Sizing A University Dinning Facility Using Optimization Based on Discrete Event Simulation

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***Abstract*– The constant increase in student populations and fluctuations in the schedules of university students impact infrastructure decisions and resource allocation in university service facilities such as dining halls. It is necessary to evaluate these fluctuations and, based on projections, determine the sizing of infrastructure and resources that allow attention within adequate operational levels of student services on university campuses. Discrete Event Simulation (DES) allows us to represent the service processes in the canteens, capturing data and trying to reflect the stochastic behavior of arrivals in order to then propose a model based on optimization that allows us to identify the optimal sizing of all the resources involved. attention. The experimentation of scenarios with the model and frequent runs based on population updates of the data based on projections to the last semesters, allows for a preventive response to ensure an adequate level of service.**

Keywords—Discrete event Simulation, Optimization based on simulation, Capacity allocation, Resource Optimization.

I. INTRODUCTION

University dining halls play a critical role in the student experience and the overall functioning of educational institutions. These spaces not only provide food for students, but also serve social, cultural, and wellness functions. However, despite their importance, university dining facilities face a number of common challenges and issues that impact their effectiveness and quality. Among the many issues associated with managing dining facilities, one of the most important is from an operational perspective. Overcrowding and long lines in dining halls are common problems, especially during peak hours. This can cause student frustration and reduce service efficiency. Lack of staff, inadequate space or poor planning can contribute to this problem. In critical scenarios, it can limit the attention of enough students, administrators, and professors because of the inability to adequately plan for infrastructure changes according to fluctuations in the university population and thus provide adequate service levels. This creates the need for a sizing tool that can use historical data, make growth predictions, and size the dining infrastructure and service level according to the incoming scenarios in order to adequately respond to changes that can be easily predicted based on these numbers.

Discrete Event Simulation (DES) models have emerged as an essential tool for managing and optimizing complex systems in a variety of domains. In the university context, where operational efficiency and student experience are priorities, the use of DES has gained popularity to address challenges in subsystems such as campus logistics, resource planning, and policy evaluation. In this scenario a proper tool that can serve to solve this dinning facility sizing problem is Optimization based on Simulation. Built over a DES model of the dining facilities will allow us to represent the operational flow of dining service and determine the required level of resources of different kinds (related to infrastructure as tables or to direct service to students as staff) based on an objective service level (specified usually as maximum expected queue time or percentile) that wants to be achieved as goal.

To present this work, Section 2 presents the literature review related to the use of discrete event simulation in university service systems. Section 3 presents the problem statement. Section 4 establishes the model proposal for this problem, while section 5 presents the detailed case study approached. Finally, in Section 6, the results are presented and analyzed to get the conclusions for the paper.

II. LITERATURE REVIEW

The use of DES in higher education administration has grown significantly in recent decades, reflecting the need for innovative solutions to complex challenges. In the early days, SEDs were primarily applied in areas such as academic records management and scheduling. For example, the pioneering work of [1] laid the foundation for using SEDs to model student flows in academic records. Over time, however, its application has expanded to a variety of university subsystems, including campus logistics, institutional policy evaluation and resource planning.

Efficient management of campus logistics is essential to ensure the safe and efficient mobility of students, staff, and visitors. DES have been used to model and optimize a variety of campus logistics processes, including the transportation of people and goods, the management of vehicular and pedestrian traffic, and the distribution of resources such as food and supplies. Also, there are many DES around situational problems around campus logistics. For example relating to the recent COVID pandemic [2] presented a DES model for optimal design and resource allocation of mobile testing stations to assure rapid results to tested students. [3] develops a DES for the optimal service of a university campus bus service, determining the optimal scheduling based on a fixed bus fleet.

DES have also been used to evaluate the impact of institutional policies on student dynamics, academic performance, and other aspects relevant to the functioning of the university. By simulating different scenarios and policies for admissions, tuition, scholarships, and other variables, universities can anticipate and mitigate possible undesirable effects and identify opportunities for improvement. For example, [4] developed an agent-based simulation model to evaluate enrolment management policies at universities and analyze their impact on the equity and efficiency of the education system. [5] used a DES with e-learning technologies in order to improve teaming processes in a university. [6] presents a DES model to help evaluate the tutoring process in a university in relation to the academic performance and also the student satisfaction.[7] developed and implemented a DES approach for PLC to help in the academic evaluation of programs related to Mechatronic and Robotic courses.[8] present a DES used in Monmouth university to assist administrators with departmental course scheduling for undergraduate courses. Reference [9] focuses on a DES on a Italian University to evaluate and optimize the level of accountability in the purchasing process.

