SIMULATION IMPROVES SERVICE AND RESOURCE ALLOCATION AT A SALON

Ganapathi Baliada Ramesh[(a)], Brittany Harju[(a)], Daniel Scipione[(a)], Kristina Vujic[(a)] ,Edward J Williams[(a)]

[(a)]Business Analytics, College of Business, University of Michigan – Dearborn, Dearborn, MI, USA

[(a)]gramesh@umich.edu, [(a)]bharju@umich.edu, [(a)]dscip@umich.edu [(a)]kvujic@umich.edu, [(a)]williame@umich.edu

ABSTRACT
Simulation, historically first used in manufacturing industries, has steadily and deservedly expanded its reach into helping service businesses evaluate and implement solutions to problems such as slow service, overutilized or underutilized resources, suboptimal scheduling, and inefficient workflow. Such service industries have included banks, retail stores, hospitals and clinics, hotels, call centers, and credit unions. In the present work, the authors used discrete-event process simulation to analyze and resolve such problems at a salon. This salon provides a complex mix of services such as haircuts and/or hair coloring, massages, manicures and pedicures, and other spa services.
This simulation modeling and analysis project successfully addressed issues such as size of the waiting area, asymmetry of utilizations across various resources, ways of handling schedules and arrival rates differing by days of the week, and best allocation of priorities among customers and tasks.

Keywords: discrete-event process simulation, work measurement, resource allocation, decision support system

1. INTRODUCTION
Historically, discrete-event process simulation was first and very extensively used to improve manufacturing operations, and extensions to warehousing and supply chain operations (e.g., stochastic optimization of a large-scale inventory-routing problem, as documented in (Lefever, Aghezzaf, and Hadj-Hamou 2018)) naturally followed. In recent years, simulation has repeatedly proved its ability to improve service operations, such as those of banks, credit unions, public transport (e.g., the work of (Otamendi and Pastor 2006) to improve bus stations), hospitals and clinics, hotels, call centers, and retail stores (e.g., the work of (Williams, Karaki, and Lammers 2002)). These improvements often arise through discovery and implementation of better scheduling policies, improved allocation of resources, redesign of process flow, or more effective allocation of typically scarce capital to fund investments such as new equipment. For example, (Baskaran, Bargiela, and Qu 2013) applied simulation to the effective scheduling of nurses. Granting of consumer credit was made faster and more efficient through the work of (Chen et al. 2004). Likewise, (Sivaramakrishnan et al. 2016) describes the successful use of simulation to improve operations at a highly specialized takeout restaurant.
The simulation study described in this paper sought improvements to a hair salon and spa, located in a suburban city in the Great Lakes region of the United States. This salon is already a highly successful “small business enterprise,” and its clientele is expanding. The wide-ranging concerns of its management included size of its waiting area, uneven resource utilization (over-utilization of some resources coupled with under-utilization of others), the understandable disappointment and annoyance of would-be customers who had to be turned away, plus typical queueing performance metrics such as average and maximum time in queues. Furthermore, the “color bar” (a small work area of the salon, equipped with a sink, where the stylists go to mix the color that will be applied to the client's hair) was already notorious as a point of congestion, since nearly half of all customers’ requests require that a worker spend preparatory time there. As is now rarely the case in large companies, but quite often the case in small independently owned enterprises, the salon owner and manager was unfamiliar with process simulation and its capabilities. When approached by a member of the project team, she was thus delighted to hear that “simulation will let us see the effects of making a change by looking at a computer, rather than by spending money and time making a highly committal and disruptive change that might not work.” The University of Michigan – Dearborn’s College of Business actively collaborates with local enterprises, as was done in this case study. Such collaboration helps business students understand ongoing enterprise concerns, a major advantage of teaching discrete-event simulation to business students (Ståhl 1996).
In the following sections, we (1) present an overview of the salon’s operations, (2) describe the collection and analysis of input data, (3) discuss the building, verification, and validation of the simulation model, (4) highlight key results from this model obtained by output analysis, and (5) present conclusions, recommendations to the salon’s management, and candidates for possible future work.

