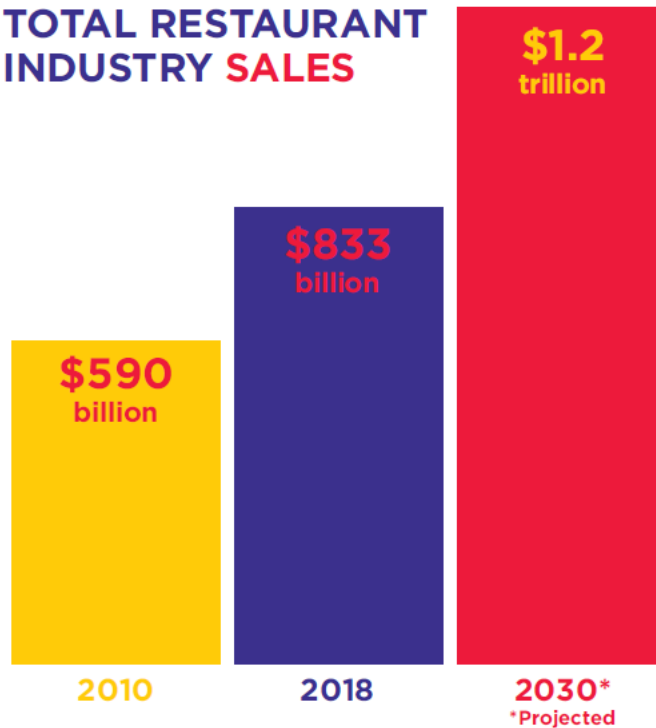


# **Optimization and Simulation Spring 2022 Project 2 - Restaurant Design**

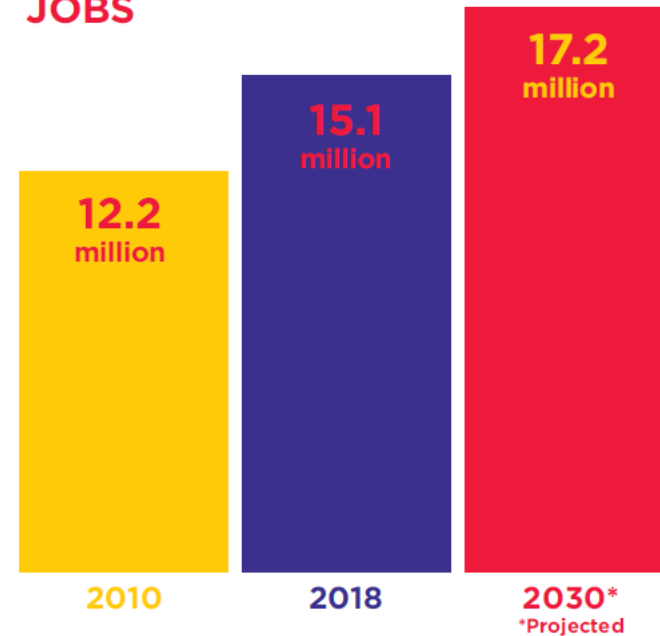
Michael Bombile  
Ismail Nejjar  
Yazan Safadi  
Shuhang Zhang

## RESTAURANT INDUSTRY SNAPSHOT IN 2030

### TOTAL RESTAURANT INDUSTRY SALES



### TOTAL RESTAURANT AND FOODSERVICE JOBS



## Intro

## Simulation

## Optimization

## Summary



2030: THE DISRUPTORS

## INFORMATION TECHNOLOGY WILL PERMEATE RESTAURANTS.

This will enable restaurants to interact in real time with an evolving digital ecosystem of apps, services and personal AI assistants (apps such as Siri (Apple) or Alexa (Amazon) that understand natural-language voice commands, complete tasks for the user, and over time "learn" their owners' preferences). All will deeply integrate into consumers' everyday decisions. It will be increasingly important for restaurants to provide accessible, detailed and accurate data. Restaurants will be able to use new data capabilities to develop dynamic menus with real-time pricing that can respond to supply-and-demand changes. Relevant data about restaurant operations will include details on nutrition, preparation methods, ingredients and supply-chain authentication.

## WHY THIS COULD HAPPEN

- ✓ Near-universal smartphone adoption.
- ✓ AI as personal assistant and gatekeeper between a brand and consumer.
- ✓ The spread of the Internet of Things (IoT), physical objects embedded with electronics, software, sensors and network connectivity that enable the objects to collect, send and receive data.
- ✓ Growth of voice search, which allows users to search the Internet by verbally asking a question via smartphone, smart device or a computer.
- ✓ Growing demand for personalized diets (e.g., allergies, weight, religion, ethics).
- ✓ Consumer choices as an expression of social and political values.



## WHY THIS MATTERS FOR RESTAURANTS

- ✓ A growing information ecosystem will require upgrades and integration of restaurant data collection and IT systems.
- ✓ Brands will market directly on virtual-assistant platforms and may find the platforms' algorithms to be highly responsive to small tweaks in restaurant pricing or other data.
- ✓ All aspects of restaurant operations will be more transparent, such as health inspections, safety training, staff certifications and food sourcing.
- ✓ Effective management of food allergens will grow in importance as consumers expect documentation of food preparation, ingredients and practices.



RESTAURANT INDUSTRY 2030 • NATIONAL RESTAURANT ASSOCIATION

# Restaurant design considerations



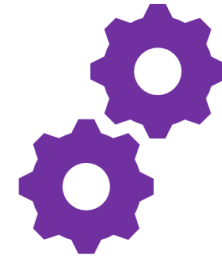
**Maximize Your  
Space**



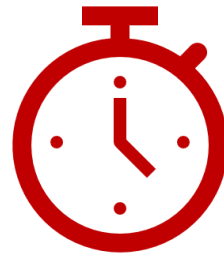
**Enhance An  
Ambiance**



**Improve Guest  
Comfort**



**Optimizes  
Workflows**



**Reduce Wait  
Times**



# ROSS

Restaurant  
Optimizer  
and  
Simulator  
Software

# Decisions



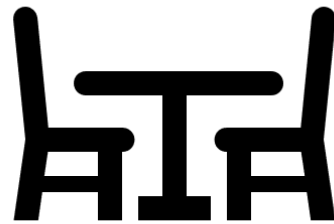
**The table arrangement:**  
**number and type of tables.**



**The seating policy:**  
**the rules that you apply to allocate**  
**customers to tables.**

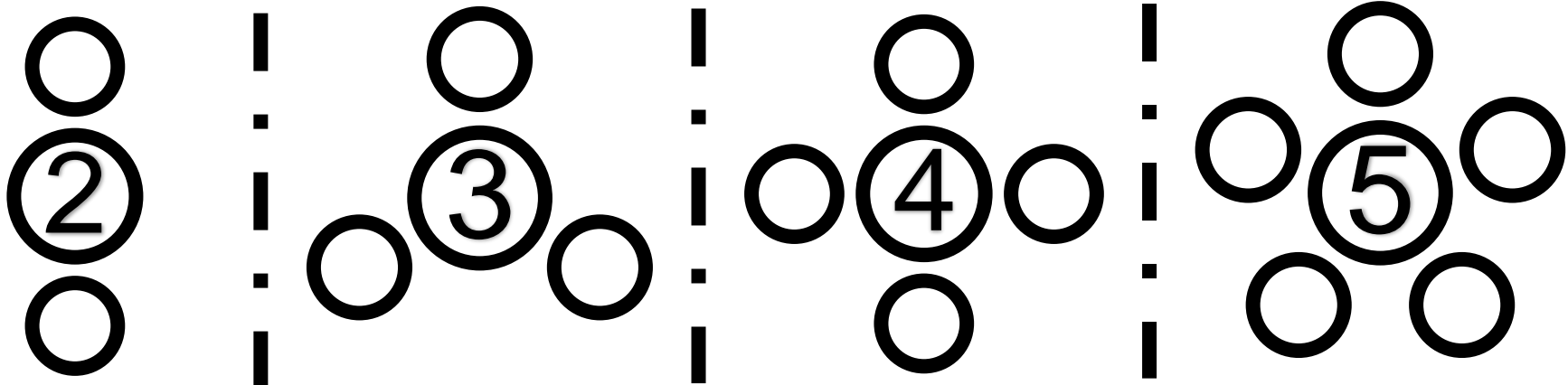
# Setup – Space and Tables

No Split  
No Merge  
Sharing



Up to 400 seats

- Table's sizes:



Intro

Simulation

Optimization

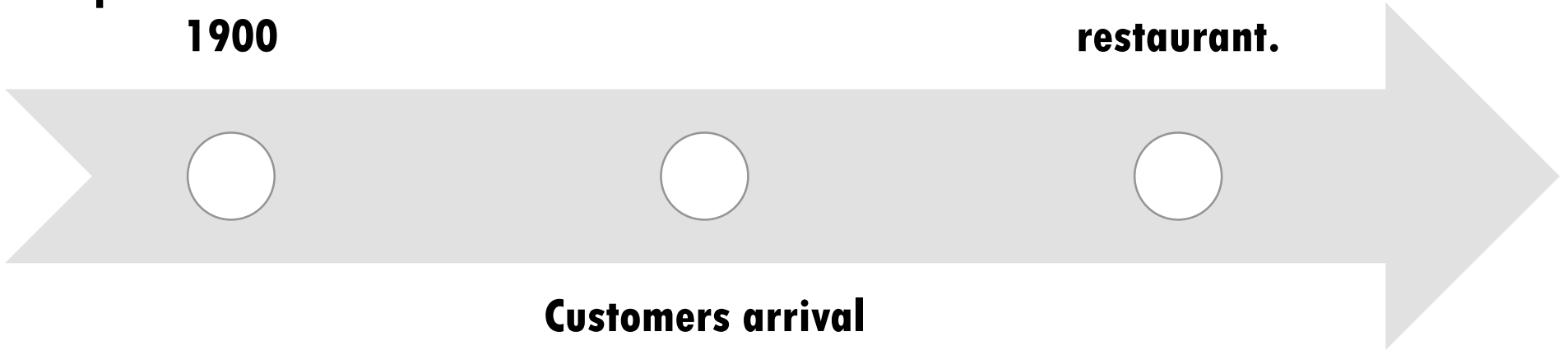
Summary

# Setup - Operation

**Operation start at  
1900**

**Operation ends when  
the last customer  
leaves the  
restaurant.**

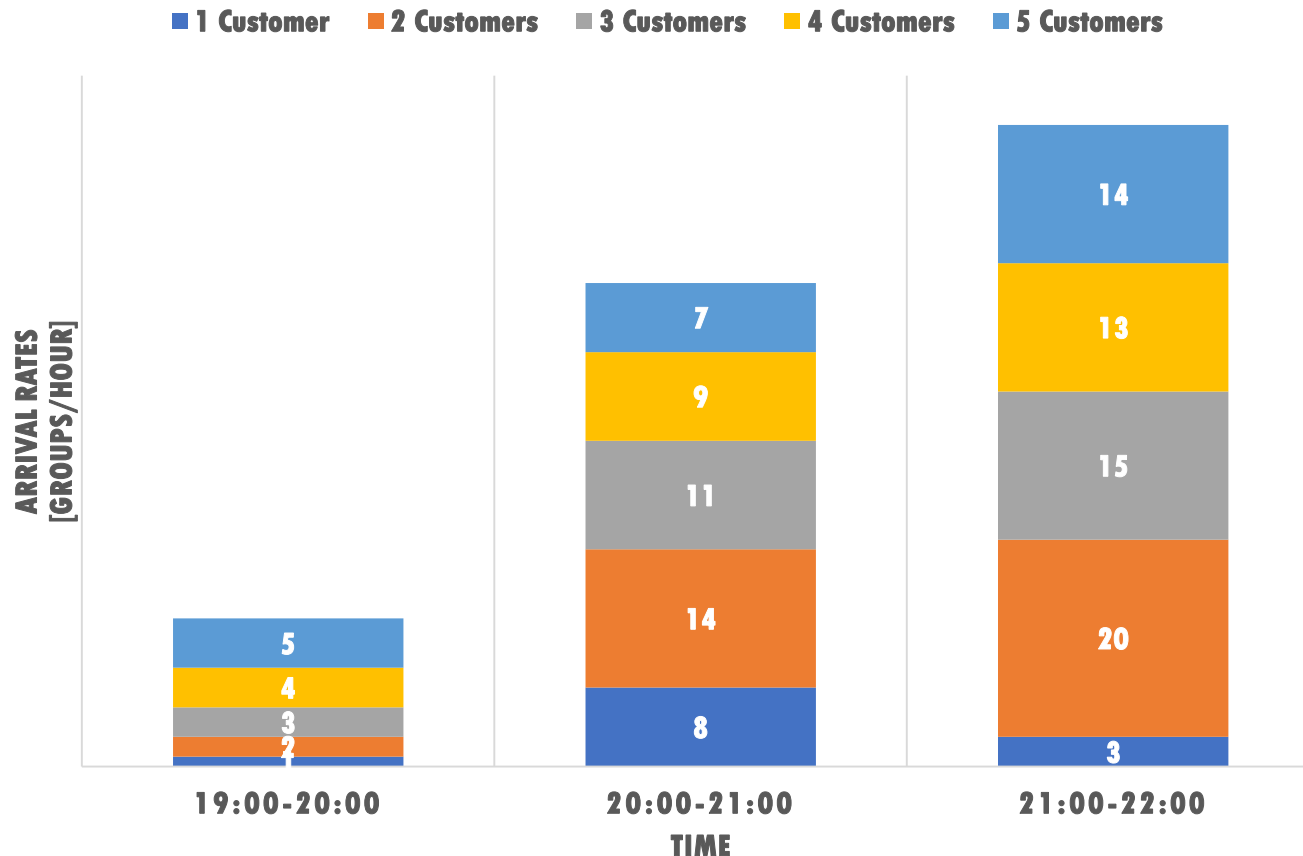
**Customers arrival  
from 19:00-22:00**



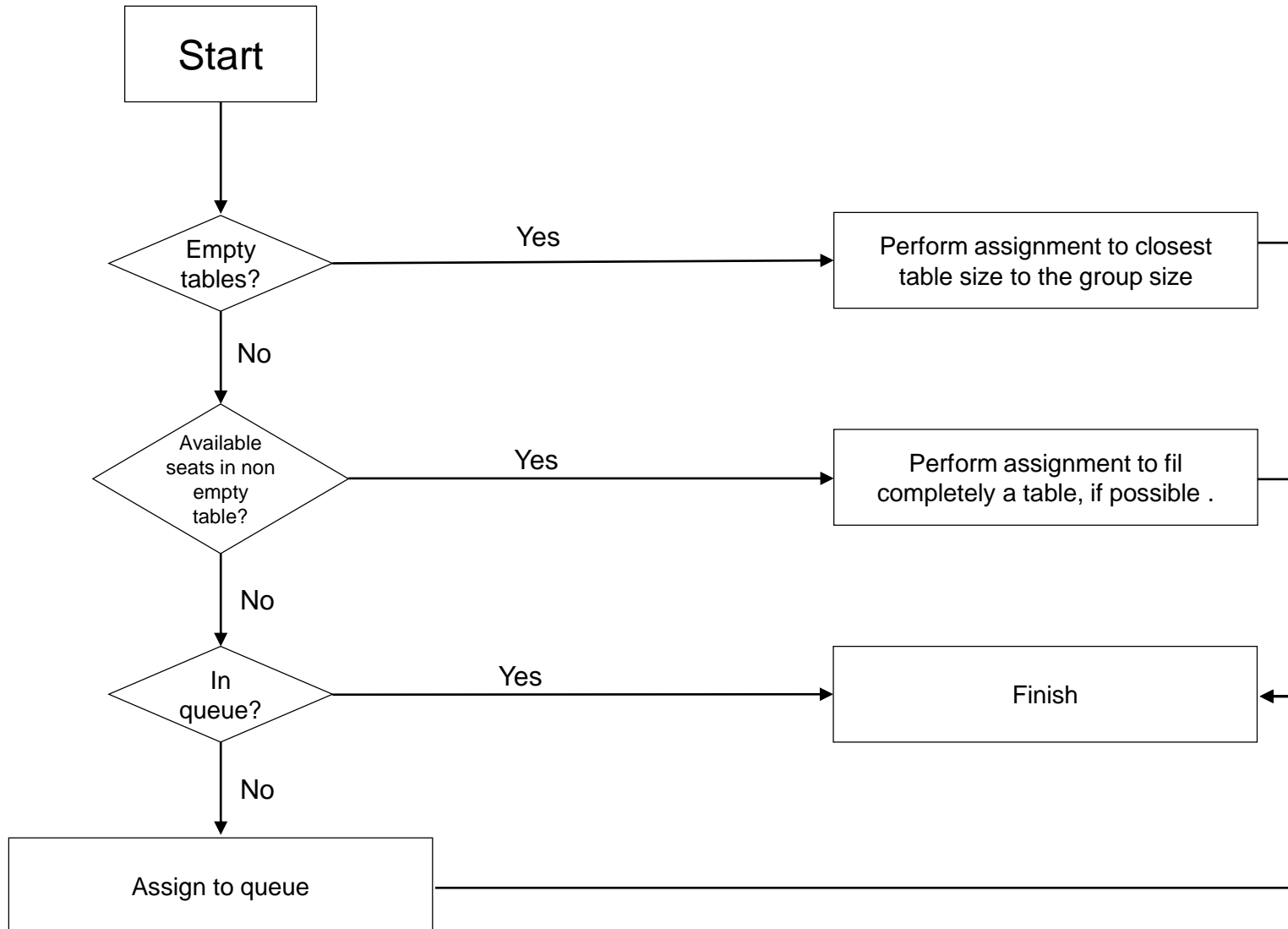


# Setup – Customer Arrivals

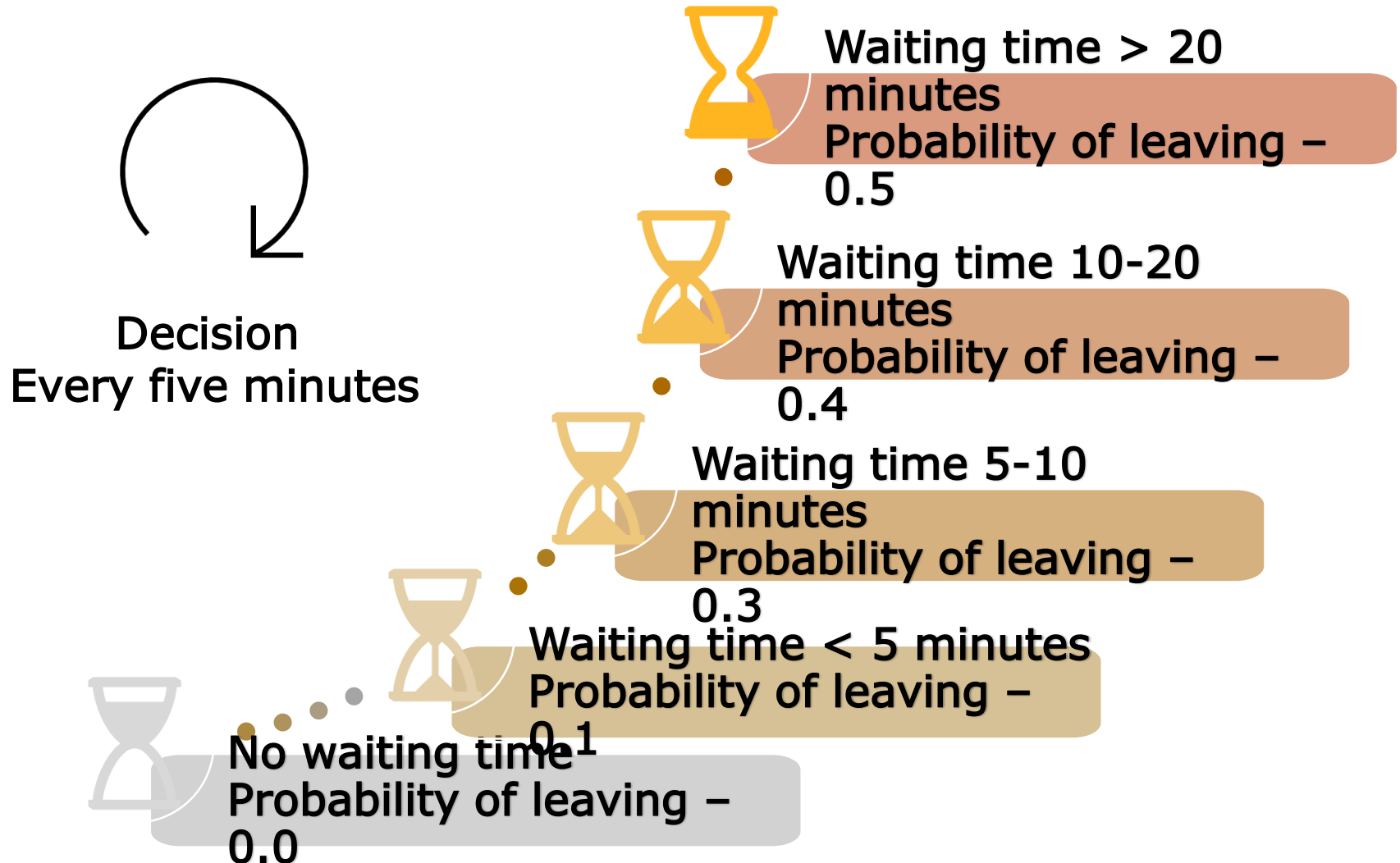
- Customer arrivals are non-homogeneous and change among group sizes.



