Capacity in University Food Services: A Simulation Analysis Based on the case of Universidad Católica del Maule

Felipe Lillo[1,*], Andrés Gonzalez[2], Pedro Severino-Gonzalez[2], Victoria Toro-Lagos[3] and Ihomara Rojas-Sepulveda[3]

[1]*Facultad de Ciencias Básicas, Universidad Católica del Maule, Talca, Chile.*

[2]*Facultad Ciencias Sociales y Economicas, Universidad Católica del Maule, Talca, Chile.*

[3]*Escuela de Ingeniería Comercial, Universidad Católica del Maule, Talca, Chile.*

Abstract: The growth of higher education enrollment implies a series of logistical challenges for Universities. One such challenges is to provide food services according to adequate quality standards. This work is motivated by the real-life case of the Universidad Católica del Maule-Chile (UCM), where a sustained growth in student enrollment has led to re-evaluating food service capacity. Determining whether the available infrastructure can serve current and projected student demand becomes particularly important. By developing a computerized simulation model based on discrete events, this study addresses the capacity usage in the UCM food services. As a result, we note that the current infrastructure can meet demand needs. However, a considerable number of users are mostly waiting for attention, which creates a feeling of agglomeration in the service.

Keywords: Computerized model, discrete event simulation, extreme value analysis, university services, service capacity.

1. INTRODUCTION

University food services have particular challenges which impede providing quality service. One major challenge in quality service terms is controlling negative perceptions (Mensah and Mensah, 2018). According to Kwun (2011), perceptions of food services on a university campus tend to be unfavorable due to various situational, contextual, and environmental limitations, repetitive menu element consumption, mediocre execution in the food and service, and general infrastructure aspects.

Food service infrastructure should be able to handle aspects including cleaning, dining room ambience, comfort level, operating days and hours, environment, and capacity (Liang and Zhang, 2009; Kim *et al.*, 2009; Klassen *et al*., 2005). However, one current restriction on the previous considerations is the physical space available for an educational system, since this resource determines service flexibility. This includes infrastructure investment aspects which educational institutions must carry out to guarantee proper service (Yu *et al*., 2022). Infrastructure administration is largely related with service capacity, so better infrastructure translates into greater service capacity (Too, 2011). When analyzing installed capacity, it is crucial to understand installation design, referring to the organization of physical installations in the location in order to promote low-cost use and optimize service quality (Tang *et al*., 2019). Projecting installed capacity is a key aspect for higher education institution management. However, it is hard to estimate optimal capacity levels due to the lack of clear methodologies and studies in this area (Velasquez *et al*., 2011).

These facts establish that capacity and infrastructure are linked elements. Infrastructure must thus adapt to universities' demands. This brings us to the question: What is the behavior of capacity within a university food service when it faces sustained growth? This question arises from the need to interpret the behavior of capacity in the face of increased user numbers in a space.

The existing literature approaches the theme of analyzing university food service infrastructure and capacity from different perspectives. There are various industries which analyze capacity, and it is studied with various methodologies. This type of analysis is thus also presented in organizations related with university food services.

When analyzing the case of Universidad del Valle in Brazil, Gil *et al*. (2016) approached the capacity problem based on the non-existence of an installed capacity standard. An optimization model was developed to determine unitary resource consumption and total consumer capacity. The model was simulated with a spreadsheet. Before sensitizing the model, a prior simulation process was done to carry out repeated cycles, for reliability and validity testing.

Ansari *et al*. (2008) simulated a university cafeteria which sought to examine student flow behavior during high traffic periods. The model examined the trajectory, choice of places and actions carried out within the lunchroom, making it possible to visualize the current scenario and identify cafeteria functioning shortfalls. The simulation thus determined

*Address correspondence to this author at the Avenida San Miguel 3605-Talca, Chile, 56-975758267, E-mail: flillo@ucm.cl

whether there were space or process problems when providing service.

Kambli *et al*. (2020) sought to improve response capacity with limited resources in the dining halls of a university campus. The study examined the independent and combined effects of reassigning capacity and line management, considering how these aspects influence customer waiting time. The simulation was carried out via the Promodel® simulation software, and included system configuration, sequence of events, process flow, and arrival and service time distributions.

The preceding literature indicates that university food service capacity has mainly been approached from the perspectives of spatial use optimization and detecting faults in the service operational functions. These cases studied the intermediate capacity of a simulation software, which was used to implement a computerized model to replicate university food service functioning.

The contribution of this study is to describe the behavior of food service capacity at Universidad Católica del Maule-Chile (UCM) under current and projected conditions (sensitivity analysis). This will let infrastructure designers estimate future space needs. For this purpose, we will develop a computerized service model and simulate their behavior considering a typical operating day. The model will be able to record and obtain statistical representations of use capacity. Unlike prior studies, the focus is capacity behavior, rather than optimization.

The rest of the article is organized as follows: Section 2 describes the methodology used in the study. Results from the simulations are shown and described in Section 3. Finally, the analysis and conclusions based on the results are provided in Section 4.

2. METHODOLOGY

2.1. Design

The study has a mixed cross-sectional design, since it includes both qualitative and quantitative elements to jointly develop the model. Data collection occurred in a given timeframe; in this case, the second semester of the year 2018. This study is also characterized by being experimental, since our computerized simulation model for discrete events will be applied to dining hall users' behavior and for sensitizing its parameters, which implies manipulating variables.

2.2. Test Subject

This study is a case study, since it analyzes a specific unit of a populational universe. The specific unit of this study is the food service belonging to Universidad Católica Del Maule (UCM). We intend to study the behavior of its capacity, which will be the principal study variable. Capacity is understood in this work as the number of students who use the dining hall at a moment in time. Their behavior is not defined by a specific value, but rather by a probability distribution (random variable).

The UCM food service is a concession with a capacity of 500 eating locations. Its layout includes two dining rooms (Dining Room 1 and Dining Room 2), a cash register sector which can serve three people at once (Two operators are always present, and the third is activated when there are over 40 people in the other two lines), a pickup zone for sweets and a pickup zone for lunches. Fig. (**1**) shows the aforementioned zones.