2. OVERVIEW OF SALON OPERATIONS

The salon under study provides a wide variety of services, and therefore is divided into two major operational areas. The hair salon provides haircuts, hair coloring, and hair styling. The spa provides massages, facials, manicures, and pedicures. A small minority of customers, on one visit, may receive multiple services from either or both parts of these areas (a possibility not addressed in this study, except for the scenario in which a customer who has received hair styling may or may not elect to visit hair coloring). Upon appointment request several months in advance, the business will reserve its facilities for use by an entire bridal party. Management of this type of business involves numerous knotty complexities – financial, operational, and interpersonal, as extensively documented by (Tezak and Folawn 2011). For example, the workers (more than twenty) have a wide range of skill sets: hair stylists (the majority), nail technicians, spa therapists, skin care specialists, masseuses, eyelash extension specialists, and airbrush makeup specialists. Management was particularly interested in salon performance metrics on weekends: The salon is open 8am-4pm Saturdays and 11am-5pm Sundays.

Customers arrive originally at a reception area, and then are directed to the waiting room. Depending on the service the customer wishes to receive, either a stylist or a spa worker will come to the waiting room, greet the customer, and escort him or her (a large majority of the customers are women) to the appropriate point in the styling area or the spa. After completion of the styling or spa service, the customer returns, without escort, to the reception area. There, before exiting, the customer will pay the bill and perhaps book a future appointment. As this study began, the manager felt herself under duress to decide quickly "Should the waiting area be expanded further or scaled back (it had recently been expanded), and how will such a decision impact both operational areas?"

3. DATA COLLECTION AND ANALYSIS

On becoming acquainted with the capabilities of discrete-event process simulation, the salon manager immediately and eagerly anticipated opportunities to improve important system performance metrics, such as:

1. Reducing the percent of clients who, upon seeing a nearly full waiting room, balk;
2. Reducing the frequency with which salon workers must stay late to finish services to their customers, and the length of time they must stay for this reason;
3. Reducing the mean and the standard deviation of the times clients receiving a specified treatment stay in the salon (customers appreciate predictability relative to their other plans for the day);
4. Keeping the utilization of various salon workers in the 70%-80% range.

Members of the analysis team, taking care *not* to instigate the Hawthorne effect (Kroemer and Grandjean 1997), visited the spa to unobtrusively observe its operations. Very remarkably and commendably, the manager had numerous data readily available. These data included schedules, varying by day of week, for the styling workers, the spa workers, and the receptionist; arrival rate of customers by hour of the business day, and a detailed breakdown of percentage of customers desiring each of eight categories of service, as shown in Table 1. Overall, three-quarters of customers visit the salon and one-quarter visit the spa.

Table 1: Percent of Customers Desiring Services

Service Requested	% of Customers
Salon	(aggregate ¾)
Hair coloring only	15
Haircut only	18¾
Haircut and hair coloring	33¾
Miscellaneous salon service	7½
Spa	(aggregate ¼)
Manicure	5
Pedicure	8¾
Massage	5
Miscellaneous spa service	6¼

Additional data included service times for all the pertinent service areas (some often shorter than five minutes, and others as long as an hour and half, and highly variable), and a blueprint of the salon floor plan. Using this blueprint to determine distances, plus a typical walking speed of 1.4 meters per second (not treated as variable across customers), permitted calculation of transit times (not negligible) between various locations within the salon. Data was also provided concerning the possibility of balking (Bhat 2015). Specifically, prospective customers typically balked if five or more people were already in the waiting area. Furthermore, the reception desk personnel would, as diplomatically as possible, "balk" customers whose requested service would clearly last well past closing time. This latter situation is very rare, partly because arrivals are by appointment, not "walk-in," and partly because if operations in the salon become backlogged, the reception desk personnel, being apprised of this, will telephone the customer ahead of appointment time to give the disappointing news.