The efficient allocation of resources is essential for the optimal functioning of a university. DES have been used to model and optimize the allocation of resources, including classrooms, laboratories, faculty, and support services. By simulating different scenarios and allocation policies, universities can identify opportunities for improvement and make informed decisions to maximize resource utilization and enhance the educational experience of students. We can find many examples of this kind of applications in the literature: [2] conducted a review of the state of the art in hybrid simulation modelling in operations research, highlighting its applicability in optimizing university resources. [10] presents a resource scheduling model of the flight training facility of Daytona Beach University. [11] developed a clustered DES to allocate and decide around adding and eliminating computers in a university campus, and decide over different architecture and operating systems to optimize a heterogenous. [12] modelled a university blood laboratory to analyze processes and solve bottleneck operations.

Within campus logistics there are many works around campus teaching facilities such as clinics in medical universities. In this sub domain we can see works such as [13] that uses a hybrid DES , Agent Based Model (ABM) for staff planning in the campus clinic facility related to overdue pregnancy outpatients. [14] proposed a DES that permits to study the workload and task distribution of nursing staff in a university clinic. [15] presents a DES model of the surgical centre of an university hospital that allowed resource allocation under low volume of surgeries. [16] developed a DES to evaluate critical scenarios for patient volume increase in a university hospital in Akershus. We can see also the work of [17] that helps with decision support in a university hospital.[18] presents the classical DES to optimize queue times for a university clinic adding many what-if scenarios to increase the robustness of solutions proposed.

These cases have shown us that DES applications have been running over the last two decades in many university subsystems, and specially in efficient resource allocation. Within this field infrastructure sizing is one optimization application based on this kind of applications. Even though there was no specific type in a university dining facility the plenty number of examples of DES usage allow the feasibility of applications of this tool to deal with decisions regarding resource allocation related to infrastructure sizing.

III. PROBLEM STATEMENT AND PROPOSAL

Within the management of dining facilities in universities, a critical problem is being able to offer adequate infrastructure in terms of capacity to serve the total volume of students, administrative staff and professors, particularly during peak lunch periods. It is common to observe in this type of system a massive agglomeration of students during peak lunch hours, mainly that has a fluctuating behaviour since it is related to the day of the week and is repeated around each exact hour around lunch time (12, 1, 2, 3 pm). This happens every day of the week, the students who require eating in the dining rooms can fluctuate depending on whether they have classes scheduled during the day and decide to stay in the lunch time slot, in addition, the specific time to go to the dining room is also influenced by the students themselves. specific time ranges. I mean that it is common for classes to end at exact times (again 12, 1, 2 and 3pm) and at that moment, depending on the distance to the dining room, massive movements begin to be generated that collapse the queues in the minutes following those close to said times. hours. After these time breaks, students may continue to arrive but less frequently until the scenario is repeated at the next exact time. In terms of flow this shows a time between arrivals highly correlated with time. This generates a multimodally repetitive peak arrival distributions in the arrival at the start of service queue in the dining rooms.

Another fundamentally critical impact is with respect to the incremental population size semester by semester of students and administrative and teaching staff if they are served by the same cafeteria. In this context, sufficient physical spaces must be offered so that the demand during peak hours for food consumption can be met at the tables and chairs in the dining rooms. It has been shown that the inability of this system to respond to this need can generate the consumption of food in inappropriate places, which can generate contamination or deterioration of other campus infrastructure, or in other scenarios, displace unsatisfied demand towards food consumption locations. food that does not necessarily safeguard the nutritional and healthy requirements that are cared for and supervised on the university campus. The determination of the capacity of the tables and chairs, as well as their location and modularity are not necessarily directly proportional to the quantity but also to consumption habits, making it necessary to think about an appropriate design of the dining rooms in conjunction with this capacity. This must allow having a modular and non-modular offer to satisfy the group or individual consumption pattern of the student population to be considered adequate sizing.

