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Simulation-Based Optimization of Resource Allocation in Seasonal Recreational Facilities Using Discrete Event Simulation and Machine Learning

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Abstract. The study proposes a simulation-based optimization framework to surmount recreational facility operational inefficiencies via spatial design, guest flow, and staff allocation. Adopting Discrete Event Simulation (DES) and Machine Learning (ML), the research optimizes capacity planning and resource allocation in the face of dynamic seasonal demands. A year's worth of operations data was utilized for statistical distribution modeling of visitor interarrival times in RStudio, categorized into low, regular, and high seasons. The simulation model, developed in AnyLogic, uncovered service bottlenecks—particularly at ticketing counters and photo points. Validation results indicated close alignment with real-world operational metrics, ensuring model validity. Actionable suggestions are provided in terms of dynamic employee scheduling and spatial reconfiguration for improved efficiency and visitor experience. By integrating DES and ML, the study contributes to sustainable operations and provides a transferable method for the optimization of service systems in weather-dependent recreational environments.

Keywords: Discrete Event Simulation, Sustainable Operations, Capacity Planning, Simulation Modeling, Machine Learning, Seasonal Recreational Systems

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1. Introduction

In recent years, operation optimization of seasonal recreational resorts became a focus as a solution to efficient services, sustainable resources, and satisfied customers. Those resorts, especially cold-climate replicas within warm-climate regions, are subject to unique operational issues derived from heterogeneous demand from travelers, restricted space, and poor labor adaptability. To address these issues, advanced analytical solutions with the ability to track dynamic relationships between visitor flow, service capacity, and resource allocation are required.

One such complex is a cold-climate recreational facility in a tropical area of Indonesia that serves as a typical example. The location simulates a snow environment in a temperature city where outside temperatures may reach more than 36°C at peak times [5]. Although it is new and popular, there have been operational inefficiencies such as inefficient layout design, long queues, and inefficient deployment of the workforce. These inefficiencies result in service bottlenecks, uneven visitor dispersion, and decreased guest satisfaction—a outcome that detracts from the economic and experiential goals of such centers.

From the operations research perspective, spatial configuration and manpower planning are two of the most significant yet underoptimized factors in high-density recreational systems. Research shows that tourist movement behavior is heavily determined by spatial configuration [6], while physical environment directly influences satisfaction and throughput [7]. Therefore, their resolution not only contributes towards enhancing operational resilience but also to larger goals of sustainable service delivery.

In order to address these problems, this study adopts a hybrid modeling approach integrating Discrete Event Simulation (DES) and Machine Learning (ML) to enhance operational planning. DES allows simulation of complex time-dependent interactions in service systems so that various configurations of resources and layout alternatives may be experimented with [9]. In parallel, ML techniques such as Artificial Neural Networks (ANN) and Genetic Algorithms (GA) aid in forecasting modeling and adaptive optimization, particularly for uncertain and variable demand patterns [10]. AnyLogic as the simulation platform facilitates dynamic and graph-based depiction of system performance [11], e.g., layout configuration [12], queuing analysis [8], and labor scheduling [13].

Even though DES has been widely applied in healthcare [14], logistics [15], and manufacturing systems, it is not very much utilized in the planning of recreational facilities, particularly cold-climate ones in non-native locations. This research fills this knowledge gap by utilizing a simulation-based approach to support sustainable resource planning, capacity design, and spatial optimization for these facilities. The end goal is to develop evidence-based operation strategies that reduce inefficiencies, maximize visitor satisfaction, and align with the long-term agenda of sustainable tourism infrastructure.

This research makes theoretical and practical contributions by integrating simulation and machine learning into a single optimization platform for service systems. The remainder of this paper is structured according to the following: Section 2 presents recent developments in DES and ML implementations in operations management. Section 3 outlines the methodology, sources of data, and model specification. Section 4 presents the findings from the simulation and optimization experiments. Finally, Section 5 concludes with key findings, implications for sustainability, and future work directions.

2. State of the Art

Over the last few decades, theme parks have evolved as sophisticated systems with spatial experience, branding, and operational sophistication. All over the globe, theme parks are not only symbols of entertainment hubs but also local economic growth stimuli, urban identity markers, and world cultural exchange leaders [1,2]. Research has highlighted that positive theme park experiences heavily enhance brand loyalty, satisfaction, and repeat visitation [3,4]. However, sustaining high levels of satisfaction is heavily dependent on operational efficiency, more so in handling queues, layout movements, and staff allocation.

In addressing such problems, Discrete Event Simulation (DES) has proved to be a suitable simulation and improvement tool for complex service systems. DES is able to model time-elapsed events and system behavior, offering insights into the utilization of resources, the identification of bottlenecks, and predicting performance [14]. Its flexibility has found widespread application in healthcare systems—such as patient flow optimisation [17], hospital decision support systems [14], and capacity planning—and manufacturing processes such as port terminal operating maintenance [18] and warehouse management [19]. Muravev et al. [20] also demonstrated the application of DES, in its hybrid configurations, for aiding decisions through the simulation of scenarios in intermodal terminals. In theme park operations, DES has also been applied to investigate visitors' flow and queue optimization, which leads to improved efficiency in services and customer satisfaction [21,22]. Those studies collectively verify DES as an effective engine for operational strategy and sustainable system design, as further discussed in Table 1.

Layout strategy is another important factor in service optimization that means the physical arrangement of facilities to mitigate congestion and increase throughput. Ineffective layout designs can add to operational vagueness, material handling cost, and visitor dissatisfaction. Slack and Jones. (2019) point out that layout design is a strategic long-term exercise, in which initial-stage inefficiencies have compounded operating impact. Kulkarni et al. (2005), define layout optimization as an issue of spatial organization with the objective of reconciling space utilization, flow efficiency, and task synchrony.

From the implementation perspective, a number of simulation computer software platforms are compatible with DES modeling, each with its own strengths. Some of them include Arena (Ardiansyah et al., 2023), ExtendSim [24], FlexSim [25], SimEvents [27], and AnyLogic, the first of which is applied within this study due to its ability for flexibility, versatility of visualization, and usage in hybrid simulation environments [31,32]. AnyLogic has performed effectively in replicating dynamic environments such as transit hubs and theme park atmospheres, where customer flow and staff deployment are both susceptible to spatial and temporal fluctuations.

Machine Learning (ML) techniques have been increasingly incorporated into simulation tools to enhance predictive power, parameter calibration, and adaptive assistance in decision-making to support DES. ML is useful when dealing with vast volumes of operational data and detecting nonlinear patterns without assumptions [33]. When used together with DES, ML has the potential to render simulation models dynamically responsive to real-time data and demand fluctuations. Applications include predictive maintenance with algorithms for anomaly detection [35], process optimization of manufacturing [34], and smart resource planning in infrastructure systems.

Verification and validation of the model are as critical in order to check for correctness and appropriateness of simulation results. Scenario analysis, benchmarking, sensitivity analysis, and conceptual validation to check conformity to actual system logic are common validation methods [36]. Cycles of data-driven review and parameter calibration are required to increase model fidelity and to improve confidence in simulation-based recommendations [38].

Work measurement is a fundamental operational simulation discipline in that it measures human task duration and allows realistic workforce schedules to be formulated. It is most important in manual material handling (MMH) work, where lifting, carrying, and moving operations must be measured to maximize physical performance and minimize fatigue [39]. Effective labor planning also provides organizational planning of staffing needs, operational costs, and skills development goals [40]. In the broader sustainability agenda, particularly the UN Sustainable Development Goals (SDG 8), tourism and recreational human resource planning must emphasize decent work conditions, flexibility, and sustainable capacity building [41].

Overall, the DES and ML integration offers a data-driven, adaptive, and scalable solution for real-world issues in seasonal recreational systems. Existing research has dealt with either system modeling or customer satisfaction, but not simultaneously; this research addresses the gap by presenting an end-to-end simulation framework improving the design, capacity planning, and sustainability of cold-climate recreational operations.