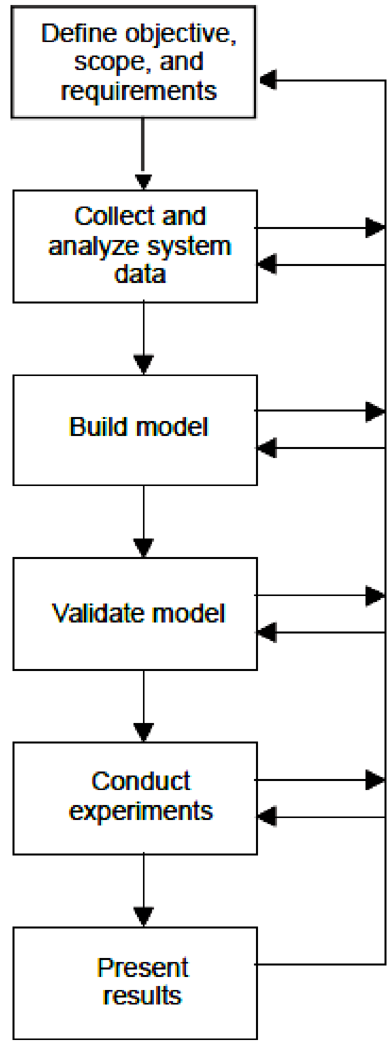

Fig. (1). Simulation procedure.

2.3. Data Gathering Techniques

A computerized simulation had to be built to perform this study, which required gathering data to represent user flows in the system. To obtain the flows, we had to know arrival times, waiting times, consumption times, the number of users who came in, peak flow hours, and how the service operated.

To begin, data was gathered regarding operativity, service procedures, and students' perceptions when using the dining hall. The following actions were taken to do so:

- Interview with concessionaries: A non-structured interview with open questions was done to find out about the operating logic and the operations carried out in the dining hall, business hours, and various user service data.

- Focus Group: This was done with 8 student participants who had experience with buying from the service. It lasted for about 40 minutes, divided into two series of principal questions and one extra. The first rounds lasted for about 15 minutes and were structured with 8 questions related to time use and 8 more questions related with dining hall infrastructure capacity. Finally, the extra series was done, which lasted for 10 minutes, and where the participants responded to 5 questions to find out about their perceptions regarding service and recommendations for possible improvements.

After these steps, information was drawn about service operativity. Data was obtained regarding times of arrival, service, and consumption, as well as the number of users served per day, daily sales records, and available spaces. The source for this data was the records kept by the service operator (concessionary) and maintained in electronic spreadsheets.

2.4. Analysis Plan

The analysis plan included developing a discrete-event simulation model describing current functioning and the development of sensitivity scenarios where some parameters were modified to see possible use capacity impacts. In this study, the simulation procedure described by Harrel (2022) is followed. Fig. (**1**) shows this type of procedure.

2.4.1. Simulation Model

As previously mentioned, this study will be done via a computerized discrete-event simulation model.

The model must be validated to establish its representativity compared to real functioning. This validation can be done through several techniques. Sargent & Balci (2017) describe various validation techniques used for simulation. Two of those techniques are applied here:

Checking for face validity: Face validity is checked by asking people who are knowledgeable about the system. For this study, this is done qualitatively via interviews with experts from the university, who knew and understood perfectly about the food service functioning.

Performing sensitivity analysis: This technique consists of changing model input values to determine the effect on the behavior of the model and its performance measurement. The model developed in this study was sensitized to study effects associated with growing demand, operating policy, and infrastructure capacity (measured by the number of users per moment of time). This sensitivity analysis is experimental, since the input variables are controlled.

The model requires cataloging service users (entities). Three specific user types were identified:

- Lunch user (student or general public), so called because they are mostly people who come into the dining hall to buy lunch. The normal route for these users is to enter through the front door and head to the cash register to pay for their lunch and obtain their pickup ticket, then continue to the lunch pickup zone, before finally using the dining rooms to eat their lunch.
- Candy user (student or general public eating in the dining hall), so called because they are mostly people who come into the dining hall to buy a snack. The normal route for these users is to enter through the main door and go to the cash register to pay for their snack and get their pickup ticket, before going over to the candy zone to take their purchase. These people can either sit in the dining room to eat, or leave the dining hall through the main door.
- Non-consuming users, who are mainly people who do not buy in the dining hall. However, they use the infrastructure for other purposes, such as accompanying another student, watching TV, studying, and more actions. When these people enter the main dining hall door, they can go use the dining room areas.

User behavior is reflected in the cash register waiting lines to pay, in order to pick up their purchase in the candy zone, or to get their lunch in the lunch zone. The preceding point depends on the time when the dining hall is used.

The different dining hall users' routes appear in Fig. (**2**).

The performance measurement to be monitored by the simulation model is the total capacity at time t, which is defined as the sum of users within both consuming areas and waiting lines at a time t. In other words, those zones where users agglomerate are considered to compute capacity. In Fig. (**2**), these zones are Dining rooms 1 and 2, waiting lines at the Cash registers, waiting line in Candy zone and waiting line in Lunch zone.

The computerized model was developed with ProModel®. This simulation software is a powerful and user-friendly commercial simulation package, designed to effectively model any discrete-event processing system. It also has continuous modeling capabilities for modeling flow in and out of tanks and other vessels.

2.4.2. Analysis Procedure

The preceding points lay the groundwork for the final model, which will be analyzed as follows:

- Developing a baseline model: Based on gathering operational data (service times, waiting, number of customers served, etc.), a statistical analysis will be done to establish the random behavior associated with service functioning events. By using goodness of fit tests, we intend to estimate the probability distributions defining these events. The estimated distributions will allow us to carry out the simulation based on the data obtained, and will comprise the baseline scenario. The model monitoring variable is the number of users within the service system by time unit. The goodness of fit test was carried out with StatFit software.
- Sensitivity analysis: Three scenarios are considered: (1) Sensitivity analysis 1, describing the behavior of the number of users in the service considering overall flow increases. This increase is estimated based on the report about projected undergraduate major enrollments, done by the administration and infra-