Each of the service-time data sets was analyzed using the specialized distribution-fitting software tools Stat::Fit® (Leemis 2002) and @RISK® (Clemen and Reilly 2014). Upon viewing the histograms of these distributions and receiving an explanation of the three parameters of a triangular distribution (minimum, mode, maximum), the salon manager felt comfortable with their use – a valuable step toward model credibility.

4. MODEL DEVELOPMENT, VERIFICATION, AND VALIDATION

Members of the project team concurred in the choice of the Simio® software [SIMulation with Intelligent Objects] (Prochaska and Thiesing 2017, Smith, Sturrock, and Kelton 2017) to construct a model of the salon's operations. Simio® provides constructs such as the Server (to model, for example, the pedicure station), the Worker (who can both escort a customer to the pedicure station and then perform the pedicure, and the Resource (e.g., the shampooing apparatus required to shampoo a customer's hair). Sequence Tables allow each Entity (customer) to visit the proper locations in the correct order, based on the type of customer (see Table 1). Virtually no incremental work is required to create a helpful animation. A screen shot of the model appears as Figure 1 in Appendix A, and one of the model's internal representation of customer sequences appears as Figure 2 in Appendix B.

At the client's explicit request, the project team built two separate models (the second largely a clone of the first), one for Saturday operations and one for Sunday operations.

An extensive array of techniques are available for model verification and validation (Sargent 2004). Among them, the analysis team undertook all of the following:

1. Temporary elimination of all randomness from the model (replacing each probability distribution by its mean) and checking results arithmetically;
2. Allowing only one entity (customer) to enter the model and checking the logical route it followed (this was done for each of the eight customer "types" in Table 1);
3. Directional analysis (Radosiński 1996), in this context, increasing customer arrival frequency and checking that queue lengths and times in queues increase as expected;
4. Executing the model time-step by time-step while closely observing the animation;
5. Using actual historical data on customer types and their arrival times (obtained from the previous week) and checking the model's predicted performance metrics against recollections of that day.

As is usual, these techniques exposed several modeling errors; after correction of those errors, model results closely (within 6%) matched historical observations. At this point the salon manager expressed confidence in the model – thus the model achieved credibility.

5. EXPERIMENTATION AND RESULTS

The salon is clearly best represented as a terminating (as opposed to a steady-state) system, opening at a specified hour each day and running until at least closing time (typically a little beyond, to allow the workers time to complete services to the last few customers). Therefore, Saturday runs lasted just over eight hours and Sunday runs just over six hours. In addition to the "base case" representing current salon operations as used for verification and validation, five additional scenarios were studied. These scenarios explored the effects of potential changes to the work schedules of the stylists, the seating capacity of the waiting area, and the capacity of the color bar. Each of these scenarios was run for ten replications, the team having verified that this number of replications would generate 95% confidence intervals, sufficiently narrow to distinguish among alternative proposals clearly (Currie and Cheng 2016).

The salon manager asked three specific questions relative to the simulation results and the scenarios chosen:

1. Should the salon increase the capacity of the waiting area beyond the current value of six customers?
2. Should the salon rearrange the scheduling of the stylists to have more than two (the current policy) stylists on duty near the end of each business day – even slightly beyond closing time?
3. Should the salon increase the capacity (i.e., the number of concurrent mixes of hair coloring possible) of the color bar?

The experimentation with the model and these scenarios provided the following unequivocal answers, obtained by comparing the results of the various scenarios via hypothesis tests and/or one- or two-way analysis of variance [ANOVA]:

1. No, the current waiting area capacity of six was completely adequate.
2. No, asking a third stylist to be available up to and just beyond closing time would be of no incremental benefit.
3. Yes, increasing the capacity of the color bar from three to six concurrent hair-coloring preparations would provide significant performance improvements listed below.

