INTERNATIONAL JOURNAL OF INDUSTRIAL MANAGEMENT
ISSN: 2289-9286 E-ISSN: 0127-564X
VOLUME 20, NO. 1, 2026, 11 - 20
DOI: https://doi.org/10.15282/ijim.20.1.2026.11961

RESEARCH ARTICLE

A discrete event simulation approach to improve the efficiency of university parcel centre services in Universiti Malaysia Pahang Al-Sultan Abdullah

Azli Azhar[1], Jack Kie Cheng[1]*, Freselam Mulubrhan[2]

[1]Faculty of Industrial Management, Universiti Malaysia Pahang Al-Sultan Abdullah, Lebuh Persiaran Tun Khalil Yaakob, 26300 Kuantan, Pahang, Malaysia
[2]Engineering and Built Environment, Sheffield Hallam University, City Campus, Howard Street, Sheffield, S1 1WB, United Kingdom

Abstract - The increasing reliance on e-commerce has led to higher demands in parcel management and customer expectations, exposing parcel centres to challenges like long waiting times and poor resource allocation. If left unaddressed, these issues may result in delays and customer dissatisfaction. This study aims to develop a simulation model for the parcel collection process at the UMPSA Parcel Centre, evaluate its efficiency using the model, and recommend alternative strategies. Discrete Event Simulation was used to generate the simulation model, and data were collected through observation and staff interviews. Several scenarios—implementing a sorting system and adding a service counter—were tested to identify the optimal solution. The results showed that these strategies successfully reduced the amount of time customers spent at the parcel centre, thus increasing overall efficiency. The findings offer practical recommendations for UMPSA and other academic institutions to improve resource allocation, reduce congestion, and improve service quality, ultimately benefiting staff and customers.

Article History

Received	:	2nd Mar 2025
Revised	:	30th Jul 2025
Accepted	:	15th Sep 2025
Published	:	26th Mar 2026

Keywords
Parcel centre
Discrete event simulation
Parcel management
Customer
Operational efficiency

1. Introduction

The parcel sector plays a vital role in modern commerce, particularly with the growth of e-commerce platforms. The surge in online purchases has led to an increase in parcel deliveries, thus benefiting the global logistics industry. The rapid expansion of parcel centres, especially during the COVID-19 pandemic, has significantly shaped the logistics ecosystem in Malaysia, with institutions like Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) establishing parcel centres to support their communities. At UMPSA, the parcel centre has transitioned from a simple mail handling service to a comprehensive parcel collection and distribution hub, which is essential for both students and staff. Operating from 3 pm to 6 pm and 9 pm to 11 pm daily, the centre manages various items, including textbooks, research materials, and personal belongings. Its success relies heavily on operational efficiency and customer satisfaction, hence serving as a crucial link between the university's administrative structure and its academic community. Despite its critical role, the parcel centre faces several challenges, including operational bottlenecks, especially during peak periods such as the start of the academic semester. These delays, coupled with difficulties in digital tracking systems and managing missing parcels, hinder the centre's ability to operate smoothly. Bottlenecks often lead to prolonged waiting times, impacting students' ability to access their parcels on time, while tracking errors can cause confusion and operational interruptions (Hasija et al., 2020; Wang et al., 2020). Furthermore, missing parcels due to mishandling or poor tracking accuracy exacerbate these issues (Seghezzi & Mangiaracina, 2022). To address these challenges, this study aims to develop a simulation model to assess the parcel collection process at UMPSA's parcel centre. By simulating the centre's operations, the study seeks to identify inefficiencies and propose strategies to improve the parcel handling process. This model will also evaluate the impact of operational changes on overall efficiency and user satisfaction, offering insights into how the centre can streamline its procedures. The significance of this research lies in its potential to enhance the operational efficiency of the UMPSA Parcel Centre and provide practical recommendations for improving parcel handling in academic institutions. It also contributes to better customer experiences by addressing bottlenecks, optimising tracking systems, and improving missing parcel management. Moreover, the insights gained from this research will be valuable not only to UMPSA but also to other universities and organisations facing similar operational challenges.

2. Literature Review

Parcel management has evolved significantly with the advancement of technology and the changing demands of consumers. Initially, manual methods were employed to manage parcels, but over time, technological advancements such as barcode scanning, Radio Frequency Identification (RFID) systems, and parcel tracking software have become standard. These innovations have improved operational efficiency, accuracy, and speed. Collaboration between academic institutions, parcel carriers, and service providers also becomes necessary to ensure high service standards and optimise parcel handling operations (Ali et al., 2022). The increasing reliance on e-commerce has led to a substantial rise in parcel volume, creating the need for parcel centres to adopt advanced technology to cope with growing demand. Automated systems, such as barcode scanning, parcel tracking software, and sorting technology, have streamlined parcel management processes. These technologies allow for faster handling, better inventory tracking, and real-time parcel updates, which significantly improve customer experience and satisfaction (Wu et al., 2024).