# Setup – Seating Policy

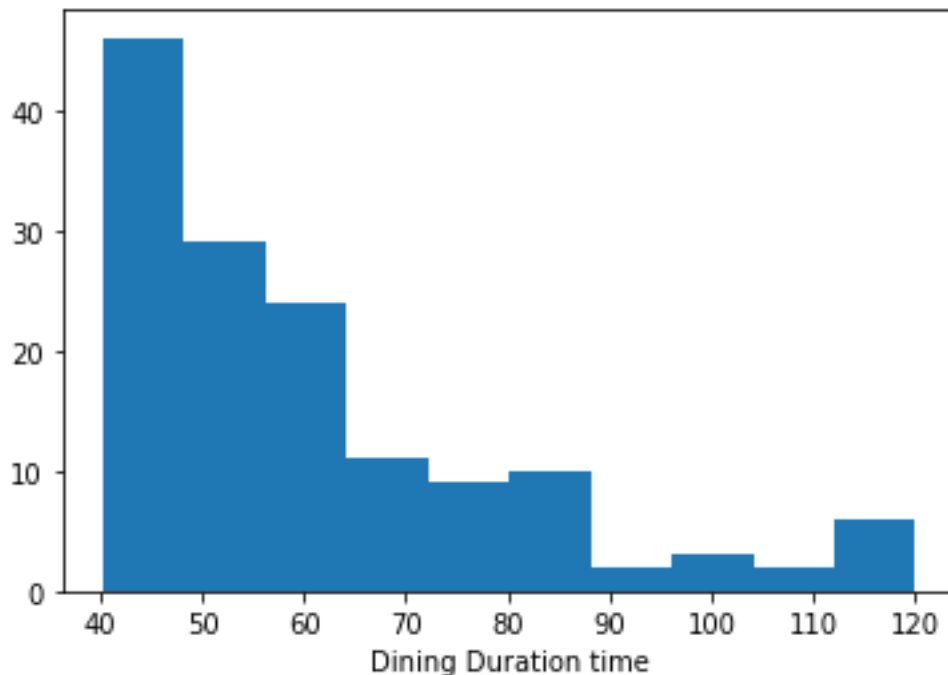


# Setup – Abandon



# Setup – Duration and Bill

- The duration of the dinner  $d$  :



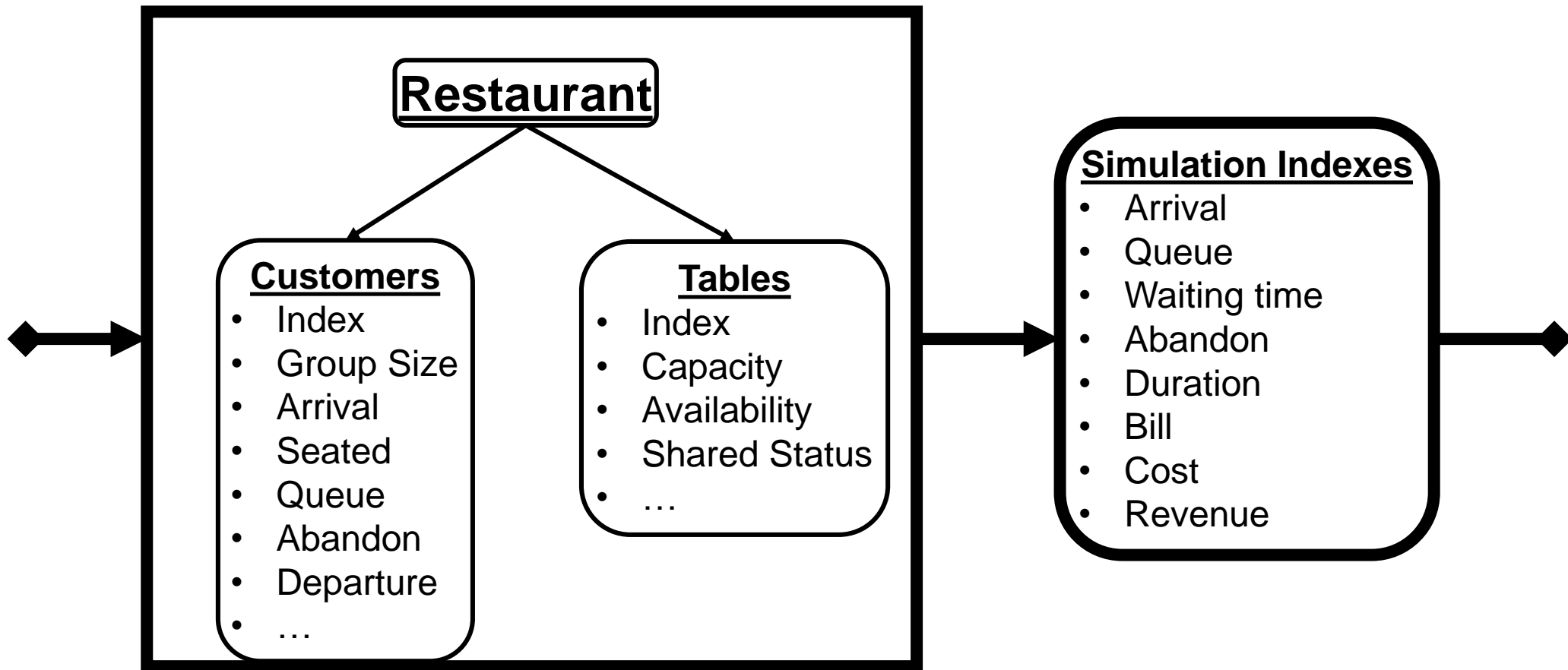
- The bill per person  $b$  can be calculated by multiplying a customer-specific consumption rate, defined by  $r$ , and the dinner duration  $d$ . The customer-specific consumption rate  $r$  is uniformly distributed between 0.5 €/minute and 1.2 €/minute.
- When a group sits together with another group at the same table, the remaining duration  $d$  decreases to  $d*0.5$ . Moreover, the consumption rate  $r$  also decreases to  $r*0.8$ .

# Setup - Cost

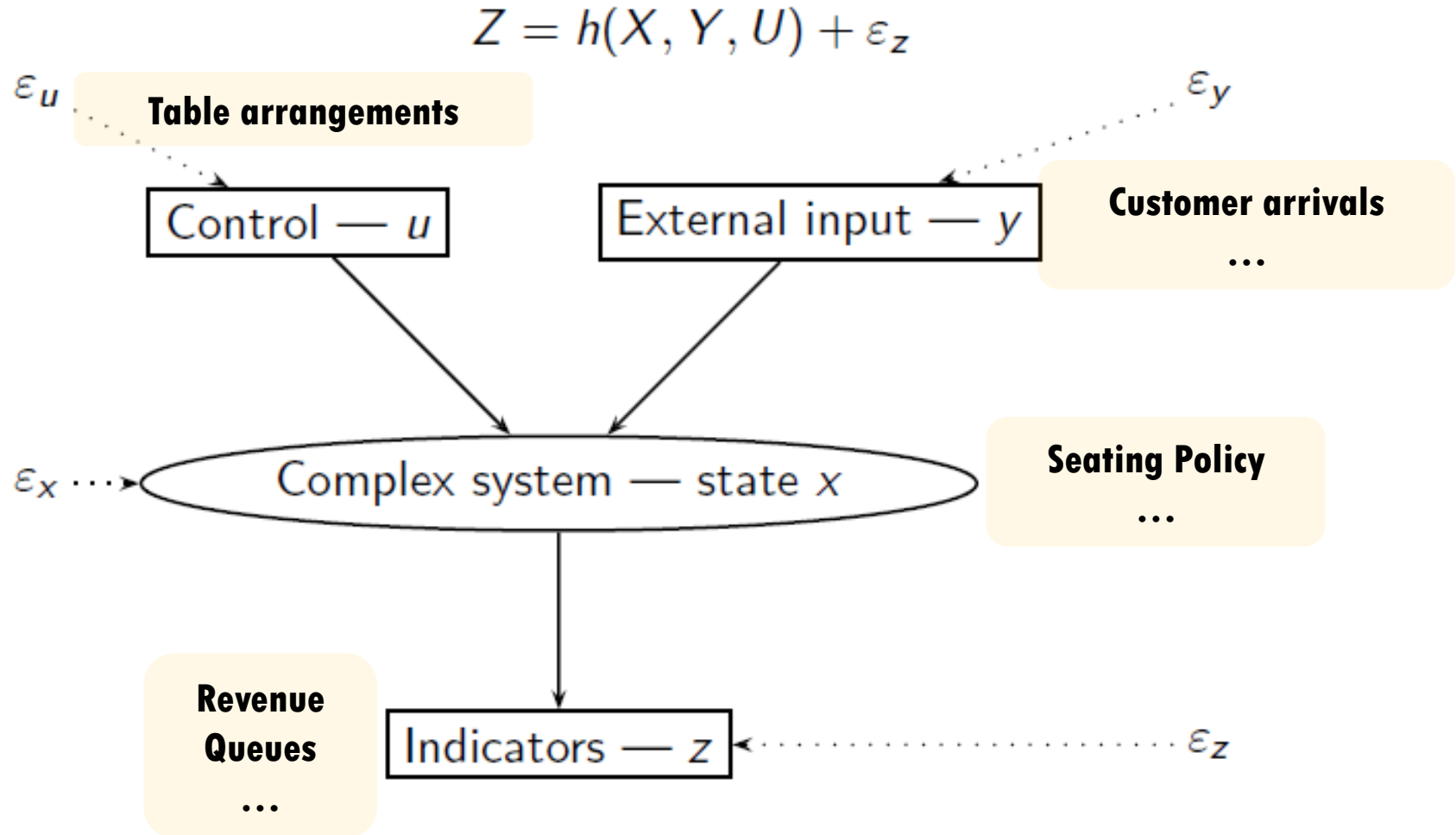


- Total Cost =  $TC \text{ [EUR]} = 0.1 \left[ \frac{\text{EUR}}{\text{min} \cdot \text{seat}} \right] \cdot (\#seats) \text{ [seat]} \cdot T_f \text{ [min]}$

# Simulation Setup



# Simulation framework



# Simulation Results

**Op.1 - 40 tables for 5 | Op.2 - 50 tables for 2, 20 tables for 5**

**Two Policies – With and without Sharing tables**



# Results – Table arrangements

Op.1  
40 tables for 5

Tables: {2: 0, 3: 0, 4: 0, 5: 40}

t = 0 [min]

Incomes: 0 [chf], Expenses: 20 [chf]

Queues: 0 [c], Abandon: 0 [c]

Avg Dinning time: 0 [min], Avg Waiting time: 0 [min]



Op.2  
50 tables for 2, 20 tables for 5

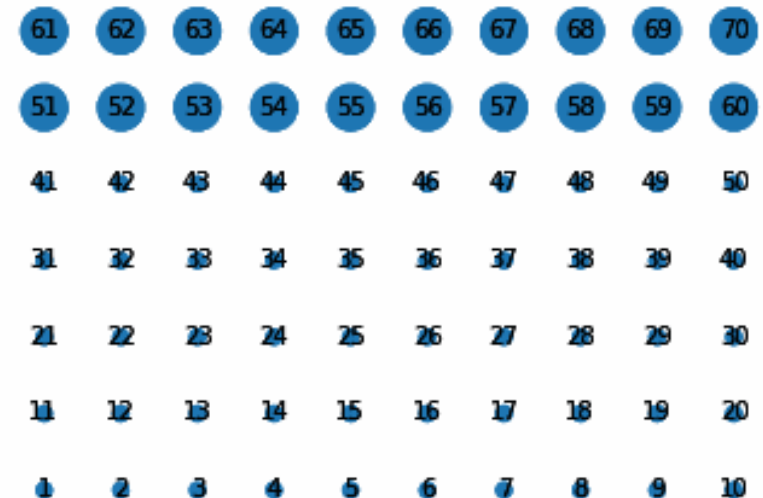
Tables: {2: 50, 3: 0, 4: 0, 5: 20}

t = 0 [min]

Incomes: 0 [chf], Expenses: 20 [chf]

Queues: 0 [c], Abandon: 0 [c]

Avg Dinning time: 0 [min], Avg Waiting time: 0 [min]



