ANALYSIS OF TARGET INVENTORY VIA DISCRETE-EVENT SIMULATION

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KEYWORDS

Discrete-event simulation, target inventory, service industry, personnel staffing

ABSTRACT

Discrete-event process simulation, originally the benefactor of the manufacturing sector of the economy, has expanded aggressively into the service sector of the economy, much to the benefit and gratitude of its new cadre of industrial engineers and management strategists. The study documented in this paper originated within a large health-care insurance provider seeking optimal strategies relative to target inventories of pending inquiries concerning insurance policy coverage and concomitant staffing levels of policy analysts. Since several clients of this insurance provider were large companies within the automotive industry, the provider dedicated significant staffing segments to the service of these accounts (hence to the employees of those automotive companies who thereby held insurance coverage). The simulation study worked within this constraint to provide management valuable strategic recommendations. Most specifically, the insurance provider wished to develop a model capable of predicting service levels (average time required to answer specific questions submitted on behalf of two major clients and average inventory level of these questions pending) as a function of number of full-time-equivalent analysts assigned to each of those clients.

INTRODUCTION

The client of this simulation study was a large health-care insurance provider whose management wished to achieve an economically and operationally efficient balance among the inventory (backlog) of pending inquiries pertinent to insurance policy coverage, the average and maximum queuing time of those inquiries, and staffing levels among the specialists assigned to respond to the inquiries. At the beginning of the study, client management was rather unfamiliar with discrete-event simulation and its analytical capabilities, even though simulation has long been used in the manufacturing sector (Banks et al. 2005). Recent examples of simulation usage within service industries, some of which were mentioned to client management, include guidance of staffing decisions in a consumer credit organization (Chen et al.), increasing the efficiency of supplying medical oxygen to the health-care industry (Costantino, DeGravio, and Tronci 2005), and the improvement of surgery staffing and services at a large hospital (Kumar and Ozdamar 2004). Presenting such examples and describing the benefits of simulation modeling as a trilogy of "sense making" (seeing patterns in seeming chaos), "knowledge creating," and support of strategic decisions clarified the value of simulation to client management. This trilogy is described, and its usage advocated, in (Greasley 2005). As a result of these introductory steps, and with the vigorous and intelligent support of a client manager (c.f. Acknowledgments), client managers and analysis became disposed to accept simulation as a valuable decision-support tool.

OVERVIEW OF CLIENT OPERATIONS

The client health-care insurance provider maintains a large specialized staff of experts to research and answer complex questions posed by its many clients. Two of these clients, both of which are large manufacturing companies in the automotive industry, each account for large numbers of questions because each has thousands of employees covered by the client's health insurance and hence likely to ask complex and detailed questions concerning their policy coverage. Therefore, as a matter of long-standing management directives, the insurance provider maintains two staffs each dedicated to service of one or the other of these corporate accounts. Since the employees' insurance policies pertinent to each of these manufacturing companies contain numerous specialized and customized features developed over a span of years, this staffing arrangement helps the insurer provide better service by retaining, instead of losing, the accumulated expertise of analysts well-versed in the complexities and intricacies peculiar to each manufacturer's insurance policy.

Proceedings 20th European Conference on Modelling and Simulation
Wolfgang Borutzky, Alessandra Orsoni, Richard Zobel © ECMS, 2006
ISBN 0-9553018-0-7 / ISBN 0-9553018-1-5 (CD)

Upon arrival at the insurance provider, a policy coverage question from either of its manufacturing-company customers goes to one of the dedicated staffs and is then assigned to a particular expert who then becomes responsible for "shepherding" it through the system until it is definitively answered ("closed") – a definitive answer is therefore the "customer deliverable." Examination of the policy coverage question and provision of a definitive, correct answer is a complex process, the more so because the United States, unlike members of the European Union, has a crazy-quilt of laws instead of a unified national system for providing health care (Katz and Wial 2006). As client managers and team leaders became comfortable with the use of discrete-event process simulation via the process described in the preceding section, the goals of this simulation study were refined to:

1. Determine the target inventory levels permitting each of the two staffs to maintain a service level (average closing time) of 21 to 28 days.
2. Develop a model capable of predicting both inventory level and average closing time as functions of the number of full-time-equivalent workers [FTEs] in each staff. (For example, one FTE may be one full-time worker or the set union of two workers each working half-time.)

DATA COLLECTION

Data collection involved, first and foremost, achieving an understanding of the complex and variegated logical steps through which policy coverage questions must travel. Data collection work began with client interviews directed toward understanding the often complex process through which coverage questions traveled between submission and return of an answer. At these interviews, client management also provided 2006 monthly forecasted receipts of incoming work, case processing rate, the percentage of cases requiring various specific attentions (e.g., that of pricing analysts, accountants, and/or registered nurses), times spent in these subsidiary areas, and current plans for number of FTEs scheduled to work. Later, at a finer level of detail, client managers and simulation analysts unobtrusively observed actual inquiry-processing vignettes, taking care to avoid provoking the Hawthorne effect (Niebel and Freivalds 2003). Furthermore, the client fortunately held, in the database archives of a proprietary management-information system, valuable process performance data which was downloaded into Microsoft Excel® for model input.