*CORRESPONDING AUTHOR | J.K. Cheng | ✉ jackkie@umpsa.edu.my

Parcel management is a multi-step process that includes accepting, sorting, storing, and distributing parcels. The initial acceptance of parcels involves logging and tracking them using barcode and RFID technology, which has replaced manual methods. This transition to technology has reduced the time required for logging and improved accuracy in parcel tracking, thus enhancing the efficiency of the entire process (Wang et al., 2020). Sorting is another critical stage in parcel management. Previously, this step was labour-intensive, but with the rise in parcel volumes, automated sorting systems using conveyor belts, scanners, and algorithms have become essential. These systems significantly reduce human error and improve sorting speed, ensuring that parcels are organised and ready for storage or distribution. This development has made parcel management more efficient and responsive to increased demand (Tan et al., 2021). The final stages of parcel management involve storing and dispatching parcels. Modern parcel centres use automated storage and retrieval systems and warehouse management software to improve storage organisation and inventory tracking. These technologies optimise space and ensure that parcels are readily accessible for quick distribution (Kshetri, 2018). Additionally, the introduction of digital platforms for customer feedback has further enhanced service quality and allowed for continuous improvement in parcel management (Nakayama & Yan, 2019).

2.1 Issues in Parcel Management

Waiting times at parcel centres can cause significant dissatisfaction among customers, especially when parcel volumes are high, and staffing is insufficient. According to Ahmad and Van Looy (2020), overwhelming parcel centres with large backlogs leads to delays. Lin et al. (2020) emphasise that peak periods exacerbate customer frustration, ultimately affecting service levels. These issues can be addressed by improving both efficiency and customer satisfaction through initiatives such as automating workflows and optimising resource allocation using dynamic queue management.

Another significant issue in parcel management is the loss or damage of parcels, often due to poor handling, theft, or inadequate packaging. Wang et al. (2020) suggest that improving tracking systems and implementing better packaging protocols are key to reducing these risks. The use of modern tracking technologies like GPS and RFID, alongside improved handling practices and staff training, can prevent damage and ensure parcel safety, thereby enhancing customer satisfaction.

2.2 Techniques Used to Solve Problems in Parcel Management

Queuing theory is valuable for optimising service operations, including reducing wait times at parcel centres. By using models such as M/M/1 and M/M/c, parcel centres can assess customer arrival rates and service times (Adan & Resing, 2015). These models help manage queue dynamics effectively, allowing for improved resource allocation and prioritisation of service. Integrating queuing systems with real-time tracking and predictive analytics enables proactive management that can enhance both service efficiency and customer experience. Furthermore, the integration of big data analytics plays a critical role in optimising parcel centre operations (Ajah & Nweke, 2019). Real-time data analysis helps parcel managers anticipate peak demand times, ensuring optimal resource allocation and improved service delivery. By using these insights, parcel centres can make informed decisions about staffing and workflows, which may reduce waiting times and improve overall service efficiency, leading to higher customer satisfaction.

Simulation is a computer program that mimics the functions of real-world processes or systems over time (Law & Kelton, 2000). It uses mathematical models and algorithms to simulate the interaction of many system components and factors, allowing the analyst to evaluate the performance of a system, identify possible weaknesses, and make improvements in the simulation. The utilisation of simulation is evidenced in numerous sectors. For instance, the manufacturing sector uses simulations for optimising production processes, increasing resource utilisation and minimising operating costs. In healthcare, simulations are used to measure patient flow, evaluate treatment procedures, and build efficient healthcare delivery systems (Basole & Bellamy, 2014). Simulation is important in parcel management because it helps optimise logistics and distribution processes. A parcel management system is a complex network of warehouses, transport routes, and delivery schedules that requires analysts to model complex systems, run multiple scenarios, and reveal potential for efficiency gains (Chen et al., 2023).

Simulating the parcel sorting process, route planning, and delivery schedule can help parcel centres to improve service quality and reduce costs. This positions simulation as an ideal tool for modelling and analysing systems across multiple sectors. It gives analysts the opportunity to test various scenarios for evaluating performance and making decisions. Simulation requires virtual model generation to mimic real-world processes, which is crucial for analysing and improving system performance. On the other hand, optimisation focuses on choosing optimal options that can increase efficiency and reduce costs in parcel management operations. This approach is vital to enhance service quality and customer satisfaction in the parcel management sector.

Discrete event simulation (DES) is a modelling technique widely used to represent and analyse systems where changes occur at specific points in time. The computer-based operation is capable of modelling different systems as networks of queues and activities within to evaluate, predict, and optimise proposed or existing systems, where changes occur on discrete epochs in time (Vázquez-Serrano et al., 2021). According to Krisnawati et al. (2022), DES can be utilised as a forecasting tool to evaluate the effects of changes on patient enrolment and investigate factors influencing hospital management quality, such as treatment time. This is highly relevant to this study because the parcel centre management process involves time (e.g., waiting time) at the pickup counter and the amount of customer time in the parcel centre.

3. Materials and Methods

3.1 Data Collection Method

This study employed two fundamental approaches, namely primary and secondary data collection. These data were analysed to identify emerging patterns, which facilitated further decision-making. This process is crucial to ensure the validity, reliability, and relevance of the data.

3.1.1 Primary data collection

Primary data collection involves methods such as surveys, interviews, observations, and experiments. In this study, interviews and observation were used to collect the primary data. A face-to-face interview was held with the parcel centre manager to understand the operations and processes of UMPSA Parcel Centre. Further interviews were also conducted with the users (e.g., students) to gain a better insight into the problems that consumers face when dealing with UMPSA Parcel Centre. Observations were also done at the research location (i.e., UMPSA Parcel Centre) to better understand the environment, operational process, and workflow dynamics. Real-time data pertaining to waiting time and the speed of parcel processing and distribution to consumers were recorded to identify any congestion or inefficiencies in the centre's operation. This observation is helpful as it provides a clear picture regarding the intricacies of handling parcels. In conclusion, the interviews and observations helped in developing a more accurate simulation model. Table 1 shows the data collection activities conducted at the UMPSA Parcel Centre.