EMPTY



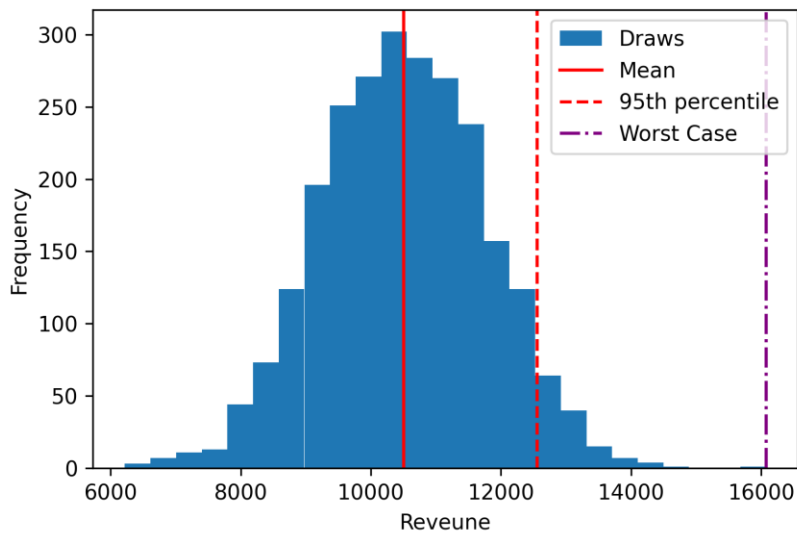
TAKEN



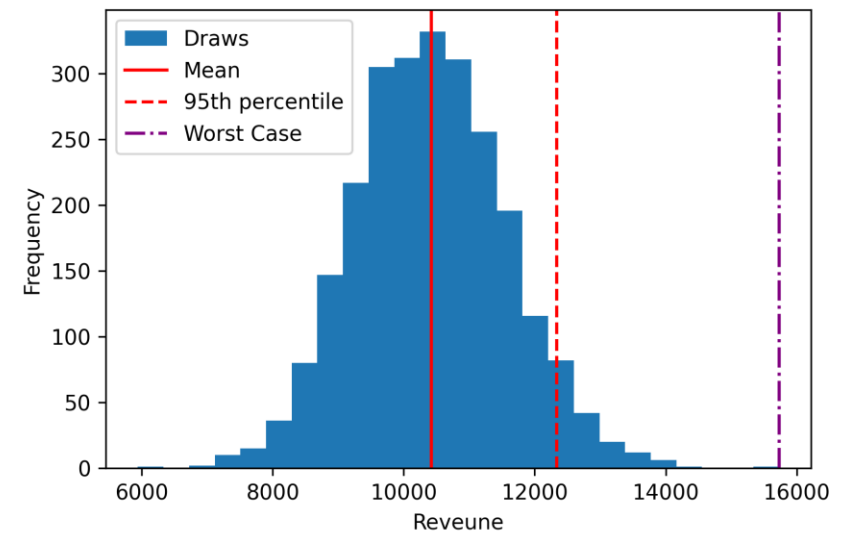
SHARED

# Results – Revenue (Op.1) (#n=5000)

Allow sharing tables

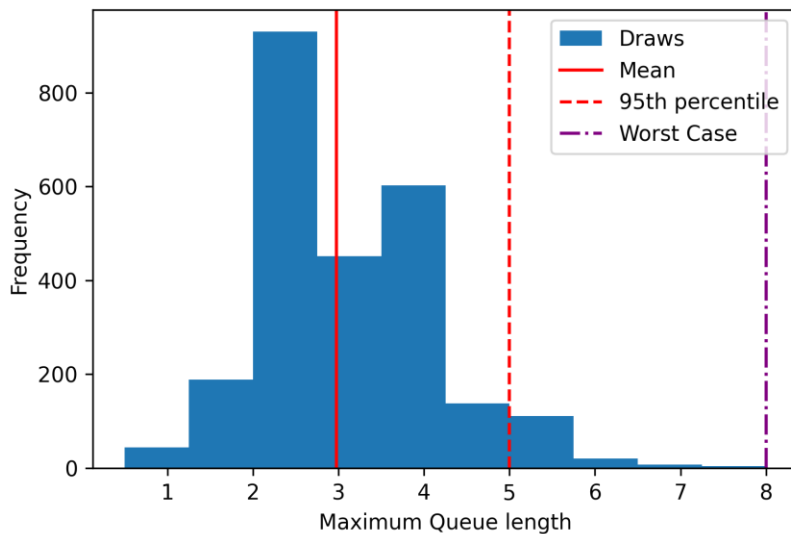


Not Allow sharing tables

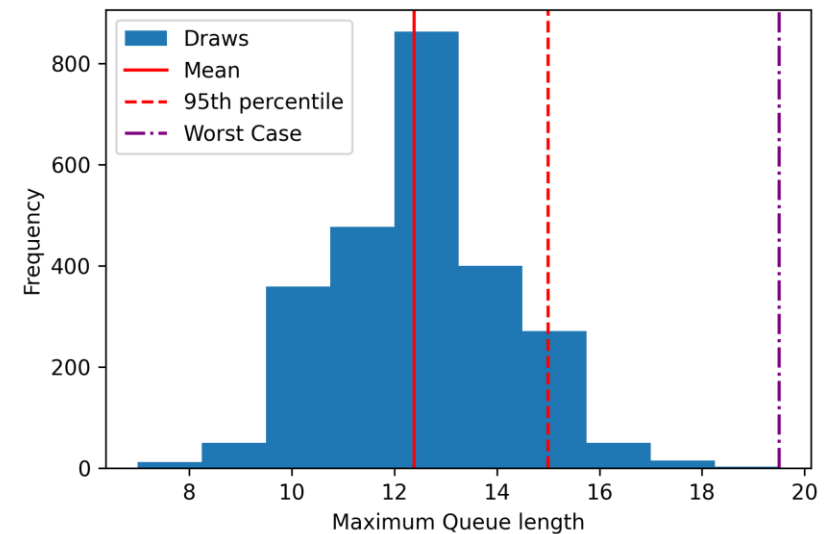


# Results – Queue (Op.1) (#n=5000)

Allow sharing tables



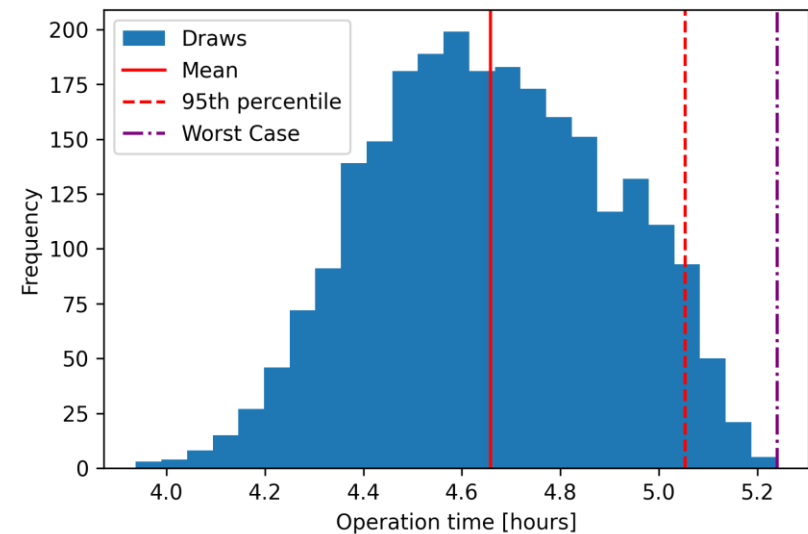
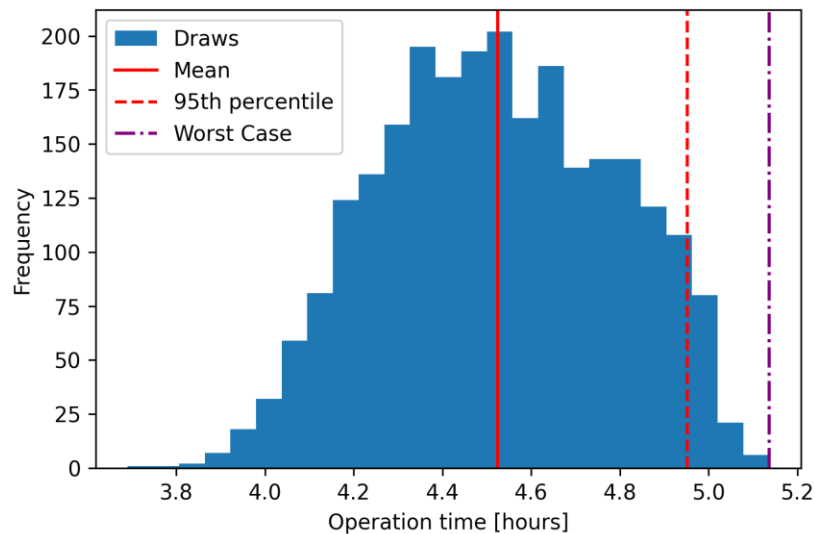
Not Allow sharing tables