Table 1. Previous studies on DES, Operation Management, Theme Park, ML and Simulation

No	Author(s) and Year	Method	Research Results
1	Cubukcuoglu et al., 2020	The study employed Discrete Event Simulation (DES) to validate the Programme of Requirements (PoR) within the context of hospital space planning.	Simulation variables such as patient arrival, hospitalization duration, and physician availability demonstrated that DES enhances operational efficiency, reduces patient waiting time, and improves overall satisfaction.
2	Ordu et al., 2023	A combined approach of DES and forecasting techniques was applied to model patient flow, hospital operations, and capacity planning.	The integration of DES with forecasting supports strategic resource allocation, enhances service quality, and increases the effectiveness of operational planning.
3	Corrotea et al., 2023	Implementation of DES in the maintenance procedures within the shipping industry.	The simulation contributed to improving maintenance efficiency, notably reducing crane downtime by 13%, and facilitated spare parts provisioning and performance evaluation.
4	Lopes et al., 2017	Utilized DES to model the soybean export logistics network in Mato Grosso, Brazil.	The model allowed for the exploration of multiple scenarios without disrupting existing logistics systems, enabling the identification of optimal solutions.
5	Morabito et al., 2021	Developed a digital twin integrated with DES for manufacturing process optimization.	The digital twin enabled accurate monitoring and forecasting, facilitating early detection of inefficiencies and supporting proactive decision-making.
6	Nahmias et al., 2015	A comprehensive analysis using theoretical models, simulations, case studies, and empirical data to examine production and operations systems.	The study highlights the significance of managing uncertainty in operations through the use of analytical methods such as simulation, queuing theory, and optimization models.
7	Saderova et al., 2021	Constructed a simulation model using EXTENDSIM8 and conducted experiments to evaluate system behavior.	The experiments provided critical insights into system performance under various conditions, guiding improvements in warehouse operations.
8	Watters et al., 2023	Combined theoretical modeling, simulation, and empirical research to examine queue dynamics in theme parks.	The research demonstrated that Queuing Theory models can effectively optimize queue management and reduce visitor wait times.
9	Zhang et al., 2022	Employed AnyLogic software for the design, modification, and optimization of a subway station simulation model.	Simulation results indicated improved passenger movement, minimizing congestion, delays, and crowding within the station environment.
10	Milman et al., 2020	Conducted a cross-sectional survey to assess how crowd density and attraction popularity influence theme park visitor experiences.	Findings revealed that perceptions of crowding significantly affect access, satisfaction, and visitor loyalty, impacting repeat visits and willingness to pay.

11	Li & Li, 2023	Developed a theme park queue simulation model incorporating a Fast Pass system at Shanghai Disneyland.	The Fast Pass mechanism was found to effectively reduce queue times and enhance visitor satisfaction.
12	Jin et al., 2018	Integrated Analytic Network Process (ANP) with One-Factor-at-a-Time (OAT) sensitivity analysis.	Results showed that the ANP-based multi-criteria framework is robust in determining optimal temporary facility layouts in construction planning.
13	Alzubaidi et al., 2021	Conducted a systematic literature review of over 300 studies related to deep learning applications.	The review provided a structured overview of core deep learning models, such as CNNs, to guide future research in various application domains.
14	Sarker, 2021	Performed a literature review examining the methodologies and applications of machine learning (ML).	The study offered broad insights into the use of ML across fields such as healthcare, cybersecurity, e-commerce, and smart infrastructure.
15	Muravev et al., 2020	Applied Multi-Agent Optimization using AnyLogic, integrating DES, Agent-Based Modeling, and System Dynamics.	The approach identified optimal configurations for intermodal terminal operations, leading to cost savings, improved handling capacity, and reduced delays.

3. Methods

3.1 Research Framework

Methodological organization is into six stages (Figure 1), beginning with problem definition and concluding with simulation validation. The principal method employed is Discrete Event Simulation (DES), chosen for its capacity to model system dynamics as discrete and time-dependent events. DES in this research was applied to simulate the entire visitor experience at a recreational facility in a cold climate, from arrival and queuing, through service encounters to exit (Figure 2). This facilitated close observation of operation inefficiencies and allowed for simulation of layout and workforce deployment improvements' scope.