Table 1. Data collection activities conducted at the UMPSA parcel centre

Date	Information Gathered	Person in Charge
26/6/2024	Observe and record the situation at UMPSA Parcel Centre to gain a better understanding of the operation.	None
27/6/2024	Gather information about the parcel centre, issues faced, and its layout.	Manager of UMPSA Parcel Centre
3/9/2024	Validate the collected data.	Manager of UMPSA Parcel Centre

3.1.2 Secondary data collection

Secondary data are information that was previously gathered by others but can be reused for current research efforts. It can be obtained through various sources, such as scientific literature, reports, archival records, and databases. Accessing these secondary data sources can help researchers gather background information or an overview of a process. In this study, secondary data involved UMPSA Parcel Centre's operational data, including parcel volume, sorting time, parcel management time, and delivery. These valuable data enable the researcher to make experiments using the developed simulation model. Additional data, such as parcel route optimisation and parcel centre warehouse storage metrics, were also collected.

3.2 Components of Discrete Event Simulation

The DES technique can be formed through the presence of several components, namely entities, resources, and variables. Each component has its own important role in the modelling process. Entities refer to any object that will move in the simulation, which can be either physical or abstract. For example, a simulation of a store often involves the use of physical entities, such as customers, products, or vehicles. Meanwhile, abstract entities are events or processes. However, entities can sometimes change—the simulation is about the production of products from raw materials to the final product. On the other hand, resources represent the equipment, facilities, and personnel involved in the system. For example, the resources involved in a fast-food store are the various types of machines, such as self-service machines, water dispensers, and cooking machines. Another example of the use of servers is the health institutions where nurses and doctors are involved in the system. Resources that are used effectively and efficiently can maximise system processing and minimise congestion. The third component of DES is variables, which describe the parameters or attributes that will change over time in response to an event or process. In this phase, the modeller can experiment with the simulation model to analyse the number of people queuing, waiting time, or inventory levels. It allows the modeller to evaluate system performance, identify inefficiencies, and obtain optimal results so that improvements can be made. In sum, DES helps to understand how complex systems function by breaking down their activities into small events, tracking essential entities and resources, and measuring critical variables.

3.2.1 Discrete event simulation steps

Simulation is a problem-solving technique widely used to simulate a real-world system or process. It involves creating mathematical or computational models to understand, analyse, and optimise system behaviour. The simulation process begins by identifying the problem and determining the objectives and scope of the simulation project. This will give an idea of the end product of the simulation. The next step is modelling, which includes the various components, interactions, and processes in the system. It serves as the basis for simulation analysis, enabling the analyst to see the process of a system that works. Therefore, accuracy is indeed crucial when implementing this modelling. Once the model is established, the data collection process begins by gathering relevant input data. Accurate data collection is important to ensure the validity and reliability of simulation results so that the simulation is accurate in the real world. This step involves checking the model's logic, equations, and assumptions against known benchmarks or theoretical expectations.

Experimental design is the next step, where certain parameters will be defined for the simulation test. This step is performed to define the scope of the simulation analysis and gather meaningful insights from the results. During simulation execution, the model processes events, updates the system state, and generates output data based on experiments and specified input data. After the simulation is run, conclusions and inferences about the behaviour of the systems are drawn based on the output data. Figure 1 presents the steps of simulation modelling (Law, 2015).

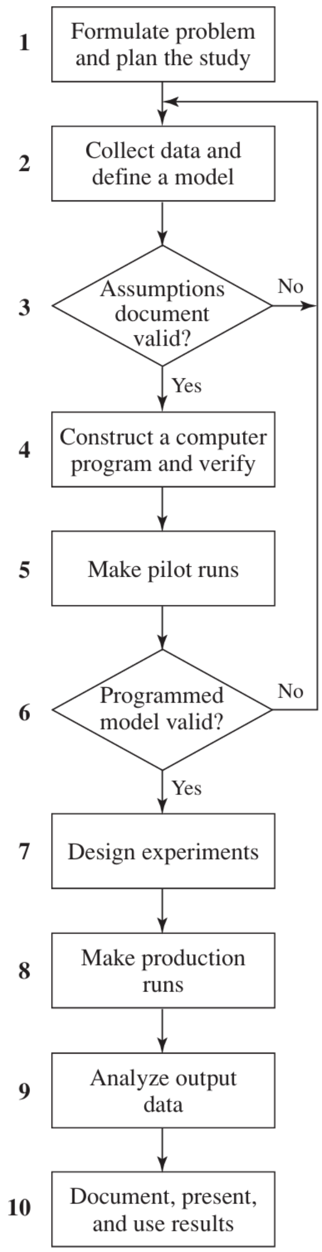

Figure 1. Simulation model process

3.2.2 Simulation software

Several software programs can be used to create this simulation model, including Arena Rockwell Automation, Simio, AnyLogic, and MATLAB Simulink. While each software has its own unique strengths, Arena Rockwell Automation remains a popular choice for its user-friendly interface, extensive features, and robust simulation capabilities. Most users use Arena Rockwell Automation to create system models and analyse and optimise systems. The drag-and-drop function makes the software easy to use, allowing users to customise these functions to represent the real world.