These answers were of high value as follows:

1. *Not* increasing the capacity of the waiting area avoided disruption and expense, and would leave space available so a "coffee and tea" area could be moved there – such an area being an amenity competitors had recently begun offering, and hence clients were coming to expect.
2. Not requiring additional stylists to be available late in the business day would avoid lowering morale among the stylists.
3. Moving the "coffee and tea" area to be adjacent to the waiting area will create space to expand the color bar. The doubling (from three to six) of color bar simultaneous capacity will decrease time a client waits in the styling chair by 19% and will decrease time a stylist stands idle waiting to work at the color bar by 27%. From the psychological viewpoint of a client, time spent waiting in the styling chair is "duller" than time spent in the waiting area: During the latter waiting time, a client can conveniently read a magazine, sip coffee or tea, or chat casually with other clients.

6. CONCLUSIONS AND FUTURE WORK

The salon manager, having become acquainted with simulation as a consequence of this study, is highly pleased with the usefulness of the results, especially since (1) the duration of the study was less than three months and (2) the study never disrupted salon operations in the slightest. She plans a prompt increase in the color bar capacity.

Plans for further work include the following:

1. "Cloning" either of these models to create a "Monday through Friday" model.
2. Adding downtimes to the simulation model to drive improvements in contingency planning.
3. Allowing modeling of more general possibilities of clients desiring more than one service.
4. Investigating whether time required at the reception area upon arrival is indeed independent (as currently assumed) of the type of service to be provided. (Interestingly, in view of the current model structure, which makes extensive use of internal data tables, revoking this assumption will require only an updated table entry, but no change to underlying model logic.) Likewise, reception area service time at departure (e.g., paying the bill and scheduling a future appointment) may differ from service time upon arrival.
5. Adding the ability to model different walking speeds – currently, all movement is 1.4 meters per second. It is plausible that stylists walk faster when not escorting a client, and that clients themselves have different walking speeds.
6. Investigating the degree to which length of waiting queues affect service times – the salon manager considers it highly likely that knowing of a long waiting line will provoke either a stylist or a spa worker to accelerate service slightly, if only by virtue of less "chit-chat" with the client.

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AUTHOR BIOGRAPHIES

Baliada Ramesh Ganapathi is a graduate student in Business Analytics enrolled with the College of Business at the University of Michigan-Dearborn. Prior to this, he studied mechanical engineering as his first graduate degree program at MVIT University, India. He has extensive experience in data analytics and data visualization with a keen eye for improving processes for companies large and small. He was a Research Assistant with the iLabs, a center for innovative research at the University of Michigan- Dearborn, where he used data analysis to advise one of Michigan's largest non-profit organizations, ACCESS. He has also had the opportunity of working with some of Michigan's top companies, including J.D. Power and DTE Energy. At DTE Energy, he was instrumental in the automation process of weekly reporting and helped in improving the efficiency of the distribution operations system. He is a student member of the Indian Graduate Student Association (IGSA) and has worked with non-profit organizations like Habitat for Humanity and Gleaners Food Bank. He was also the recipient of the Non-Resident Graduate Tuition Differential Scholarship (NRTD) for Fall 2017 and Winter 2018. His email address is gramesh@umich.edu.

Brittany Harju is a graduate student in business analytics enrolled with the College of Business at the University of Michigan-Dearborn. Her bachelor's degree is in operations management from the Kelley School of Business at Indiana University. She has experience in data governance and quality as a Master Data Specialist at Carhartt, Incorporated. She was also responsible for data accuracy and data integrity at Trinity Health as a Business Applications Specialist. Her email address is bharju@umich.edu.

Daniel Scipione is a graduate student in the M.S. Business Analytics program enrolled with the College of Business at the University of Michigan-Dearborn. Prior to this, Daniel earned a B.S. in biology at the University of Michigan-Ann Arbor. Daniel has always had an interest in statistics, science, and mathematics. He decided that the Business Analytics program matched his analytical background. During his time at the University of Michigan - Dearborn business school, he completed an internship during the summer of 2017 as a data analyst with Fiat Chrysler Automobiles. Daniel will be graduated in May of 2018. He just recently secured a full-time job offer with Urban Science in Detroit, MI, and will begin his job May 1, 2018. His e-mail address is dscip@umich.edu.

