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Simulation project: Cinedom

Bachelor Seminar

in the Area Supply Chain Management

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1 Introduction

Cinemas are usual places for entertainment and time spending. People of all ages and interests visit cinemas to watch premiers of new movies, having a qualitative service and enjoyable time. The movie and cinema market appears in every city in every country and faces competition from streaming services. As the number of cinema visitors worldwide is decreasing in the last few years, the importance of relationships and satisfaction with the service becomes a key factor in saving customers.

Currently, cinemas follow a classic method of service for selling tickets and snacks or drinks with queues for every stage. This classic system creates long delays and waiting times, which could be one of the reasons for customer retention or short customer lifetime value. Businesses in other areas have implemented new ideas for optimizing the current situation. In this study, we want to research a new service model for cinemas and investigate any improvements in reducing the overall waiting time & changes in the capacities.

The 4th biggest city in Germany, Cologne, has a broad number of available cinemas. Cologne offers 40 different movie theaters with the Cinedom being the biggest one. We will choose the Cinedom in Cologne for this case study as it is the 5th biggest cinema in Germany and hosts a big amount of guests.

For our main analysis, we will use simulation as it allows us to investigate a complex real-world system, evaluate changes, and test new scenarios before implementing ideas in the real world. Using modern data collecting and analyzing programming languages and applications, the simulation process could be as simple as well as difficult and precise. We will simulate the Cinedom process and create a new service model in the Application AnyLogic, which is one of the leading simulation modeling software for businesses and allows the creation of detailed models.

The simulation process will include descriptions of the conceptual modeling, data collection, and data analysis with Python for the input parameters, a showcase of the classic and proposal model in AnyLogic. In the end, we will analyze the outcomes of both models and suggest a switch or not to the proposed model.

2 Conceptual Modeling

To enhance understanding of our representative System and to promote system details of our model, we have built our conceptual model.

The overall goals of the simulation study are the followings:

- Evaluate the performance of the system using a simulation model
- Investigate the proportion of customers purchasing snacks in the cinema and the waiting process at the snack bar
- Determine potential changes to the process to reduce customer's waiting time at the snack bar and the total time in the system

Performance measures that will be used during the evaluation:

- Customer's average time in the system (objective: to minimize)
- Customer's average waiting time (objective: to minimize)

As the process flow diagram (see Appendix B) shows, entities, in this case, refers to customers, who enter the cinema, they are generally faced with two decisions, whether they need to purchase movie tickets and whether they want to purchase snacks. The processing sequence is fixed, which means that when an entity needs to implement both actions, purchasing movie tickets has a higher priority. Both actions increase the time entities stay in the system, and after completing them, entities leave the system.

Functionality and interaction of the subsystems:

- Ticketing counters: FIFO queue, one service time distribution only
- Ticketing machines: FIFO queue, one service time distribution only
- Snack bar counters: broken down into four stages (queuing→ordering →preparing →payment), FIFO queue, one service time distribution for each stage

Simplifying assumptions:

- 1 agent type only (every arrived group of customers is considered as one entity in the system)
- 6 types of customers formed through three decisions (purchasing tickets online or in the cinema; purchasing tickets at the ticketing counters or on ticketing machines; whether to purchase snacks)

- Same length of paying time for all paying methods at the snack bar
- Once customers enter the queue of purchasing snacks, they don't renege
- Cinema staff and machines work efficiently

Limitations of the model:

- Fixed processing sequence (the purchase of movie tickets has higher priority than the purchase of snacks)
- Fixed processing sequence at the snack bar (queuing →ordering →preparing →payment)
- 3 Servers with fixed resources (3 Ticketing counters; 5 Ticketing machines; 6 snack counters)

3 Input Analysis

The data for this study was gathered by us in collaboration with the managers and employees at the Cinedom. For the input analysis, we observed the customer's waiting time in queues for buying tickets and snacks, and the duration of the buying, ordering, preparing and paying processes at the ticket and snack counters. Other important parameters are the customer's total time in the system and the number of people in a group. Probabilities of customers with tickets bought online, at the cash desk, or ticket machine and probabilities of customers with or without snacks were also calculated to compute joint probabilities (for variables explanation see Appendix C).

The collection process itself involved interviews with the staff and own timer records with stopwatches at every stage inside our case study system. The analyzed period is 3 weekends during rush hours between 19:00 and 21:00.