The joint approach highlights a problem that needs to be solved quantitatively with a sufficiently robust decision-making aid tool. In the first phase, a tool is required that allows taking the current and projected data and representing the process logic with all the possible particularities observable. Once this logic is built, it is necessary to seek to define suitable levels of service for the dining rooms, based on standards for the sector or a maximum desirable waiting time so that the sizing of all the resources involved in the dining room service can be optimized. human resources, and infrastructure to meet the desired service times for students and consumers in general in the dining halls. What is proposed under this context is precisely the use of a tool that has been widely used in systems within universities on issues related to the allocation of resources such as the DES, since the literary review demonstrates its value in solving this problem. type of problems. On this basis, it is also necessary to develop an optimization model based on simulation for the optimal sizing of resources and recommend the resource and infrastructure allocation decisions to be implemented periodically after updating the data to the model in repetitive periods.

III. THE SIMULATION MODEL OF THE DINING FACILITY

The simulation model of the dining facilitate includes the sub models shown in Figure 1. The general overview model logic contains a Definition and configuration sub model where the general setup of the model is defined, and all necessary DES definitions are stated. The data reading sub model handles the connection to the external files that contains data related to the student arrival per type of dish and time frame break down into 5 minutes intervals. The general students are generated and start the logic of the model in two possible sub models: Virtual or in person dish purchase. The first implies that the students bought their dishes before lunch time using a virtual platform host by the university and the second one that they buy their dish directly in the dining facility when they arrive at lunch time. After buying their dishes, there are two general types of possible purchases, the standard orders, and the special orders. Standard orders in university systems usually refer to standardized plates of fixed prices and limited known quantities that the university offers each day. Standard orders contain an entrance, main dish and dessert and a drink. Beside from dish also dining facilities offer a much abroad variety of dishes with varying number and types each day that usually have a higher price. If the student bought a standard order they must go into a sequential flow of sub models: Entrance pick up, Main dish pick up and Dessert pick up. If the student bought a special order all its content can be pick up in a different space in the dining facility that we will label as the Special orders pick up. Once the students got their orders, they usually go to find an available place alone or with their groups to get a seat and get lunch. After finishing they exit the system. Rockwell Arena was used to build up the simulation model.

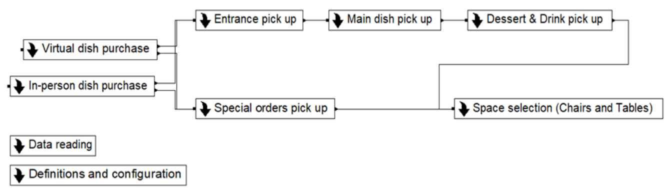

Fig. 1 Sun model structure for the simulation model

The detailed explanation of each sub models to further grasp the particularities of the system will be explained in the next sections.

A. Data Reading

In this sub model, the student information contained in an external file is extracted and load into the model. The data from each student who bought a special or standard order is transferred to variables and attributes contained in the model, so it will be available for the entity definition and the dish selection presented in the overall logic explained earlier.

To record each student the data related to the date of the transaction, time of the purchase, mode of purchase, student code and type of dish purchased is read from the external file. This external file is directly obtained as a detailed log report from the university information system. If the purchase was other than a standard order extra data is also recorded containing the exact list of contents in the special order, and the amounts of each of this contents (a student can only buy 1 standard order of any subtype due to university restrictions, however in a special order there is no limit on how many items of each type available he can buy).

B. Definitions and configuration

In this sub model two main types of Elements are defined. In the first place the overall setup Elements as Replicate and Project are defined stating the base time unit of the model, number of replications and the overall fields for automatic reporting with the Siman Summary Report. In the other side all the definition Elements are stated including the Queues, Resources, Stations, Sequences, Attributes, Variables, Expressions, Files and Failures elements.

C. Virtual dish purchase

This sub model contains the general process logic for student who decide to buy their dishes using the university application / information system usually before lunch time each day. The process logic starts with the overall creation logic of student entities in this module and based on the attributes assigned to each student entity by the data reading module and an attribute defined to differentiate virtual or not virtual purchase (as a binary coded value) the ones with value of 1 represent student entity that will perform a virtual transaction and remain in this sub model, while the rest of student entities with value of 0 are directly translated to labels to the next sub model. It's important to mention that this sub model doesn't actually include resource that limit transaction in terms of queues or tangible resources, since the actual purchase is virtual. The entities immediately after creation are put on a hold and directly redistributed to one of the possible arrive dates directly to the standard order pick up (in this case starting sub model is Entrance pick up) or to the Special-order pick-up module depending of the purchase they made.