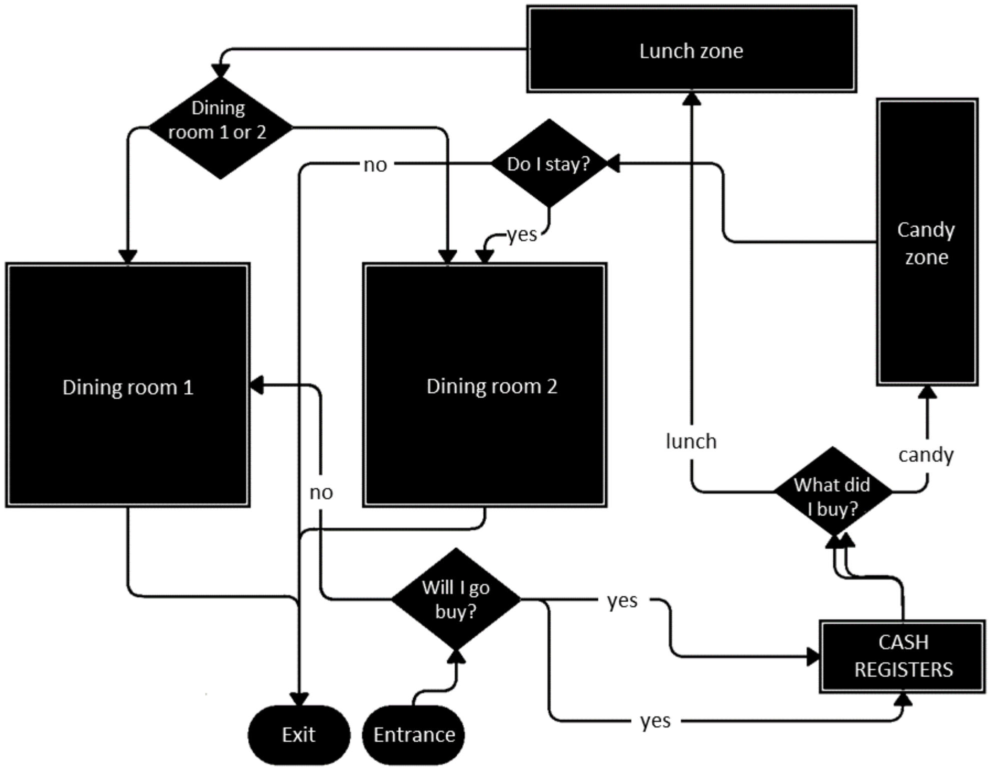

Fig. (2). Layout and behavior in student flow in the UCM food service.

structure directorate. (2) Sensitivity analysis 2, describing the behavior of the number of users in the service when the peak hour is decongested. For this, the model is sensitized to consider a "dosing" of user numbers during a time lapse greater than peak time. (3) Sensitivity analysis 3 is a combination of the previous analyses. Here, we increase user numbers before the peak hours (in order to decongest the peak time of the current scenario) as well as increasing the lunches which did not require cash register service. This meant that the user was able to obtain their lunch pickup ticket without going to the register, allowing them to go directly to the lunch pickup zone. In practice, this could be equivalent to using ticket dispensers outside the premises, or using mobile apps for distribution.

3. RESULTS

3.1. Arrivals and Service Times

To analyze the results of the simulation model, we began by recreating the actual operational scenario faced by the UCM dining hall, which is taken as the model baseline. The estimation performed considers the determination of total capacity in lines and consumption zones. To perform the simulation, we considered the probability distributions associated with the arrivals of entities (users) into the system together with waiting and service times (Table **1**).

Table **1** shows that users seeking to buy lunches have a system arrival distribution with a Triangular (20,835,835) (minimum, mode, maximum). Based on concessionary records, we determined that 80% of users went to the registers to make their purchases, while 20% went directly to the lunch bar.

Table 1. Entry (Arrival) Distributions and Times by Event Time Happening in the Dining Hall.

Event	Time / Distribution
Lunch user arrivals	Triangular (20,835,835)
Candy user arrivals	Normal (150,60)
Various user arrivals	5% dining hall capacity
Non-consuming students' dining hall stay time.	U (75±15) minutes.
Cash register service.	U (45±15) seconds.
Candy hand-over.	U (3±1) minutes.
Candy consumption in dining rooms 1 and 2.	U (20±5) minutes.
Lunch handover when passing by pickup bar.	U (45±15) seconds.
Lunch consumption before 13.15 hrs.	U (30±15) minutes.
Lunch consumption between 13.15-14.00 hrs.	≈ 20 minutes.
Lunch consumption after 14.00 hrs.	U (10±5) minutes.

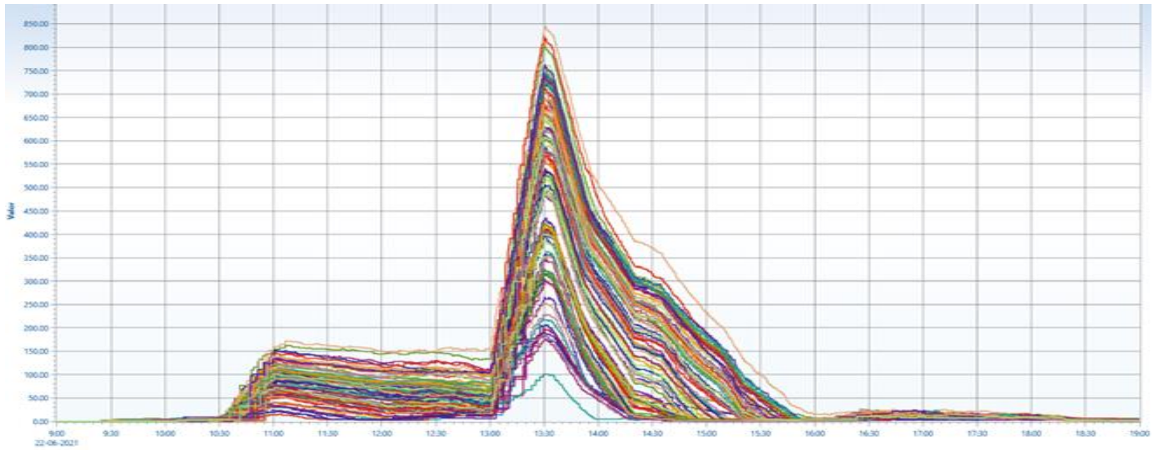

Fig. (3). Behavior of total capacity (users) for 100 iterations under the baseline scenario.