3.1 Dataset Input distributions and probabilities

The sample sizes and the different statistical data like means, standard deviations, minimum and maximum values & the percentiles for the variables can be observed in the following Python output (see Figure 1) from the *Input Distributions.csv-File*:

	interarrival People	interarrival time	ticket machine	ticket cashier	Snack #People	snack queue	snack ordering	snack preparing	snack paying	Total time Snackbar
count	66.000000	66.000000	29.000000	27.000000	69.000000	69.000000	69.000000	69.000000	69.000000	69.000000
mean	2.833333	9.212121	67.965517	78.481481	2.115942	235.238261	29.614348	41.674058	26.834203	333.360870
std	1.514883	6.710532	13.184089	28.823562	0.653863	195.198585	20.423795	25.269330	29.855605	202.755166
min	1.000000	0.000000	42.000000	34.000000	1.000000	10.650000	5.070000	1.480000	1.180000	60.880000
25%	2.000000	4.000000	59.000000	58.500000	2.000000	68.720000	13.900000	22.160000	11.540000	161.920000
50%	2.000000	7.500000	67.000000	77.000000	2.000000	217.890000	24.080000	33.050000	18.880000	298.040000
75%	3.000000	13.000000	74.000000	97.500000	2.000000	358.090000	40.500000	62.040000	29.180000	468.490000
max	11.000000	28.000000	103.000000	138.000000	4.000000	869.070000	109.800000	96.610000	192.790000	949.490000

Figure 1: Descriptive statistics of the Input Parameters (Python output)

The data for the probabilities are stored in the *Input probabilties.csv-File*. This dataset describes the number of customers which had an online or a printed ticket from the machine or the cash desk and whether they had or not snacks or drinks. The following dataset can be observed in the following Python output (see Figure 2):

	Online ticket	Printed ticket	Machine	Cashier	With snacks	Without snacks
0	113	36	16	36	137	24

Figure 2: Count of visitors according to tickets and snacks buying place (Python output)

3.2 Probability analysis

The following formula (see Formula 1) describes the joint probabilities (event A and B) of two or more events:

$$P(A \text{ and } B) = P(A) * P(B)\,. \tag{1}$$

A list of probabilities for each variable can be found in the *Appendix D.*

For the distribution fitting we used the *Input Distributions.csv-File*, common Python Libraries for data analysis (*Pandas*, *NumPy*, *SciPy*) and the distribution fitting library *fitter*, which uses 80 distributions from the SciPy library and calculates the most probable distribution and the best parameters. A list of fitted distributions can be found in the *Appendix E.*

We will explain in detail how we computed the distributions with an example of the waiting time in the queue at the Snack bar:

Firstly, 6 common distribution were chosen to compute the fitting: chi-squared, gamma, lognormal, normal, uniform.

Secondly, for each distribution the fitter library computed the sum square of erros, Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC) (see Figure 3).

	sumsquare_error	aic	bic
expon	0.000203	1469.073198	-870.242696
gamma	0.000222	1483.025393	-859.933948
norm	0.000280	1516.151888	-848.195199
uniform	0.000318	1355.018698	-839.481658
lognorm	0.000488	1751.953916	-805.644219

Figure 3: Goodness-of-fit on different distributions (Python output)

Thirdly, the fitted distribution is being checked on a plot of the collected data (see Figure 4).

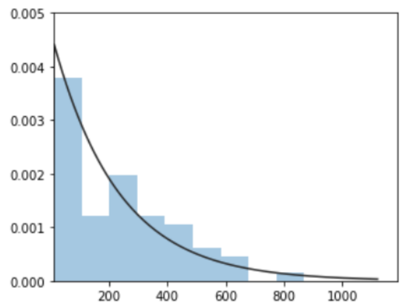

Figure 4: Fitted distribution on dataset (Python output)

In the end, extract the parameters for AnyLogic (see Figure 5).

```
Parameters used for Anylogic:
(10.65, 224.58826086956518)
```

Figure 5: Extracted parameters from the fitted distribution

4 Simulation of Process in AnyLogic (Status quo)

To build our models the application AnyLogic was used. AnyLogic can simulate methodologies in different fields like healthcare, supply chains, business processes, project and asset management, road traffic and pedestrian dynamics with high detail and explicit analysis.