Kristina Vujic is a graduate student in the Business Analytics program enrolled with the College of Business at the University of Michigan-Dearborn. Her first graduate degree is in Economics from Wayne State University where she also completed her undergraduate degrees in Mathematics and Economics. She currently works as an engineering business lead in the Budget & Forecasting group for Global Propulsion Systems at General Motors Corporation. Prior to this, she was a trade preference analyst with STTAS qualifying goods for free trade under various free trade agreements. Her email address is kvujic@umich.edu.

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®, or Arena®. 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. A paper he co-authored with three of his simulation students won "best paper in track" award at the Fifth International Conference on Industrial Engineering and Operations Management, held in Dubai, United Arab Emirates, in March 2015. His email addresses are ewilliams@pmcorp.com and williame@umich.edu.

APPENDIX A

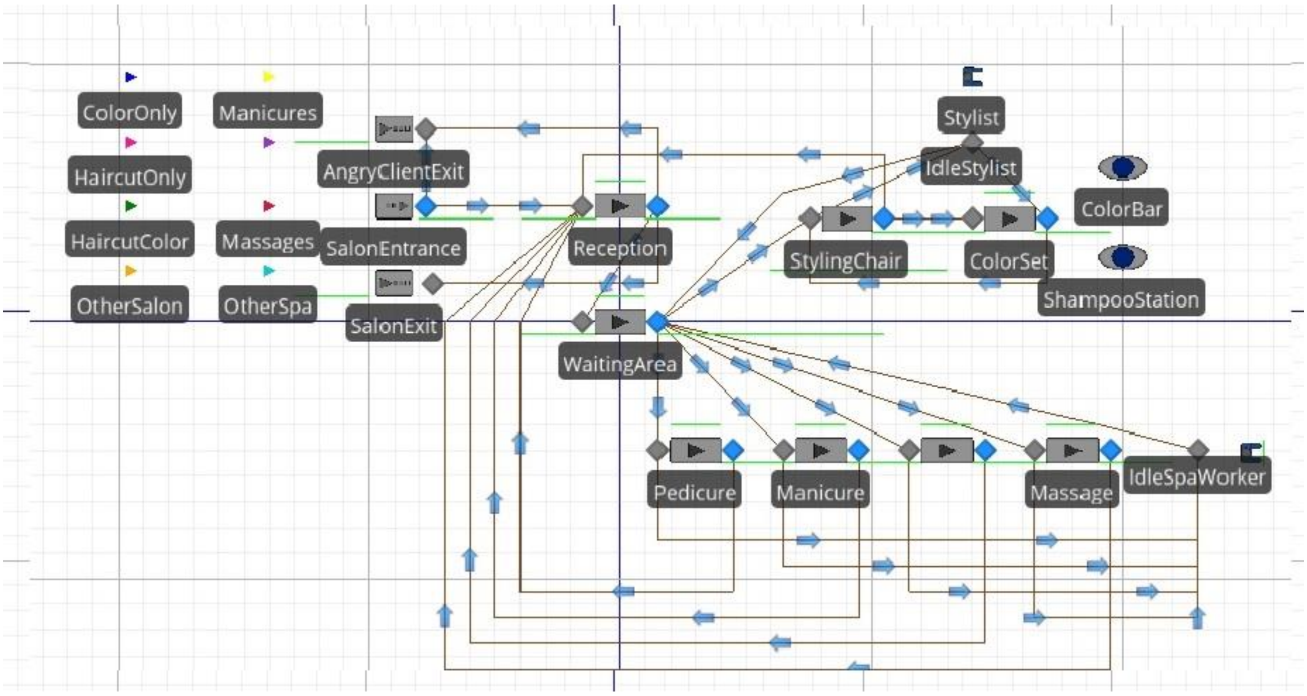
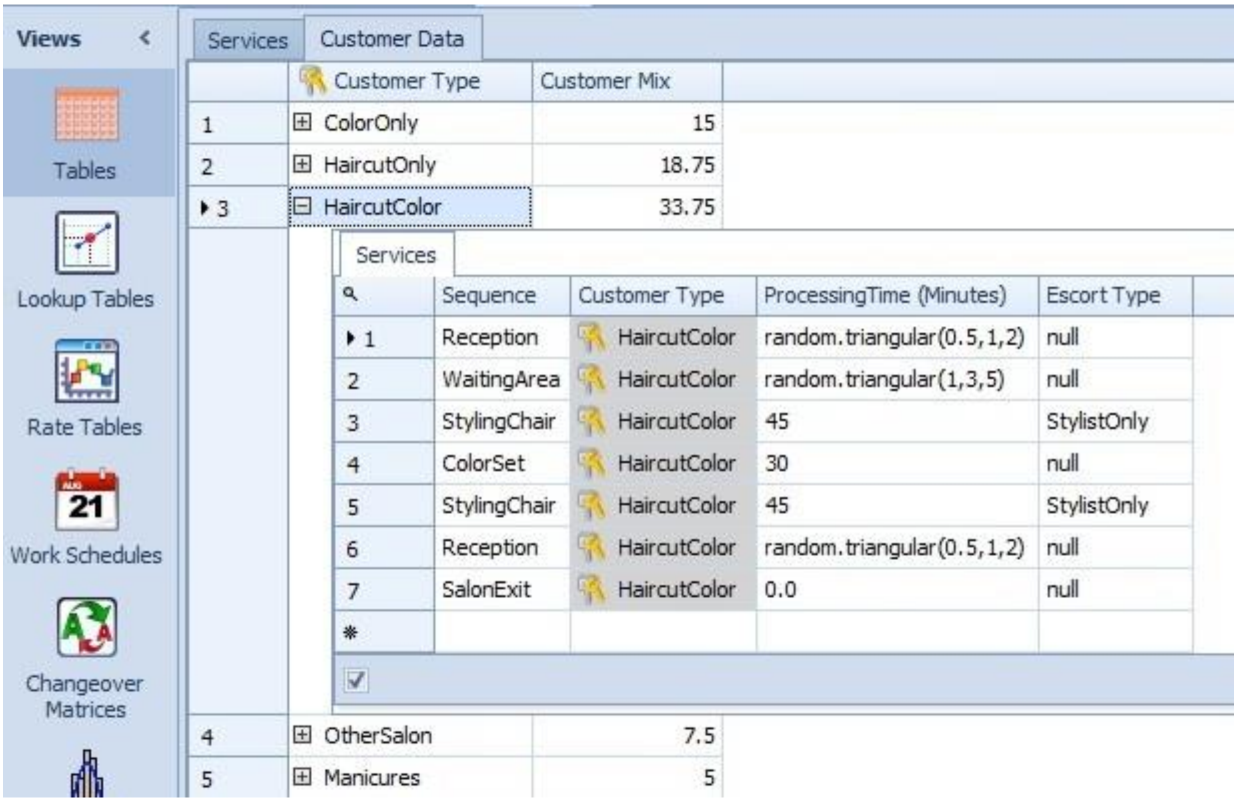


Figure 1: Screen of the Simio® Model Layout

APPENDIX B



	Customer Type	Customer Mix
1	ColorOnly	15
2	HaircutOnly	18.75
3	HaircutColor	33.75

Services

	Sequence	Customer Type	ProcessingTime (Minutes)	Escort Type
1	Reception	HaircutColor	random.triangular(0.5,1,2)	null
2	WaitingArea	HaircutColor	random.triangular(1,3,5)	null
3	StylingChair	HaircutColor	45	StylistOnly
4	ColorSet	HaircutColor	30	null
5	StylingChair	HaircutColor	45	StylistOnly
6	Reception	HaircutColor	random.triangular(0.5,1,2)	null
7	SalonExit	HaircutColor	0.0	null

	Customer Type	Customer Mix
4	OtherSalon	7.5
5	Manicures	5

Figure 2: Simio® “Relational Database” Internal Data Representation