# Results – Operation time (Op.1) (#n=5000)

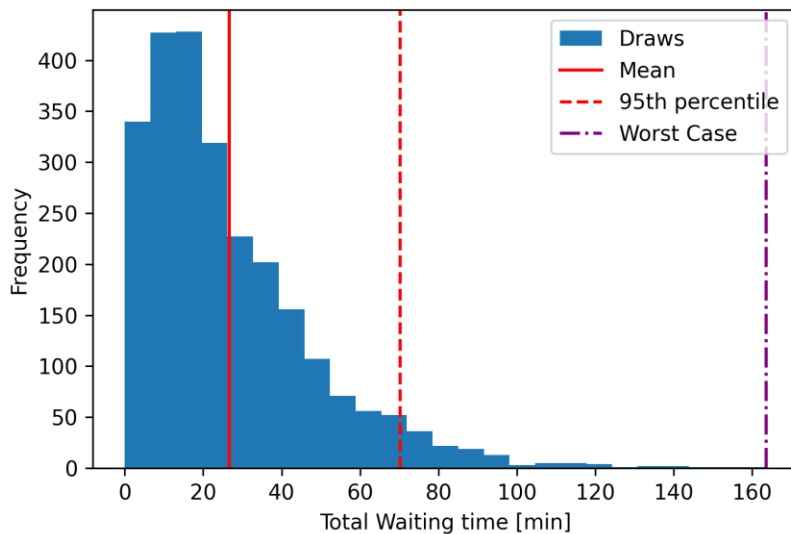
Allow sharing tables

Not Allow sharing tables

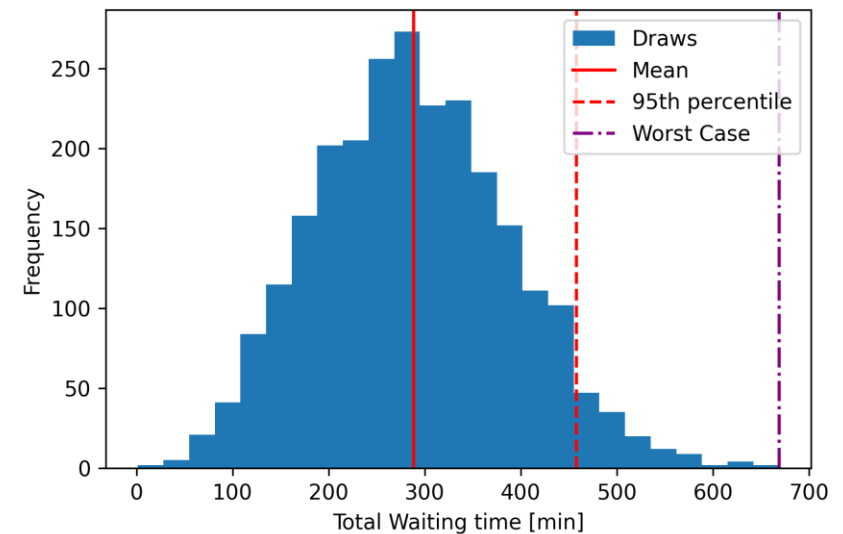


# Results – Waiting time (Op.1) (#n=5000)

Allow sharing tables



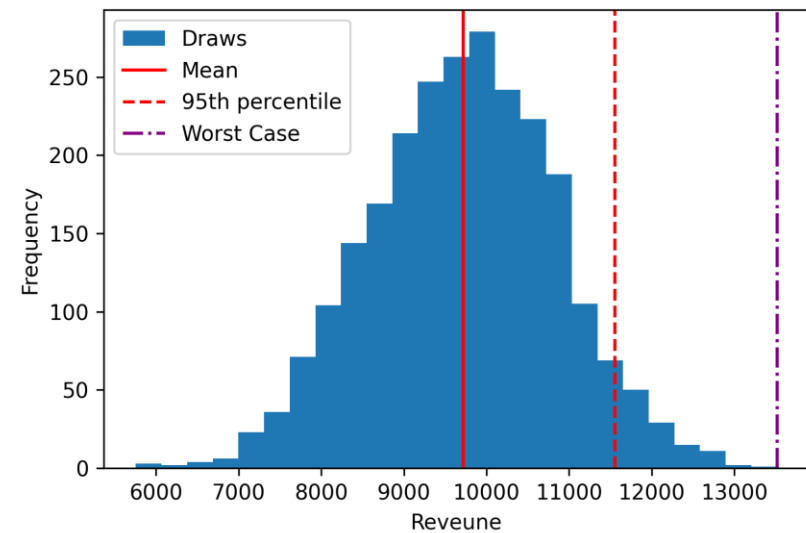
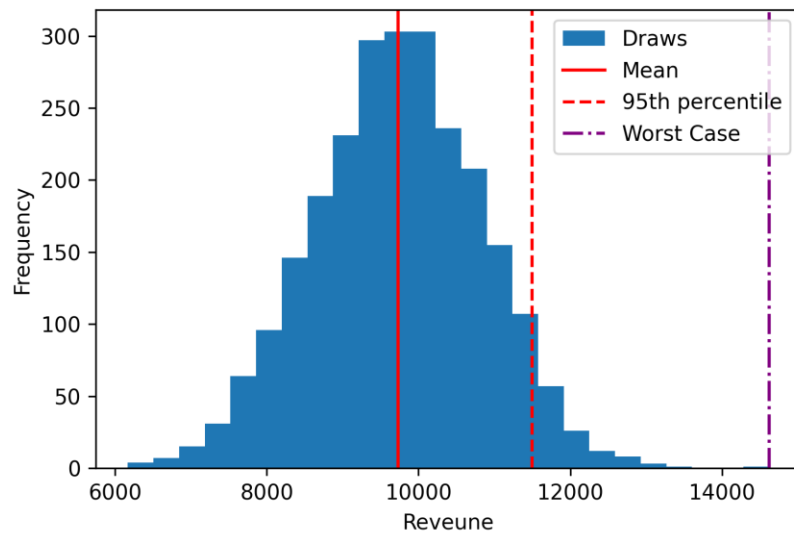
Not Allow sharing tables



# Results – Revenue (Op.2) (#n=5000)

Allow sharing tables

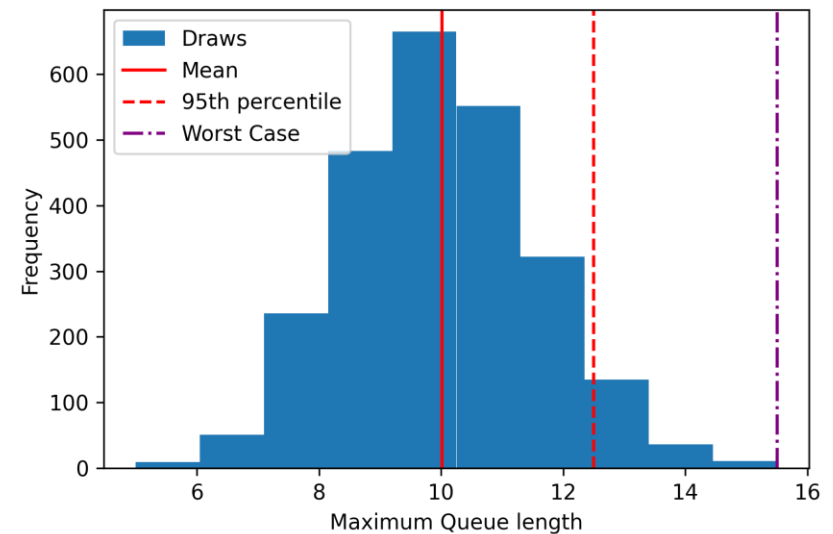
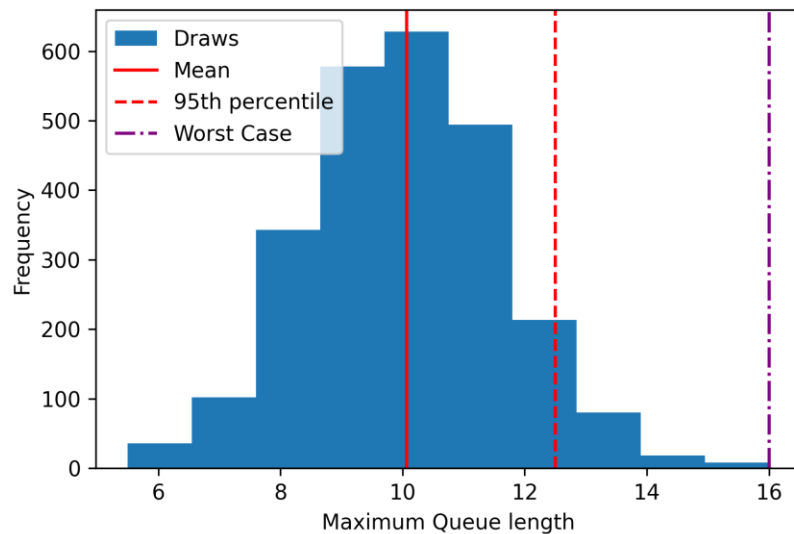
Not Allow sharing tables



# Results – Queue (Op.2) (#n=5000)

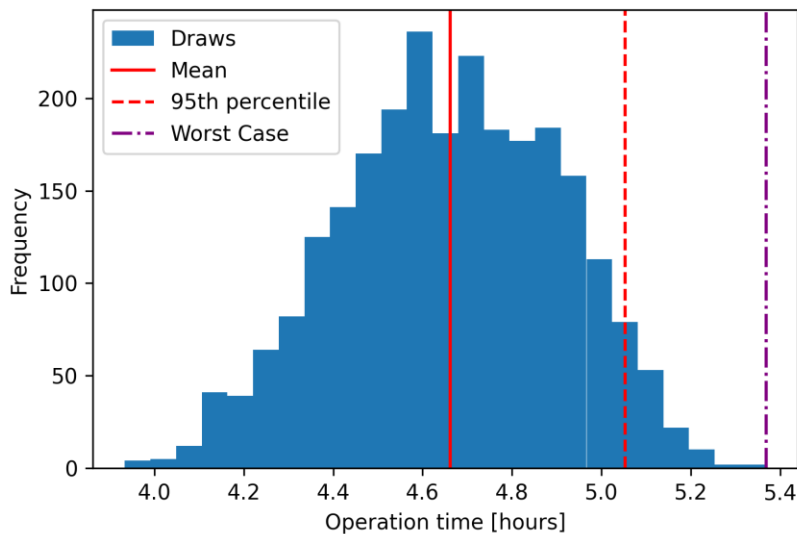
Allow sharing tables

Not Allow sharing tables

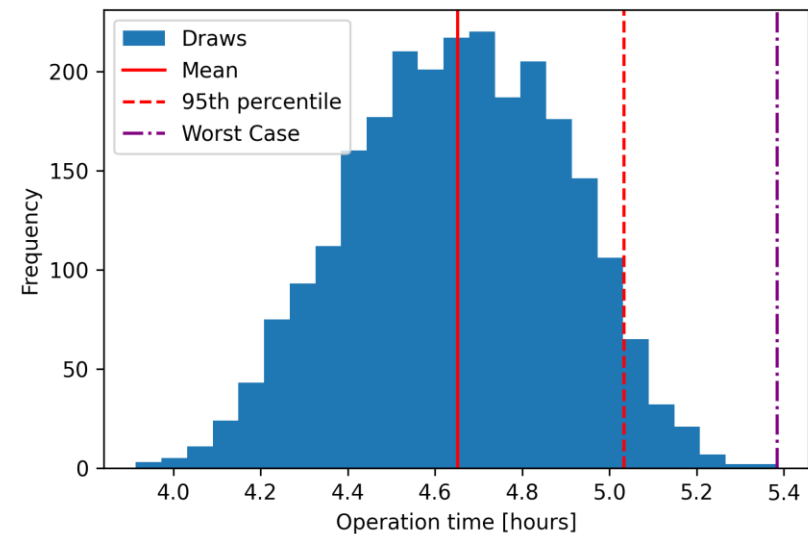


# Results – Operation time (Op.2) (#n=5000)

Allow sharing tables



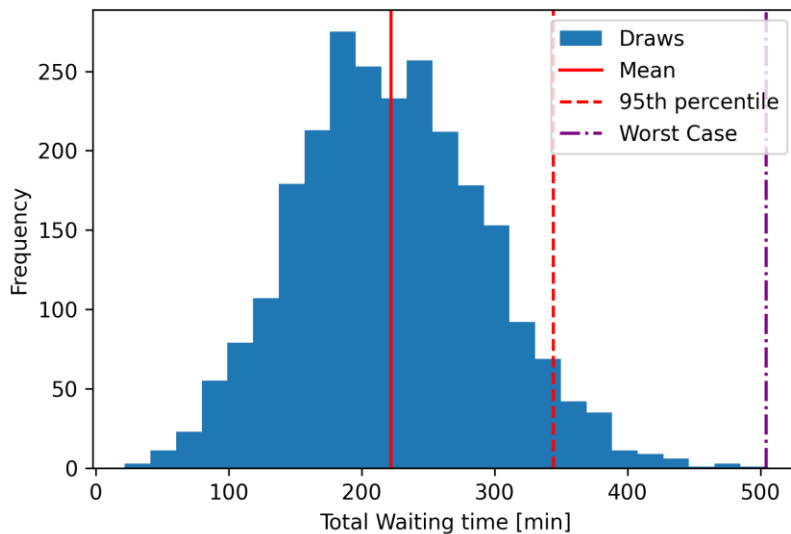
Not Allow sharing tables



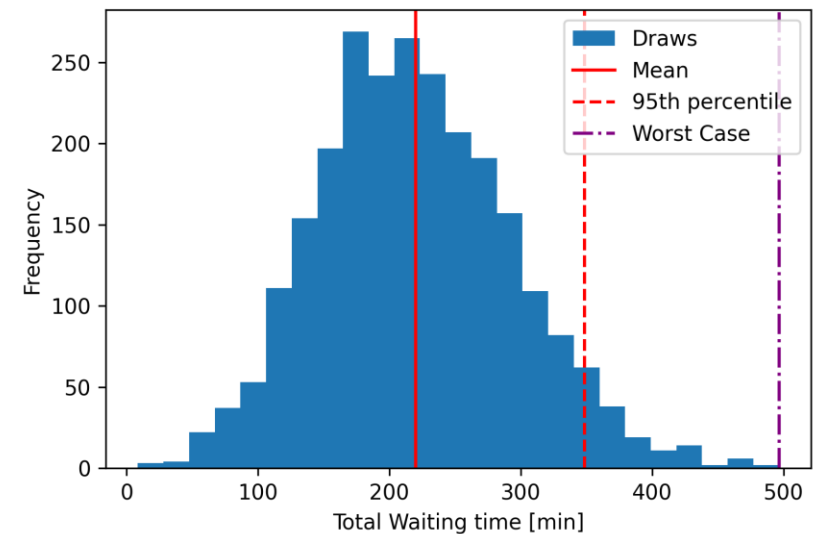


# Results – Waiting time (Op.2) (#n=5000)

Allow sharing tables



Not Allow sharing tables



# Summary

No Obvious Bias Observed.

