*32nd European Modeling & Simulation Symposium*
17th International Multidisciplinary Modeling & Simulation Multiconference

ISSN 2724-0029 ISBN 978-88-85741-44-7 © 2020 The Authors.
DOI: 10.46354/i3m.2020.emss.011

# Society 5.0: A Simulation Study of Self Checkout Operations in a Grocery Store

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## Abstract

Society 5.0 refers to a technology-based human-centered society that integrates cyber-physical systems and uses advanced technology to improve everyday life. Past and present queuing systems, such as grocery stores, will transition to Society 5.0. Queues in grocery stores are part of the shoppers' everyday routine. Changes in grocery stores' queues involve the replacement of servers by self-checkout machines. Nowadays, a continuously increasing number of grocery retailers have been adopting a self-service checkout approach as a waiting time-saving solution. This paper utilizes simulation to examine the queues in a grocery shop and compare the waiting time of shoppers and throughput during checkout in counter service and self-service. Point of Sales (POS) system transaction data from a grocery store were analyzed and used in the simulation model. Alternative scenarios were modeled and simulated to understand how a different number of cashiers and self-service machines will impact the throughput and customers' waiting time. The results provide insights on the flow efficiency and effectiveness of the checkout operations under different configurations.

**Keywords:** Society 5.0, hybrid simulation, discrete event simulation, agent based modeling, queuing system, dynamic scheduling

## 1. Introduction

Queues in organizations that offer certain services, such as grocery stores, are inevitable and part of the shoppers' everyday routine. These queuing systems will transition to Society 5.0. Society 5.0 refers to a technology-based human-centered society that integrates cyber-physical systems and uses advanced technology to improve everyday life and system performance. This concept is based on the 4th Industrial revolution, commonly known as Industry-4.0, which will enable us to improve the quality of life and tackle existing challenges. Several factors determine the level of the grocery store's performance and affect customer satisfaction, such as availability, quality, and cost of various products, as well as waiting times. Waiting time during checkout is a very important indicator of the level of the store performance and has an impact on customer satisfaction. Melachrinoudis & Olafsson (1995) studied the factors that help customers determine which supermarket to choose for shopping. One of the most important rating factors was the waiting time. Customers prefer stores with short queues and tend to complain about long waiting times. According to a survey conducted by the grocery industry's trade magazine, Progressive Grocer, 86.9% of customers rated short lines at the checkout an important factor when choosing a supermarket. Thus, it is evident that the speed of service is important.

Waiting times are generally higher during Fridays and weekends compared to the rest of the weekdays when the number of customers is lower and the cashier-staffed counters remain mostly idle. One change in queuing in Society 5.0 involves the replacement of servers by self-checkout machines. Grocery stores have adopted self-checkouts as a potential solution to provide shorter queues and reduce customers' waiting times.

This paper aims to evaluate the flow efficiency and effectiveness of the checkout operations by modeling a grocery store considering different configurations of cashier-staffed billing counters and self-service machines. The authors developed a simulation model using the AnyLogic simulation software and used published POS data from a grocery store (Antczak & Weron, 2019) to determine which configurations could reduce customer waiting times. The different configurations were simulated and the results were analyzed in terms of waiting time and throughput. The results provide useful insights on how the employment of different numbers of cashiers and self-service machines affect the customer waiting time.

The remainder of the paper is organized as follows: Section 2 provides a literature review on the use of modeling and simulation for improving operations in grocery stores. Section 3 describes the design and implementation of the simulation model. Section 4 presents the simulation of the different configurations of cashier-staffed billing counters and self-service machines and the results for each configuration. Finally, Section 5 discusses the conclusions and future work.