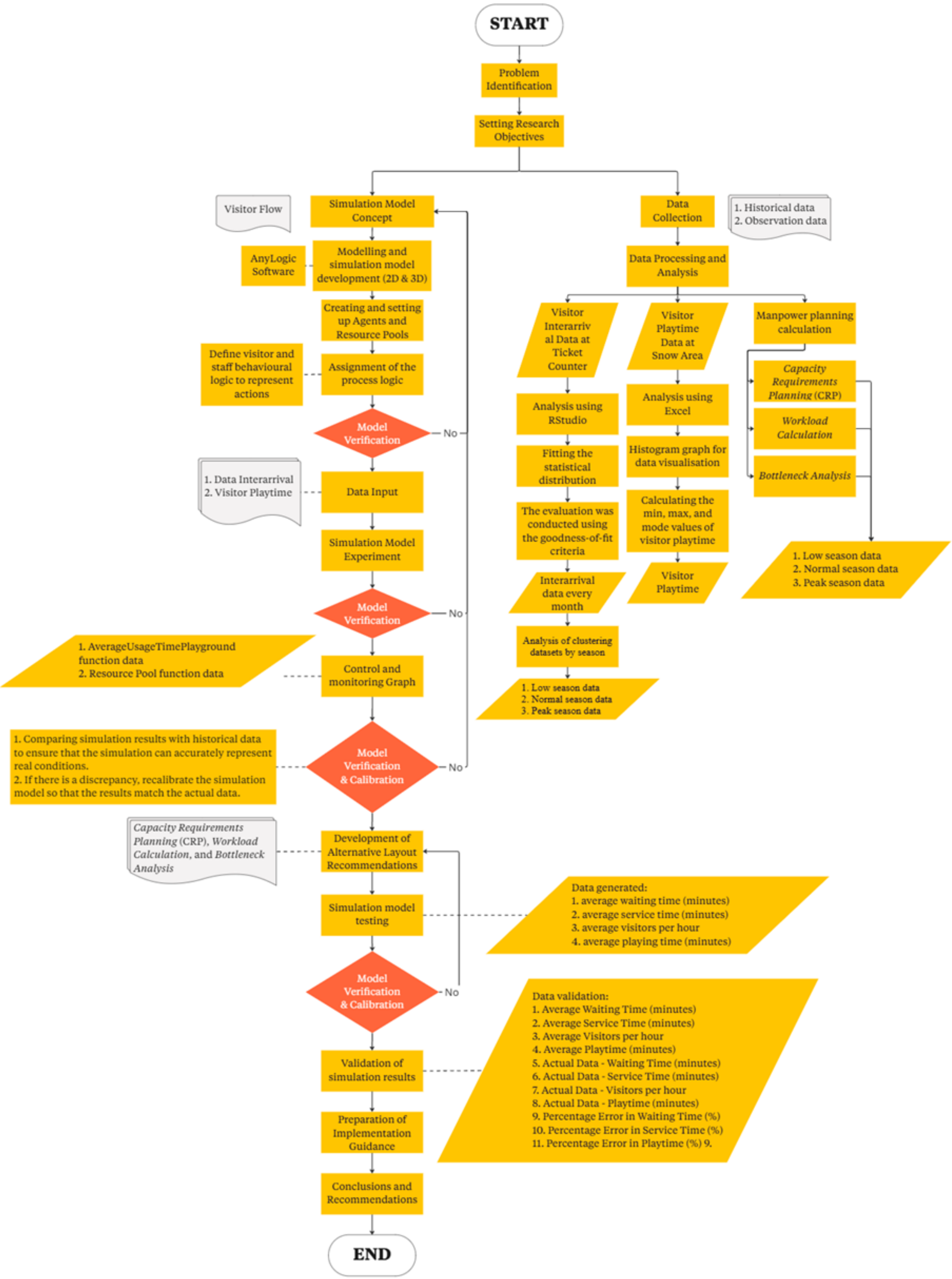

Figure 1. Research framework combining DES and ML for operation optimization

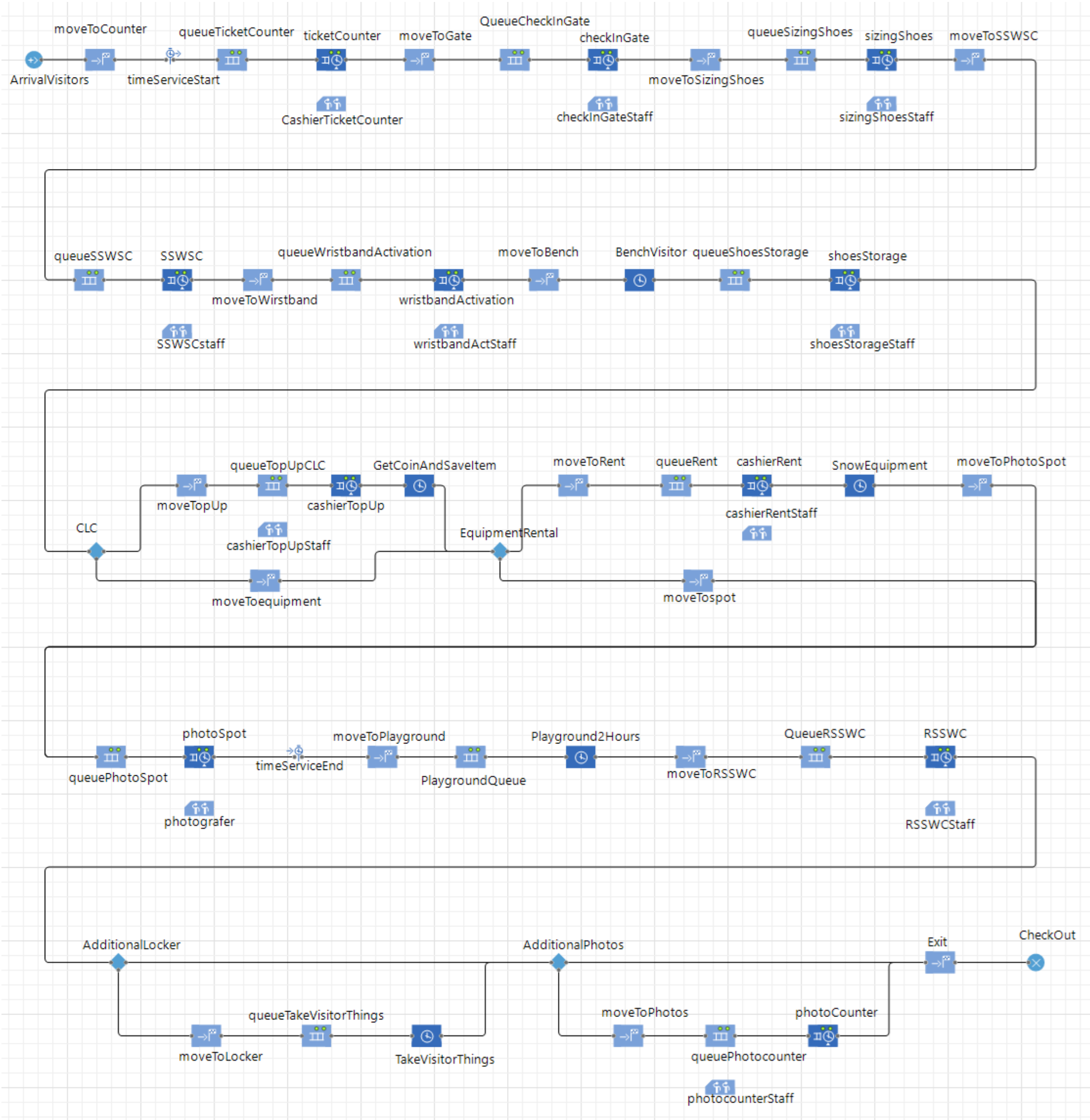

Figure 2. Visitor flow model developed in AnyLogic simulation environment

3.2 Data Collection

A one-year operational data set (January–December 2023) was formulated upon primary and secondary data sources. Primary data were gathered according to structured observations, interview meetings, and direct time recordings. Secondary data were gathered from internal operation records, public documents, and system records. A list of collected data types and sources is depicted in Table 2.

Table 2. Data Collection Overview

No	Data Type	Categories	Collection Method
1	Counter and Event Data	Primary	Collected through direct observation and structured surveys
2	Visitor Flow	Primary	Acquired via systematic direct observation and survey instruments
3	Manpower Allocation	Primary	Obtained through on-site observation and personnel surveys
4	Operating Hours and Peak Periods	Secondary	Sourced from official operational schedules
5	Ticket Pricing and Additional Fees	Secondary	Extracted from official websites and informational brochures
6	Registration and Payment Systems	Secondary	Retrieved from internal IT system databases

3.3 Data Processing and Simulation Input

Simulation input variables—interarrival times and service times particularly—were modeled using distribution fitting techniques. RStudio was used to identify each month's visitor data best-fit probability distribution by comparing Lognormal, Weibull, Gamma, and Exponential distributions. Evaluation metrics used included AIC, BIC, Kolmogorov-Smirnov, and Anderson-Darling tests for statistical strength.

In order to capture seasonality, operational periods were divided into three segments: low, normal, and high seasons. Separate simulation scenarios were run for each segment, increasing the ecological validity of the model outputs.

3.4 Simulation Model Design

A conceptual representation of the system was constructed to capture key service nodes and visitor flow routes. The simulation was implemented in AnyLogic, enabling visualization of dynamic flows, utilization of resources, and bottlenecks in processes. Key model assumptions included queue capacities, average service times, and station capacities. The simulation was run in replication mode to capture stochastic variation and provide statistically significant output measures.

3.5 Workforce Optimization Strategy

Labour planning was addressed through a combination of Capacity Requirements Planning (CRP), Workload Analysis, and Bottleneck Identification—each modified to service systems with fluctuating demand patterns.

3.5.1 Capacity Requirements Planning (CRP)

Equation 1 is used for the calculation of total service time per hour at each counter:

$$T_j = N \times W_p \tag{1}$$

Equation 2 is used for the calculation of total working hours per day at each counter:

$$H_j = \left(\frac{T_j \times O}{60}\right) \tag{2}$$

Equation 3 is used for the calculation of number of each staff required per counter:

$$S = \left\lceil \frac{H_j}{W_s} \right\rceil \tag{3}$$

Where Tj represents the total service time per hour (in minutes), N is the average number of visitors per hour, Wp means the service time per visitor at counter (in minutes), Hj indicates the total working hours per day (in hours), O stands for the operational hours per day (in hours), S is the number of staff required, and Ws represents the working hours per staff member per day (in hours).

3.5.2. Workload Calculation

Equation 4 is used for the calculation of total workload on each counter:

$$W_j = P \times W_p \tag{4}$$

Equation 5 is used for the calculation of total workload of all counters:

$$W_{total} = \sum_{j=1}^{n} W_j \tag{5}$$

Where Wj represents the total workload on each counter j (in minutes), P is the number of visitors per day, Wp means the service time per visitor at counter (in minutes), W_total is the total workload for all counters before and after the playground, and n is the total number of counters.

3.5.3 Bottleneck Analysis

Equation 6 is used for the calculation of identifying bottlenecks based on capacity:

$$\mathrm{C_j} = \frac{60}{\mathrm{W_p}} \tag{6}$$

Equation 7 is used for the calculation of total workload level of all counters:

$$\mathrm{U_j} = \frac{\mathrm{P_j}}{\mathrm{C_j}} \tag{7}$$

Where Cj represents the capacity of visitors that can be served at counter j (in hours), Wp denotes the service time per visitor at counter j (in minutes), Uj is the utilization level at counter j, and Pj is the number of visitors per hour at counter j (in hours).

3.6 Model Validation

Results from simulations were validated against actual operating records using 30 replications for every season scenario. The output parameters such as queue size, waiting time, and throughput were validated against measured values in 2023 (Table 3). The validation process delivers both the structural credibility and predictive reliability of the model.

3.3 Data Processing for Simulation Model Input

Machine learning-based statistical analysis techniques have been used within this research to process the data collected and determine the most suitable statistical probability distribution for each month of the data set. The whole data processing pipeline was conducted within RStudio, which is a programming environment offering a wide range of libraries in favor of statistical analysis, e.g., distribution fitting and goodness-of-fit testing. The data, from January to December 2023, provides key data on visitor interarrival times at the ticket counter as well as activity average time spent in the snow area.

