from underestimating and overestimating offset, in part, especially for facilities with many brief cases and those where the last cases of the day in many operating rooms are often performed by surgeons with no preceding cases (i.e., the cases can be moved among operating rooms).[24] Second, the decision of the room in which a case is performed, or whether a case is done today versus tomorrow or soon afterwards, is obvious (e.g., a 3 h estimated case will not fit into a 1 h opening, regardless if the surgeon's estimate is 2.8 h or the historical estimate is 3.1 h).[24]

Some decisions involving case duration prediction are different, unrelated to estimating the mean operating room time of individual cases. For example, for single specialty rooms with little potential to move cases (e.g., interventional radiology), predictions for case scheduling are for the set of cases in the room, not for single cases.[4,7] For example, if one surgeon follows another in a room and a brief gap is added to the turnover interval between cases,[9,19] a 90% upper prediction limit for the duration of the last case can be calculated to assure at most 10% risk of overutilized time.[9,24] That calculation can include variability around the mean duration (expected value) of the case and incorporate not only historical data, but also surgeon and scheduler estimates.[16] For lists with all cases that are common procedures, means and standard deviations of durations for each case can be used to estimate the probability that the list ends in over-utilised time.[7]

Jiao and colleagues[2] considered the decision most affecting staff working late: prediction of the times remaining in ongoing cases, especially those cases taking longer than estimated.[6,13,17] These predictions can be used when assigning staff for pending add-on cases or for choosing which add-on case to start next with the objective of reducing overutilised time.[13,17] Such predictions are inaccurate if made using the surgeon/schedulers' estimates or the means of historical durations by procedure.[2,6,13] These decisions should be the principal software concern for displays and recommendations for operating room decision-making on the day of surgery.[13] We are unaware of any current health records that provide such predictions, further showing the importance of this work.[2,6,13]

Computer support for estimating times remaining in ongoing cases is especially important because the estimates and resulting decisions are not intuitive.[6,13] Consider a case with many (>30) historical data for the procedure and a mean duration before the case starts of 5.0 h.[13,14] By 5.0 h, most (56%) cases have finished, but among the 44% not ended the mean (expected value) of time remaining is 1.5 h, not 0 h.[13] By 6.0 h, 23% of cases are ongoing, but among those the mean time remaining is 1.3 h.[13] Such conditional expectations for time remaining cannot be calculated in one's head yet are integral to the multiple decisions made (rationally) on the day of surgery.[6,13,17]

Recommendations based on these results for common and uncommon procedures

When there are many historical data (>30) by procedure, the surgeon/scheduler's case length estimate does not contribute substantively to the estimated time remaining in cases.[6,13] However during the case there is value in knowing if the surgeons have started surgical closure or an equivalent milestone has been reached (e.g., preliminary surgical item count has been completed).[2,13] Computer calculations are necessary, not just detailed queries of the surgeon.[6,8,13] Even with >10 historical cases, the importance of a surgeon/scheduler estimate is small.[12] In contrast, when cases have few or no historical data, the Bayesian methods' relative weightings of the surgeon/scheduler estimate becomes nearly complete, because there are no historical data to use.[6,12,14,19] The variability around the surgeon/scheduler's estimated case duration can be calculated separately for services[11] or the overall value used to pool all services.[6,19] With the latter approach, the Bayesian method for estimating times remaining in cases is equivalent to applying the surgeon/scheduler estimate.[2,6,19] Consequently, performance for estimating case end time is limited (i.e., there is substantial value to having ≥4 historical data for most procedures).[12,19] One way to address this limitation is to update the original scheduled estimate.[6] Once cases exceed this estimate by 10 min, a popup message on the anaesthesia computer asks for "your best guess of when the patient will exit the operating room."[6] Jiao and colleagues used anaesthesia medication and case event data retrospectively to infer that cases were approaching their end time.[2]

For the Bayesian estimating process, the value of the surgeon/schedulers can be quantified in units of equivalent numbers of historical cases, a weighting parameter, τ.[6,12] There is a graduated, relative contribution of the scheduler/surgeon and historical estimates. For example, when the value of the surgeon/scheduler estimate is $\tau = 3.0$ historical cases, for cases with 12 or more historical durations for the scheduled procedures, the surgeon/scheduler's estimate has a small (20%) effect on the calculated duration; $3.0/(12+3.0) = 0.2$.[12] In contrast, when there is just 1 historical datum for the same procedure, the surgeon/scheduler estimate makes a larger (75%) contribution; $3.0/(1+3.0) = 0.75$.[6] It has been observed previously, but not for the hospitals in the study of Jiao and colleagues,[2] that for most cases either there were <3 or >10 historical data for the procedure, so functionally either the surgeon/scheduler estimate or the historical data dominated,[12] depending on the cases and procedures.[12,14,19]