3.2.3 Validation and verification

The validation process ensures that the simulation model is accurate with the actual system. A model cannot be a reference if it is not accurate with the actual system. On the other hand, verification confirms whether a model is modelled with the correct concept and specifications. This process helps create credibility and reliability while also assisting in making decisions based on model output. The Mean Absolute Percentage Error (MAPE) is a metric that can be used by model makers to perform verification and validation. It measures the accuracy of a simulation model by comparing the predicted value generated by the simulation with the actual observational value. MAPE acts by calculating the average error between simulation output and expected results from known test data. A low MAPE percentage indicates that the implementation of the model almost matches the expected value. The metric is also useful to measure validation by comparing the output of the simulation model with real-world data, with a low MAPE percentage suggesting that the simulation's output is accurate to the real world. MAPE is calculated by Equation (1) (Khairina et al., 2019). Table 2 concludes that if the MAPE percentage value is less than 5%, the model is not biased. In other words, it is accurate with the actual data (Djamali, 2018).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Actual_i - Forecasted_i}{Actual_i}\right| \times 100 \tag{1}$$

where n is number of observations; $Actual_i$ is the observed value from real-world data; $Forecasted_i$ is the predicted value from the simulation

Table 2. Accuracy level of mean absolute percentage error

MAPE Percentage	Analysis
MAPE < 5%	Very Accurate
5% < MAPE < 10%	Accurate
MAPE > 10%	Not Accurate

3.2.4 Face validation

Face validation plays an important role during the design phase of the simulation model. It is highly dependent on the expertise and consideration of subject-matter experts, who will review model assumptions, input data, and model output. This will confirm whether the developed DES model is consistent with the actual system. Additionally, discrepancies and errors can be identified and addressed before the model is used for scenario testing. Face validation can build trust and credibility among stakeholders because it ensures that the model is based on practical reality and in line with expert expectations. In this study, face validation was conducted with the manager of the parcel centre.

4. Results and Discussion

4.1 Model Logic of Operation of UMPSA Parcel Centre

In this study, DES was used to model the **workflow** at the UMPSA Parcel Centre. The model is intended to mimic real-world operations and evaluate the efficiency of the system. Figure 2 depicts a model logic that describes the actual workflow at the UMPSA Parcel Centre. The workflow in Figure 2 starts with two 'Create' modules representing the two types of entities involved in the process: parcel and customer. The first 'Create' module is Parcel Arrived, where the parcel is in the parcel centre and is introduced to the simulation. Next, the staff recorded all parcels upon their arrival at the parcel centre. The 'Record' module is used during this recording process. The parcel is then routed to the Stored Parcel Station, where the 'Route' and 'Station' models are involved to direct the entities to move and be temporarily stored. This Stored Parcel Station uses the 'Proses' module. Finally, the parcel is sent to the Pickup Counter to be picked up by the customer. The 'Assign' module is involved in this process. Similarly, the second 'Create' module, labelled Customer Arrives at the Counter, introduces the customer into the system. The customer enters the parcel centre and then moves to the Registration Counter to register. The 'Route and Station' module is involved during the customer's journey to the Registration Counter, while the 'Process' module is used to represent the Registration Counter. After registration, they are directed to the Pickup Counter to pick up their parcel. Similarly, the 'Route and Station' and 'Process' modules are used for this process. Once the intake process is complete, the customer moves to the Customer Exit Station and exits the system. The modules involved are 'Assign', 'Route and Station', and 'Dispose'. Figure 3 shows the animation resembling the actual operation of the UMPSA Parcel Centre.

Table 3. Key performance indicators

Metrics	Base Case	Scenario 1	Scenario 2	
Number of Customer Out	150	150	150	
			Pickup Counter 1	Pickup Counter 2
Average customer waiting time at the pickup counter (Minutes)	55.56	4.12	4.25	4.02
Average number of customers waiting in queue	3	1	1	1
Total customer spend time in the parcel centre (Minutes)	93.53	13.8	5.05	4.82

4.1.1 Base case

The base case consists of a single pickup counter, and no sorting process is implemented. This resulted in higher congestion, where the average customer waiting time at the pickup counter was 55.56 minutes and the average number of customers waiting in line was three (see Table 3). The total time spent by customers at the parcel centre was 93.53 minutes, indicating significant delays.