MODEL BUILDING, VERIFICATION, AND VALIDATION

Since the client owned copies of the discrete-event simulation software WITNESS®, and had personnel who felt comfortable viewing animations of models built using it, this software was used at the client's request. WITNESS®, like many other simulation software packages, provides concurrent construction of a model and its (two-dimensional) animation, plus standard constructs like Machines, Buffers, Resources, and Histograms (Mehta and Rawles 1999). WITNESS® further provides interfaces to read model input data from Microsoft Excel® and write model output likewise, thereby facilitating further statistical analyses.

The processing rate (closing rate) of written inquiries was modeled, after consideration and testing of several alternative approaches, based on a customized empirical distribution. Daily data were taken for the total number of inquiries closed by the employees of a section during a day and the number of hours required to close them. Because of changes implemented in the past and discovered during extensive interviews with client management, only the last six months' worth of data was used, lest the data model fall victim to a significant discontinuity. Based on these daily closing rates observed, an empirical distribution was created and used within the WITNESS® model.

As described above, any particular inquiry may be sent to one or many of a variety of technical support areas during the process of its resolution. Very fortunately – a luxury often unavailable to the simulation analyst (Leemis and Park 2006) – the client's computer system allowed historical tracking of how long numerous inquiries spent on each of the external areas that they visited. Many such sums of times spent in external areas per inquiry represented data points used to create another empirical distribution. Like the closing-rate distribution, this one was used in the WITNESS® model after test samples from it passed localized validation tests.

Model verification and validation methods included close examination of the animation, step-by-step execution of the model and following the logical path of a single entity through it, and structured walkthroughs of the model logic with colleagues (Sargent 2004). Additionally, use of Little's Law in the form $L_s = \lambda \times W_s$ (average number in system and average time in system) (Nelson 1995) provided reassuring confirmation of model results and sensitivity analyses. After some of the archived system performance data had been used as model input, other such data corresponding to performance metrics (e.g., minimum, average, and maximum "dwell time" of inquiries in particular departments) were used in model validation.

RESULTS AND CONCLUSIONS

After performing several experiments and sensitivity on the different parameters, it was found that there is a one-to-one relationship between average inventory and average closing time (service level). In other words, given a service level, there is only one target inventory that will support it, inasmuch as average closing time is a monotonically increasing in target inventory.

Figure 1 (at the end of the paper) shows the relationship between average inventory in the department and the average closing time. This relationship is independent of all parameters (number of FTEs, percent of cases sent out, time in external areas, queuing discipline (FIFO, LIFO, etc) and it depends only on the cases' arrival rate (forecasted receipts) – as shown in Figure 2 immediately following. The percent of cases sent out, the time elapsed in external areas, and queuing discipline have no impact on the number of scheduled FTEs required to maintain a desired inventory (and therefore provide a particular service level of choice).

The results found by application of Little's Formula verified those found by sensitivity analysis via simulation. Under all scenarios run (except with the one with an increased arrival rate), the same average inventory resulted in the same average closing time. The distinguishing feature among all of those scenarios was the number of FTEs required to maintain the inventory level – exactly the predictive capability the client desired.

The problem of setting target inventories to satisfy a service level, which in the client's original perception was a difficult multivariate problem, was thus simplified. Specifically, to achieve an average closing time for inquiries of between 21 and 28 calendar days (the target) the client needed only to adjust the number of FTEs used. It became demonstrably unnecessary for the client managers to concern themselves with minutiae of routing control, readjustment of flow procedures, and other now extraneous concerns. It is critical to monitor the actual cases' arrival rate compared to the forecasted values used when this study was done. As previously shown, changes in the volume received, in the absence of an adjustment to the target inventory, will result in an increased average closing time.

SUMMARY AND ANTICIPATED FURTHER WORK

During the last eight months, the model has proved accurate in its twin aims of:

1. Enabling the client to maintain a service level of 21 to 28 calendar days by maintaining an inventory of 1700 to 2400 pending inquiries
2. Providing accurate anticipated response times to the employees of the two large automotive clients.

Anticipated model refinements include, in the short term, specific predictions of the metric "expected percentage of cases closed within fewer than ***x*** days," where ***x*** is input as frequently as desired by the client. A longer-term addition to the analysis will be more detailed examination of impacts of workers' "lost time" (e.g., vacations, sickness, jury duty, and other absences from the office) and "non-production time" (time present in the office but doing other tasks (e.g., attending staff meetings or submitting monthly reports). The client has now become confident in the powers of simulation and welcomes their further use.

ACKNOWLEDGMENTS

The authors express high gratitude to Dr. Ali Gunal, a manager and internal consultant of operations engineering at the client company, for valuable information, assistance, and encouragement throughout this simulation study.