D. In person dish purchase

Student entities with value of zero in the virtual purchase arrive in this module and they are assigned using a random distribution an arrival time to the dining facility. Since this student need to make the purchase in person, they must go thought a queue and a service process with a cashier resource to complete the purchase transaction. Statistics about queue number and times are collected in this sub module. Once the students complete the purchase, they could choose the same sub modules as students with virtual purchases, going to the Entrance Pick Up sub module if they bought a standard plate or to the Special order pick up if they bought a special order.

E. Entrance pick up

This is the first sequential sub model for student entities who bought a standard order. In this sub model students make a queue to pick the entrance of their standard order. Entrance is supplied from the kitchen and given to students by staff within this sub module. The sub module contains a linear and straightforward process logic with up to "k" staff for the process attention. The service time for this process is obtained using stochastic variables obtained from sufficient samples using simple random sampling from times obtained within the model, Historical rate of failures is model also through a specific failure characterized and assigned to staff in this sub model. Automatic data collection includes queue numbers, times, and resource efficiency and number seized.

F. Main dishes pick up

This is the second sequential sub model for student entities who bought a standard order. In this sub model students make a queue to pick the main dish of their standard order. The main dish is supplied from the kitchen and given to students by staff within this sub module. The sub module contains a linear and straightforward process logic with up to "j" staff for the process attention. The service time for this process is obtained using stochastic variables obtained from sufficient samples using simple random sampling from times obtained within the model, Historical rate of failures is model also through a specific failure characterized and assigned to staff in this sub model. Automatic data collection includes queue numbers, times, and resource efficiency and number seized.

G. Dessert and drinks pick up

This is the third sequential sub model for student entities who bought a standard order. In this sub model students make a queue to pick the dessert and drink of their standard order. The dessert is supplied from the kitchen and given to students by staff within this sub module. The same happens with drinks right after the dessert. The sub module contains a linear and straightforward process logic with up to "l" staff for the process attention. The service time for this process is obtained using stochastic variables obtained from sufficient samples using simple random sampling from times obtained within the model, Historical rate of failures is model also through a specific failure characterized and assigned to staff in this sub model. Automatic data collection includes queue numbers, times, and resource efficiency and number seized.

H. Special orders pick up

This sub model is for student who purchased a special order. Special orders can contain any number of different products unlike the standard order that has a standardized entrance, main dish, dessert and drink that have a continue mass production process in the dining facility kitchen. This means that even though the service process is direct and simple towards the student entity, an internal black box process runs with specific different times depending on the type of product included in the special order. To get the most accurate possible estimations for the process and based on the data read from the special orders many stochastic variables were sampled and analysed with input analyser to have a specific preparation time in kitchen reflected in different stochastic variables per dish and product. In case of multiple product preparations, the process is run in simultaneous meaning that even though the kitchen is a black box with not a high level of detail capacity at least for dish preparations is reflected for special orders. This will be referred as the kitchen capacity "m". Once the dish is prepared is delivered by the kitchen and handed to the student entity by another staff of capacity "n". The service time for this process (deliver of the plate) is obtained using stochastic variables obtained from sufficient samples using simple random sampling from times obtained within the model, Historical rate of failures is model also through a specific failure characterized and assigned to staff in this sub model. Automatic data collection includes queue numbers, times, and resource efficiency and number seized for both the kitchen and staff.

I. Space selection

In this final sub model, all student entities with an order in hands try to allocate a seat in the dining facility to eat their lunch. To simplify the logic and not overcomplicate with multiple possible preferences for allocation of table and chairs that can be seen in usual layout of dining facilities, the limited resources are considered within two different zones. Inside the dining facility and outside the dinning facility. In each zone there is a limited number of chairs available for student usage. Tables won't be considered a limited resource because in this type of systems modular arrangements are usually established allowing student to easily move tables around different possible small, medium sized or large sized tables to fit the student groups. Also, there is a system restriction that is common to observe in this type of sub systems in which chair or table reservation isn't allowed during peak times or using the tables and space for other different purposes than eating so this maximizes resource allocation during peak times for lunch consumption. Also, there is an important limitation in these systems that poses as a favourable element for logic simplification and that is that most of student go for standard orders, and since this is restricted to personal purchase and pick up the possibility of table reservation is severely reduced. Automatic data collection in this las sub models includes queue numbers, times, and resource efficiency and number seized.

