

# Simulation Helps Local Grocery Store Compete Effectively Against Large Chains

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**Abstract**—Historically, discrete-event process simulation was used first and most often to the study and benefit of manufacturing processes. Its domains of use have steadily expanded during approximately the last half-century to include supply chain operations, computer networks, health care, and retail service. All of these economic domains exhibit intense competitiveness. The application of simulation presented in this paper involves a local, traditional grocery store facing competitive pressure from an encroaching “big-box” chain store. As a countermeasure, management wished to assess potential investment in a self-checkout system to supplement staffed checkout lanes. An analysis using discrete-event process simulation greatly aided this assessment of the ability of self-checkout lanes to improve customer service by reducing wait times.

**Keywords**—Process simulation; retail service; business process modelling; queuing

## I. INTRODUCTION

Discrete-event process simulation has long been used to improve operations in manufacturing, warehousing, and supply chain operations. More recently, its use has expanded rapidly into general transportation, computer networks, call centers, retail service, and delivery of health care. The last two of these inevitably involve business process modeling, as discussed in [1] with particular emphasis on call centers. Explicitly in the retail sector, [2] used simulation, coupled with examination of virtual reality environments, to model and improve retail store facilities. Also, [3] applied simulation to improve staffing policy at retail checkout in a pet-supplies store. The case study [4] describes the application of simulation to the receiving area of a large retail store. Even more recently, [5] applies both simulation and data envelopment analysis (DEA) to the logistics of the dairy department and its associated supply chain (critical because of high spoilage concerns) of supermarkets and hypermarkets.

## II. CONTEXT OF PROJECT

Big-box grocery stores have attracted customers away from smaller traditional grocery stores with low prices and the convenience of “one-stop” shopping for everything from produce to paint supplies. These big-box grocery stores offer the advantage of lower prices, more product options, and the additional benefit of self-checkout systems for a quick

shopping experience. A recent retailing study [6] reports 77% of respondents bought groceries from big-box stores, such as Wal-Mart and Target, in 2013, and 96% of respondents had plans to purchase groceries from these retailers in 2014. These bigger, low-cost alternatives have applied significant pressure to the smaller, locally owned grocery stores that are struggling to keep their customer base, as more big-box grocery stores are built.

Self-checkout systems have played a major role in promoting convenience within the customer experience. In 2010, self-checkout suppliers realized \$524,100 worldwide and project an 84% growth over five years [7]. Self-checkout technology can dramatically reduce customer wait times and save on labor costs (essentially, the customer does much of the work); big-box stores have exploited these competitive advantages.

Increased competition from a recently opened 24-hour big-box grocery store has encroached on the customer base of a local traditional grocery store, the client of this project. The store owner wishes to analyze potential investment in a self-checkout system. At the cost of significant capital investment (\$17,000 per self-checkout stand), installation of one to four such stands may potentially improve customer satisfaction (by virtue of checkout options and reduced queuing times). Furthermore, self-checkout stands will presumably reduce staff workload and labor costs, and these reductions would predictably become more significant over time as regular customers who select the self-checkout stands become more familiar and comfortable with their use. The store owner sought consulting assistance, and specifically the construction, verification, validation, and analysis of a discrete-event process simulation model to assess potential return on investment.

## III. DATA COLLECTION AND ANALYSIS

The client grocery store is open seven days a week, from 6am until midnight; the store owner was adamant about not changing this policy. Cashier staffing levels during the course of each 18-hour day were readily available; with six checkout lanes on the floor, no more than six cashiers are ever on duty at any one time.

Next, data were collected concerning arrival rates of customers. These data were observed over two 18-hour days, one a weekday and one a weekend day. Project time constraints

unfortunately prevented the collection of data for each of the seven days of the week, although both the client and the analyst were well aware that shopping rates differ among both the five weekdays and the two weekend days. To assess the magnitude of the approximation thus required, and prepare for later sensitivity analysis, the generic data in [8] proved highly useful.

Next, four categories of data were collected concerning the checkout process:

1. Checkout times at a cashier in the grocery store under study.
2. The amount of time spent shopping (interval between entry and checkout).
3. Checkout times at a self-checkout stand in a similar grocery store.
4. The proportion of customers electing the self-checkout option in that store, based on a comparison of line lengths at the cashiers and the self-checkout stand(s).