## 2. State of the art

Modeling and simulation (M&S) has been extensively used in manufacturing, warehousing, and supply chains to improve the operations and performance of various facilities. M&S and, particularly, discrete event simulation (DES) and agent based modeling (ABM), have also been increasingly applied in the service sector, such as retail and grocery stores. Recent studies have explored how the combination and/or integration of different modeling and simulation paradigms, like DES and ABM, can help us solve real world complex problems (Mykoniatis & Angelopoulou, 2020). Improving grocery store operations is one of these challenges that have been approached by various studies in the past.

Williams et al. (2002) used discrete-event process simulation to analyze, specify, and improve operational policies in a large retail store. This study dealt with the issue of congestion in the opening and closing of cash-register lanes during a business day. The local Pet Supplies "Plus" store was analyzed in this study. The goal of the study was to prevent long checkout times and high variance of checkout times which reportedly annoy customers. The results recommended that the store management should implement a single waiting queue leading to the next available checkout station.

Previous studies have also shown that grocery stores that have chosen to install self-checkout systems have a comparatively lower average waiting times in the queues than stores with only staffed cash counters. Gruber et al. (2015) investigated the installation of self-checkout machines at a local traditional grocery store as a potential investment to improve customer satisfaction and reduce operational costs. Self-checkout systems have made a huge impact on retail and grocery stores. Local traditional grocery stores face tough competition by large grocery stores, like Walmart and Target in the U.S., that have adopted self-checkout machines aiming to reduce waiting times and operational costs and increase customer satisfaction. Gruber et al. (2015) constructed, verified, and validated a discrete-event simulation model to assess the potential return on investment for the installations. The results indicated that by replacing two of the cashier counters with two self-checkout systems, there would be considerable improvements which would lead to a reduction in average waiting time in queues, reduction in labor costs, and no change in average cashier utilization.

## 3. Simulation Model Description

Modeling and simulation is a way to try different options to improve operations in retail and grocery stores. This work uses the AnyLogic simulation software to model and simulate the checkout process at a local grocery store that employs both cashiers and self-checkout machines. The model can be used to examine different configurations and update best practices related to checkout operations in Society 5.0. The customers arrive at the store, they go shopping and then, they have two choices to check out. They can choose the cashiers which have separated queues for customers, or self-checkouts with a single queue. After checking out, they leave the system.

### 3.1. Study Design

The model was implemented using discrete event simulation and agent based modeling elements. This model focuses only on the checkout operation and does not take into consideration the shopping time of the customers.

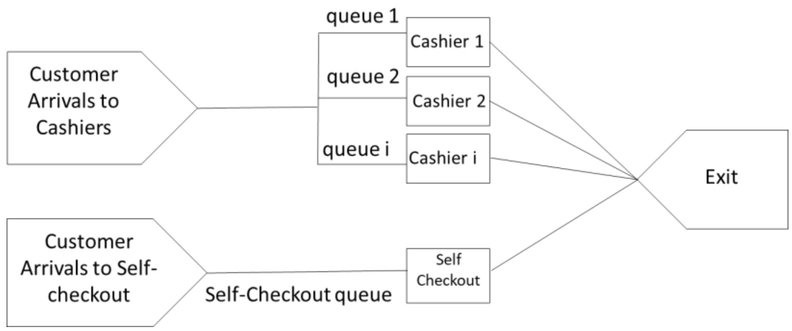


**Figure 1.** Simulation model logic of the grocery store checkout operation.

At the beginning of the simulation, the customers (entities) arrive to the checkout area and choose one of the two checkout options (cashier or self-checkout). Then, the customers enter the corresponding checkout queue, wait for an amount of time (if there is another customer in front of them), process the items - unload, scan, bag - by themselves or with the help of the cashier, pay, and exit the system. Each cashier has an individual queue, while the self-checkout machines share a single queue. Figure 1 illustrates the model's logic.

The data were retrieved from published POS transaction times recorded for each customer at the cashier counters and the self-checkout machines in that store (Antczak & Weron, 2019). These data allowed us to obtain the number of transactions for each checkout option and the recorded transaction times, for any given timeframe. The recorded transaction times in the POS dataset were split into two different portions.