IV. CASE STUDY

A dining facility in a private university in Lima, Perú is taken as a reference of a case study for this model. In this section, detailed information about of (1) the analysis of the information, (2) design of a simulation model of the dining facility operation and (3) validation of the model will be exposed.

A. *Input Data Analysis*

For the elaboration of the model, diverse sources of information are used. Among the main ones are the following:

• Dataset for order purchased obtained from the university information system reports,
• Resource capacity per dining facility
• Historical information from onsite sampling of service times per dining facility and process.

The information is analysed and classified to determine the input data of the model.

B. *Orders Purchased*

Figure 2 shows a small extract from the data set for orders purchased obtained from the information report systems.

Reserve	Code	Time	Hour	Minute	Second	Day	Month	Dining Facility	Dish	State	Name	Type
697795	00003568	8:27 a. m.	8	27	0	1	4	2	1	V	TEZEN RAMOS, PABLO	3
697796	20102646	8:29 a. m.	8	29	0	1	4	2	1	V	OLASQUIA LLAMOCA, MARIA LUISA	1
697798	20080478	8:30 a. m.	8	30	0	1	4	3	1	V	CANAL RODRIGUEZ, GABRIELA	1
697797	20084722	8:30 a. m.	8	30	0	1	4	3	1	V	RAMOS LLERENA, RICARDO ANDRE	1
697800	02005021	8:31 a. m.	8	31	0	1	4	2	1	V	ZAPATA RAMIREZ, GLORIA NELLY	3
697799	20090032	8:31 a. m.	8	31	0	1	4	2	1	V	FLORES SOTIL, DIEGO GERSON	1
697801	20088016	8:32 a. m.	8	32	0	1	4	2	1	V	AGURTO ZEGARRA, ANGELA MARIA	1
697802	20099092	8:32 a. m.	8	32	0	1	4	2	1	V	AGURTO ZEGARRA, NATHALY ALEJANDRA	1
697803	20101901	8:32 a. m.	8	32	0	1	4	2	1	V	AVALOS ROJAS, CESAR RICARDO	1
697807	20079042	8:33 a. m.	8	33	0	1	4	4	1	V	MAGNI CHINCHAY, MARTIN JOSE	1
697805	20100287	8:33 a. m.	8	33	0	1	4	2	1	V	CALVO AGUILAR, LUIS FELIPE	1
697804	20101906	8:33 a. m.	8	33	0	1	4	2	1	V	GONZALES ESPINOZA, LUIS ANTONY	1
697806	20112961	8:33 a. m.	8	33	0	1	4	2	1	V	MENDOZA MONTESINOS, LEONOR BISNARDA	1
697808	20078217	8:34 a. m.	8	34	0	1	4	4	2	V	PORCEL CORNEJO, TELY BLADIMIR	1
697811	20078232	8:34 a. m.	8	34	0	1	4	4	2	V	HERRERA ROMERO, TANIA	1
697809	20100395	8:34 a. m.	8	34	0	1	4	4	1	V	YZU ROSSINI, BRUNELLA	1
697810	20110922	8:34 a. m.	8	34	0	1	4	2	1	V	FLORES HUANCA, AXEL LEONEL	1
697812	20099007	8:35 a. m.	8	35	0	1	4	4	1	V	QUISPE DIAZ, JORGE MANUEL	1
697814	20051244	8:37 a. m.	8	37	0	1	4	2	1	V	CORDERO HIJAR, MAGRIT FELICITA	1
697813	20090227	8:37 a. m.	8	37	0	1	4	2	1	V	ARAUJO BARRIENTOS, ANTONIO	1

Fig. 2 Extract from the data se report of purchased orders

This data set contains the historical detailed purchase of every special and standard order from each dinning facility. This are read as attributes for each student entity created and contains the following data.