- We can assume that, for better customer experience, the restaurant should not put different groups of customers together.
- This assumption is to be checked with further analysis.

Intro

Simulation

Optimization

Summary

# Optimization



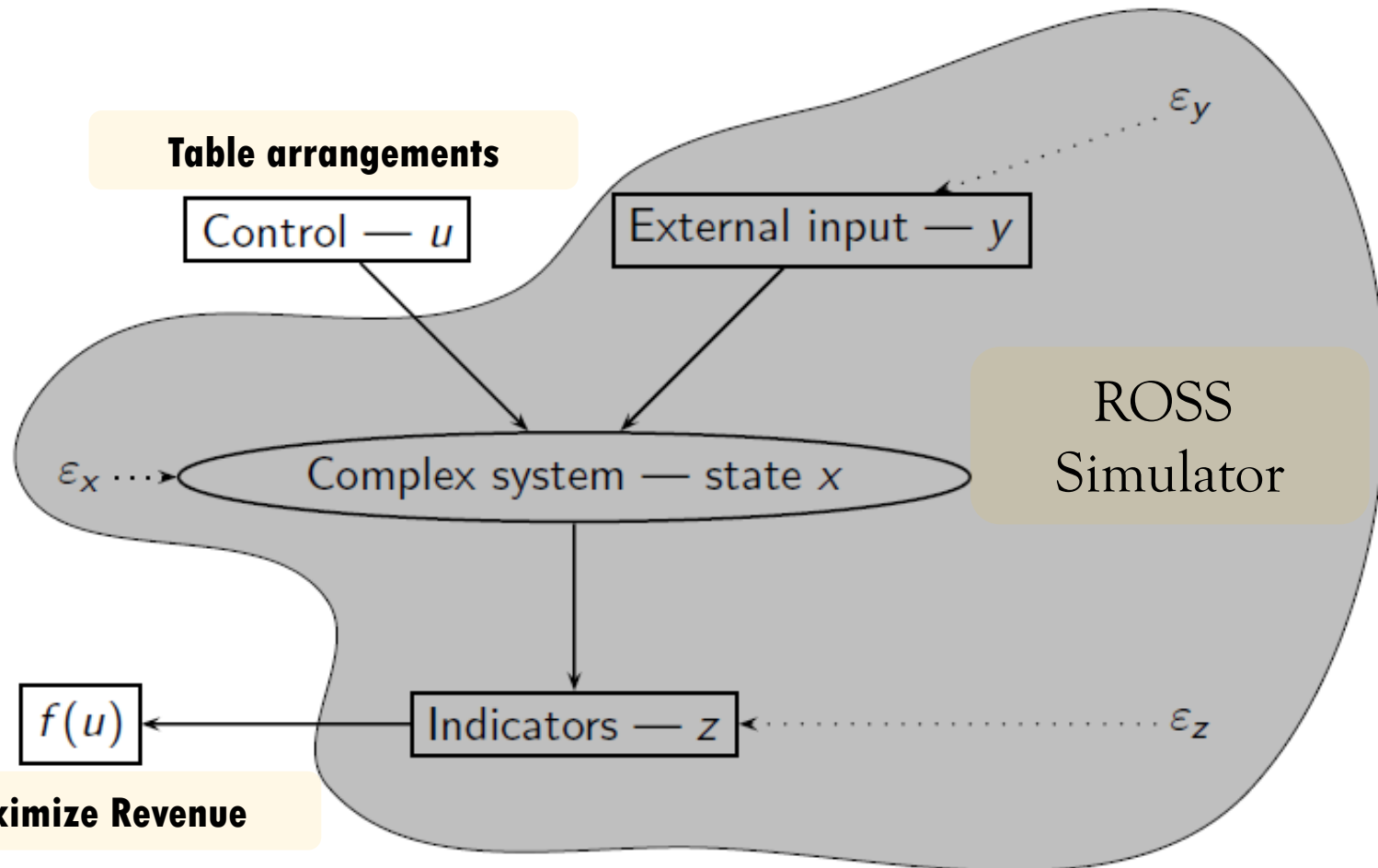
Intro

Simulation

Optimization

Summary

# Optimization



# Optimization

- Optimize over table arrangements, for maximized Revenue during open hours
- Method: Neighborhood search. Changing the number of tables of each size by 1, each arrangement would have at most 8 neighbors
- Algorithm: Simulated Annealing (Allows cost function to increase for searching larger area)

# Optimization

## Optimization

There are plans for a major renovation, after which the restaurant will be able to accommodate up to 400 seats. The owner is interested in knowing the best configuration of the seats as well the capacity of the restaurant. We disregard renovation costs and our only interest is the maximization of the daily revenue.

For the optimization project, you are requested to:

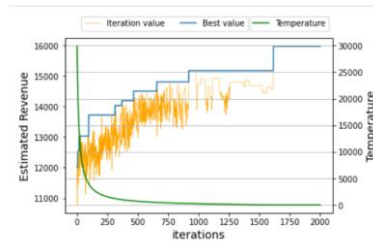
- Identify the decision variables of the problem.
- Define the objective function
- Design an optimization algorithm and apply it to solve the problem. The value of the objective function is evaluated by discrete event simulation.
- Like in the simulation project, the objective function can reflect various policies of the decision maker: whether they want to optimize over the average, best, worst, or certain percentile of the objective function distribution. Decide what your position is and justify it, or present results for several alternatives.
- Compare the result of your algorithm with the seating policies described in the simulation project.
- For the best configuration that you have found, use your creativity and design a new seating policy that would lead to a lower cost solution.

We decide to optimize over the average value of the Revenue because we already know the revenue almost follows normal distribution. And we believe it's a representative value to estimate the long-term performance of the restaurant,

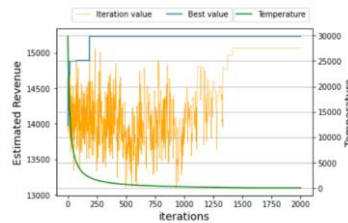
# Optimization – Initial solutions

- Finding Initial solutions with multiple coarse optimization (#n=2000)
- No Variance Reduction applied, average of 10 runs used to estimate mean

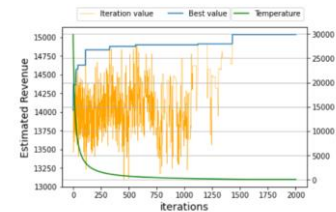
SHARING



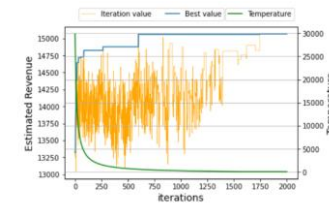
Optimized Table arrangement:  
[19, 18, 4, 20]



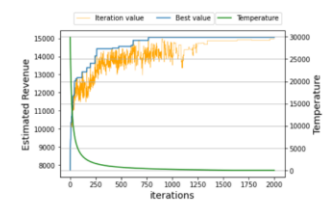
Optimized Table arrangement:  
[23, 11, 17, 14]



Optimized Table arrangement:  
[21, 10, 3, 27]

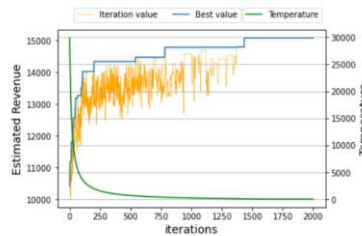


Optimized Table arrangement:  
[20, 20, 8, 15]

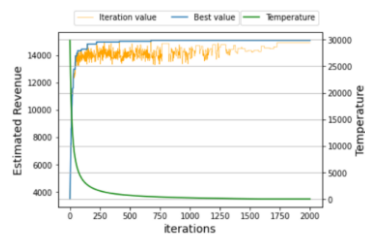


Optimized Table arrangement:  
[18, 13, 16, 13]

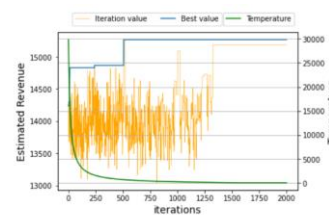
NO SHARING



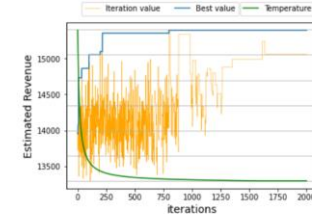
Optimized Table arrangement:  
[7, 30, 2, 27]



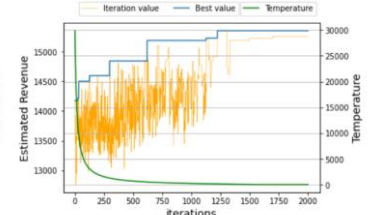
Optimized Table arrangement:  
[24, 7, 23, 14]



Optimized Table arrangement:  
[20, 9, 12, 20]



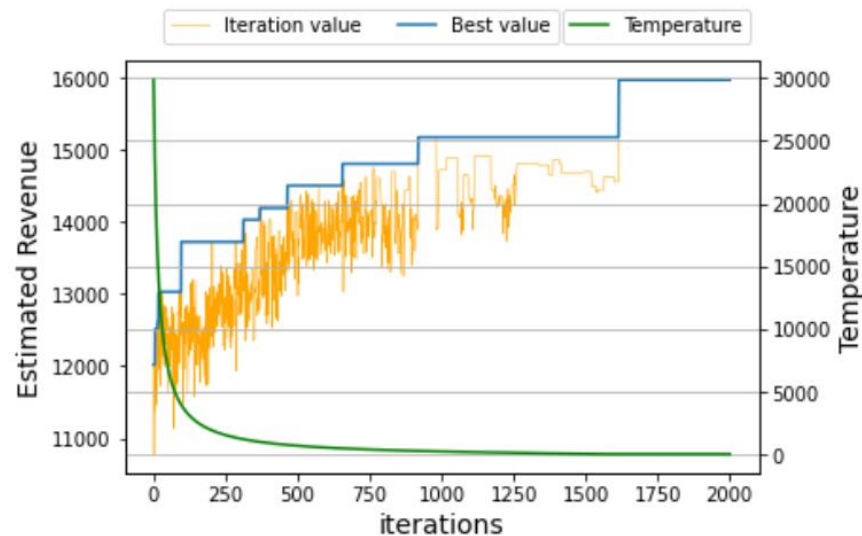
Optimized Table arrangement:  
[25, 14, 10, 18]



Optimized Table arrangement:  
[22, 16, 5, 22]

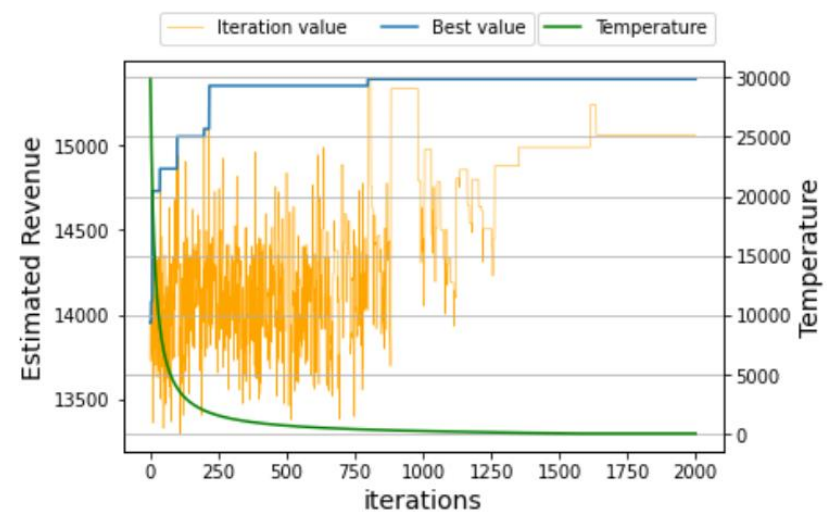
# Optimal Initial solutions

Allow sharing tables



Optimized Table arrangement:  
[19, 18, 4, 20]