The first portion represented the time required for the scanning of the items and acceptance of the payment, while the second portion represented the time required for giving back change, bagging of the items, and the idle time until the next customer. Data points, where either the first or the second portion was equal to zero, were omitted. Distributions were fitted to the sum of these times, for each of the aforementioned processes.

The POS dataset does not contain interarrival times or arrival rates. To extract an approximate arrival rate, we used a theoretical model (a Non-Homogeneous Poisson Process, NHPP) with transactional data. We approximated the arrival rate of an NHPP at a certain hour by the average number of transactions within this hour. Tables 2 and 3 present the hourly arrival rates during peak hours (11:00 - 14:00) on Fridays for cashiers and self-checkout, respectively. The arrival rate distributions during these three hours are changing, so we have to set up two arrival rate schedules: one for the cashiers and one for the self-checkout.

**Table 1.** Mean Arrival Rate for each interval Cashiers at peak times

| Interval | Average | Hours | Rate |
|---|---|---|---|
| Friday, 11:00-12:00 | 313 | 1 | 313 |
| Friday, 12:00-13:00 | 281 | 1 | 281 |
| Friday, 13:00-14:00 | 286.75 | 1 | 286.75 |

**Table 2.** Mean Arrival Rate for each interval Self-checkout at peak times

| Interval | Average | Hours | Rate |
|---|---|---|---|
| Friday, 11:00-12:00 | 61.75 | 1 | 61.75 |
| Friday, 12:00-13:00 | 64 | 1 | 64 |
| Friday, 13:00-14:00 | 60.5 | 1 | 60.5 |

### 3.2. Discrete Event Simulation Model Setup

Before simulating the model, the model parameters need to be setup. Figure 1 shows the DES process flow logic of the grocery checkout operations. Customers arrive at the checkout and proceed to either one of the cashier counters or a self-checkout machine. The model includes three self-checkout machines with a service time distribution of 31 + gamma (85.4, 1.63) seconds. The number of cashiers changes dynamically per hour with a service time distribution of 10 + gamma (34.8, 2.21) seconds. Each cashier has its queue. The number of cashiers is dynamically changing during each hour of the day, according to a cashier schedule.

The service times include the scanning of items, payment, and bagging, including idle time. The idle time is the time between two transactions and is not part of the service activity. However, during peak hours only, the impact of the idle time on the service time can be eliminated, allowing us to obtain information about the service time itself. Thus, the simulation period was set up to Friday, 11:00 - 14:00. We only used the POS data for Fridays during peak hours (11:00 - 14:00) in 2019 for the data analysis.

As a rule of thumb, Law and McComas (1990) recommended running at least 3 to 5 replications. However, this cannot guarantee stochasticity for any given model. Thus, the number of replications is calculated using the confidence interval method (with specified precision). The model was set-up to run for 30 replications for different configurations.

### 3.3. Model Limitations and Assumptions

Assumptions are essential when creating a simulation model. It is not feasible to include all the possible events that will occur in reality. Therefore, during this system analysis, the following assumptions were taken into consideration:

- The store operates on Friday from 11 am to 2 pm.
- The customers are assumed to have entered the store and shopped for a certain amount of time before moving to the checkout.
- There is no balking or reneging. All customers that enter the checkout process will complete the process. All customers will wait in the queue until they are served.