- Order ID
- Student code
- Time of purchase
- Hour's component of time of purchase
- Minutes component of time of purchase
- Seconds component of time of purchase
- Month component of date of purchase
- Date of purchase
- Dining facility ID
- Dining facility name
- Type of order
- Order description.
- Last state
- Transaction state
- Name of the student

All the aforementioned data are loaded into the model in the Data Reading sub model and transferred to different attributes in order to identify the type of order each student bought, the type of purchase made, the dining facility where he had his lunch and the time and date of the purchase so the described logic earlier and work around the classification for this attributes per student entity.

C. *Resource Availability*

For most of the described sub models there are different resources needed to run the model. For each of the following per dining facility the starting capacity for each day during the simulation horizon is obtained from the staff planning. The list of resources per dining facility includes the following:

- Staff for onsite purchases
- Staff for entrance pick up
- Staff for main dish pick up
- Staff for dessert and drink pick up

- Staff for special order pick up
- Kitchen capacity for special orders
- Chairs inside dining facility
- Chairs outside dining facility.

D. Onsite Sampling

To get the stochastic distribution of service times in all the different pick-up processes explained and the time for lunch consumption inside or outside data obtained from onsite sampling is obtained and analysed to find the variables that the model will use. Figure 3 shows for example the data sampled onsite in onsite order purchase in one of the dining facilities.

Data Information						CCI Format				
Day	Month	Year	Dining	Responsible	Format	Number	Hour	Minute	Second	Time instant
8	11	2023	Dining 1	Pedro Silva Vera	CCI	1				
8	11	2023	Dining 1	Pedro Silva Vera	CCI	2	11	38	15	11:38:15
8	11	2023	Dining 1	Pedro Silva Vera	CCI	3	11	38	29	11:38:29
8	11	2023	Dining 1	Pedro Silva Vera	CCI	4	11	38	45	11:38:45
8	11	2023	Dining 1	Pedro Silva Vera	CCI	5	11	39	29	11:39:29
8	11	2023	Dining 1	Pedro Silva Vera	CCI	6	11	39	56	11:39:56
8	11	2023	Dining 1	Pedro Silva Vera	CCI	7	11	40	23	11:40:23
8	11	2023	Dining 1	Pedro Silva Vera	CCI	8	11	42	41	11:42:41
8	11	2023	Dining 1	Pedro Silva Vera	CCI	9	11	43	46	11:43:46
8	11	2023	Dining 1	Pedro Silva Vera	CCI	10	11	46	47	11:46:47
8	11	2023	Dining 1	Pedro Silva Vera	CCI	11	11	47	35	11:47:35
8	11	2023	Dining 1	Pedro Silva Vera	CCI	12	11	47	46	11:47:46
8	11	2023	Dining 1	Pedro Silva Vera	CCI	13	11	48	10	11:48:10

Fig. 3 Extract from the data se report of purchased orders,

This online sampling also allows to characterize the arrivals to both the onsite purchase and the entrance pick up and special-order pick-up processes. This is analysed and characterize per small intervals and then used to models the onsite arrivals to the different dining facilities using a non-stationary exponential distribution based on the inverse of the average time per time interval. An example of this analysis is presented with the average times in the entrance pick up for all the dining facilities in Figure 4.

V. RESULTS AND DISCUSSIONS

Based on the simulation models described before as a mean to obtain the solution in terms of resource sizing for the dining facilities an Optimization based on Simulation model is build and run. In previous works we have already seen the value generated upon the usage of optimization based on simulation for resource sizing [19]. In this case the optimization will be run hosting every resource related to process service and infrastructure services meaning that all resources listed in section 4.1.2 will post as controls. The objective will be to reduce the complete transaction time in the dining facilities considering as constraints for the process not exceeding upon 5 minutes in average for any pick-up time in standard order pick up, and due to the additional kitchen delay, no more than 10 minutes in special order pick up in the facilities and no more than 3 minutes in queue times related to chair assignment for lunch consumption.