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MARCELO ZOTTOLO, born in Buenos Aires, Argentina, came to the United States to finish his college studies. He was graduated from the University of Michigan - Dearborn as an Industrial and Systems Engineer in December 2000, and subsequently earned his master's degree in the same field in June 2004. He was awarded the Class Honors distinction and his Senior Design Project was nominated for the Senior Design Competition 2001. This project studied the improvement of manufacturing processes for the fabrication of automotive wire harnesses, ultimately proposing an automation tool leading to improvements in future designs. Additionally, he was co-author of a paper on simulation in a distribution system which earned a "best paper" award at the Harbour, Maritime, and Simulation Logistics conference held in Marseille, France, in 2001. He is currently working for Production Modeling Corporation as a Simulation Engineer. There, his responsibilities include building, verifying, validating, and analyzing simulation models in WITNESS®, ProModel®, and SIMUL8® for large corporate clients; he also presents in-house training seminars. His email address is mzottolo@pmcorp.com

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Queuing Discipline Sensitivity to Forecasted Receipts of Inquiries

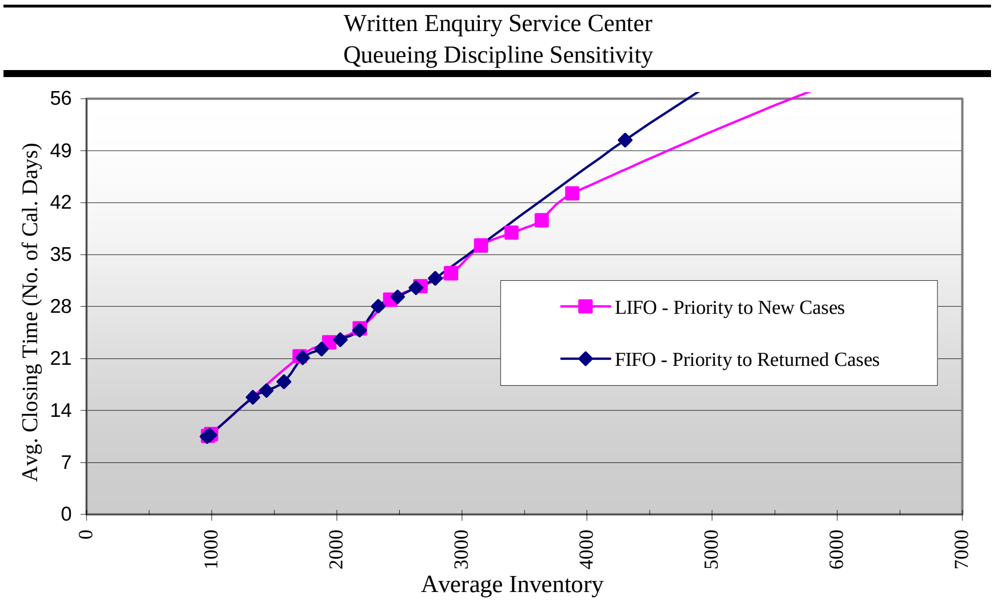

Figure 1. Average Inventory versus Average Closing Time. The relationship between the variables is unaffected by the queuing discipline

Sensitivity of Closing Time to Forecasted Receipts

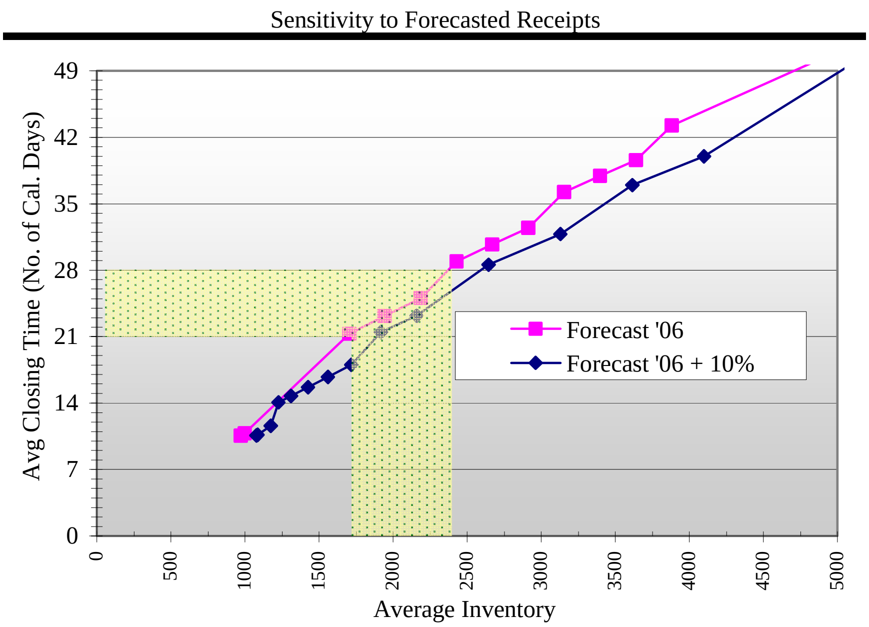

Figure 2. Average inventory versus scheduled FTEs. When FTEs are the constraint, the queuing discipline has an impact on the number of FTEs required to maintain a certain inventory