Not Allow sharing tables



Optimized Table arrangement:  
[25, 14, 10, 18]

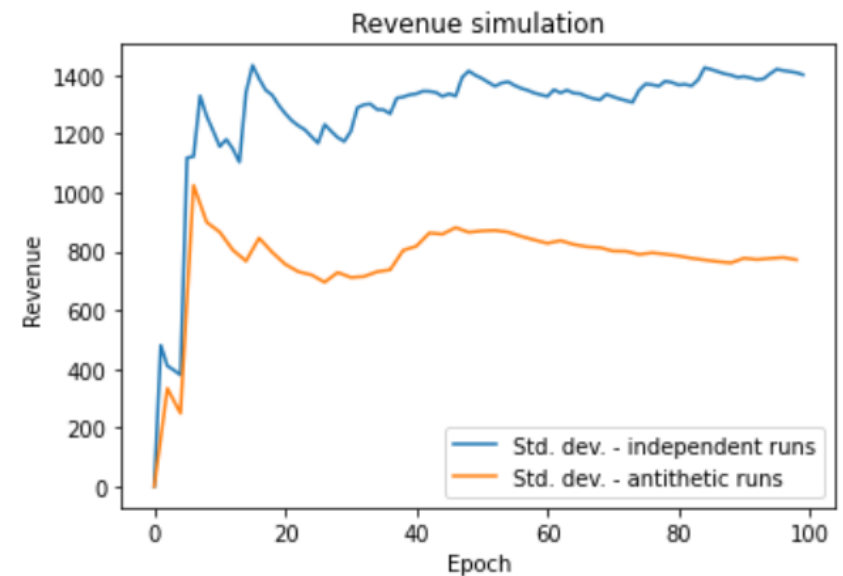
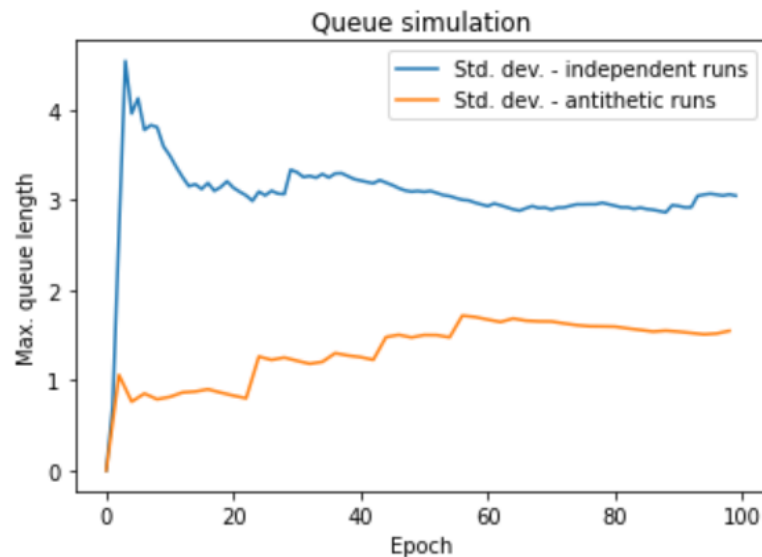


## These solutions are only for reference

- Because an average of 10 runs is not a good estimate of the real mean value
- It is also observed that the optimized table arrangements are quite different, but the optimized revenue is almost constant around 15000.

# Apply Variance Reduction to the simulator

- With a hoped accuracy of 0.5, the standard deviations are reduced:
- (Example  $u_0=[19,18,4,20]$ , allow sharing)
- We choose runtime = 124 instead 100 for better error tolerance

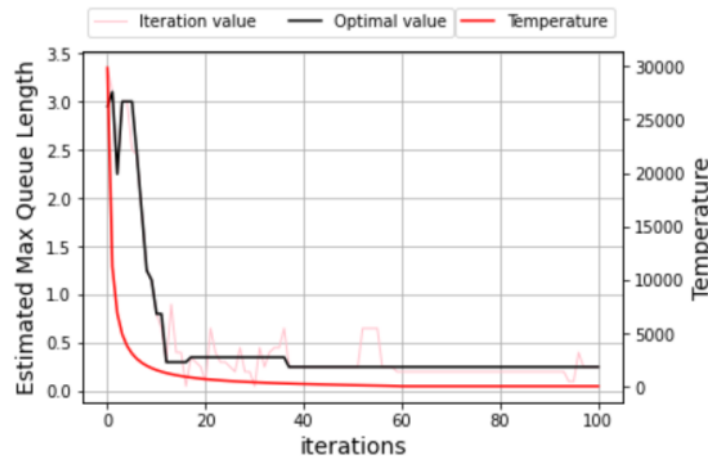
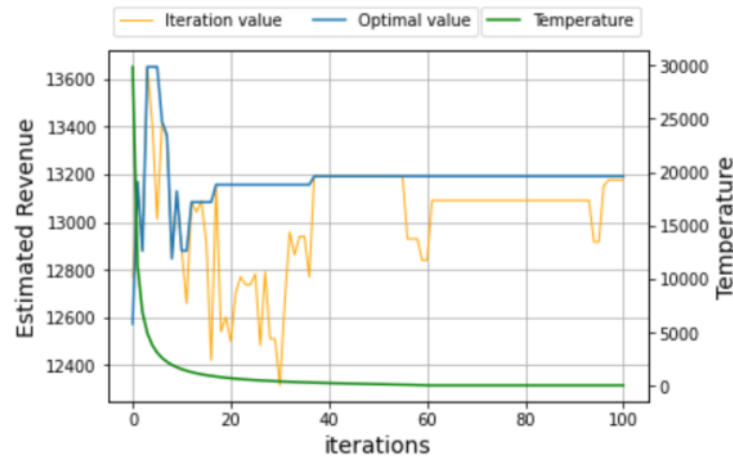


# Multi-Objective Optimization

- We might want to minimize the length of waiting queue of our restaurant, at a cost of Revenue, for better customer experience and staff well-being
- Add weight\*maximum queue length as an evaluation term to the cost function. The weight value indicates how much revenue are we willing to give up for optimizing the queue length by 1 people. Here we chose 1000(CHF)

```
def cost_function(max_queue_mean, Rev_mean, queue_weight=1000):  
    return -1*Rev_mean+max_queue_mean*queue_weight
```

# Multi-Objective Optimization example

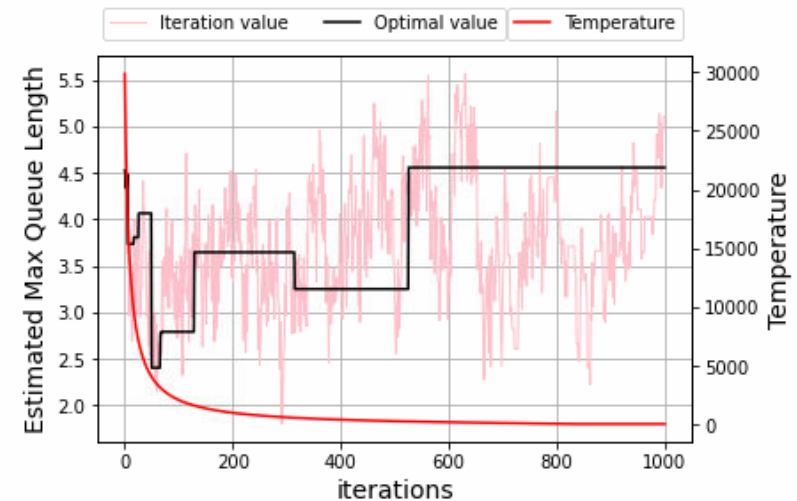
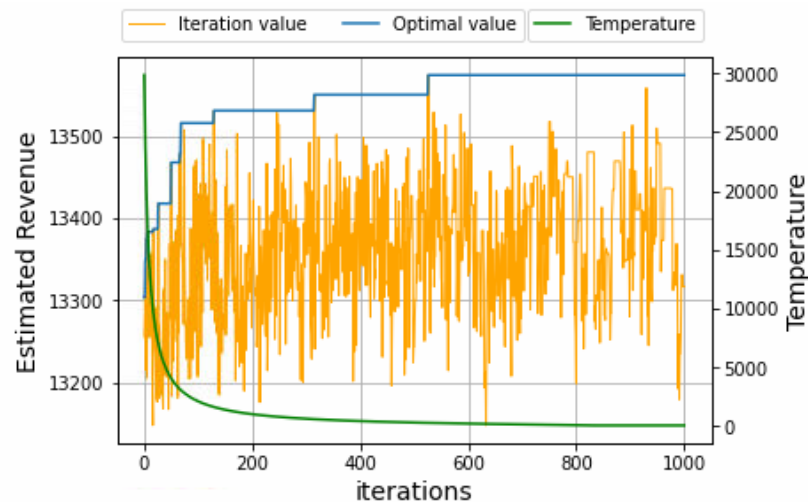


- This very coarse optimization example shows how our multi-objective optimizer accepts lower revenue to shorten the queue

Optimized Table arrangement:[19, 19, 5, 29]  
Corresponding Revenue:13191.57CHF  
Corresponding max queue length:0.25  
Running time:214.69 seconds

# Results – Case 1

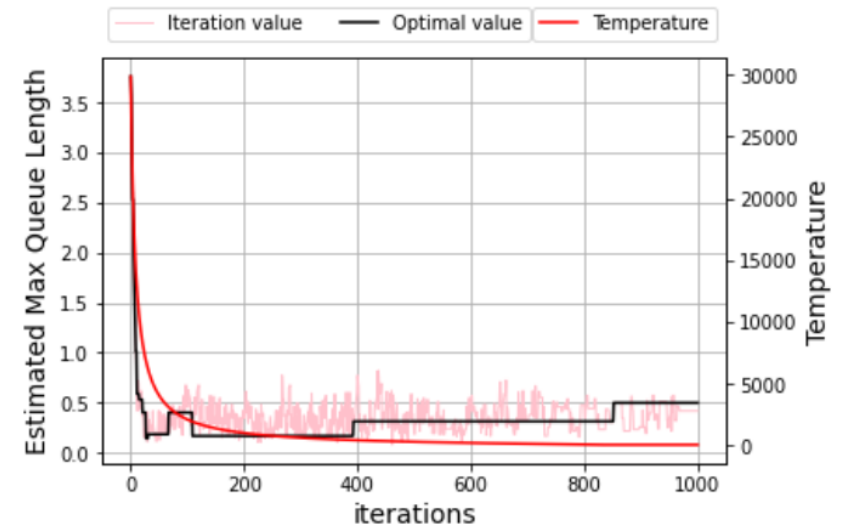
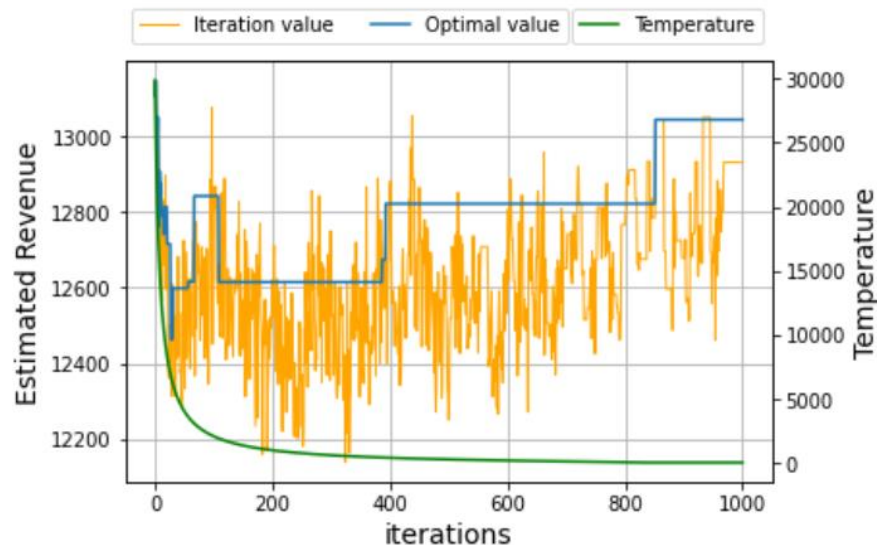
- Allow sharing, with Variance reduction, Optimize only Revenue
- $U_0=[19,18,4,20]$