## 4. Simulation results and discussion

Once the model's input parameters are set up, we simulated the model to observe the changes in the checkout process metrics and observed the checkout animation. The checkout process metrics include: the overall throughout, the number of customers served by the self-checkout machines, the number of customers served by cashiers, the average waiting time at the self-checkout, and the average waiting time at the cashiers for each of the following configurations:

- Scenario 1: Base model. Simulation with 3 self-checkout machines and dynamically changing number of cashiers. Table 3 summarizes the number of cashiers per hour.
- Scenario 2: Simulation with only self-checkout machines with fixed schedule and a single queue. The number of self-checkout machines was set to 12 from 11:00 to 14:00. Table 4 summarizes the new arrival rate for each interval.
- Scenario 3: Simulation with only cashiers with dynamic schedule. The three self-checkout machines were replaced by cashiers. Table 3 summarizes the number of cashiers per hour, while Table 4 includes the new arrival rate for each interval.
- Scenario 4: Simulation with only self-checkout machines with dynamic schedule and individual queues. The cashiers were replaced by self-checkout machines. Table 3 summarizes the number of self-checkout machines per hour, while Table 4 includes the new arrival rate for each interval.

**Table 3.** Number of cashiers per hour each scenario

| Interval | Scenario 1 | | Scenario 2 | Scenario 3 | Scenario 4 |
|---|---|---|---|---|---|
| | Cashier | Self-checkout | Self-checkout | Cashier | Self-checkout |
| 11:00-12:00 | 8 | 3 | 12 | 11 | 11 |
| 12:00-13:00 | 9 | 3 | 12 | 12 | 12 |
| 13:00-14:00 | 8 | 3 | 12 | 11 | 11 |

**Table 4.** Mean Arrival Rate for each interval for Scenarios 2 and 3

| Interval | Average | Hours | Rate |
|---|---|---|---|
| Friday, 11:00-12:00 | 374.75 | 1 | 374.75 |
| Friday, 12:00-13:00 | 345 | 1 | 345 |
| Friday, 13:00-14:00 | 347.25 | 1 | 347.25 |

The Base Model (Scenario 1) that represents the current operation of the system was simulated, verified and validated through comparison with the real world system. Various techniques were used for verification and validation of the base model. First, the model was tested for one customer in order to verify the total time in the system. The model was also verified by observing the animation of the simulation output. Moreover, the simulation mean for the throughput was computed and compared with the throughput obtained from the real dataset. Based on the POS transaction data, the total number of transactions that occurred on Fridays ranged from 809 to 957. The simulated total number of transactions ranges from 884 to 935 (± 4.209). Since, the simulated data are within the real-world data range, the base model was considered valid.

Validating the Base Model allows the development of the alternative scenarios 2, 3, and 4, and gives sufficient evidence to show that implementing them in the real world may improve the system or not. The simulation results for the scenarios are summarized in Tables 5-8. Waiting times increased in scenario 3 compared to scenario 2. Also, the system throughput is higher in scenario 2 than scenario 3. The reason may be that the number of cashiers is less than the self-checkout machines and is allocated based on a dynamic hourly schedule, while self-checkout machines are fixed to 12. Also, there are differences in the queue designs: cashiers have individual queues to serve the customers but self-checkouts have only one queue for all customers. Therefore, we modeled and simulated Scenario 4, where cashiers are replaced by self-checkout machines with dynamic schedule and individual queues. In this scenario, we assumed the same dynamic schedule that the cashiers had.

The throughput in Scenario 4 reduces by approximately 50% compared to scenarios 2 and 3, while the waiting time increases to approximately one hour.

**Table 5.** Simulation results of scenario1 for 30 replications for Scenario 1

| Metrics | Average | Min | Max | Standard Deviation | Half-width |
|---|---|---|---|---|---|
| Throughput of the grocery store | 913 | 884 | 935 | 11.288 | 4.209 |
| Number of customers served by the self-checkout machines | 737 | 728 | 747 | 4.422 | 1.648 |
| Number of customers served by cashiers | 176 | 146 | 189 | 11.046 | 4.118 |
| Waiting Time at the cashier counter(minutes) | 17.04 | 10.14 | 22.2 | 2.82 | 1.08 |
| Waiting Time at the self-checkout(minutes) | 5.04 | 1.26 | 16.8 | 3.84 | 1.44 |