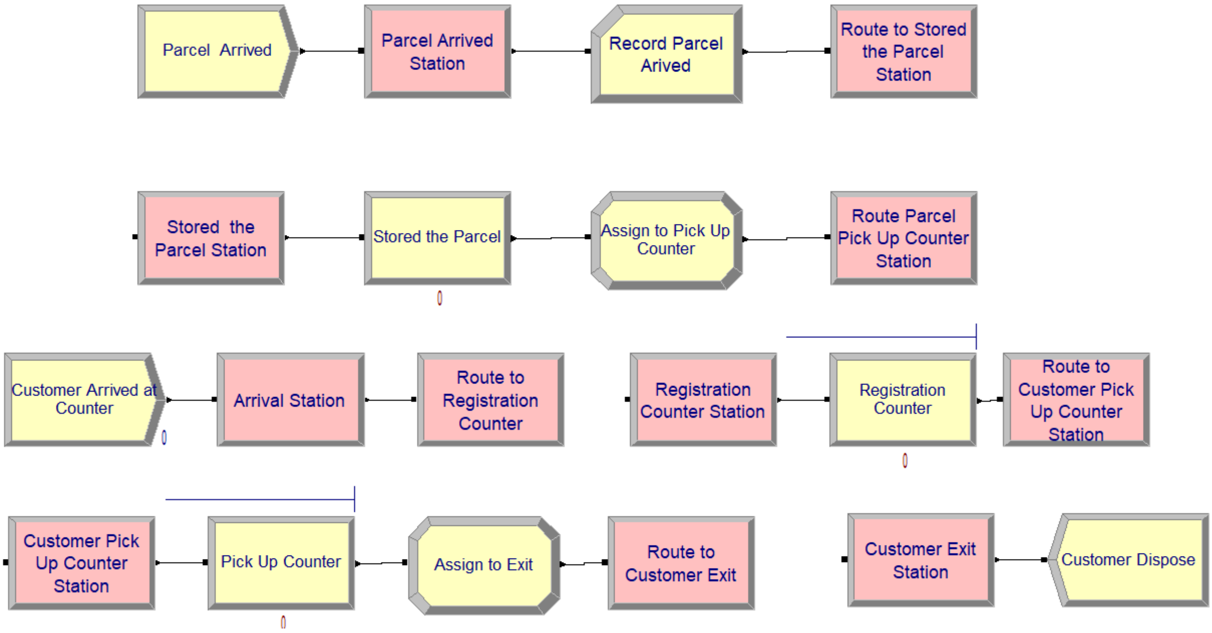

Figure 2. Model logic of UMPSA parcel centre workflow process

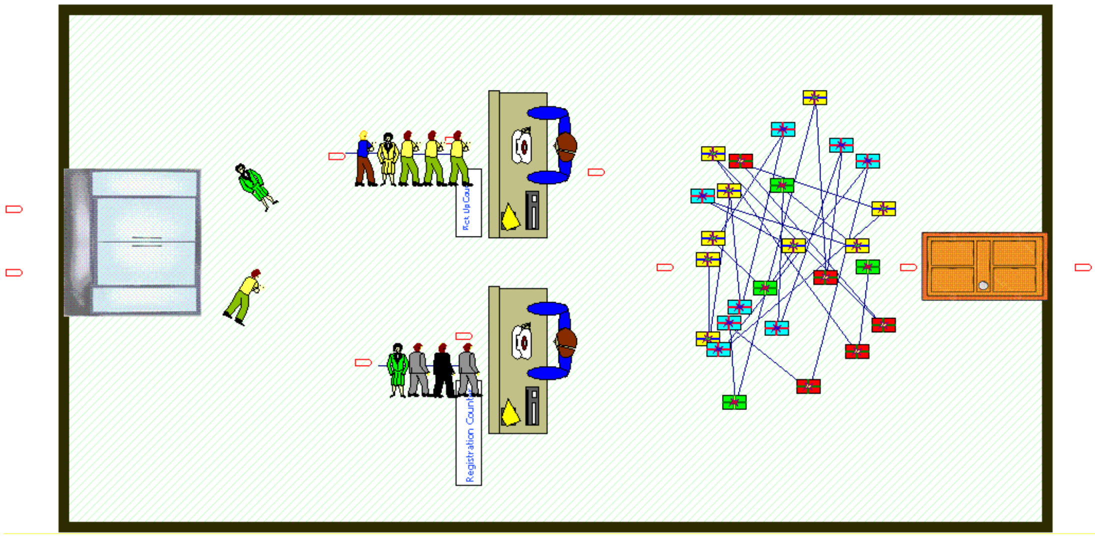

Figure 3. Animation model of UMPSA parcel centre (Base case)

4.1.2 Validation – Mean absolute percentage error

To ensure the accuracy and reliability of this simulation model, MAPE was calculated by comparing the simulation output with real-world data collected during the observation process. The observation data revealed that the total number of incoming customers and parcels was 150. This was similar to the output from the simulation model, making an MAPE percentage of 0.0%. According to Djamali (2018), a value less than 5% indicates that the model is highly accurate and compatible with the actual system. With this confirmation, the study can proceed to the next step, which involves testing the system under various scenarios to explore potential improvements and optimise the parcel processing workflow.

4.2 Scenario Testing

The base case problem is long customer waiting time at the pickup counter, which resulted in customer dissatisfaction. The number of customers waiting in line is also large, thus increasing the total time customers spend in the parcel centre. This shows poor efficiency in the existing system. To address this problem, two scenarios were proposed and tested using a 'what if' analysis. The first scenario applied one pickup counter with sorting process, while the second scenario tested two pickup counters without sorting process. Both scenarios were examined to compare their performance and determine which setup would result in a more efficient parcel processing system.

4.2.1 Scenario 1 - Single pickup counter with sorting process

The base case workflow design with no sorting process resulted in parcels scattering everywhere in the parcel centre. This prolonged the time to find the parcel and send it to the counter. Subsequently, the idea of using the sorting process was to make a comparison between the base case and Scenario 1 to determine whether it can reduce the time. In Scenario 1, the parcel sorting process was introduced before the customer reached the single pickup counter. This process streamlined parcel arrangements, where parcels were sorted according to the delivery company. It resulted in an average waiting time of 4.12 minutes at the pickup counter and only one customer waiting in line. The total time spent by each customer at the parcel centre was 13.8 minutes. Figure 4 shows the process for Scenario 1.