Since there is a significant effect of seasonality on theme park operations, it is absolutely essential that simulation inputs properly reflect temporal dynamics to ensure model realism. In order to more accurately address this, monthly arrival numbers were divided into three seasonal segments: low season, regular season, and peak season. Three simulation runs were thereby developed reflecting these operating modes. In order to identify the most appropriate distribution for the interarrival times, several candidate distributions—Lognormal, Weibull, Gamma, and Exponential—were contrasted. The distributions were tested using a suite of goodness-of-fit tests that encompassed the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Kolmogorov-Smirnov, Cramer-von Mises, and Anderson-Darling tests to find by how much the greatest statistical fit deviates.

3.4 Design Model Simulation

The initial step in the simulation modeling is the examination of various scenarios of operation *(see Figure 2)*. This is begun by the development of a conceptual model describing the major components of the snow theme park system. The model captures visitor flow between points of service and the interaction at each counter. Key assumptions of the simulation are identified clearly, including maximum queue lengths at points of service and estimated average service time. Simulation model was implemented on AnyLogic software, enabling dynamic visualization of operation flows with the possibility to reveal bottlenecks and interrelations that can possibly impede the efficiency of service.

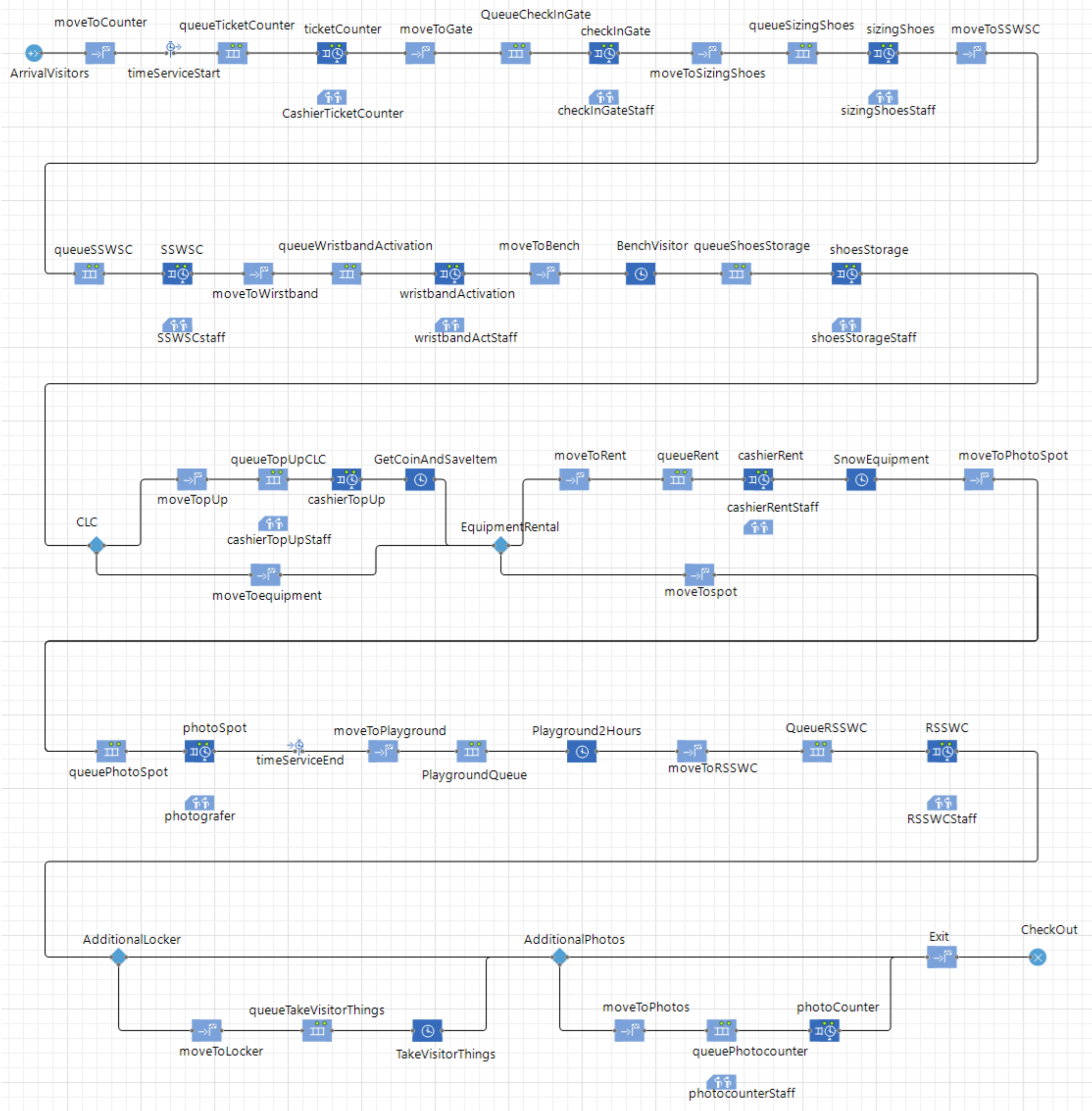

Figure 2. Process model illustrating the flow of visitors within the simulation environment developed using AnyLogic.

3.5 Manpower Planning

To ensure a critical analysis of workforce requirements in the snow theme park, existing research integrates Capacity Requirements Planning (CRP), Workload Calculation, and Bottleneck Analysis methods. The integrated approach offers variation in arrival of visitors, variability in service time, seasonal pattern of demand, and restriction on operation, hence facilitating precise manpower planning in harmony with the actual needs of the park.

3.5.1 Capacity Requirements Planning (CRP)
Equation 1 is used for the calculation of total service time per hour at each counter:

$$T_j = N \times W_p \tag{1}$$

Equation 2 is used for the calculation of total working hours per day at each counter:

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Equation 3 is used for the calculation of number of each staff required per counter:

$$S = \left\lceil \frac{H_j}{W_s} \right\rceil \tag{3}$$

Where Tj represents the total service time per hour (in minutes), N is the average number of visitors per hour, Wp means the service time per visitor at counter (in minutes), Hj indicates the total working hours per day (in hours), O stands for the operational hours per day (in hours), S is the number of staff required, and Ws represents the working hours per staff member per day (in hours).

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3.6 Validation of Simulation Results
Validation of the simulation results entails ensuring the model-calculated data against empirical observation. The two comprehensive data sources underpinning the exercise include the actual operating data assembled in *Table 3* and simulated data calculated from 30 replications of the model for three various seasonal conditions within one year. Such a validation ensures the authenticity and reliability of the simulation in reflecting real theme park operations.

4. Results and Discussion
This section interprets the simulation and analytical results, framed around operational optimization, sustainability implications, and generalizability.

4.1 Interarrival Data Processing and Seasonal Segmentation

Visitor interarrival data from 2023 was processed in RStudio using statistical distribution fitting and goodness-of-fit testing to inform accurate simulation inputs. Monthly data variations (Table 3) were aggregated into three operational seasons:

- Low Season: Feb, Mar, May, Aug, Sep
- Regular Season: Apr, Jun, Jul, Oct
- Peak Season: Nov, Dec, Jan

Table 3. Monthly Visitor Interarrival Data and Fitted Distributions

	Year 2023	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	Number of Visitors	13223	7157	7117	12227	7117	12908	11939	4103	7327	9924	20839	23820
	Statistic Probabilities	Lognormal	Lognormal	Lognormal	Lognormal	Weibull	Weibull	Lognormal	Weibull	Lognormal	Lognormal		Lognormal
Parameter	**Meanlog (μ):**	4.772	6.283	5.346	4.654			4.856		5.540	5.701		4.651
	Sdlog (σ):	1.291	1.165	1.250	1.287			1.256		1.317	1.153		1.252
	Min (Threshold):	1	4	1	1	1	1	1	3	1	2		1
	Alpha (α):					380.92	232.21		740.79				
	Beta (β):					0.950	0.953		0.853				

For each season, lognormal distributions provided the best fit (based on AIC, BIC, and p-values), as detailed in Tables 4, 5, and 6, and visualized in Figures 3, 4, and 5.