The second type of users who bought candy, called candy students, had a Normal distribution (150, 60) (mean, standard deviation), which was slightly over-estimated in its parameters since the concessionary data were only available for one service register.

Finally, the third user type, called the non-consuming student, was estimated at 5% of dining hall capacity.

Table **2** describes the behavior of daily student flow at different times. Records from the service operator allowed us to determine the distribution, which showed a peak for lunch requests between 13:00 and 13:30 hrs. This allowed us to distribute the random number of daily arrivals during the operating day. The distribution for users who bought candy was also estimated and processed.

Table 2. Daily Arrival Distribution by Type of Student Analyzed.

Service Hours Per Day	Lunch Student Distribution (%)	Candy Student Distribution (%)
9:00-10:00	---	1.00%
10:00-10:30	---	2.00%
10:30-11:00	---	60.00%
11:00-12:00	---	5.00%
12:00-13:00	5.00%	5.00%
13:00-13:30	94.80%	1.00%
13:30-14:00	0.14%	1.00%
14:00-14:30	0.05%	0.00%
14:30-15:00	0.01%	0.00%
15:00-16:00	---	0.00%
16:00-17:00	---	15.00%
17:00-18:00	---	10.00%
18:00-18:30	---	0.00%

The simulation model is executed with these data, considering 100 iterations (days) of system functioning. Each iteration records total capacity value (user numbers) during the working day, i.e., from 9:00 to 18:30 hrs.

3.2. Baseline Scenario Analysis

Fig. (**3**) presents the behavior of total service capacity (users) for the baseline scenario, considering 100 model iterations (each iteration is visualized with a different color). Our result was that the average peak capacity is 536 users. The horizontal axis represents times of the day, and the vertical axis shows capacity values (number of users) within the system. Peak use occurs between 13:00 and 13:30 hrs.

Fig. (**4**) shows the distribution (histogram) of maximum capacity values for each iteration executed under the baseline scenario. We can see that the capacity of 500 places is exceeded over 60% of the time.

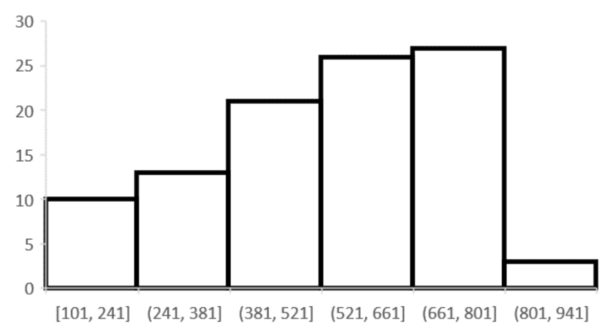

Fig. (4). Maximum capacity histogram (horizontal axis) under baseline analysis.

Fig. (**5**) shows the maximum capacities of the dining room 1 and 2 zones for the 100 iterations. The maximum capacity value recorded for both dining rooms is 302 users, while on average 237 students occupied dining rooms 1 and 2.

Subsequently, with the baseline already validated, sensitivity analyses were done to study the behavior of capacity under changes in the parameters associated with user flow. It should be remembered that total capacity at a moment in time is defined as the total number of users waiting at the registers, in the lunch and candy zones, and in the locations associated with dining halls 1 and 2.

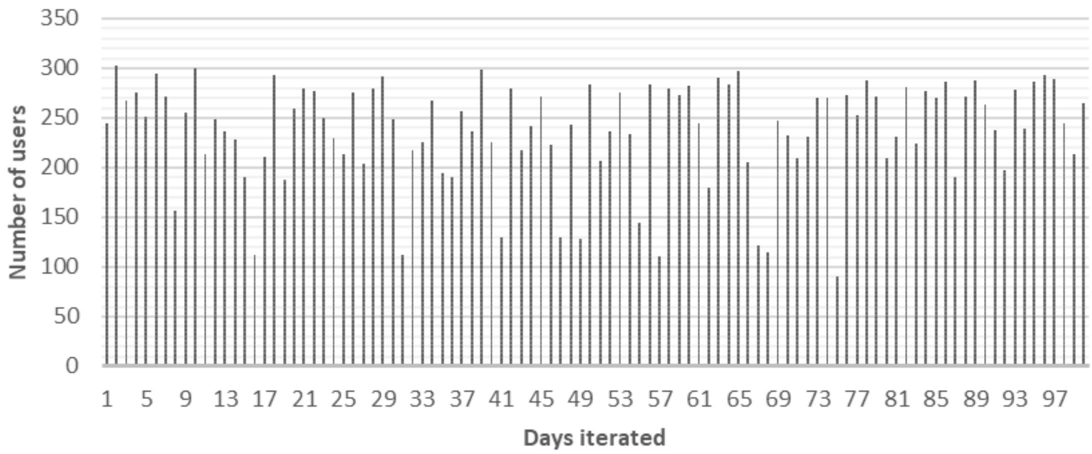

Fig. (5). Total maximum capacity of dining halls 1 and 2 in the baseline scenario.

Table 3. Projection of Undergraduate Enrollment Increases.

Year	Enrollment	Variation %
2020	7616	---
2021	8085	6%
2022	8941	11%
2023	10064	13%
2024	10964	9%
2025	11814	8%
2026	12464	6%
2027	12864	3%
2028	12964	1%

3.3. Sensitivity Analysis 1

In this scenario, the user flow is increased by 13%. This value is obtained based on the report projecting enrollment in undergraduate programs, according to the UCM administration and infrastructure directorate (Table **3**).

By carrying out this increase, we seek to put the model through an extreme flow scenario, considering that 13% is the highest value projected in terms of new entries for the University.

Fig. (**6**) shows the distribution of maximum capacity for Sensitivity Analysis 1, which then sees a 13% increase of the number of users in the model. Figure 6 shows that over 60% of the time, capacity exceeds 500 service places.

Fig. (**7**) shows total capacity behavior for 100 iterations (each iteration is a different color). The average peak is 567 lunches, 31 units above the baseline. X-axis is hours of the day; y-axis is maximum capacity value.