Average Service Time per Dining Facility

5 minute interval

Time interval	Dining 1	Dining 2	Dining 3	Dining 4	Overall
11:30:00 a. m.		01:20	00:41	02:07	00:55
11:35:00 a. m.	00:32	00:48	00:16	01:38	00:35
11:40:00 a. m.	00:57	01:01	00:21	01:07	00:40
11:45:00 a. m.	01:00	00:51	00:59	00:54	00:57
11:50:00 a. m.	00:46	00:42	00:15	00:51	00:29
11:55:00 a. m.	00:50	00:35	00:10	00:56	00:31
12:00:00 p. m.	00:47	00:52	00:57	01:04	00:56
12:05:00 p. m.	00:47	00:52	01:05	01:15	01:01
12:10:00 p. m.	00:49	01:00	01:08	01:32	01:07
12:15:00 p. m.	00:48	01:08	00:22	01:10	00:42
12:20:00 p. m.	00:53	00:53	00:17	01:18	00:39
12:25:00 p. m.	00:45	01:03	00:14	01:11	00:37
12:30:00 p. m.	00:45	00:49	00:12	01:19	00:32
12:35:00 p. m.	00:45	00:47	02:07	01:16	01:50
12:40:00 p. m.	00:45	01:03	02:53	01:41	02:28
12:45:00 p. m.	00:49	00:45	01:09	01:21	01:04
12:50:00 p. m.	00:46	00:45	00:28	01:41	00:45
12:55:00 p. m.	00:53	00:44	00:15	01:32	00:38
1:00:00 p. m.	01:04	00:58	00:05	01:28	00:46
1:05:00 p. m.	00:58	01:22	00:06	01:11	00:53
1:10:00 p. m.	01:07	01:18	00:08	01:22	00:49
1:15:00 p. m.	00:49	01:25	00:40	01:22	01:01
1:20:00 p. m.	00:43	01:08	00:13	01:25	00:47
1:25:00 p. m.	00:53	00:51	00:08	01:33	00:39
1:30:00 p. m.	00:47	00:47	00:15	01:30	00:35
1:35:00 p. m.	00:47	00:45	00:10	02:01	00:38
1:40:00 p. m.	00:42	00:44	00:12	01:36	00:33
1:45:00 p. m.	01:06	00:58	00:08	01:21	00:31
1:50:00 p. m.	01:04	00:49	00:09	02:03	00:39
1:55:00 p. m.	01:07	00:37	00:07	01:26	00:27
2:00:00 p. m.	01:14	01:34	00:08	01:34	00:36
2:05:00 p. m.	00:47	00:37	00:08	01:50	00:33
2:10:00 p. m.	01:36	00:37	00:10	02:04	00:36
2:15:00 p. m.	00:59	00:41	00:09	02:25	00:33
2:20:00 p. m.	00:38	00:54	00:09	01:51	00:24
2:25:00 p. m.		00:50	00:09	02:22	00:21

Fig. 4 Average service time per dining facility

Due to the nature of terminal type of the dining processes over 5000 simulations were run to find the proper solution combining all possible scenarios from control combinations. This led to an optimal solution respecting the stated constraints with a resource sizing as described in Table 1.

TABLE I
RESOURCE SIZING FOR DINING FACILITIES

Resources	Dinning facility			
	1	2	3	4
Staff for onsite purchases	1	2	3	2
Staff for entrance pick up	1	2	2	1
Staff for main dish pick up	2	3	4	2
Staff for dessert and drink pick up	1	2	2	2
Staff for special order pick up	2	2	3	2
Kitchen capacity for special orders	5	8	10	4
Chairs inside dining facility	105	182	350	142
Chairs outside dining facility.	98	152	422	128

These capacities correspond to acceptable values within the operating range defined by the university administrator. Under these results, it is also possible to ensure waiting times below the critical limits defined in the conceptualization of the problem. The results obtained consider a projected operating horizon of up to 1 years, at which time the historical data of the model built based on new data available for capacity planning of the next operating period must be updated based on the operational changes that are made. Based on these results we have shown the viable usage of Optimization based on simulation to be carried on in this type of university sub systems.

The use of discrete event simulation models in university subsystems has proven to be a valuable tool for improving operational efficiency, strategic planning, and informed decision making. From campus logistics management to resource planning and institutional policy evaluation, DES provide a flexible and powerful way to model, analyze, and optimize complex systems in university environments.

As technology and methodology continue to advance, the role of DES in higher education management is expected to continue to grow. Future research can address current challenges, such as obtaining accurate data and effectively communicating results, and explore new applications, such as simulating learning experiences in virtual environments. With interdisciplinary collaboration and a user-centered approach, DES models have the potential to transform university management and improve the educational experience for students and staff.

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