**Table 6.** Simulation results of scenario1 for 30 replications for Scenario 2

| Metrics | Average | Min | Max | Standard Deviation | Half-width |
|---|---|---|---|---|---|
| Throughput of the grocery store | 750 | 745 | 756 | 3.194 | 1.191 |
| Number of customers served by the self-checkout machines | 750 | 745 | 756 | 3.194 | 1.191 |
| Number of customers served by cashiers | - | - | - | - | - |
| Waiting Time at the cashier counter(minutes) | - | - | - | - | - |
| Waiting Time at the self-checkout(minutes) | 27.18 | 19.38 | 30.84 | 2.58 | 0.96 |

**Table 7.** Simulation results of scenario1 for 30 replications for Scenario 3

| Metrics | Average | Min | Max | Standard Deviation | Half-width |
|---|---|---|---|---|---|
| Throughput of the grocery store | 740 | 733 | 749 | 3.655 | 1.363 |
| Number of customers served by the self-checkout machines | - | - | - | - | - |
| Number of customers served by cashiers | 740 | 733 | 749 | 3.655 | 1.363 |
| Waiting Time at the cashier counter(minutes) | 29.34 | 25.02 | 34.32 | 2.22 | 0.84 |
| Waiting Time at the self-checkout(minutes) | - | - | - | - | - |

**Table 8.** Simulation results of scenario1 for 30 replications for Scenario 3

| Metrics | Average | Min | Max | Standard Deviation | Half-width |
|---|---|---|---|---|---|
| Throughput of the grocery store | 376 | 372 | 380 | 1.995 | 0.744 |
| Number of customers served by the self-checkout machines | 376 | 372 | 380 | 1.995 | 0.744 |
| Number of customers served by cashiers | - | - | - | - | - |
| Waiting Time at the cashier counter(minutes) | - | - | - | - | - |
| Waiting Time at the self-checkout(minutes) | 59.28 | 55.8 | 62.76 | 1.62 | 0.6 |

This indicates that the cashier schedule would not work for the self-checkout during peak hours and that more self-checkout machines need to be available from 11:00 to 14:00, such as in Scenario 2.

However, none of the three alternative scenarios improved the throughput, which suggests that replacing all cashiers with self-checkout machines may not be the best alternative.

## 5. Conclusions and future work

In this work, the checkout operation of a grocery store was modeled and simulated using discrete event and agent based simulation approaches. Different configurations were evaluated for efficiency in terms of waiting time and throughput. The model provided insights into how different configurations can affect the customer waiting times. The results can be used to determine configurations for transitioning to Society 5.0. It should be noted that a certain proportion of customers needs to be willing to accept this new technology for the changes to work effectively and to maintain the same level of service. Younger customers are generally more likely to accept changes in the queuing system compared to older customers.

This project also lays the groundwork for future work where more options can be explored, such as operational and other costs related to each configuration or different queue designs and checkout policies (i.e. shoppers with less than 10 items use express counter) during different days of the week.

Although improvements such as increasing the number of cashiers or adding more self-checkout machines will reduce waiting times, the cost associated with such decisions should also be taken into consideration. For example, increasing the number of cashiers may require the installation of additional cash counters along with the hiring of cashiers (labor cost). The replacement of some of the cashier staffed counters with self-checkout systems also has an associated cost.

Future efforts will simulate additional scenarios while incorporating the associated costs to determine also the effectiveness of each scenario in terms of operational costs. Dynamically changing schedules will also be further explored. When the arrival rate to the system is changing substantially during the day, a dynamic staff schedule needs to be in place, as well. If we overstaff the system, the labor cost will be high. On the other hand, if we understaff the system, the customers' waiting time will be high. One approach that we will use to find these optimal staff numbers is optimization. The limitation of this approach is that we need to know exactly at what time of the day the arrival rate changes, which is not always simple and possible. A second approach that we will use to overcome this limitation is the application of artificial intelligence to estimate the number of staff without having information about the change points in the arrival rates.

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