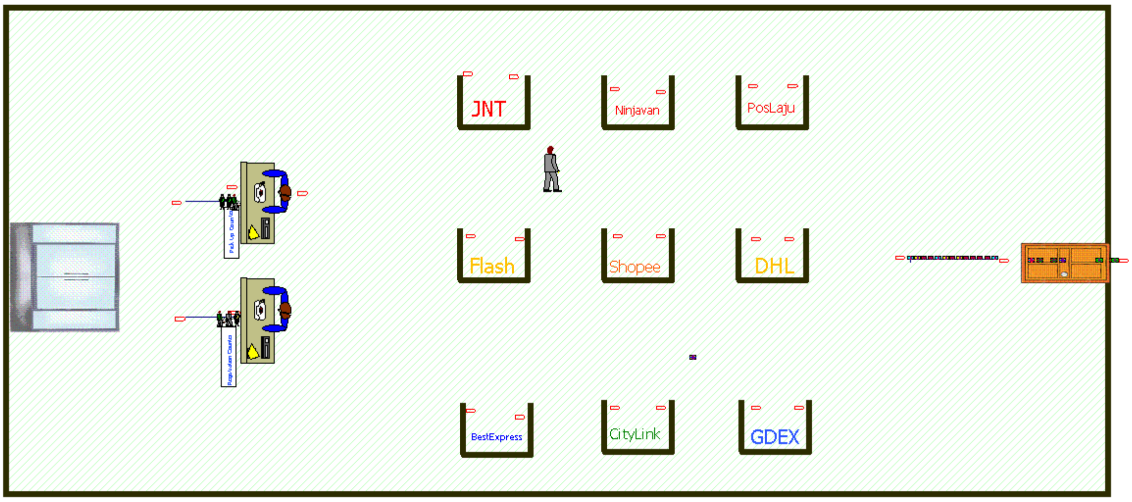

Figure 4. Animation model of Scenario 1 - Single pickup counter with sorting process

4.2.2 Scenario 2 – Two pickup counters without sorting process

The base case workflow design only had one pickup counter with prolonged waiting time for customers to get their parcels, making the waiting line to be long. Hence, another pickup counter was added to compare the base case and Scenario 1 to determine whether it can reduce the time. Figure 5 shows the process for Scenario 2. The setup included two pickup counters operating without a sorting process. For Pickup Counter 1, the average customer waiting time was 4.25 minutes, with only one customer waiting in line. The total time spent by each customer in the parcel centre was 5.05 minutes. For Pickup Counter 2, the average customer waiting time was 4.02 minutes, with typically one customer in line. The total time spent at the parcel centre was 4.82 minutes. Table 3 presents the comparison of results between the base case, Scenario 1, and Scenario 2.

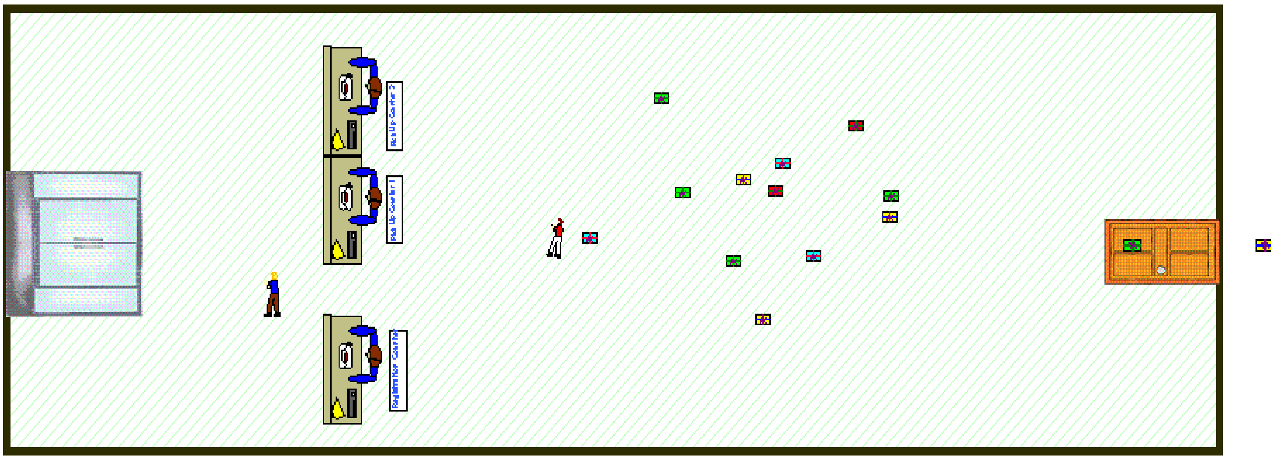

Figure 5. Animation model of Scenario 2 – Two pickup counters without sorting process

