Simulation Improves Service and Operations at a Franchise Resale Store

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Abstract

In the early years of the lengthening history of usage of discrete-event system simulation, its primary domain of application was manufacturing and assembly operations; indeed, the automotive industry was one of its early adopters. In the last few years, the range of application of this valuable industrial-engineering analytics tool has greatly expanded to include delivery of health care services (e.g., hospitals, clinics, pharmacies), improvement of supply chains via application to warehousing and transport operations, government services such as airports and mass transit networks, and the consumer sector (hotels, retail stores, and delivery of services such as grooming and hair care). The project described in this paper is an application of discrete-event process simulation to a resale retail store (one of a franchise) which buys and resells gently used children's clothing, toys, books, equipment, and furniture. The project successfully addressed challenges faced by the store management; these challenges comprise long queues (especially for resale), misallocation of resources, and consequent dissatisfaction of store employees, customers seeking to buy from the store or sell items no longer needed to the store.

Keywords
Discrete-event process simulation, Retail sales, Service industry, Resource utilization, Queueing system performance metrics

1. Introduction
Historically, the first extensive uses of discrete-event process simulation were in the manufacturing sector of the economy, and this usage continues to expand and deepen (Wenzel et al. 2019). In intervening years to the present, applications of discrete-event process simulation have expanded extensively into health care (Bruballa et al. 2015), transportation systems (Vögl et al. 2018), military applications (Jnitova, Elsawah, and Ryan 2017), public utilities (Szpak, Tapamo, and Roy-Aikens 2008), and the retail/service sector. Examples of simulation studies in the retail service sector are (Vallette et al. 2009), which studied process improvement in the receiving area; (Siebers et al. 2008), which examined various customer experiences via agent-based simulation; and (Ramesh et al. 2018), which used simulation analysis to reallocate service personnel at a hair-styling salon.
The remainder of this paper is organized as follows: The next section presents an overview of the operation of the store from the viewpoints of both buyers and consigners. Next, we describe the data required by the model and describe the collection of those data. Next, we present the process of building, verifying, and validating the simulation model. Subsequently, we describe the results provided by the model and our analysis of them, leading to recommendations provided to the franchisee management. and owners. We conclude with a summary of the project and indications of likely future work.

2. Overview of Store Services and Operations
Once Upon a Child is a retail resale store that buys and sells gently used children's clothing, toys, books, equipment and furniture. This store is part of a franchise and is unique in that the suppliers are everyday customers. Therefore, there are two categories of customers: "buy-customers" or Customers, who purchase items from the store and act as suppliers, and "sell-customers" or Suppliers who sell their items to the store. It is relatively uncommon, but entirely plausible, that a particular person plays both roles on one visit to the store; for example, the mother of a child one year old may sell clothes fitting a small baby and buy toys appropriate for this child. The primary stakeholder is the store owner; the secondary stakeholders include the employees and customers/suppliers. The business problems addressed by this project are (1) the store is experiencing long queues in its buying process and (2) may be inappropriately utilizing its resources. "Dual-role" stores (e.g., pawnshops, consignment shops) have these typical "problems in dual," pertaining to both types of customers, as described in (Horwitz and Shilling 1989). The analytical problems confronted by such stores are receiving increased attention; for example, (Bányai, Bányai, and Illés 2017) have proposed a "black-hole" algorithm to optimize their supply chains.

The general process flow is as follows:

1. Customer/supplier comes into the store.
    - 1.1. If a customer, he or she goes directly to the browsing station.
    - 1.2. If a supplier, he or she goes directly to the check-in station to check-in the items.
        - 1.2.1. A supplier may decide to move on to the browsing station after checking-in their items. In this case, he or she will become a customer.
        - 1.2.2. Supplier may stay a supplier and move on to the combiner station to meet with their items prior to check-out.
        - 1.2.3. The Bins will remain at the Supplier station for processing while the Supplier shops or waits.
2. A customer in the browsing station may pick items to purchase
    - 2.1. If picked items to purchase, he or she will move on to the cashier station to check-out.
    - 2.2. If items were picked for purchase by a Supplier, the Supplier-customer will collect the items he or she brought in for processing before moving to the cashier station to check-out.

After checking out at the cashier station, individual suppliers and customers will exit the system.