Fig. (**8**) shows that the maximum user value for both dining halls does not exceed 300 users after the 13% increase, while its average reaches 231 users.

3.4. Sensitivity Analysis 2

For this scenario, we sought to decongest peak hour in the dining hall. We thus increased the number of users by 35% before the peak congestion hours (between 12:00 and 13:00 hrs).

Fig. (**9**) presents the histogram associated with the maximum capacity values of the iterations in the scenario for sensitivity analysis 2. We considered an increase of 35% in the number of users before peak hours (between 12:00 and 13:00 hrs). This scenario shows that capacity values above 500 happen in around 25% of all iterations.

Fig. (**10**) shows the behavior of service capacity (total users) for the sensitivity analysis. The average peak is 397 lunches. The x-axis represents hours of the day, and the y-axis represents total capacity values.

Fig. (**11**) shows the maximum capacities of dining halls 1 and 2 for 100 iterations. The maximum value after a 35% increase in user arrivals before peak hours is 287 users, while on average it is 209 students.

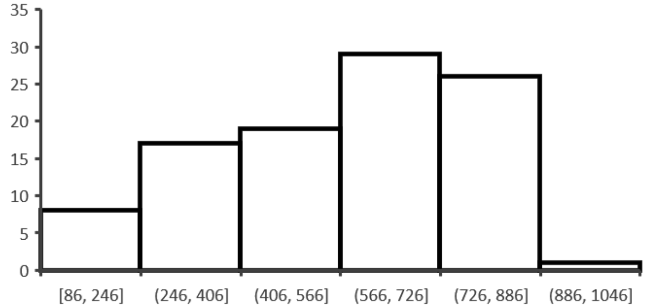

Fig. (6). Maximum capacity histogram (horizontal axis) under sensitivity analysis 1.

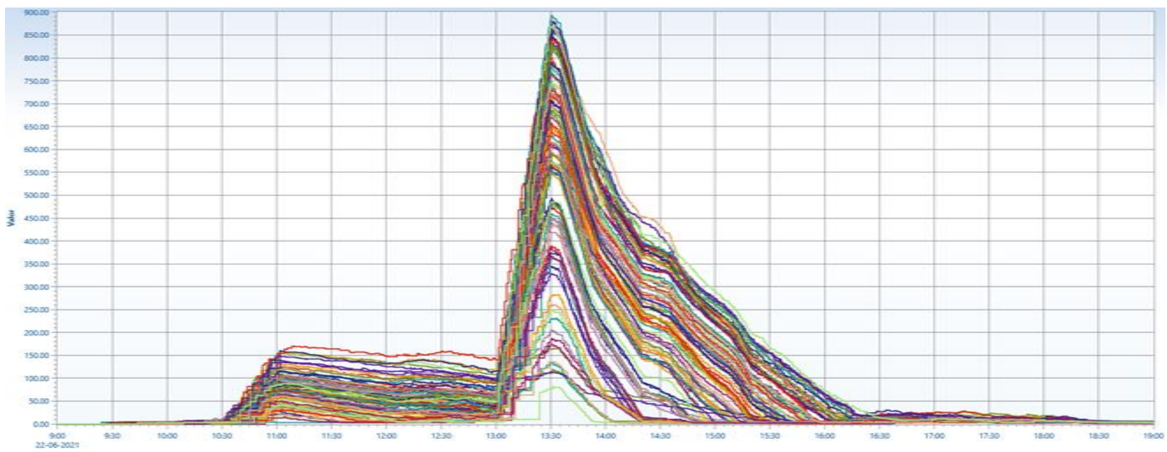

Fig. (7). Total capacity behavior (users) for the 100 iterations under the sensitivity analysis 1 scenario.

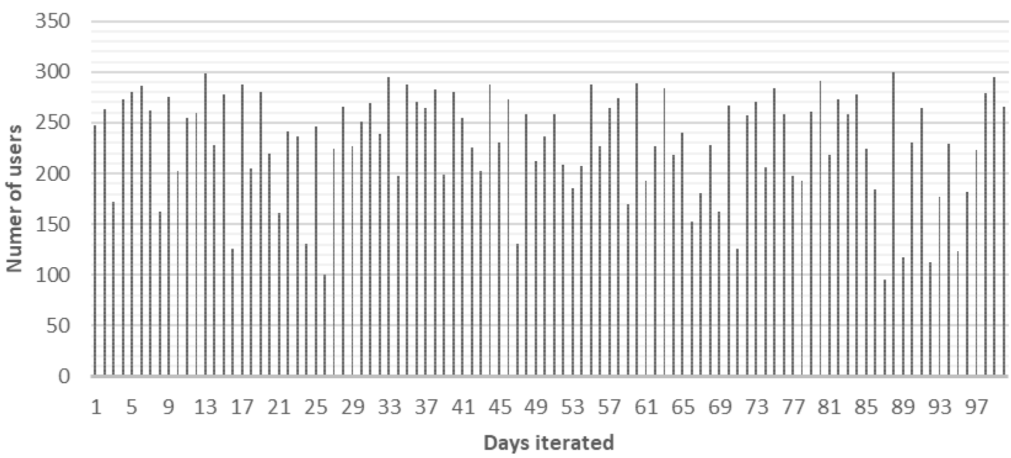

Fig. (8). Maximum total capacity of dining halls 1 and 2 under sensitivity analysis 1.

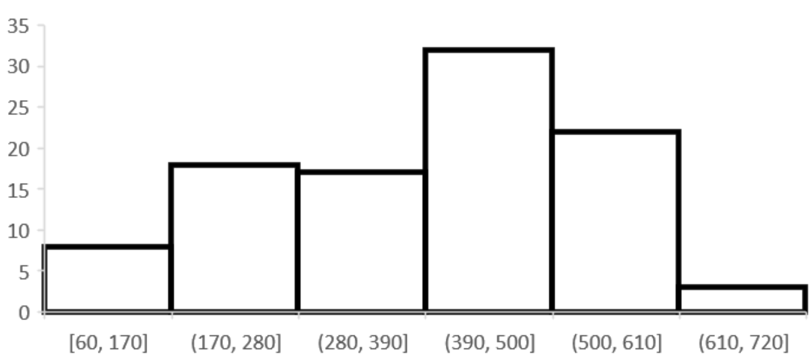

Fig. (9). Maximum capacity histogram (horizontal axis) under sensitivity analysis 2.