4.3 Discussion

Objective 1 was addressed by developing the DES model of the parcel collection process at the UMPSA Parcel Centre. It included important parameters, such as queue waiting time, queue lengths, and throughput. This provides a reliable basis for assessing congestion and operational inefficiencies, especially during peak periods, thus validating the initial analysis of delays and disruptions in the parcel handling system. Objective 2 evaluated the efficiency of the package collection process. The simulation model successfully revealed several inefficiencies, including long waiting times and high queueing congestion. The results highlight opportunities for improvement, particularly in staffing levels and process restructuring. Objective 3 aimed to recommend alternative strategies for improving the efficiency of the parcel collection process. This was achieved through the two scenarios in the DES model. Each scenario was made different from the base case, allowing for a comparison of the potential improvement. For example, the DES results showed improvement in Scenario 1 by using one pickup counter with sorting process. It was found that the average customer waiting time at the pickup counter was faster (4.12 minutes) compared to the base case (55.56 minutes). The average number of customers waiting in the queue was also reduced, from three customers in the base case to only one customer in Scenario 1. A significant improvement was also evident in the amount of time customers spend at the parcel centre, from 95.53 minutes in the base case to 13.80 minutes in Scenario 1. In Scenario 2, two pickup counters were applied without sorting process. The results revealed a decrease in the average customer waiting time at the pickup counter, from 4.25 minutes in Scenario 1 to 4.02 minutes in Scenario 2. The average number of customers waiting in the queue also decreased, from three customers in the base case to only one customer at each pickup counter in Scenario 2. Lastly, customers also spent less time in the parcel centre, from 95.53 minutes in the base case to 5.05 minutes for Pickup Counter 1 and 4.82 minutes for Pickup Counter 2 in Scenario 2.

The results from both scenarios underscore the potential for significant improvements in the parcel collection process at the UMPSA Parcel Centre. By implementing the strategies tested in the DES model, the centre can achieve a more efficient and customer-friendly operation. The reduction in average waiting times and queue lengths in both scenarios highlights the importance of optimising the number of pickup counters and incorporating a sorting process. These changes not only enhance the speed of service but also improve the overall customer experience by minimising delays and reducing congestion (Tosti & Bottani, 2021). Furthermore, the findings suggest that a flexible approach, where the number of counters and the inclusion of sorting processes can be adjusted based on demand, can provide the best results. This adaptability will allow the UMPSA Parcel Centre to efficiently handle varying levels of customer traffic, particularly during peak periods (Garn et al., 2024). In conclusion, DES has proven to be a valuable tool for identifying inefficiencies and testing potential improvements in the parcel collection process. The implementation of the recommended strategies can lead to significant operational enhancements. Future research could focus on further refining these strategies and exploring additional scenarios to continue improving the efficiency and effectiveness of the UMPSA Parcel Centre's operations (Bottani & Casella, 2024). The results demonstrate that the recommended improvements adding counters or improving the process can reduce waiting time, which will benefit the parcel centre in terms of efficiency and customer satisfaction.

5. Conclusions

In conclusion, the results of this study denote that DES can be used to improve the process at the parcel centre. The main problems identified include significant delays at the pickup counters due to the absence of a sorting system and fewer pickup counters. The simulations showed that the long customer waiting time in the base case, which was 55.56 minutes, can be significantly reduced through two improvement scenarios. Scenario 1, which introduced early sorting, succeeded in reducing the waiting time to 4.12 minutes, while Scenario 2, which added another pickup counter, reduced the waiting time to 4.25 minutes at the first counter and 4.02 minutes at the second counter.

The results of this study have a positive impact on UMPSA operations by providing practical guidance to improve the efficiency of the work process at the Parcel Centre. Improvements, such as the sorting of pickup parcels and the addition of counters, clearly help reduce customer congestion and speed up workflow. This will enhance customers' satisfaction and further improve the image of the parcel centre. These findings carry two important implications. First, from a practical point of view, this study provides concrete guidance to UMPSA to improve logistics processes and customer management. Strategies such as early sorting or increasing the number of recruitment counters can be used as a model to improve other operations in the university. Second, from an academic point of view, this study shows that DES is an effective tool for identifying problems and testing solutions in logistics systems or educational services. The results of this study can also be used as a foundation for further studies in other sectors, such as logistics, public services, or retail. However, the simulation model used was only capable of modelling the process in a basic way, without being able to depict the entire complexity of the actual operation at the UMPSA Parcel Centre. Moreover, the study could not examine the impact of external factors, such as sudden and unexpected changes in the flow of customers. The full dependence on the regularity of the data might not fully predict the impact of unusual conditions that could affect daily operations at the parcel centre. This limitation affects the feasibility of the model in dealing with unplanned situations. Future studies are advised to utilise advanced technology, such as an automatic sorting system, to increase the accuracy and effectiveness of the model in depicting the real situation. They can also create a hybrid model that combines automation and human labour. This approach has the potential to increase operational efficiency and improve customer experience, in line with the latest technological developments. Additionally, the parcel centre can consider modelling numerous other scenarios, such as the sorting scenario according to where students live. This is because students at UMPSA live at different residential colleges (e.g., Students Residences 1, 2, 3, and 4) and off campus. The parcel centre can use the model to see if the results are positive.

Acknowledgements

The authors wish to convey their highest gratitude to the UMPSA Parcel Centre for the provision of support and resources needed for this study.

Funding
This work was supported by the Social Science Research Grant from Universiti Malaysia Pahang Al-Sultan Abdullah (Grant number: RDU233407).