The arrival data and the checkout-time data ((1) and (3)) were then analyzed with the help of a distribution fitter [9], namely Stat::Fit®, in search of closed-form distributions capable of representing the interarrival times, shopping times, and checkout times within the simulation model. The interarrival times were accurately characterized as exponential (i.e., Poisson process) with means varying by time of day (and weekday versus weekend) during the 18-hour time the store is open. The shopping times were triangular, with a mode significantly less than the mean. The checkout times, both at a cashier and at a self-checkout stand, were also very nearly triangular and approximately symmetric (mode  $\approx$  mean). The probability any one customer (whether single shopper or family group) would use self-checkout was represented as Bernoulli, with parameter dependent upon the lengths of the cashier and self-checkout lines. Observation also suggested assuming independence of successive customers' choices thereby made. Examination of a sequence of choices made by customers under steady-state conditions revealed neither positive nor negative autocorrelation among the choices made by successive customers.

#### IV. MODEL BUILDING, VERIFICATION, AND VALIDATION

Simio® simulation software [10], [11] was used to build the simulation model of the grocery store. The model entities are Customers, and the servers are Shopping, Cashier Checkout, and Self-scan Checkout. The model also has two resources: Self-scan Cashier and Store Manager (in Simio®, a "resource" is immovable, appropriate here). Customers enter the model and arrive at the store entrance according to an arrival rate table. After arriving, customers then proceed to shop in the store for a length of time from one to sixty minutes. When the customers have finished their shopping, they travel to one of the checkouts and spend a random amount of time at checkout, from fifteen seconds to five minutes, before exiting the store. While at a cashier checkout, a customer may require the assistance of the store manager. When this occurs the store

manager resource is seized and remains with the customer throughout their checkout and is then released. Observations and literature suggest that the store manager's attention is needed for 5% of customers. Likewise, the self-scan cashier's attention may be needed to assist customers at the self-scan checkout. The self-scan cashier resource follows the same process as the store manager, and 25% of self-scan customers (a markedly higher proportion than at a cashier) require assistance. The model assumes, in accordance with observation, that all customers who enter the store will transit the entire model process of shopping and checking out, so neither renegeing nor balking occurs.

In the base-case model, customers use only the cashier checkout. The number of cashier checkout lanes available follows a schedule based upon the actual staffing schedule of the grocery store. In some of the scenarios tested, customers could use either the cashier checkout or the self-scan checkout. Historical data suggest that 60% of customers use the cashier checkout and 40% use self-scan checkout. In the model, customers choose the shorter checkout line of the two, with ties going to the cashier checkout. The actual breakdown in the scenarios varied around 67% using cashier and 33% using self-scan.

Verification and validation techniques [12] included structured walkthroughs, detailed "step-mode" examination of the animation (automatically built as the simulation model was built), and close monitoring of the output metrics: self-scan vs. cashier checkout, average customer wait time, and cashier utilization; to match historical and collected data. Status labels for number of arrivals, self-scan checkout customers, cashier checkout customers, and cashiers available were used to verify and validate the arrival rates, customer checkout breakdown, and cashier schedules. In addition, status plots for cashier checkout and self-scan checkout were used to verify and validate the utilization rates. After adjustments to the model and correction of errors, the final model coordinated to 5% tolerance with system observations and historical data.

#### V. OUTPUT ANALYSIS AND RESULTS

After verifying the model within the simulation team and validating it with the store owner, 100 replications of a full week (Monday – Sunday, with hours of operation from 6AM - midnight) for each of four scenarios: zero (base case), two, three, and four self-scan checkout scanners were run. It was already known that removing one cashier lane would free sufficient floor space for two self-scan checkouts – indeed, one appeal of self-checkout lanes is their relatively low space requirement. Therefore, the scenario of adding one such lane was never included in the analysis. Since the model is a terminating system, inasmuch as the store opens empty-and-idle at 6am daily, no warm up time was necessary [13]. In the three experimental scenarios, since the number of self-scan checkouts was varied from two to four, the cashier checkout schedules were updated accordingly.

With reference to the most important performance metrics, the output results were examined on the basis of 95% two-sided confidence intervals. Since 100 replications were run, these confidence intervals were gratifyingly narrow and without overlap. These results indicated that replacing two of

the cashier checkout lines with two self-scanners would, in recompense for the (significant) initial investment, produce several worthwhile improvements:

1. Reduction of average waiting time at a cashier from above 5 minutes to below 2 minutes (more than a 60% reduction).
2. Reduce weekly labor cost by 14%.
3. Achieve a wait time of less than 3½ minutes at each of the self-scan checkouts.
4. Leave the average cashier utilization nearly unchanged.