Table 4. Distribution Fit - Low Season

Distribution	Parameter	Loglikelihood	AIC	BIC	Chi-square Statistic	p-value Chi-square
Lognormal	meanlog = 5.435, sdlog = 1.293	-49926.7	99857.44	99871.15	32.561	7.39E-05
Exponential	rate = 0.0021	-50265.8	100533.6	100540.5	-	-
Normal	mean = 473.6037, sd = 681.437	-55760.9	111525.7	111539.4	-	-
Weibull	shape = 0.844, scale = 428.37	-50061.9	100127.9	100141.6	-	-

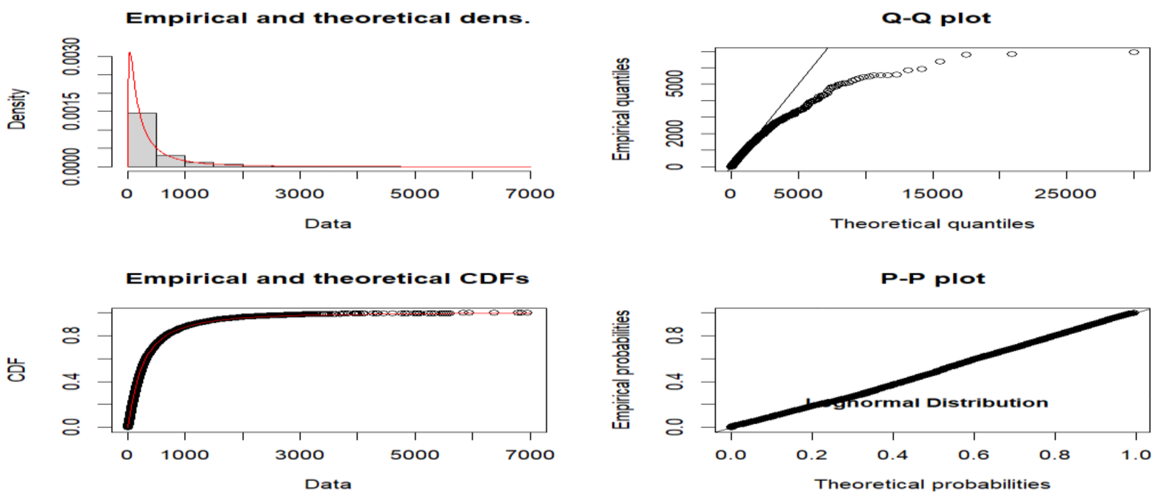

Figure 3. Distribution Fit Visual - Low Season

Table 5. Distribution Fit - Regular Season

Distribution	Parameter	Loglikelihood	AIC	BIC	Chi-square Statistic	p-value Chi-square
Lognormal	meanlog= 4.946, sdlog = 1.271	-64417.2	128838.5	128852.8	12.988	0.1123
Exponential	rate = 0.003043	-65172.2	130346.3	130353.5	-	-
Normal	mean= 293.816, sd = 504.657	-74532.8	149069.5	149083.9	-	-
Gamma	shape = 0.797, rate = 0.002663	-65010	130023.9	130038.3	-	-
Weibull	shape = 0.829, scale = 260.021	-64787.5	129579	129593.4	-	-

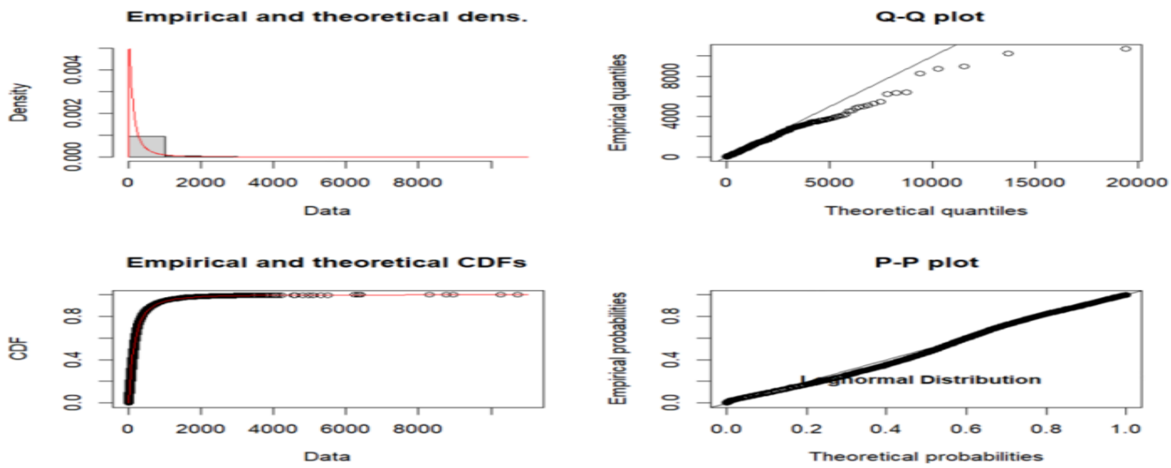

Figure 4. Distribution Fit Visual - Regular Season

Table 6. Distribution Fit - Peak Season

Distribution	Parameter	Loglikelihood	AIC	BIC	Chi-square Statistic	p-value Chi-square
Lognormal	meanlog = 4.700, sdlog = 1.268	-45515.9	91035.81	91049.56	8.6016	0.377
Exponential	rate= 0.00439479	-46021.9	92045.72	92052.59		
Normal	mean =227.6101, sd = 380.9034	-52708.2	105420.5	105434.2		
Gamma	shape = 0.7901, rate = 0.003479	-45916.2	91836.44	91850.19		
Weibull	shape = 0.8349, scale = 202.7685	-45763.1	91530.2	91543.95		

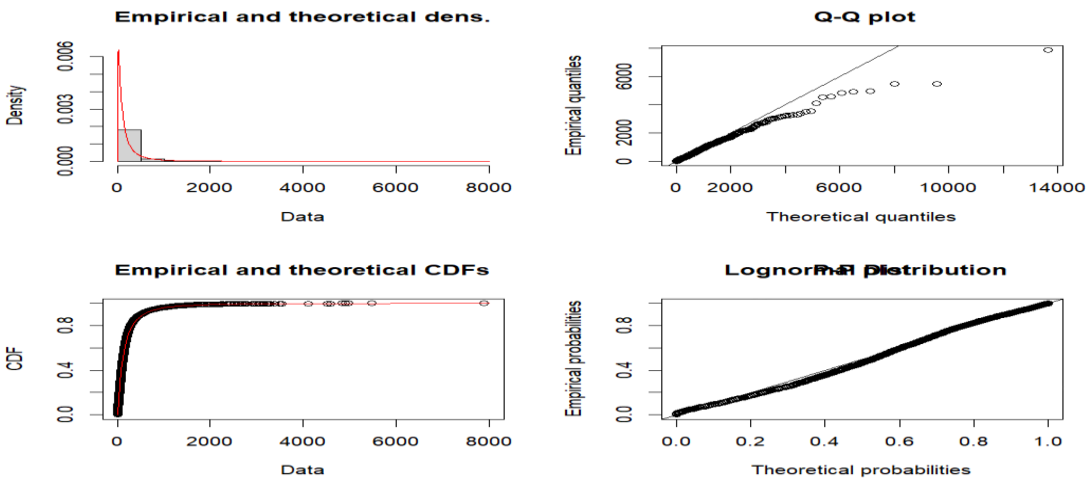

Figure 5. Distribution Fit Visual - Peak Season

Table 7. Summary of Seasonal Interarrival Parameters

	Season	Low Season	Ave/day	Regular Season	Ave/day	Peak Season	Ave/day
	Statistic Probabilities	**Lognormal**		**Lognormal**		**Lognormal**	
Parameter	**Meanlog (μ):**	5.435	219	4.946	392	4.700	643
	Sdlog (σ):	1.293		1.271		1.268	
	Min (Threshold):	1		1		1	
	Max (Triangular)	6951		6392		7870	
	Mode (Triangular)	51		31		46	

This seasonal modeling ensures that simulation inputs align with operational variability, forming a robust base for capacity planning.