3. Data Collection and Analysis

The simulation analysts first became familiar with basic franchise operational policy. The store is currently open 10am-8pm Monday through Saturday, and 12pm-6pm on Sunday. At least three employees must be on duty at all times. Employees are on duty half an hour before opening and half an hour after closing to perform opening and closing tasks such as tidying displays and reconciling cash registers. Typically, there are at least two employees assigned as cashiers and item processors, but this role can have a fluctuating number of employees, including zero. There can be a maximum of four employees assigned to the buying area at once, due to space constraints. There are currently two cash registers for processing suppliers. Buys are accepted throughout all open hours. All buys must be completed before the employees leave for the night, and even before closing tasks can be performed. Customers bring in varying amounts of bins full of items, which the store agreed to limit to a maximum of four for this simulation.

The simulation analysts were graciously granted access to data from the store owner. These data included the number of daily buys, number of daily sales, and the daily average total time in the queue for buys. The analysts collected data manually on service times for both the Cashier station and the tasks at the Supplier Processing stations. These data are analogous to those documented by (Dekimpe 2020). Furthermore, the analysts collected data on Customer and Supplier interarrival times for the days Monday through Saturday; the franchise is conspicuously less busy on Sundays, so those data were, by agreement, excluded from the project scope.

Then, using the distribution-fitting software Stat:Fit (Benneyan 1998) and (Leemis 2002), daily arrival distributions for both Suppliers and Customers were generated for use in the simulation model, shown in Table 1.

Table 1. Distributions Generated for Customer and Supplier Interarrival Times by Day of Week.

Day of the Week	Customer Interarrival Time [hours]	Supplier Interarrival Time [hours]
Monday	3+Random.Lognormal(0.912, 0.998)	3+Random.Exponential(3.32)
Tuesday	3+Random.Lognormal(1.23, 0.707)	Random.Lognormal(0.532, 0.296)
Wednesday	Random.Normal(6.97, 2.21)	Random.Lognormal(0.504, 0.329)
Thursday	2+Random.Lognormal(0.887, 0.688)	Random.Lognormal(0.157, 0.322)
Friday	5+Random.Exponential(2.39)	Random.Uniform(1, 2.59)
Saturday	Random.Normal(8.41, 2.93)	Random.Normal(2.1, 0.732)

4. Model Development, Verification, and Validation

Before undertaking the construction of the simulation model, in extensive discussions with the client management, the following assumptions were documented and agreed upon:

1. All workers are cross-trained (i.e., each worker can function as a Cashier or work at the Supplier Station); the benefits of cross-training are amply documented by (Yang and Takakuwa 2017).
2. We assume that workers work according to a two-shift schedule and that workers are reliable 100% of the time, i.e., worker absenteeism was not included in the model.
3. We assume that Suppliers and Customers are not the same and that 36.7% of Suppliers become Customers (based on the average given by the stakeholder).
4. The store will strictly impose a four-bin buying limit.
5. Since we had only six weeks' worth of data to use for our model, coupled with a tight time constraint, we assume that this six-week period is representative of future operations and that sale and buy volumes will be similar to the data observed.
6. We didn't have data on exact arrival times, so our team had to cross-reference the Number of Daily Sales and Number of Daily Buys data with Google in order to create a distribution, and we assume those data to be reasonably representative.
7. The time spent shopping was assumed to be exponentially distributed with a mean of 30 minutes

Members of the project team concurred in the choice of the Simio® software [SIMulation with Intelligent Objects], well-documented in both (Prochaska and Thiesing 2017) and (Smith, et al. 2018) to construct a model of the operations at this retail store. Simio® provides constructs such as the Server (to model, for example, the browsing floor, the check-in station, and the cashier), the Combiner (enabling a Supplier and the bins of goods a Supplier brought for resale to be properly matched at payment and check-out time), the Worker (capable of traveling between different parts of the model to undertake various correctly prioritized duties), and the Entity (e.g., enabling process flow and execution logic to be clearly distinguished between Suppliers and Customers). A partial two-dimensional screen shot of this model is shown in Figure 1 below. This animation provides useful cues; for example, Servers are gray when idle, green when in use, and white when off-shift. The recent work (Robinson 2014) describes the value of such animation, while stressing that animation supplements, but does not replace, verification and validation. From this screen, a three-dimensional animation is only two clicks away.