For psychological reasons, reduction of the average wait time at a cashier below five minutes – a significant threshold – was deemed especially worthwhile [14]. However, as shown in the Table I of results (Appendix), adding even two more self-checkout stands (for a total of four) would produce improvements less important on a practical basis, although still significant on a percentage basis. For example, the two additional stands would reduce wait time at a traditional cashier by nearly half (from 1.77 minutes to 0.90 minutes) – although this improvement is much less psychologically significant to the typical customer.

Based on these experiments and consultations with the store owner, the final recommendation of the consultants is to replace two traditional cashiers with one self-scan cashier to assist customers utilizing the two new self-scan systems. Due to the high costs of \$17,000 per self-scan system, the consultants recommend purchasing two systems instead of the original four proposed and analyzed in the business problem. With the purchase of two self-scan systems at \$17,000 each, the store owner expects to recoup his investment of \$34,000 within one year – a highly favorable return on investment (ROI). A major contributor to this favorable ROI is the labor saving of one cashier, to be realized in practice in the form of increased flexibility in assigning different work tasks to the other current cashier.

## VI. AFTERMATH AND FUTURE WORK

Having documented the merits of implementing two new self-scan systems to the grocery store owner (who has decided to do so), the consultants recommend continuing to monitor and update the model based on new data regarding the self-scan systems over the course of the next year. The consultants also suggest further exploring options to increase cashier utilization via more detailed analyses of scheduling tables and customer arrival rate tables. The consultants recommend endeavoring to increase cashier utilization to the typically optimal 80% (this percentage is a well-accepted guideline to balance the trade-off between excessive queue lengths on one hand against unduly low resource utilization on the other hand) to realize the full benefits of proper staffing solutions and benefits of the investments made in labor. Also, relative to the fourth category of data concerning the checkout process, the store owner has recently become interested in whether the proportion of customers selecting self-checkout (probably highly correlated with customer demographics) varies by time of day and/or day of week. Analysis of such data within the simulation model, which could be undertaken simply by

making the probability of self-checkout time-dependent, could lead to profitable fine-tuning of staffing decisions. Taking a longer and more nuanced view, the success of this project has piqued interest of other small and/or local merchants and businesses in the analytical power of simulation and the help it can potentially provide.

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**EDWARD J. WILLIAMS** holds bachelor's and master's degrees in mathematics (Michigan State University, 1967; University of Wisconsin, 1968). From 1969 to 1971, he did statistical programming and analysis of biomedical data at Walter Reed Army Hospital, Washington, D.C. He joined Ford Motor Company in 1972, where he worked until retirement in December 2001 as a computer software analyst supporting statistical and simulation software. After retirement from Ford, he joined PMC, Dearborn, Michigan, as a senior simulation analyst. Also, since 1980, he has taught classes at the University of Michigan, including both undergraduate and graduate simulation classes using GPSS/H™, SLAM II™, SIMAN™, ProModel®, SIMUL8®, Arena®, or Simio®. He is a member of the Institute of Industrial Engineers [IIE], the Society for Computer Simulation International [SCS], and the Michigan Simulation Users Group [MSUG]. He serves on the editorial board of the International Journal of Industrial Engineering – Applications and Practice. During the last several years, he has given invited plenary addresses on simulation and statistics at conferences in Monterrey, México; İstanbul, Turkey; Genova, Italy; Rīga, Latvia; and Jyväskylä, Finland. He served as a co-editor of Proceedings of the International Workshop on Harbour, Maritime and Multimodal Logistics Modelling & Simulation 2003, a conference held in Rīga, Latvia. Likewise, he served the Summer Computer Simulation Conferences of 2004, 2005, and 2006 as Proceedings co-editor. He was the Simulation Applications track coordinator for the 2011 Winter Simulation Conference and the 2014 Institute of Industrial Engineers annual conference, and will be the Manufacturing Track coordinator for the 2015 Winter Simulation Conference. His email address is williams@umich.edu.

#### REFERENCES

[1] Hlupic, Vlatka, and Vesna Bosilj-Vuksic. 2004. Business process modelling using SIMUL8. In Proceedings of the 16th European Simulation Symposium, eds. György Lipovszki and István Molnár, 191-196.