The status quo model (see Figure 6) begins with the exogeneous event of customer's arrival (Source) and afterward faces the 1st selectoutput (TicketOrNo) to decide if customers bought tickets online or need to buy them at the ticket counter. Following the customers who have to buy tickets, they face another 2nd selectoutput (MachineOrCashier) if they will buy tickets at the Machine or Cashdesk. Both processes include a queue and a delay with distribution parameters from the 3rd chapter. All entities move to the 3rd selectoutput (Snackbar) to divide into customers which buy or don't buy snacks or drinks. The snack bar process includes a Seize (QueueSnackbar) and Release (release) object which represents the queue for the snack bar and seizes the customers before the Ordering object and releases them after the Paying object. This represents the capacity of 6 snack bar counters in real life and relates to the ResourcePool object (SnackbarCounters). The released customers leave the system in the Sink object (Sink).

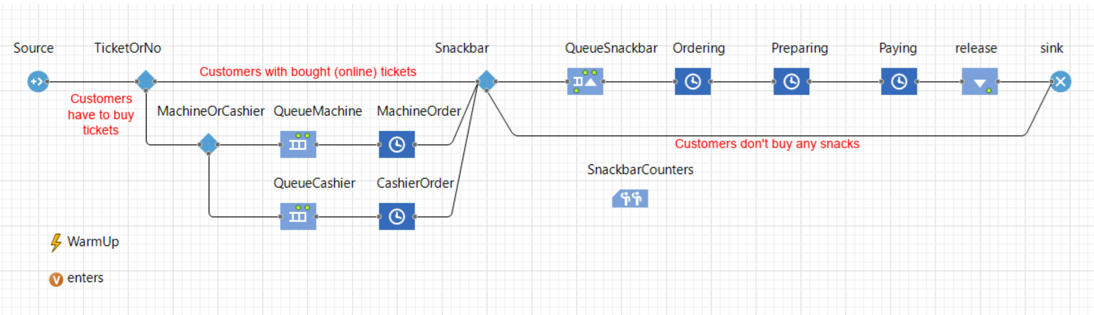

Figure 6: Status quo model in AnyLogic

The simulated model time is 7200 seconds (2 hours) with a 600 seconds (10 minutes) Warm-up (WarmUp) phase, which represents the Cinedom and customer interacting during a usual rush hour at weekends between 19:00 and 21:00. The model is being simulated with 10 replications.

We haven't divided the agents into agent types, as we generalize the customers. Additionally, we ignore the group sizes which go through our model, because there is no significant correlation between the group size and all other variables (see Figure 7).

```
interarrival People   -0.01
interarrival time     -0.04
ticket machine         0.25
ticket cashier         0.00
Snack #People          1.00
snack queue            0.14
snack ordering         0.11
snack preparing        0.22
snack paying           0.33
Total time Snackbar    0.22
```

Figure 7: Correlation between Group sizes (Snack #people) and all variables (Python output)

5 Process Optimization

The results of the model simulation match reality. With the increasing advancement of digitalization of the ticketing system, nearly 76% of the customers choose to purchase movie tickets online. The capacities of the ticketing counters and ticketing machines are fully sufficient for the offline ticket purchasing, we can observe from the model's data output that there is almost no queuing and waiting time at the ticketing counter and ticketing machine. This also explains why the customer's average time in the system is so close to the customer's average waiting time. By observing the behavior of the customers in the Cinedom, we also learned that the queuing situation at the snack bar is the part that really needs to be optimized. The queuing problem in cinemas mainly arises when purchasing snacks. This matches the results of the model as well. Therefore, in this part of model process optimization, we will focus on the optimization of the queuing problem at the snack bar. (See Appendix F)

Therefore, in terms of system optimization, we eliminated the possibility of purchasing tickets at the ticketing counter and merged the two processes of purchasing tickets and snacks into one. The ideas are that:

- The capacity of ticketing machines will remain the same, but each machine will be reprogrammed so that customers can also order snacks from the ticketing machines.
- The snack bar counters will be converted into a pick-up point.

Entities still face two choices when enter the system and when decisions are made, they will come to a joint queue, regardless of their demands. Customers' Orders are sent in real-time to the staff in the snack bar, who begin to prepare the orders immediately. When an order is completed, customers will be called to pick up by numbers. There will be still a very small queue at the pick-up point, but by running the simulation, the system works so efficiently that we can almost ignore the queue.