4.2 Visitor Duration Analysis

Figure 6 presents the histogram of visitor durations in the snow area. The majority (1,990 visitors) spent approximately 119 minutes, aligning with the intended 2-hour session model.

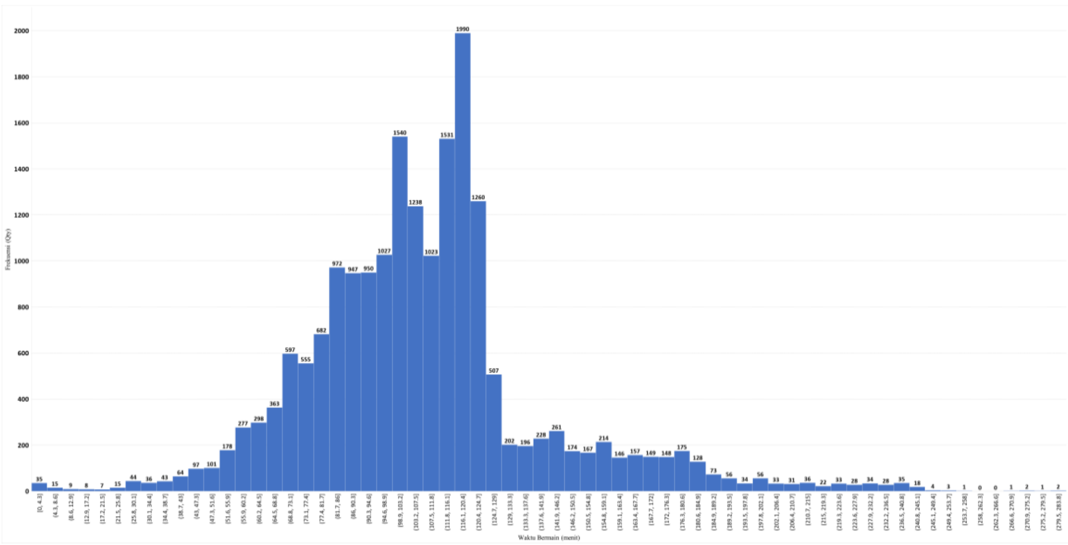

Figure 6. Histogram of Visitor Time in Snow Play Area

Outliers (e.g., 283 minutes) were attributed to wristband errors. These findings support time allocation efficiency and facility throughput assumptions.

4.3 Simulation Execution and Resource Monitoring

The simulation, executed in AnyLogic over 30 replications per season, included 11 key service counters. Resource pools and usage time graphs (Figures 7 and 8) confirmed real-time load dynamics and system responsiveness.

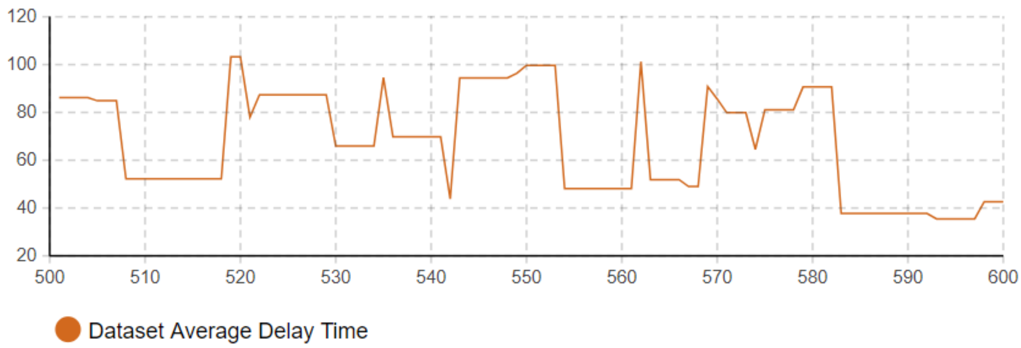

Figure 7. Average Usage Time Graph

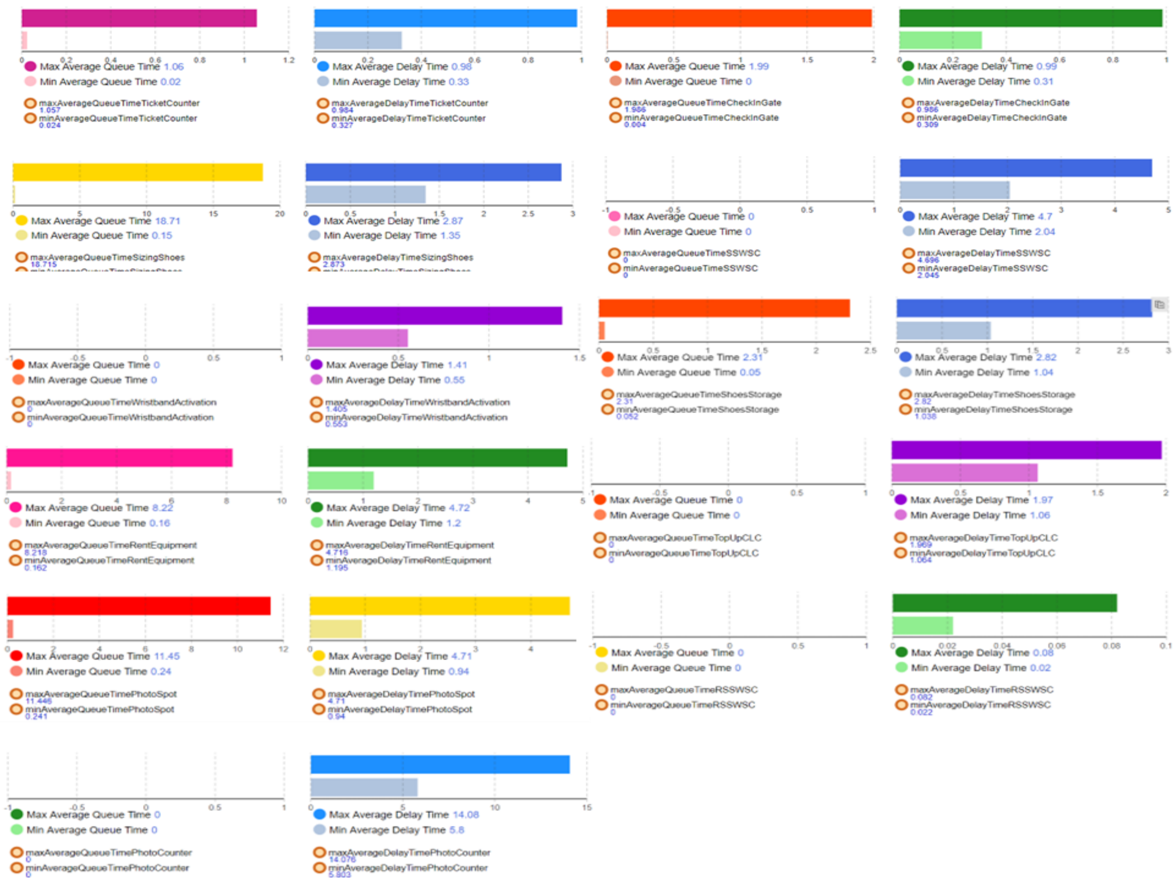

Figure 8. Resource Pool Graph

Table 8 summarizes average waiting time, service time, throughput, and visitor playtime.

Table 8. Simulation Output Summary by Counter

No	Counters and events with visitors	Average Waiting Time (minutes)	Average Service Time (minutes)	Average visitors per hour	Average Playtime (minutes)
1	CashierTicketCounter	15.2	5.9	21	
2	CheckInGateStaff	0.0	0.5	21	
3	SizingShoesStaff	0.7	1.9	21	
4	Snow shoes, Wristband & Socks Counter	0.0	3.3	21	
5	WristbandActStaff	0.0	1.0	21	
6	ShoesStorageStaff	0.5	1.8	20	146.8
7	CashierTopUpStaff	0.0	1.5	5	
8	CashierRentStaff	0.0	3.0	16	
9	Photografer	33.3	2.8	18	
10	Returning Snow Shoes, & Wristband Counter	0.0	0.1	14	
11	PhotocounterStaff	1.2	10.0	12	

Peak delays at the ticket counter and photographer station suggest opportunities for dynamic staffing or self-service integration.