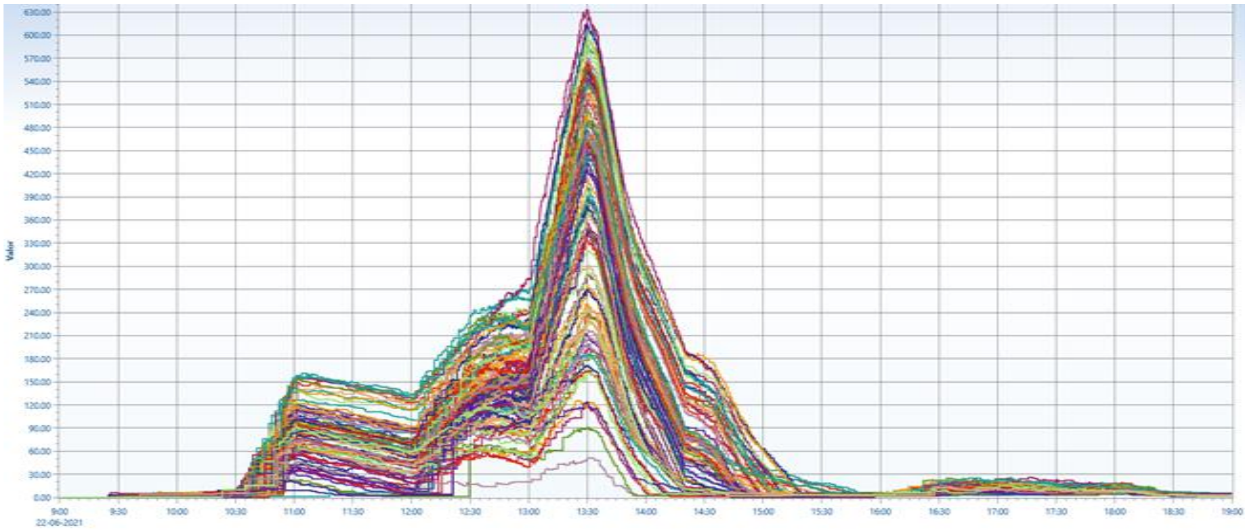

Fig. (10). Total capacity behavior (users) for the 100 iterations under sensitivity analysis 2 scenario.

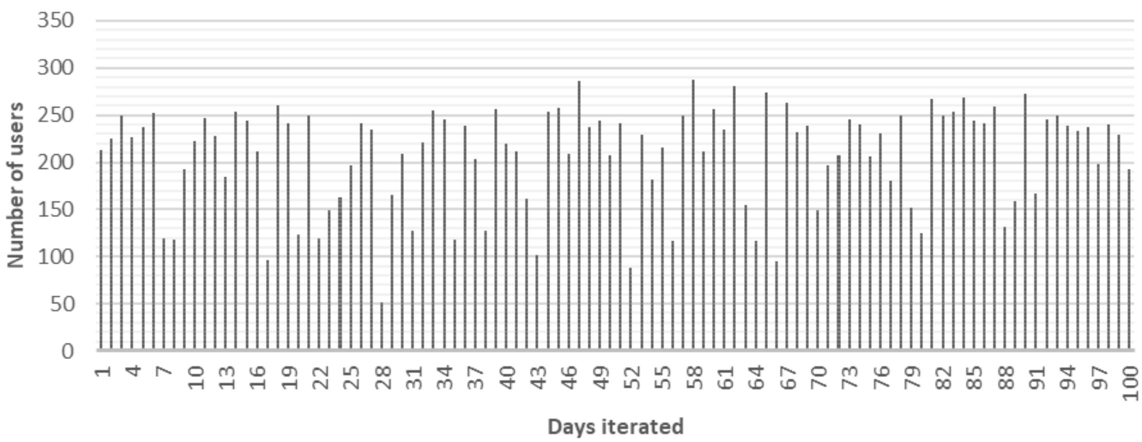

Fig. (11). Maximum total capacity of dining halls 1 and 2 under sensitivity analysis 2.

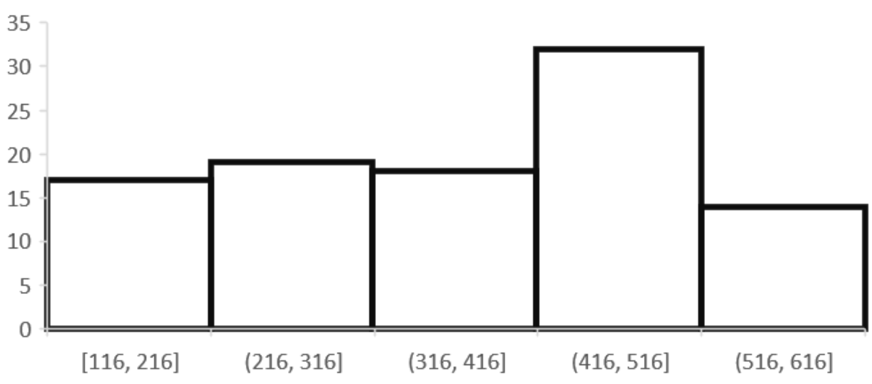

Fig. (12). Maximum capacity histogram (horizontal axis) under sensitivity analysis 3.

3.5. Sensitivity Analysis 3

A combination of the previous analyses was done, where users were increased before peak hours (to decongest the peak hours of the present scenario) along with an increase in users picking up lunch without using the cash register (lunch tickets external to the service).

Fig. (**12**) presents the histogram associated with behavioral distributions of maximum dining hall capacity for a typical operating day under the analysis scenario. We can see that maximum capacity when facing a 35% rise in the number of users before peak hours and a 60% rise in direct-to-line sales exceeds 500 users 30% of the time.