Another important aspect of our process optimization is the conversion of multiple-line queues into a single-line queue with multiple checkout points. A single line queue promotes fairness and helps avoid line-switching when there's a shorter line. We will apply this single-line queuing method to the joint queue, as it is the only place in the cinema where queuing is still required. source

The overall goals of the simulation study remain the same.

Performance measures of the new model are:

- Customer's average time in the system
- Customer's average waiting time

Functionality and interaction of the subsystems:

- 3 different purposes of the usage of the reprogrammed ordering terminals: all follow FIFO queue, one service time distribution for each
- Snack bar pick-up windows: FIFO queue, one service time distribution only

Additional simplifying assumptions:

- The use of ordering terminals is commonplace for every customer, no ticketing counters are needed
- The delay of purchasing movie tickets or snacks from the ordering terminal is identical with the delay of purchasing movie tickets or snacks from old model setup

New limitations of the model:

- 2 Servers with fixed resources (6 ordering terminals; 6 snack pick-up windows)
- No fixed processing sequence, as the purchase of movie tickets has the same priority as the purchase of snacks

By running the new model we can see that it works efficiently and the process performance has been so much enhanced without increasing any available capacities, and the customer's average waiting time and the total time in the system has been significantly reduced.

6 Output Analysis and Evaluation

After computing both models of the status quo and proposed improvement, collected datasets and measures were extracted and filled in the *Output analysis.csv*- and *Capacity_comparison.csv-files*. The *Output analysis.csv-file* contains the means from 10 simulation replications with random seeds (unique simulation runs) of the variables for the status quo model and the improved model (time in the system, total waiting time, waiting times at the queues at the ordering machines, cash desks and snack bar, pickup-windows).

Different statistical measures like means, standard deviations, minimum and maximum values & the percentiles for the variables can be observed in the following Python output (see Figure 8):

	Replication No.	OldtimeInSystem	OldTotalWaiting	OldQueueMachine	OldQueueCashier	OldQueueSnackbar	NewtimeInSystem	NewTotalWaiting	NewQueueOrder	NewQueuePreparing
count	10.00000	10.000000	10.00000	10.0	10.00000	10.00000	10.000000	10.000000	10.000000	10.000000
mean	5.50000	442.761200	413.95010	0.0	4.10610	409.84400	84.670900	1.963800	1.725200	0.238600
std	3.02765	65.545606	74.74142	0.0	4.10166	75.60475	3.451386	1.528181	1.414302	0.328598
min	1.00000	365.179000	321.59700	0.0	0.00000	320.08300	79.732000	0.545000	0.391000	0.000000
25%	3.25000	401.690250	361.54200	0.0	0.83350	353.18750	81.783500	0.965750	0.681250	0.021000
50%	5.50000	428.415500	410.60550	0.0	2.72150	407.60300	85.246000	1.358000	1.220500	0.107000
75%	7.75000	470.704750	448.25500	0.0	7.66900	447.27275	87.023750	2.699000	2.478750	0.241000
max	10.00000	577.139000	562.35200	0.0	11.08200	561.33400	89.682000	4.830000	4.687000	0.922000

Figure 8: Descriptive statistics of the Output Parameters after 10 replications (Python output)

To compare both models we used the student's t-test to test whether the means of the corresponded samples from the status quo and improved model are significantly different. Our means of the 10 replications which we compare are the total time in the system (status quo: 442.76 seconds; Improved: 84.67 seconds) and the total waiting time (status quo: 413.95 seconds; improved: 1.96 seconds). Our Null hypothesis is that the means of the samples are equal. With a p-value in both cases smaller than 0.05, we can reject the Null hypothesis and conclude that there is significant evidence that the means aren't equal with a 95%-confidence level. Both 95%-confidence intervals don't overlap with each other and support our statements (see Figure 9 and 10).

```
stat=17.252, p=0.000
There is no significant evidance that the means are equal

 95% Confidence Interval Status Quo model
(395.87269773748255, 489.6497022625175)

 95% Confidence Interval improved model
(82.20192736238704, 87.13987263761297)
```