[2] Bruzzone, Agostino, Simone Viazzo, Francesco Longo, Enrico Papoff, and Chiara Briano. 2004. Simulation and virtual reality applied to modelling retail and store facilities. In Proceedings of the 2004 Summer Computer Simulation Conference, eds. Agostino G. Bruzzone and Edward Williams, 76-81.

[3] Williams, Edward J., Mohamed Karaki, and Craig Lammers. 2002. Use of simulation to determine cashier staffing policy at a retail checkout. In Proceedings of the 14th European Simulation Symposium, eds. Alexander Verbraeck and Wilfried Krug, 172-176.

[4] Valette, Marissa A., Prajwal Khadgi, Reinaldo Moraga, Ehsan Asoudegi, and Omar Ghrayeb. 2009. Simulation in retail: A case study for process improvement in the receiving area. Proceedings of the 2009 Winter Simulation Conference, eds. M. D. Rossetti, R. R. Hill, B. Johansson, A. Duncan, and R. G. Ingalls.

[5] Reiner, Gerald, Christoph Teller, and Herbert Kotzab. 2014. Analyzing the efficient execution of in-store logistics processes in grocery retailing – The case of dairy products. In Production and Operations Management 22(4):924-939.

[6] Study: Traditional retail categories are blurring'. King Retail Solutions. King Retail Solutions, 2013. Web. 2 April 2014. <[http://issuu.com/kingretail/docs/krs\\_infographic\\_issuu/3?e=7220236/6703671](http://issuu.com/kingretail/docs/krs_infographic_issuu/3?e=7220236/6703671)>.

[7] Anand, Anika. Welcome valued customer ... to more self-checkouts. Today News. NBC News, 22 July 2011. Web. 2 April 2014. <[http://www.today.com/id/43729757/ns/today-today\\_news/t/welcome-valued-customer-more-self-checkouts/#.UzycLfdXTo](http://www.today.com/id/43729757/ns/today-today_news/t/welcome-valued-customer-more-self-checkouts/#.UzycLfdXTo)>.

[8] Goodman, Jack. "Grocery shopping: Who, where and when." The Time Use Institute. October 2008. PDF file <<https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0CE0QFjAA&url=http%3A%2F%2Ftimeuseinstitute.org%2FGrocery%2520White%2520Paper%25202008.pdf&ei=QLiVU4rIMNGmyAToi4HYAQ&usq=AFQjCNHRFSs5L5cpHN5Ju2ZyZYQZ3Mam5Q&sig2=gD2gIk5Jgez0bR-LZJdLfw&bvm=bv.65177938,d.aWw>>.

[9] Chung, Christopher A. 2004. Simulation modeling handbook. Boca Raton, Louisiana: CRC Press.

[10] Thiesing, Renee and C. Dennis Pegden. 2013. Introduction to Simio. Proceedings of the 2013 Winter Simulation Conference, eds. Raghu Pasupathy, Seong-He Kim, and Andreas Tolk.

[11] W. David Kelton, Jeffrey Smith, and David Sturrock. 2013. Simio and simulation: Modeling, analysis, applications, 3<sup>rd</sup> edition. Learning Solutions.

[12] Sargent, Robert G. 2004. Validation and verification of simulation models. In Proceedings of the 2004 Winter Simulation Conference, Volume 1, eds. Ricki G. Ingalls, Manuel D. Rossetti, Jeffrey S. Smimth, and Brett A. Peters, 17-28.

[13] Law, Averill M. 2007. Simulation modeling and analysis, 4<sup>th</sup> edition. New York, New York: The McGraw-Hill Companies, Incorporated.

[14] Gorney, Leonard. 1981. Queueing theory: A problem-solving approach. San Francisco, California: Petrocelli Books, Incorporated.

#### APPENDIX

TABLE I. OUTPUT PERFORMANCE METRICS RESULTS

Experiment	Max # Cashier Checkout Lanes	Cashier Utilization	Self-Scan Utilization	Avg Cust. Wait (Cashier) min	Avg. Cust. Wait (Self-scan) min	Weekly Labor Cost
No self-scanners	6	61.94%	--	5.16	--	\$5,034.24
2 self-scanners	4	62.17%	36.80%	1.77	3.13	\$4,304.64
3 self-scanners	4	62.07%	33.58%	1.00	1.19	\$4,304.64
4 self-scanners	4	62.09%	32.70%	0.90	0.90	\$4,304.64