4.4 Manpower Planning Scenarios

4.4.1 Capacity Requirements Planning (CRP)

CRP results indicate substantial differences in staffing needs across seasons (Tables 9-11). Peak seasons demand more than twice the labor of low seasons.

Table 9. CRP - Low Season

No	Counters and events with visitors	Average Service Time (minutes)	Average visitors per hour	Total Service Time per Hour (minutes)	Total Working Hours per Day	Number of Staff Required	
1	CashierTicketCounter	5	28	140	18.67	2.33	3
2	CheckInGateStaff	0.30	28	8.40	1.12	0.14	1
3	SizingShoesStaff	1.30	28	36.40	4.85	0.61	1
4	Snow shoes, Wristband & Socks Counter	3	28	84	11.20	1.40	2
5	WristbandActStaff	3	28	84	11.20	1.40	2
6	ShoesStorageStaff	3	28	84	11.20	1.40	2
7	CashierTopUpStaff	5	28	140	18.67	2.33	3
8	CashierRentStaff	1	28	28	3.73	0.47	1
9	Photografer	1	28	28	3.73	0.47	1
10	Returning Snow Shoes, & Wristband Counter	3	28	84	11.20	1.40	2
11	PhotocounterStaff	10	28	280	37.33	4.67	5
		Total manpower requirement					23

Table 10. CRP - Regular Season

No	Counters and events with visitors	Average Service Time (minutes)	Average visitors per hour	Total Service Time per Hour (minutes)	Total Working Hours per Day	Number of Staff Required	
1	CashierTicketCounter	5	49	245	32.67	4.08	**5**
2	CheckInGateStaff	0.30	49	14.70	1.96	0.25	**1**
3	SizingShoesStaff	1.30	49	63.70	8.49	1.06	**2**
4	Snow shoes, Wristband & Socks Counter	3	49	147	19.60	2.45	**3**
5	WristbandActStaff	3	49	147	19.60	2.45	**3**
6	ShoesStorageStaff	3	49	147	19.60	2.45	**3**
7	CashierTopUpStaff	5	49	245	32.67	4.08	**5**
8	CashierRentStaff	1	49	49	6.53	0.82	**1**
9	Photografer	1	49	49	6.53	0.82	**1**
10	Returning Snow Shoes, & Wristband Counter	3	49	147	19.60	2.45	**3**
11	PhotocounterStaff	10	49	490	65.33	8.17	**9**
	Total manpower requirement						**36**

Table 11. CRP - Peak Season

No	Counters and events with visitors	Average Service Time (minutes)	Average visitors per hour	Total Service Time per Hour (minutes)	Total Working Hours per Day	Number of Staff Required	
1	CashierTicketCounter	5	80.38	401.9	53.59	6.70	**7**
2	CheckInGateStaff	0.30	80.38	24.11	3.22	0.40	**1**
3	SizingShoesStaff	1.30	80.38	104.49	13.93	1.74	**2**
4	Snow shoes, Wristband & Socks Counter	3	80.38	241.14	32.15	4.02	**5**
5	WristbandActStaff	3	80.38	241.14	32.15	4.02	**5**
6	ShoesStorageStaff	3	80.38	241.14	32.15	4.02	**5**
7	CashierTopUpStaff	5	80.38	401.9	53.59	6.70	**7**
8	CashierRentStaff	1	80.38	80.38	10.72	1.34	**2**
9	Photografer	1	80.38	80.38	10.72	1.34	**2**
10	Returning Snow Shoes, & Wristband Counter	3	80.38	241.14	32.15	4.02	**5**
11	PhotocounterStaff	10	80.38	803.8	107.17	13.40	**14**
	Total manpower requirement						**55**

4.4.2 Workload Analysis

Workload assessment revealed cumulative demand across all counters. Table 12 to Table 14 show seasonal variations in minute-level workloads.

Table 12. Workload - Low Season

No	Counters and events with visitors	Average Service Time (minutes)	Average visitors per day	Total workload per minute per day
1	CashierTicketCounter	5	219	**1095**
2	CheckInGateStaff	0.30	219	**65.70**
3	SizingShoesStaff	1.30	219	**284.70**
4	Snow shoes, Wristband & Socks Counter	3	219	**657**
5	WristbandActStaff	3	219	**657**
6	ShoesStorageStaff	3	219	**657**
7	CashierTopUpStaff	5	219	**1095**
8	CashierRentStaff	1	219	**219**
9	Photografer	1	219	**219**
10	Returning Snow Shoes, & Wristband Counter	3	219	**657**
11	PhotocounterStaff	10	219	**2190**
	Total Workload (Wtotal)			**7796.4**

Table 13. Workload - Regular Season

No	Counters and events with visitors	Average Service Time (minutes)	Average visitors per day	Total workload per minute per day
1	CashierTicketCounter	5	392	**1960**
2	CheckInGateStaff	0.30	392	**117.60**
3	SizingShoesStaff	1.30	392	**509.60**
4	Snow shoes, Wristband & Socks Counter	3	392	**1176**
5	WristbandActStaff	3	392	**1176**
6	ShoesStorageStaff	3	392	**1176**
7	CashierTopUpStaff	5	392	**1960**
8	CashierRentStaff	1	392	**392**
9	Photografer	1	392	**392**
10	Returning Snow Shoes, & Wristband Counter	3	392	**1176**
11	PhotocounterStaff	10	392	**3920**
	Total Workload (Wtotal)			**13955.2**

Table 14. Workload - Peak Season

No	Counters and events with visitors	Average Service Time (minutes)	Average visitors per day	Total workload per minute per day
1	CashierTicketCounter	5	643	**3215**
2	CheckInGateStaff	0.30	643	**192.90**
3	SizingShoesStaff	1.30	643	**835.90**
4	Snow shoes, Wristband & Socks Counter	3	643	**1929**
5	WristbandActStaff	3	643	**1929**
6	ShoesStorageStaff	3	643	**1929**
7	CashierTopUpStaff	5	643	**3215**
8	CashierRentStaff	1	643	**643**
9	Photografer	1	643	**643**
10	Returning Snow Shoes, & Wristband Counter	3	643	**1929**
11	PhotocounterStaff	10	643	**6430**
	Total Workload (Wtotal)			**22890.8**

4.4.3 Bottleneck Identification

Utilization levels (Uj ≥ 1) identified recurring bottlenecks in counters like Cashier, Snow Gear, and Photo stations.

Table 15. Bottleneck - Low Season

No	Counters and events with visitors	Average Service Time (minutes)	Capacity per visitor (hour)	Average visitors per hour	Utilisation Level	Bottleneck (Yes/No)
1	CashierTicketCounter	5	12	28	2.33	Yes
2	CheckInGateStaff	0.30	200	28	0.14	No
3	SizingShoesStaff	1.30	46.15	28	0.61	No
4	Snow shoes, Wristband & Socks Counter	3	20	28	1.40	Yes
5	WristbandActStaff	3	20	28	1.40	Yes
6	ShoesStorageStaff	3	20	28	1.40	Yes
7	CashierTopUpStaff	5	12	28	2.33	Yes
8	CashierRentStaff	1	60	28	0.47	No
9	Photografer	1	60	28	0.47	No
10	Returning Snow Shoes, & Wristband Counter	3	20	28	1.40	Yes
11	PhotocounterStaff	10	6	28	4.67	Yes

Table 16. Bottleneck - Regular Season

No	Counters and events with visitors	Average Service Time (minutes)	Capacity per visitor (hour)	Average visitors per hour	Utilisation Level	Bottleneck (Ya/No)
1	CashierTicketCounter	5	12	49	4.08	Yes
2	CheckInGateStaff	0.30	200	49	0.25	No
3	SizingShoesStaff	1.30	46.15	49	1.06	Yes
						Yes
4	Snow shoes, Wristband & Socks Counter	3	20	49	2.45	
5	WristbandActStaff	3	20	49	2.45	Yes
6	ShoesStorageStaff	3	20	49	2.45	Yes
7	CashierTopUpStaff	5	12	49	4.08	Yes
8	CashierRentStaff	1	60	49	0.82	No
9	Photografer	1	60	49	0.82	No
						Yes
10	Returning Snow Shoes, & Wristband Counter	3	20	49	2.45	
11	PhotocounterStaff	10	6	49	8.17	Yes