Optimized Table arrangement:[26, 14, 10, 14]  
Corresponding Revenue:13574.28CHF  
Corresponding max queue length:4.556451612903226  
Running time:7356.40 seconds

## Results – Case 2

- Allow sharing, with Variance reduction, Optimize both Revenue and Queue
- $U_0=[19,18,4,20]$



Optimized Table arrangement:[25, 17, 16, 19]

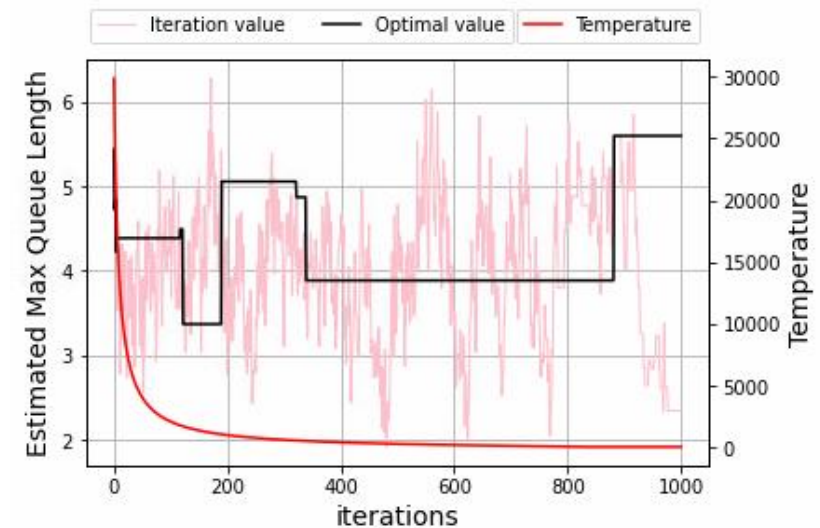
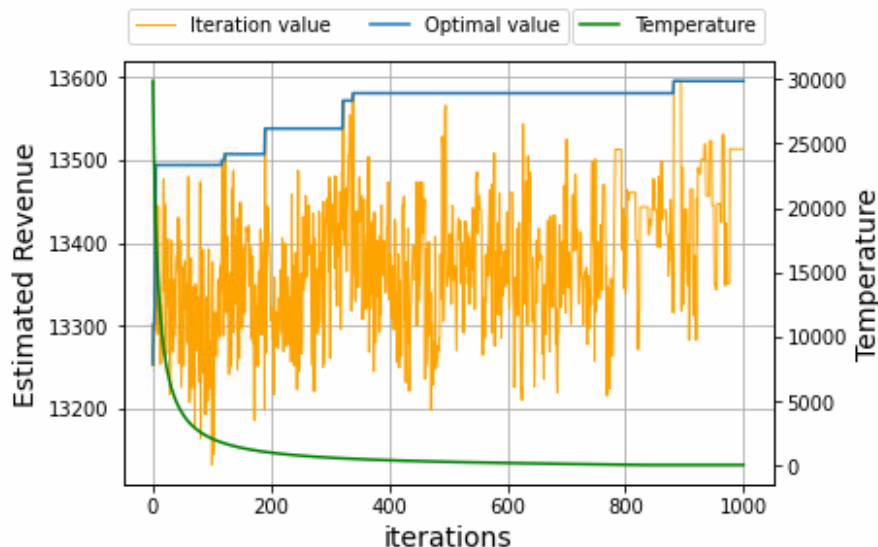
Corresponding Revenue:13044.90CHF

Corresponding max queue length:0.5

Running time:14927.99 seconds

## Results – Case 3

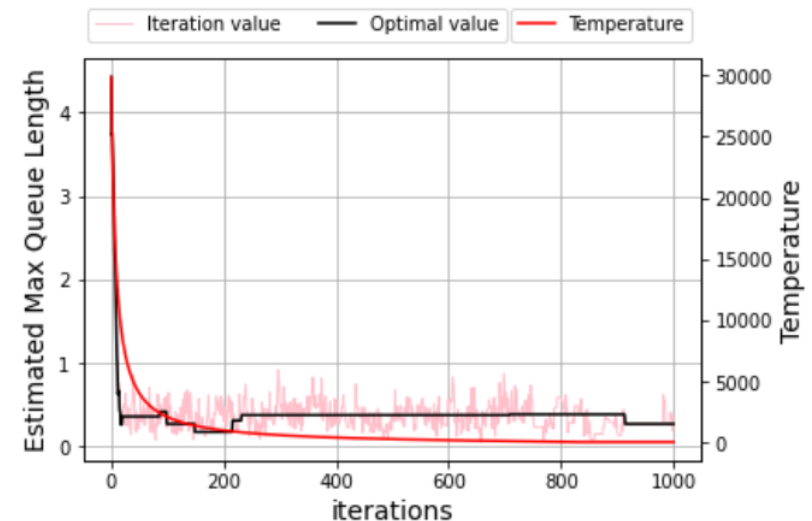
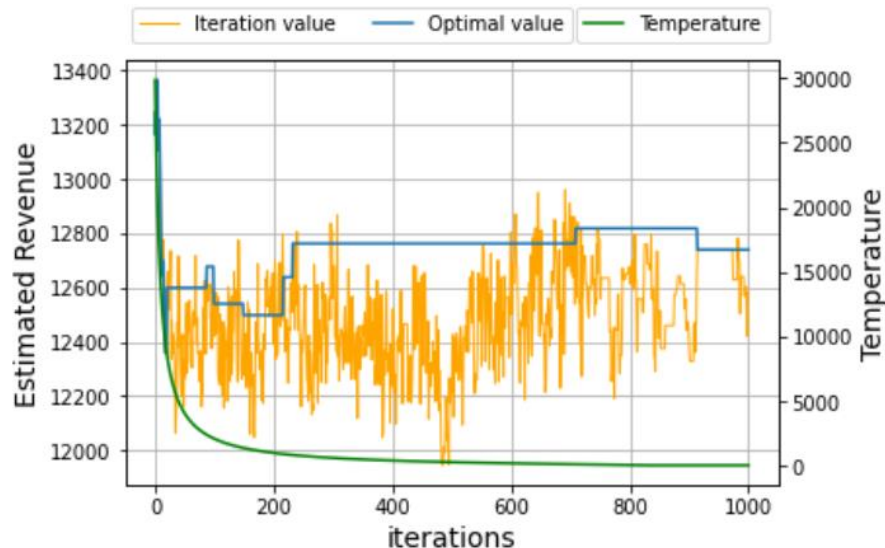
- No sharing, with Variance reduction, Optimize only Revenue
- $U_0=[25,14,10,18]$



Optimized Table arrangement:[23, 13, 10, 16]  
Corresponding Revenue:13595.30CHF  
Corresponding max queue length:5.596774193548386  
Running time:7215.58 seconds

## Results – Case 4

- No sharing, with Variance reduction, Optimize both Revenue and Queue
- $U_0=[25,14,10,18]$



Optimized Table arrangement:[21, 21, 14, 22]

Corresponding Revenue:12739.68CHF

Corresponding max queue length:0.27419354838709675

Running time:13050.71 seconds



# Results

## Optimized

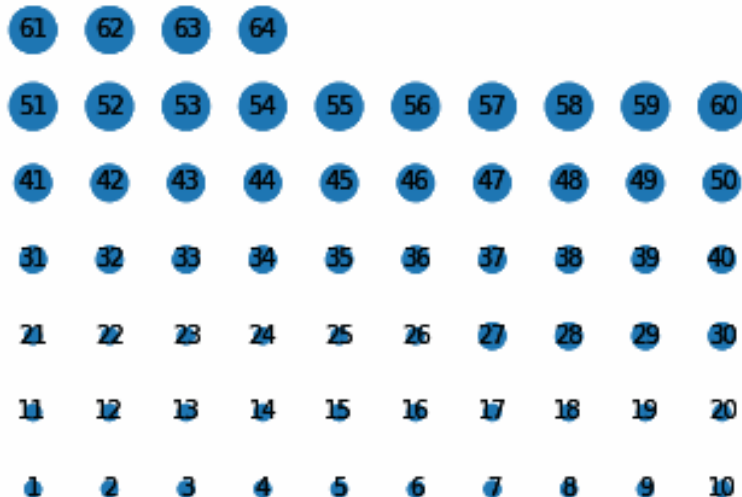
Tables: {2: 26, 3: 14, 4: 10, 5: 14}

t = 0 [min]

Incomes: 0 [chf], Expenses: 20 [chf]

Queues: 0 [c], Abandon: 0 [c]

Avg Dinning time: 0 [min], Avg Waiting time: 0 [min]



## Given

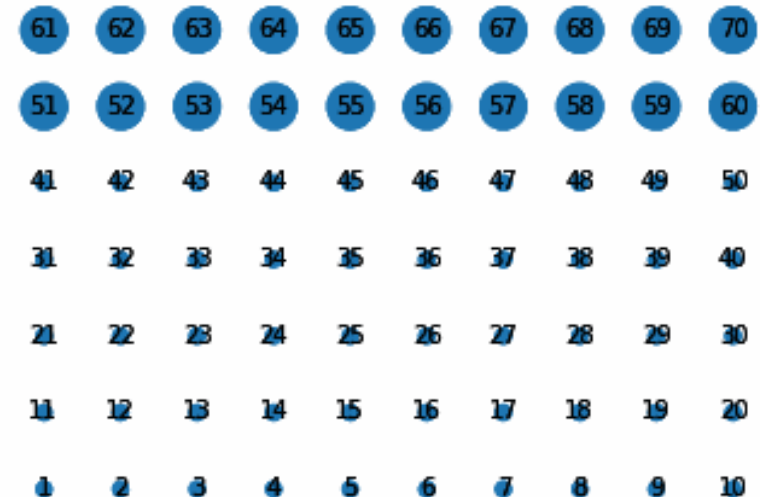
Tables: {2: 50, 3: 0, 4: 0, 5: 20}

t = 0 [min]

Incomes: 0 [chf], Expenses: 20 [chf]

Queues: 0 [c], Abandon: 0 [c]

Avg Dinning time: 0 [min], Avg Waiting time: 0 [min]



EMPTY



TAKEN



SHARED

# Summary

- Optimization of restaurant operation is needed.
- Simulation framework for restaurant design is achieved.
- Utilization of multi-objective optimization can increase revenue and reduce queues.

# THANK YOU!



## ROSS

Restaurant  
Optimizer  
and  
Simulator  
Software

## TEAM:

Michael Bombile

Ismail Nejjar

Yazan Safadi

Shuhang Zhang