There are multiple managerial epidemiology studies for rare procedures, scheduled cases with limited or no historical procedural data.[14] These studies show why statistical methods should incorporate the surgeon/scheduler estimate, not neglect it entirely, in lieu of historical data, and *vice versa*.[17] In the USA, 36% of outpatient cases had procedures performed, overall, once per facility per year.[20] In Texas, 33% of hospital discharges had procedures observed just once statewide during the quarter.[18] Using 3 years of data at one teaching hospital, 5% of cases during the next year lacked historical data by procedure.[16] Using Current Procedural Terminology codes from four teaching hospitals with >200,000 cases, 9.3% of cases were of procedures scheduled only once ("singletons").[21] A fundamentally important feature of operating room management and case duration prediction is that many surgical cases are of rare (uncommon) procedures.

However, the epidemiology of Jiao and colleagues' data are unlike those reported previously, with significantly larger percentages of singletons (48% among >70,000 cases)[2] than in the earlier studies.[14,16,18,20,21] Among cases in the main training dataset, there were overall 2.0 cases per procedure.[2] That was not because of limitations to specialties with nearly all procedures rare (e.g., paediatric cardiac catheterization),[4] their specialties included orthopaedic surgery, ophthalmology, and obstetrics.[2] The high percentage of singleton cases did not occur because of limited historical data (e.g., following implementation of a new information system).[2] Rather, "procedure name was a short free-text description of the … procedure(s) intended to be performed,"[1] including laterality (Table 1). This matters because the Bayesian estimates for the longest durations that cases may take (e.g., 90% upper prediction limits) are unbiased, but precision depends heavily on having historical data,[16] frequently absent in the data used by Jiao and colleagues.[1,2] There is especially large variability in estimated case durations when there are 0–3 historical case durations,[19] as in the studies by Jiao and colleagues.[1,2] Such absence was a matter of analysing the procedures as semi-structured text,[1,2] different from previous managerial epidemiology studies that used structured procedure vocabularies.[14,18,20,21]

Showing one way to make decisions for organizations using literal text descriptions for procedures is valuable,[1,2] including how to compensate if unable to analyse structured procedure codes. We do not know performance compared with the alternative of asking the anaesthesia practitioner electronically for their estimate of the time remaining.[6] Asking was slightly better (median 4.7 min) than applying a Bayesian method.[6] We recommend studying the improvement using Jiao and colleagues' neural network approach (based on semi-structured[1,2] text) versus asking the anaesthesia practitioners in the room about how much time is remaining. Asking if closure has started can be equivalent.[13]

Cases have been scheduled using structured vocabularies for >25 years (e.g., Current Procedural Terminology codes).[3,13,16,21–25] We are unaware of any electronic health record with an intraoperative module that does not fully support use of such vocabularies (e.g., Epic OpTime, Epic Systems, Verona, WI, USA, Table). When procedures are scheduled using a structured vocabulary, supplemental data to adjust case duration predictions are known (e.g., surgeon and positioning).[4,10] Multiple clinical decisions also depend on the software understanding the procedures (e.g., reviewing appropriateness of the procedures for the facility, preoperative laboratory tests including type and screen and blood inventory, and postoperative bed usage and ward).[4] We thus recommend hospitals use structured vocabularies for procedure scheduling, thereby facilitating clinical and managerial decision-making and analysis.

Declarations of interest

The Division of Management Consulting of the University of Iowa's Department of Anesthesia provides consultations to corporations, hospitals, and individuals. FD receives no funds personally other than his salary and allowable expense reimbursements from the University of Iowa and he has tenure with no incentive program. FD and his family have no financial holdings in any company related to his work, other than indirectly through mutual funds. Income from the consulting work is used to fund Division research. A list of all the Division's consults is available at https://FranklinDexter.net/Contact_Info.htm. RHE and AAM have no conflicts of interest to declare.

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