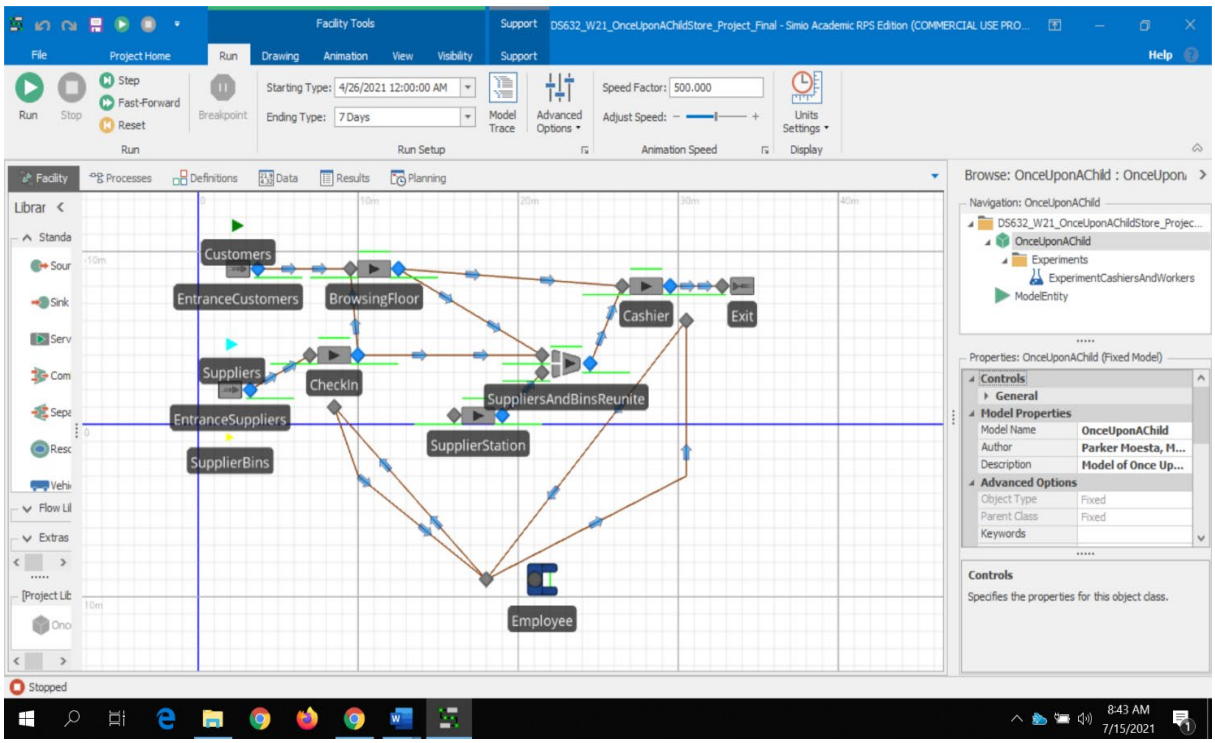

Figure 1: Two-dimensional screen shot of the Simio® Model Layout

Verification and validation of the model used the following traditional and time-tested techniques described in (Sargent 2011):

- Meetings (structured walkthroughs with explicit agendas based on detection or suspicion of problems) among the project team, as vigorously recommended by (Weinberg 1971).
- Sending *one* entity (each of the four entity types described above was chosen in turn) through the model and tracking, on a trace provided by the software on request, every step taken by that entity
- Replacement (temporarily) of all expressions representing stochastic variation within the model by constants, followed by arithmetic checks
- Checking that every routing path placed in the model has non-zero traffic – a route with zero traffic during an entire run was either indicative of a logic error, or was unnecessary clutter and therefore removed (the verification process encountered both of these situations)
- Common-sensical direction of change (e.g., do queue lengths and waiting times increase when the cycle time of a clerk is increased -- do they decrease when the number of clerks on duty is hypothetically increased?)

In terms of verifying our model to ensure it was properly representing the operations of the store, we compared our baseline model outputs to the empirical data we have to check for congruence. We first looked at the weekly average number of total customers and suppliers from our observed data, which was 598, and matched it to the weekly total of 639 outputted from our model. We then proceeded to look at the weekly average numbers of customers and suppliers, which were 467 and 123, respectively. This nicely matched our model's output of 478 customers and closely matched the output of 161 suppliers.

Once we verified that the model was giving output numbers for average service times and arrivals of customers and suppliers within an acceptable range compared to the raw data, we ensured that the model followed the layout as given to us by the stakeholder. To validate the model, we could not obtain high-quality stakeholder input, but ensured that we could properly display differing combinations of resources to fulfill the stakeholder's desire to reduce long queues and excessive time in the system for both customers and suppliers. This is achieved through the experiments portion of our simulation model.