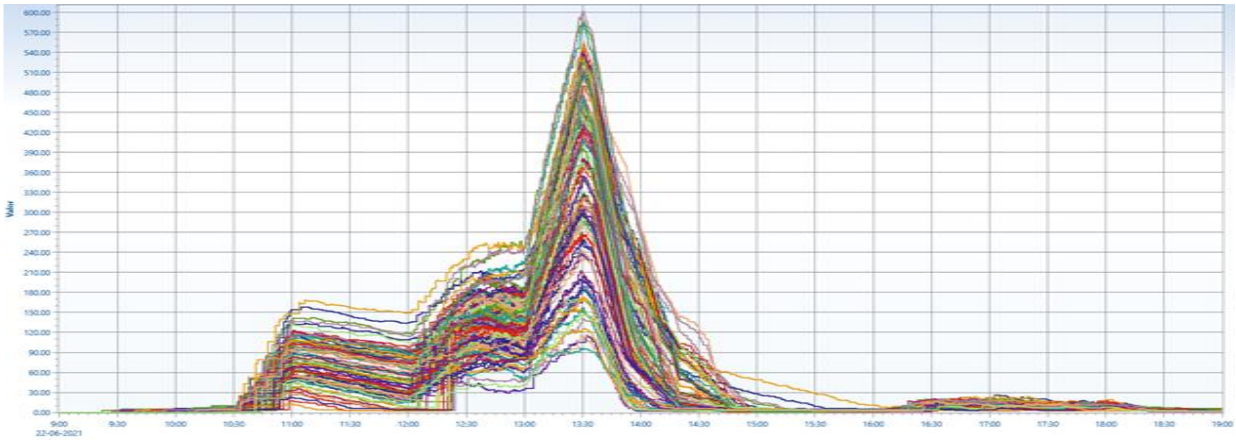

Fig. (13). Total capacity behavior (users) for 100 iterations under sensitivity analysis 3.

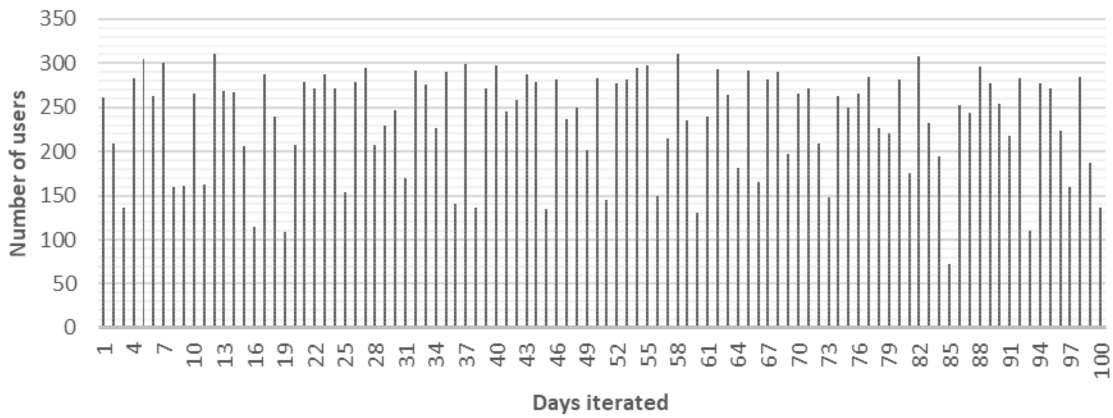

Fig. (14). Maximum total capacity of dining halls 1 and 2 under sensitivity analysis 3.

Fig. (**13**) describes the behavior of total capacity in sensitivity scenario 3. The average peak is 374 users; the horizontal axis represents the time of day. Each iteration is represented with a different color.

Fig. (**14**) shows the maximum capacities of dining halls 1 and 2. This graph was done based on sensitivity analysis 3. We can see maximum capacity in the face of a 35% rise in user numbers before peak hours, and a 60% rise in direct pickup from the lunch zone. Maximum total capacity value for dining halls 1 and 2 is no more than 311 users. Meanwhile, on average there are 236 people using the dining hall in this scenario.

3.6. Extreme Value Analysis

The work done by Fisher and Tippett (1928) provided the necessary theoretical grounding to approach extreme usage capacity events. It is well known that for n random Gaussian variables which are independent and identically distributed (IID), their maximum value is asymptotically bounded by expression (1).

$$\mu + \sigma\sqrt{2\log n} \tag{1}$$

Where μ and σ are the median and standard deviation, respectively.

The Fisher and Tippett theorem lets us establish that under regular conditions, the distribution of a sequence of random maximum values and generated IID converges asymptotically towards a GEV distribution, whose density H_c is given by equation (2)

$$h(x;u,b,c) = \frac{1}{b}\left[1 + c\left(\frac{x-u}{b}\right)\right]^{\left(\frac{1}{c}\right)-1} \exp-\left[1 + c\left(\frac{x-u}{b}\right)\right]^{-\frac{1}{c}} \tag{2}$$

for $1 + c\left(\frac{x-u}{b}\right) > 0$, where $\mu \in \mathrm{R}$ is a location parameter, $b \in \mathrm{R}$ is a scale parameter, and $c \in \mathrm{R}$ is the form parameter. For different values of c, this distribution contains the Fréchet ($c > 0$), Gumbel ($c = 0$) and Weibull ($c < 0$) distributions.

A goodness of fit test was done based on the Kolmogorov-Smirnov test to establish the data fit level on total capacity obtained from the baseline scenario, with these results:

Kolmogorov-Smirnov statistic	=	0.08416
P-Value	=	0.45
Parameters c, u, b	=	-0.485, 478.87, 203.80.

Since a P-Value above 0.1 was obtained, the fit to the GEV distribution is confirmed (Clauset *et al*., 2009). We can thus estimate the probability of exceeding the 500-seat capacity, which is given for the base line by $P\ (x \geq 500) = 0.593$.

4. RESULTS, ANALYSIS, AND CONCLUSIONS

The aim of this study was to describe the behavior of capacity in university food services. To this end, we reviewed the behavior of food services at Universidad Católica de Maule.

Sensitivity analyses allowed us to establish possible system behaviors under future operating conditions. In particular, we determined that by increasing enrollment numbers, total capacity exceeds 500 service points. However, dining hall usage level does not surpass 500 users. This situation also appears in the other sensitivity scenarios. Together, the analysis of extreme values supports that there is a considerable chance of exceeding 500 service points. We also determined that carrying out policies based on decongesting waiting systems by making students use the system before peak hours does not generate any significant drop in total capacity peaks. Finally, by implementing a combined sensitivity strategy considering the two previous scenarios, we found better results, since total capacity (users in the system) does not exceed 500 service points.