Figure 9: total time in the system: t-test and 95% Confidence Interval

```
stat=17.427, p=0.000
There is no significant evidance that the means are equal

 95% Confidence Interval Status Quo model
(360.4833088092144, 467.41689119078563)

 95% Confidence Interval improved model
(0.8706051920001847, 3.056994807999815)
```

Figure 10: total waiting time in the system: t-test and 95% Confidence Interval

Capacities for the improved model don't need to be increased as the model already show improvements. It would be even possible to decrease the capacities. As example, the reduction of ordering machines to 4 could improve the total time by 1.548 seconds and the waiting time by 1.171 seconds (see Appendix G)

7 Conclusion

To better understand the queuing problem in Cinedom and further to better analyze and evaluate the situation, we have built a conceptual model to describe the physical and social aspects of Cinedom in an abstract way. Based on real-life data we've collected in the Cinedom and with help of mainly Python and other data processing software, we got reliable data which later has been imported to our model in Anylogic.

We have used our conceptual model as the underlying logic, and with the help of simplified assumptions, we've built the simulation model in anylogic. We simulated the model with exactly 2 hours, the same time length we've chosen to collect data during the cinema's rush hours, and with a 10 minutes warm-up phase. From the data output of 10 replications of the model, we can understand that the main queuing problem in cinemas arises in the snack bar, which is also perfectly in line with reality.

Therefore, our optimization for the model focused on solving the queuing problem in the snack bar. With only reprogramming of the ticketing machines so they can also be used as ordering Terminals for both purchasing tickets and snacks, and the queue management, the conversion of multiple-line queues to a single-line queue, a significant reduction of customer waiting time in the queue and the total time in the system can be observed. From the part of the evaluation, we can learn that the customer's total time in the system has dropped by around 81% and the customer's waiting time has dropped by almost 96%. The change from the old model to the new model is not only very cost-effective, which means no need for the cinema to purchase any additional equipment but can also greatly improve the efficiency of the snack area staff. For example, they no longer need to communicate with customers about order details but only need to focus on order preparation.

There are still more ways that can reduce customers' waiting time or queue length in a cinema to give better services and improve customers' cinema experience. For example, a self-serve snack bar. This not only directly eliminates the time to prepare orders for the cinema staff but also greatly reduces the waiting time for customers.

Appendix

Appendix A – Authors for each section

Daniil Sideris (Team member A)	Chenyu Zhang (Team member B)
Introduction	Conceptual Modeling
Input Analysis	Process Optimization
Simulation of Process in Anylogic	Conclusion
Output Analysis / Evaluation	

Table A: Section authors between Team member A and B

Appendix B – Process flow diagram status quo model

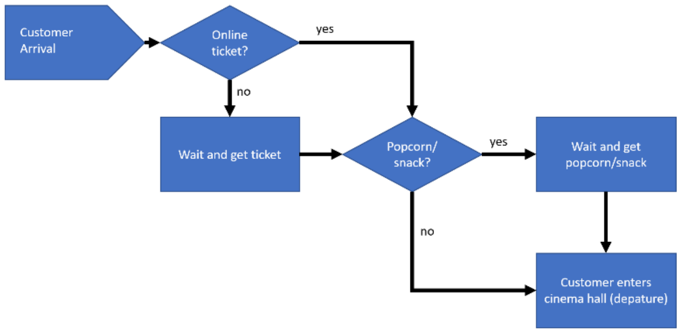

Figure A: Process flow diagram status quo model

Appendix C – Variables and parameters explanation (sorted alphabeticaly, ascending)

Cashier	Number of customers with tickets from the cash desk
Interarrival People	Number of customers arriving
Interarrival time	Time between customer arriving
Machine	Number of customers with tickets from the ordering machine
NewQueueOrder	Waiting time at the ordering machine in the improved system

NewQueuePreparing	Waiting time at the snack bar (pickup window) in the improved sysytem
NewtimeInSystem	Total time in the improved system
NewTotalWaiting	Total waiting time in the improved system
OldQueueCashier	Waiting time at the cash desk in the status quo system
OldQueueMachine	Waiting time at the ordering maching in the status quo system
OldQueueSnackbar	Waiting time at the snack bar in the status quo system
OldtimeInSystem	Total time in the status quo system
OldTotalWaiting	Total waiting time in the status quo system
Online ticket	Number of customers with online tickets
Printed ticket	Number of customers with printed tickets
Replication No.	Number of simulation replications
Snack #People	Group sizes at the snack bar
Snack ordering	Ordering time at the snack bar
Snack paying	Paying time at the snack bar
Snack preparing	Order preparing time at the snack bar
Snack queue	Waiting time at the snack bar
Ticket cashier	Service time at the cash desk
Ticket machine	Service time at the ordering machine
Total time snackbar	Total time spent at the snack bar including the waiting time
With snacks	Number of customers with snacks or drinks
Without snacks	Number of customers without snacks or drinks