5. Experimentation and Results

Our baseline model consisted of a total of four workers, two assigned to the cashier and two assigned to item processing. This model operated for seven days a week, from 10AM to 8PM Monday-Saturday and 12PM-5PM on Sunday. Under the baseline configuration, there were a total of 542 customers over the week period with an average number of 2.58 customers in the store at any one time (of higher interest than traditionally, because of the relatively small size of the store coupled with precautions attributable to the COVID-19 pandemic). On average, customers spent a total of 58 minutes, with a maximum of 291 and a minimum of 7.6 minutes at the store. Amongst this time, customers spent only an average of 4.7 minutes being processed at the cashier, and with an average number of 0.299 customers in the cashier system at one time, indicating that they usually didn't have to wait in line. In addition to customers, there were also a total of 161 suppliers who also visited the store and 64 of those suppliers also converted to customers. Among all suppliers, there were an average of 1.24 and maximum of 14 in the store at any one time, who spent an average of 77.7 minutes there. In terms of the Supplier Station itself, suppliers spent an average of 17 minutes being processed with a maximum time of 124 minutes. This ultimately translates into an overall employee utilization rate of 24.96%, with a utilization rate of 23% and 17.1% for the Cashier and SupplierStation server, respectively.

There are twelve scenarios in the Simio® experiment, summarized in Table 2l on the next page. Each scenario represents a different combination of Cashiers and Workers. The minimum number of Cashiers is one, and the maximum is three. This is because the store clearly needs at least one cash register to function, but there is insufficient space for more than three cash registers. The minimum number of Workers is three, as specified by the stakeholders. The maximum number of workers is six, to allow for space for the employees to move around while still performing their tasks efficiently. The responses include the average time in system in minutes for suppliers, the average time in system in minutes for customers, the overall worker utilization, and the overall cashier utilization rate.

These scenarios ran for a set of 15 replications, with no warm-up time. The store and model are terminating, so there is no need for a warm-up period (Nakayama 2003). Each replication ran seven days, to demonstrate one cycle of the weekly open hours. The fifteen replications provide the equivalent of a quarter's worth of data to work with, plus an extra two weeks for a buffer. The experiment was conducted with a 95% confidence level. For the response results, the scenarios with three workers had the highest worker and cashier server utilization rates, which would show resource efficiency, but performed the worst for Supplier and Customer time in system,

with more than 50 minutes in the system on average for Customers, and more than 85 minutes in the system on average for Suppliers. The scenario with six workers and three cash registers performed the best for Customer average in system, and second-best for Supplier average time in system, but had disappointingly low Cashier and Worker utilization rates. Average times in the system for both Customers and Suppliers were statistically indistinguishable for many of the scenarios in the experiment, suggesting that it may not be cost-beneficial to add excessive amounts of cash registers and/or workers. To balance out the need for a higher utilization rate (to keep employee wage costs low) with a desire to serve Customers and Suppliers in the least amount of time on average in the system, the analysts recommended the implementation of five Workers and two Cashier servers to the client. This scenario leaves the Customers and Suppliers with an average time in system of 39.3 minutes and 48.1 minutes, respectively, and Cashier and Worker utilization rates of 16.3% and 16.9%, respectively.

Table 2. Four Performance Metrics for Each of the Twelve Scenarios

#Workers	#Cashiers	Workers' Util.	Cashiers' Util	Suppliers TIS (min)	Customers TIS (min)
3	2	29%	25%	93	61
4	2	22%	18%	56	43
5	2	17%	16%	48	39
6	2	14%	16%	48	39
3	1	27%	38%	138	104
4	1	20%	30%	71	57
5	1	16%	30%	57	50
6	1	14%	29%	57	50
3	3	29%	20%	85	51
4	3	22%	13%	55	41
5	3	17%	12%	48	39
6	3	14%	11%	48	39

6. Conclusions and Future Work

Of the twelve scenarios assessed above, the four with two cashiers each were the most appealing to management. Simio® readily provides charts which make comparisons of performance metrics across scenarios quick and convenient; the chart below (Figure 2) shows Customers' average time in system for two Cashiers and each of three, four, five, and six workers.

In a "look-back" of the project, before formulating recommendations, the analysts and the clients (themselves highly statistically literate) examined the initially disconcerting frequency of lognormal distributions fitting interarrival times frequently. The exponential distribution, due to its memoryless property, is very often the leading – sometimes almost the only – candidate. In this context, a detailed reading of the seminal paper by (Limpert, Stahel, and Abbt 2001) provided valuable reassurance.

These and similar results for other performance metrics persuaded the analysts to recommend, and the client management to adopt, the "2 Cashiers, 5 Workers" policy. Fewer workers resulted in noticeably long lines, whereas a sixth Worker, alongside two Cashiers, yielded only an insignificant improvement in system performance. The franchisee management has implemented this suggestion and is pleased with the improved performance metrics, which match simulation predictions within 4%.