Sub-utilization of the dining halls could indicate the existence of a "feeling" of excessive agglomeration, which would be mainly concentrated in the waiting zones (lines at cash registers, lunch pickup zones, and for candy). This "sensation" could be considered as a "psychological service component", causing a perception of infrastructure overuse and lack of space. Users normally must wait to access products or services, since available service capacity may be insufficient to instantly handle the demand. This idea aligns with Alvarado and Trespalacios (2016) who address the psychological effects of waiting. The authors indicated that an important factor for approaching situations generated by waiting is to continually seek operational measures to improve user satisfaction while they are not being served, since wait times can never be totally eliminated from a service.

From an operational perspective, implementing a pay totem outside the service or mobile applications for early purchasing could help decongest the system, mainly at the cash registers. Incentivizing the use of more extended lunch times could considerably reduce usage peaks. These measures are supported by the results of Sensitivity Analysis 3, where a combined action was more effective.

Theoretically speaking, the problem addressed by this study is related to an extreme value situation that needs to be addressed in operational terms. Hence, this work has introduced the GEV distribution as a useful tool to strategically plan food service operations in terms of the likelihood that an overcapacity event occurs. In this regard, the authors suggest Abdulali et al. (2022) which reviews the use of the GEV distribution in application scenarios.

Future studies may go deeper into studying the psychological component for university users, and how such a component could be included within a simulation model. For example, the development of simulation approaches capable of including the propositions contrived by Maister (1984) could be worthy of investigation.

LIST OF ABBREVIATIONS

GEV	=	generalized extreme value
IID	=	independent and identically distributed
UCM	=	Universidad Católica del Maule

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding this work.

ACKNOWLEDGEMENTS

The authors thank the Dirección de Presupuestos – UCM for its collaboration in doing this work.

REFERENCES

Abdulali, B. A. A., Abu Bakar, M. A., Ibrahim, K., Ariff, N. B. M., & others. (2022). "Extreme Value Distributions: An Overview of Estimation and Simulation". *Journal of Probability and Statistics*, 2022.

Alvarado, Jorge A. and María C. Trespalacios. 2016. "Understanding the Evaluation of Waiting Time from Consumer Psychology: Effects of Expectations and Time Fillers." *Innovar* 26(62):57-68.

Ansari, Aysha, Emily García, Samuel Jih and Amrita Ray. 2008. "Simulation and Analysis of the Hill Dining Center." *Industrial Operations Engineering* 474(Simulation Project), 1-9.

Clauset, Aaron, Cosma R. Shalizi and Mark Newman. 2009. "Power-law Distributions in Empirical Data." *SIAM Review* 51(4):661-703.

Fisher, Ronald A. and Leonard H. Tippett. 1928. "Limiting Forms of Frequency Distributions of the Largest or Smallest Member of a Sample." *Mathematical Proceedings of the Cambridge Philosophical Society* 24(2):180-90.

Gil, Cristian, Pablo C. Manyoma and Juan P. Orejuela. 2016. "Simulation-optimization Model to Determine the Installed Capacity of an Educational Services System." *Revista Lasallista de Investigación* 13(1):141-55.

Harrell, G. R. B. C. K. (2022). *Simulation Using Promodel 2nd Edition by Charles R. Harrell, Biman K. Ghosh , Royce O. Bowden B01_0247*. McGraw-Hill.

Kambli, Ashish, Akhouri A. Sinha and Sharan Srinivas. 2020. "Improving Campus Dining Operations Using Capacity and Queue Management: A Simulation-based Case Study." *Journal of Hospitality and Tourism Management* 43:62-70.

Kim, Woo G. Christy Y. Ng and Yen-soon Kim. 2009. "Influence of Institutional DINESERV on Customer Satisfaction, Return Intention, and Word-of-mouth." *International Journal of Hospitality Management* 28(1):10-7.

Klassen, Kenneth J., Elzbieta Trybus and Arundhati Kumar. 2005. "Planning Food Services for a Campus Setting." *International Journal of Hospitality Management* 24(4):579-609.

Kwun, David. 2011. "Effects of Campus Foodservice Attributes on Perceived Value, Satisfaction, and Consumer Attitude: A Gender-difference Approach." *International Journal of Hospitality Management* 30(2):252-61.

Liang, Xi and Shuai Zhang. 2009. "Investigation of Customer Satisfaction in Student Food Service: An Example of Student Cafeteria in NHH." *International Journal of Quality and Service Sciences* 1(1):113-24.

Maister, D. H. (1984). *The psychology of waiting lines* (pp. 71-78). Boston: Harvard Business School.

Mensah, Ishmael and Rebeca Mensah. 2018. "Effects of Service Quality and Customer Satisfaction on Repurchase Intention in Restaurants on University of Cape Coast Campus." *Journal of Tourism, Heritage & Services Marketing* 4(1):27-36.

Sargent, R. G., & Balci, O. (2017). "History of verification and validation of simulation models". *2017 Winter Simulation Conference (WSC)*, 292–307.

Tang, Tie-Qiao, Bo-Tao Zhang and Chuan-Zhi Xie. 2019. "Modeling and Simulation of Pedestrian Flow in University Canteen." *Simulation Modelling Practice and Theory* 95, 96-111.

Too, Eric G. 2011. "Capability for Infrastructure Asset Capacity Management." *International Journal of Strategic Property Management* 15(2):139-51.

Velasquez, Pablo, Juan P. Cabrera and Cristiam A. González. 2011. "Methodology to determine the installed capacity of an academic program." *Estudios Gerenciales* 27(121):143-58.

Yu, Fangyan, Xiong Na, Liang Chen and Yanping Xu. 2022. "Design of Risk Prevention and Early Warning System for EPC Mode of University Infrastructure Project." Pp. 1131-7 in *Frontier Computing Proceedings of FC 2021*, edited by J. C. Hung, N. Y. Yen and J. Chang. Singapore: Springer.

Received: Nov 30, 2022 Revised: Nov 05, 2022 Accepted: Dec 30, 2022