Table 17. Bottleneck - Peak Season

No	Counters and events with visitors	Average Service Time (minutes)	Capacity per visitor (hour)	Average visitors per hour	Utilisation Level	Bottleneck (Ya/No)
1	CashierTicketCounter	5	12	81	6.75	Yes

2	CheckInGateStaff	0.30	200	81	0.41	No
3	SizingShoesStaff	1.30	46.15	81	1.76	Yes
4	Snow shoes, Wristband & Socks Counter	3	20	81	4.05	Yes
5	WristbandActStaff	3	20	81	4.05	Yes
6	ShoesStorageStaff	3	20	81	4.05	Yes
7	CashierTopUpStaff	5	12	81	6.75	Yes
8	CashierRentStaff	1	60	81	1.35	Yes
9	Photografer	1	60	81	1.35	Yes
10	Returning Snow Shoes, & Wristband Counter	3	20	81	4.05	Yes
11	PhotocounterStaff	10	6	81	13.50	Yes

These findings justify predictive staffing and resource allocation based on seasonal patterns.

4.5 Model Validation

The simulation was validated using historical data to compute percentage absolute errors (Tables 18–20). Most counters show acceptable deviations (±5%), confirming high model fidelity.

Table 18. Validation - Low Season

No	**Counters and events with visitors**	**Actual Data**				**Simulation Result Data**				**Percentage of Actual vs Simulation Comparison**		
		Ave Waiting Time (mins)	Ave Service Time (mins)	Provided Playtime (mins)	Ave visitors per hour	Ave Waiting Time (mins)	Ave Service Time (mins)	Ave Playtime (mins)	Ave visitors per hour	Perc of Waiting Time (%)	Perc of Service Time (%)	Perc of Playtime (%)
1	CashierTicketCounter	10	5	120	28	14.1	6.0	122	21.0	-0.4	-0.2	0.0
2	CheckInGateStaff	0.5	0.3		28	0.0	0.5		21.0	1.0	-0.7	
3	SizingShoesStaff	2	1.3		28	0.8	1.9		21.0	0.6	-0.5	
4	Snowshoes, Wristband&Socks Counter	0.5	3		28	0.0	3.3		21.0	1.0	-0.1	
5	WristbandActStaff	0.5	3		28	0.0	1.0		21.0	1.0	0.7	
6	ShoesStorageStaff	1	3		28	0.0	1.8		19.9	1.0	0.4	
7	CashierTopUpStaff	2	2		28	0.0	1.5		5.9	1.0	0.2	
8	CashierRentStaff	10	1		28	12.3	3.0		15.3	-0.2	-2.0	
9	Photografer	5	1		28	22.0	2.8		17.4	-3.4	-1.8	
10	Returning SnowShoes, & Wristband Counter	0.5	3		28	0.0	0.1		13.3	1.0	1.0	
11	PhotocounterStaff	0.5	10		28	0.1	10.0		11.8	0.7	0.0	

Table 19. Validation - Regular Season

No	Counters and events with visitors	Actual Data			Simulation Result Data			Percentage of Actual vs Simulation Comparison	
		Average Waiting Time (minutes)	Average Service Time (minutes)	Provided Playtime (minutes)	Average Service Time (minutes)	Average visitors per hour	Average Playtime (minutes)	Percentage of Service Time (%)	Percentage of Playtime (%)
1	CashierTicketCounter	10	5	120	6.0	26.7	124.0	-0.2	0.0
2	CheckInGateStaff	0.5	0.3		0.5	26.7		-0.7	
3	SizingShoesStaff	2	1.3		1.9	26.7		-0.5	
4	Snowshoes, Wristband & Socks Counter	0.5	3		3.3	26.7		-0.1	
5	WristbandActStaff	0.5	3		1.0	26.7		0.7	
6	ShoesStorageStaff	1	3		1.8	25.2		0.4	
7	CashierTopUpStaff	2	2		1.5	7.6		0.2	
8	CashierRentStaff	10	1		3.0	17.5		-2.0	
9	Photografer	5	1		2.8	19.0		-1.8	
10	Returning Snow Shoes, & Wristband Counter	0.5	3		0.1	14.0		1.0	
11	PhotocounterStaff	0.5	10		10.0	12.5		0.0	

Table 20. Validation - Peak Season

No	Counters and events with visitors	Actual Data			Simulation Result Data			Percentage of Actual vs Simulation Comparison	
		Average Waiting Time (minutes)	Average Service Time (minutes)	Provided Playtime (minutes)	Average Service Time (minutes)	Average visitors per hour	Average Playtime (minutes)	Percentage of Service Time (%)	Percentage of Playtime (%)
1	CashierTicketCounter	10	5	120	6.0	43.4	138.0	-0.2	-0.2
2	CheckInGateStaff	0.5	0.3		0.5	43.3		-0.7	
3	SizingShoesStaff	2	1.3		1.9	43.3		-0.5	
4	Snowshoes, Wristband & Socks Counter	0.5	3		3.3	43.2		-0.1	
5	WristbandActStaff	0.5	3		1.0	43.2		0.7	
6	ShoesStorageStaff	1	3		1.8	41.3		0.4	
7	CashierTopUpStaff	2	2		1.5	12.1		0.3	
8	CashierRentStaff	10	1		3.0	31.4		-2.0	
9	Photografer	5	1		2.8	36.2		-1.8	
10	Returning Snow Shoes, & Wristband Counter	0.5	3		0.1	26.9		1.0	
11	PhotocounterStaff	0.5	10		10.0	23.4		0.0	

Observed gaps (e.g., underestimating photo booth queues) can inform future iterations with more granular behavioral data.

4.6 Discussion and Sustainability Implications

Key takeaways include: - **Dynamic Staffing**: Simulation-driven staffing minimizes idle labor and overloads, improving cost-efficiency. **- Sustainable Operations**: Reducing queue time improves energy use per guest served, aligning with SDG 12. **- Scalable Framework**: The DES-ML hybrid can be adapted to other seasonally impacted leisure facilities (e.g., ski resorts, water parks).

These results reinforce the strategic value of simulation not only in optimization but in long-term sustainability planning.

5. Conclusions

Through this research, it was the intention to evaluate the appropriateness of current service counter layout and staffing methodology in a cold-climate leisure facility by utilizing Discrete Event Simulation (DES). By simulating the entire operation process across seasons of visits, the research identified inefficiencies—in terms of unnecessary waiting times at the Photographer and Ticket Counter—that compromise service quality under peak demand times. Simulation outputs, fueled by machine learning-inspired input handling, provided detailed insight into resource utilization, service time variability, and seasonal bottle points.

The integration of DES with Capacity Requirements Planning (CRP), Workload Analysis, and Bottleneck Identification allowed for systematic reallocation of manpower usage. Not only does this approach improve throughput in operations, but it also supports sustainable facility management, ensuring effective utilization of resources without labor or spatial redundancy. The findings highlight the centrality of data-driven decision-making in optimizing performance in visitor-intensive environments, where satisfactory levels are a critical indicator of sustainability.

Specifically, the research introduces an extendable simulation model for other seasonal or visit-based facilities beyond the snow theme park context investigated. Others include ski resorts, indoor complexes, or public transportation terminals under peak season demands. The synergy in methodology between DES and machine learning techniques (e.g., distribution fitting with RStudio) also offers a reproducible method for integrating empirical data with simulation procedures, increasing the precision and transferability of operations research in practice.

Subsequent research is encouraged to incorporate visitor segmentation (i.e., age, group type, visit purpose) into behavior modeling to further enhance decision-support systems. Additionally, the potential integration of DES with Agent-Based Modeling (ABM) could yield greater insights into visitor interactions, spatial behavior, and emergent crowd dynamics. Exploration of external uncertainties—such as promotional events, weather variability, or energy use patterns—would also improve the alignment of simulation models with higher-level objectives in sustainable and resilient operations planning.

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