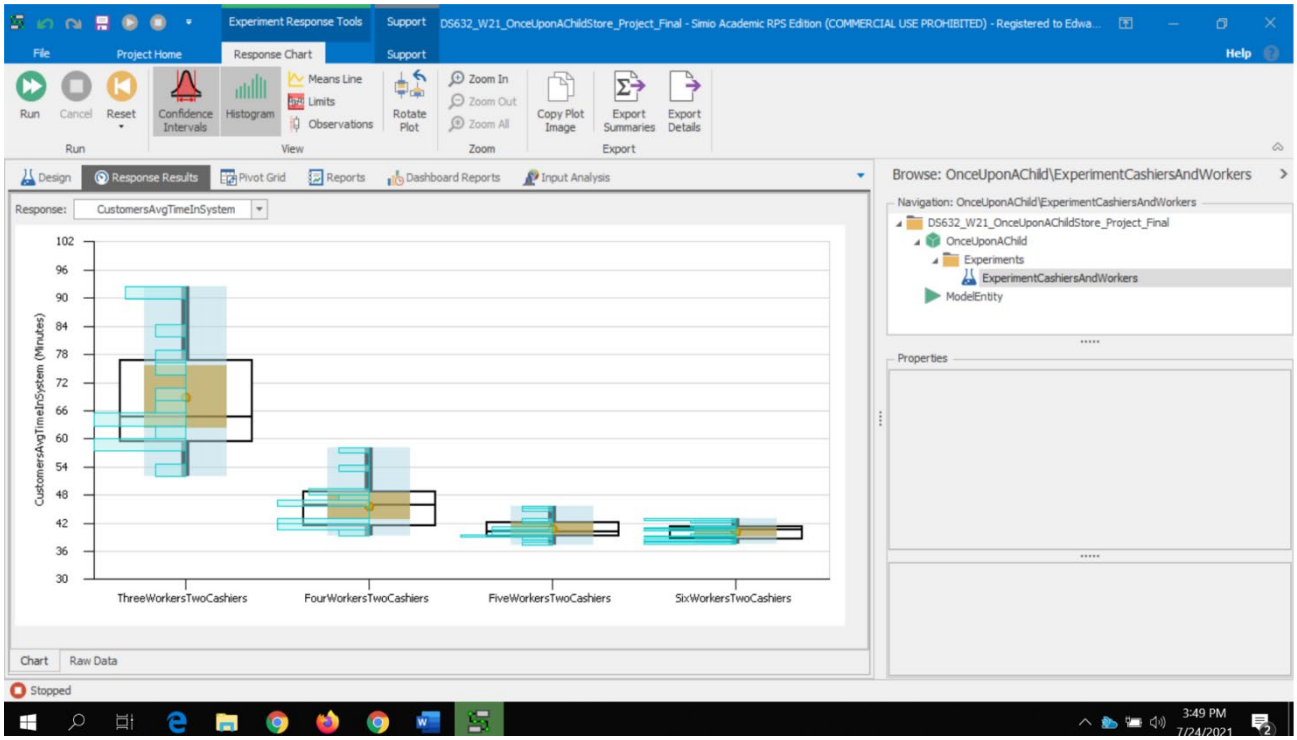

Figure 2. Customers' Average Time in System for Two Cashiers; Three, Four, Five, or Six Workers

While this particular model was built with metrics specific to the Once Upon A Child store in a relatively small town in mid-Michigan, the methodology can be applied to other locations within the broader franchise. To do this, data must be collected on the locations' service times and arrival rates, as well as the distribution for the time Customers spend in the stores. For new locations, service times can be derived from other locations in the region and the arrival rates can be approximated through the new location's population and the current arrival rates experienced by existing regional locations. An extension of the work in this model could be to examine the effect of various realistic Employee Work schedules on the average time spent in the system for both Customers and Suppliers, analogously to recent work by (Yung et al. 2020). In this model, the number of Employees remains constant throughout the day, but could conceptually be any combination of different employees and shifts to achieve that number of Employees. In the actual system, the Employees have constraints on their availability and desired shift schedule, making such flexibility more complex to model. Further work could add varying shifts with differing Employees, who may also have their own service time distributions. These components could be combined to create a more realistic simulation that could prove useful in determining an optimal work schedule that allows for an acceptable amount of waiting time in the system for Customers and Suppliers alike.

Another extension of this work would be to add balking and reneging components typically experienced by businesses of this type. For our simulation, we were unable to obtain data regarding typical balking and reneging behavior within the store. However, this would give a more complete simulation of the business model (as appears in (Pazgal and Radas 2008) and would allow the stakeholder to more accurately target efforts towards eliminating either or both of these profitability-reducing behaviors.

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Edward J. Williams holds a master's degree in mathematics (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. 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]. 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 Proceeding's 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.