Appendix D – Probabilities

We got the following Probabilities of customers with (status quo):

- Tickets bought online: 75.83%
- Tickets bought at the cash desk and ordering machine: 24.16%
- Tickets bought at the ordering machine: 30.77%
- Ticket bought at the cash desk: 69.23%
- Snacks: 85.01%
- Without snacks: 14.9%
- Tickets bought online and with snacks: 64.54%
- Tickets bought online and without snacks: 11.31%
- Tickets bought at the cash desk and with snacks: 14.23%
- Tickets bought at the cash desk and without snacks: 2.49%
- Tickets bought at the ordering machine and with snacks: 6.32%
- Tickets bought at the ordering machine and without snacks: 1.11%

Additional Probabilities (improved model) of customers with:

- Tickets bought online and with snacks: 64.54%
- Tickets bought online and without snacks: 11.31%
- Tickets bought at the ordering machine and with snacks: 20.56%
- Tickets bought at the ordering machine and without snacks: 3.6%

Appendix E – Fitted distributions

Distributions used in AnyLogic:

- Interarrival Time: lognormal(2.2121, 0.5943, 1.48)
- Ticket Machine: lognormal(4.1590, 0.1956, 42.0)
- Ticket Cashier: lognormal(4.6944, 0.2526, 34.0)
- Snack Queue: exponential(10.65, 224.5883)
- Snack Ordering: gamma(1.4013, 17.7216, 5.07)
- Snack Preparing: gamma(2.8497, 15.5137, 1.48)
- Snack Paying: lognorm(3.0277, 0.7901, 1.18)

- Total Time Snackbar: chi2(2.9064, 60.88)

Special distributions for the improved model:

- Ordering only snack: lognorm(3.6285, 0.6914, 13.46)
- Ordering Tickets and snack: exponential(86.2230, 32.47)
- Ordering Ticket: lognormal(4.1590, 0.1956, 42.0)

Appendix F – Process flow diagram improved model

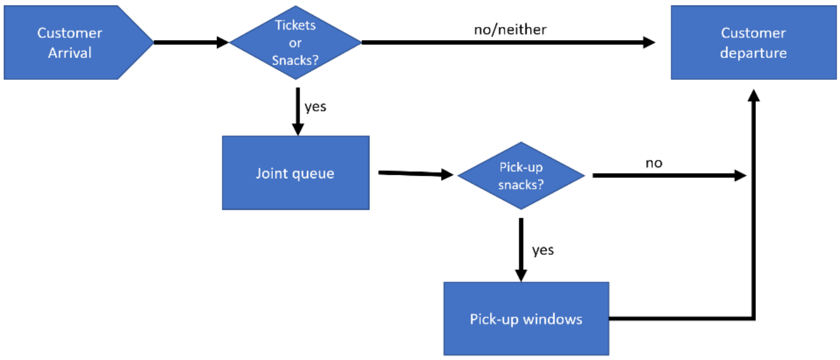

Figure B: Process flow diagram improved model

Appendix G – Capacities comparison

Machine	Preparing	Total Time	OrderQueue	PreparingQueue
4	**4**	179.457	106.023	4.415
4	**5**	161.508	90.672	0.723
4	**6**	161.285	92.269	**0.141**
5	**4**	99.206	10.445	7.025
5	**5**	96.064	11.348	1.227
5	**6**	97.569	14.064	0.232
6	**4**	89.594	1.57	5.305
6	**5**	**86.749**	**1.474**	1.224
6	**6**	**88.297**	**2.645**	**0.325**

Machine = Capacity of the ordering machine. Preparing = Capacity of the preparing window. Total time = Total time in the system (improved). OrderQueue = Waiting time at the ordering machine. PreparingQueue = Waiting time at the pickup window.

Table B: Capacities time comparison