Declaration of Competing Interest
The authors declare no conflicts of interest.

CRediT Authorship Contribution Statement
Azli Azhar (Methodology; Data curation; Writing - original draft; Resources)
Jack Kie Cheng (Conceptualization; Formal analysis; Visualisation; Supervision)
Freselam Mulubrhan (Validation)

Availability of Data and Materials
The data supporting this study's findings are available on request from the corresponding author

Ethics Declarations
Although the study did not involve human or animal subjects, it was conducted in accordance with the research policies of Kyambogo University and the organisations.

Generative Artificial Intelligence Declarations
The authors claim that artificially intelligent-assisted technologies in the form of generative AI were not used to generate content, ideas, or theories. We have just utilised AI to enhance readability and refine the language. This was used with extreme human control and oversight. The authors take full responsibility for reviewing and approving the content.

References
Adan, I., & Resing, J. (2015). Queueing Systems. Retrieved from https://www.win.tue.nl/~iadan/queueing.pdf

Ahmad, T., & Van Looy, A. (2020). Business process management and digital innovations: A systematic literature review. Sustainability, 12(17), 6827.

Ajah, I. A., & Nweke, H. F. (2019). Big data and business analytics: Trends, platforms, success factors and applications. Big Data and Cognitive Computing, 3(2), 32-40.

Ali, A. H., Gruchmann, T., & Melkonyan, A. (2022). Assessing the impact of sustainable logistics service quality on relationship quality: Survey-based evidence in Egypt. Cleaner Logistics and Supply Chain, 4, 100036.

Basole, R. C., & Bellamy, M. A. (2014). Supply network structure, visibility, and risk diffusion: A Computational Approach. Decision Sciences, 45(4), 753–789.

Bottani, E., & Casella, G. (2024). Discrete-event simulation in logistics and supply chain management: A scientometric perspective. Production & Manufacturing Research, 12(1), 2415038.

Chen, J. C., Chen, T. L., & Lee, Y. H. (2023). Simulation optimization for parcel hub scheduling problem in closed-loop sortation system with shortcuts. Simulation Modelling Practice and Theory, 124, 102728.

Djamali, R. A. (2018). Dynamic system invention on the development of hulled agro-industry for supporting food autonomy in Papua. Journal of Basic Applied Scientific Research, 8(1), 6-66.

Garn, W., Aitken, J., & Schmenner, R. (2024). Smoothly pass the parcel: Implementing the theory of swift, even flow. RAIRO-Operations Research, 58(5), 4197-4220.

Hasija, S., Shen, Z. J. M., & Teo, C. P. (2020). Smart city operations: Modeling challenges and opportunities. Manufacturing & Service Operations Management, 22(1), 203-213.

Khairina, D. M., Muaddam, A., Maharani, S., & Rahmania, H. (2019). Forecasting of groundwater tax revenue using single exponential smoothing method. E3S Web of Conferences, 125(1), 1–5.

Krisnawati, F., Anugroho, D. M. R., Rachmawati, L. Y., & Asrol, M. (2022). Discrete event simulation modeling with arena for combination of manual queue and fast track queue in hospital. Jurnal PASTI (Penelitian dan Aplikasi Sistem dan Teknik Industri), 16(3), 251-260.

Kshetri, N. (2018). Blockchain's roles in meeting key supply chain management objectives. International Journal of information management, 39, 80-89.

Law, A. M. & Kelton, W. D. (2000). Simulation modeling and analysis. New York: McGraw-Hill.

Law, A. (2015). Simulation modeling and analysis. McGraw Hill Education.

Lin, Y. H., Wang, Y., He, D., & Lee, L. H. (2020). Last-mile delivery: Optimal locker location under multinomial logit choice model. Transportation Research Part E: Logistics and Transportation Review, 142, 102059.

Nakayama, S., & Yan, W. (2019). The package redelivery problem, convenience store solution, and the delivery desert: Case study in Aoba Ward, Yokohama. Journal of Urban Management, 8(3), 355-363.

Seghezzi, A., & Mangiaracina, R. (2022). Investigating multi-parcel crowdsourcing logistics for B2C e-commerce last-mile deliveries. International Journal of Logistics Research and Applications, 25(3), 260-277.

Tan, Z., Li, H., & He, X. (2021). Optimizing parcel sorting process of vertical sorting system in e-commerce warehouse. Advanced Engineering Informatics, 48, 101279.

Tosti, M., & Bottani, E. (2021). Discrete-event simulation in logistics: a critical review and framework for classification. In Proceedings of the 23rd International Conference on Harbour, Maritime and Multimodal Logistics Modelling and Simulation (HMS 2021) (pp. 70-76). I3M Conference.

Vázquez-Serrano, J. I., Peimbert-García, R. E., & Cárdenas-Barrón, L. E. (2021). Discrete-event simulation modelling in healthcare: A comprehensive review. International journal of environmental research and public health, 18(22), 12262.

Wang, P., Guo, B., Wang, Z., & Yu, Z. (2020). ShopSense: Customer localization in multi-person scenario with passive RFID tags. IEEE Transactions on Mobile Computing, 21(5), 1812-1828.

Wu, C. D., Zhu, J. J., Hsu, C. Y., & Shie, R. H. (2024). Quantifying source contributions to ambient NH3 using Geo-AI with time lag and parcel tracking functions. Environment international, 185, 108520.