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Forecast-guided simulation for optimizing cargo handling personnel requirements

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ABSTRACT

The increase in the number of cargo handling at the Ahmad Yani Airport Domestic Cargo Terminal has reached 217.18% from 2009 to 2019, but decreased by 47% in 2020 due to the COVID-19 pandemic. It will affect the service in cargo handling, especially the number of personnel and facilities. This research was conducted to determine the optimal number of Cargo handling personnel at a logistics company in 2024. The forecasting methods used are Linear Moving Average, Double Exponential Smoothing Brown's, and Simple Linear Regression, where these methods will be compared to see which method has the smallest error value. Then a cargo handling simulation model will be created for this company in 2024 to find out the optimal number of Cargo handling personnel at the logistics company uses ARENA Simulation Software. The results show that in 2024 with the simple linear regression method (which has the smallest error) around 7,816,594.9 kg of Cargo is predicted as incoming Cargo, and around 7,847,581.01 kg of Cargo is predicted as outgoing Cargo in that year at the logistics company. And from the simulation model, it is found that to optimize the number of cargo handling personnel, the number of additional personnel required is 1 Aviation Security, Dispatcher, and Transporter.

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1. INTRODUCTION

During the pandemic of Covid-19, the number of passengers on domestic flights has decreased. This is due to restrictions on human movement, which are aimed at preventing the transmission of the virus. However, there was one flight service that experienced a slight decrease compared to passenger flights during the pandemic, namely cargo flight services.

Based on the information from Kompas.com in their article entitled "Air Cargo, the Future of the National Aviation Business" on a national scale. This statement indicates that in 2020, the amount of air cargo transported by national airlines will only decrease slightly compared to the decrease in the number of passengers. In the first quarter of 2021, Angkasa Pura I served 105,411 tons of air cargo. Then it is predicted to increase at the end of 2021.

In addition, in an article published by DetikFinance.com entitled "Domestic Flights Can Recover This Year, International in 2023, Secretary General of INACA Bayu Sutanto stated that Indonesian domestic flights will start to rebound in 2022 and optimally like a pandemic in 2024. International flights are predicted to recover in 2024 and optimally in 2026. Several recent studies reported that air cargo transportation recovered faster than passenger transportation after the COVID-19 pandemic due to the rapid growth of e-commerce activities and logistics demand [1]–[3]. This condition increases operational pressure on airport cargo terminals and requires more adaptive workforce planning strategies.

The company in this study operates in the field of airport cargo services. Based on data issued by the Central Bureau of Statistics in its publication entitled Air Transportation Statistics, from 2009 to 2019, the amount of cargo unloaded and loaded at the logistics company experienced an increasing trend from 7,952,832 kg in 2009 to 17,271,966 kg in 2019. When the pandemic hit in 2020, the number of loadings and unloadings of cargo at logistics companies decreased to 9,027,003 kg due to restrictions on people's movements and fewer flights [4]. Post-pandemic, there has been an increasing trend in cargo in recent years. In this way, the amount of cargo unloaded and loaded will return to normal.

By looking at the amount of Cargo transported, it can be noted that in cargo transportation services, the support of personnel who have the ability and effective aviation safety facilities is needed [5]. This is because air cargo handling is one aspect that supports flight safety. This paper will simulate cargo handling using Arena Software to find the optimal condition. The result of the simulation can be used to adjust the number of personnel and facilities.

Cargo handling at air terminals, both for incoming and outgoing processes, faces complex challenges such as space constraints, unbalanced workloads between shifts, and pressure on service times [6]. In this context, determining the right number of personnel is crucial for efficient operations without overstaffing or understaffing. To evaluate personnel placement needs and efficiency, a discrete simulation approach with Arena software is a popular method of choice [7]. Discrete simulation is known as a flexible modeling method to represent the behavior and interactions of each system element [8]. The discrete simulation approach can be used to analyze and make improvements to existing systems. Discrete simulation is usually implemented at the operational level where transactions, processes, and flows of entities and variability are important factors [9]. Discrete simulation can be used in developing models to improve system performance [10] and to rearrange and modify existing systems [11]. Modeling using discrete simulation is essential to prevent damage to the real system caused by changes in policies/activities [12].

This simulation allows detailed modeling of the cargo process, from receiving goods, security checks, storage, to loading, so that management can test various scenarios of workforce configuration. Nsakanda et al. [13] showed that this approach is able to identify bottlenecks and provide a quantitative basis for compiling optimal work schedules and shift rotations. Efficiency in cargo handling is measured through indicators such as lead time, throughput, personnel utilization, and the level of loss or damage to goods. The results of Drljača et al. [14] show that increased efficiency can be achieved through a combination of the optimal number of personnel and simulation-based workflow arrangements. The Arena was used to simulate a scenario of reducing personnel in the outbound process, and found that reductions without flow adjustments actually decreased system performance. In contrast, the combination of shift arrangements and task redistribution increased utilization[15]–[17]. Overall, the scientific literature supports that the use of Arena-based discrete simulations can provide a comprehensive picture of operational efficiency and workforce requirements at air cargo terminals. This approach not only helps adjust the number of personnel to the actual workload but also supports long-term strategic planning in dealing with the growth in volume and complexity of logistics processes[18].

The use of Discrete-Event Simulation (DES) has been widely utilized in various sectors such as cargo, supply chain, baggage security checks, passenger queues, public services, waste management, and healthcare, as seen in research [7]–[11], [19]–[22]. Recent studies also show that discrete-event simulation can effectively support operational decision-making, workforce allocation, and bottleneck reduction in airport logistics systems [23]. However, the application of this method in the context of air cargo handling in Indonesia is still limited and tends to focus on increasing process efficiency or reducing waiting times, rather than on determining the optimal number of workers based on changes in cargo volume. Meanwhile, logistic companies' cargo volume experienced significant growth between 2009 and 2019 and a sharp decline in 2020 due to the COVID-19 pandemic, resulting in drastic changes in service capacity and personnel requirements. Previous research has been able to describe the need for operational adaptation, but there has been no integration of forecasting and simulation methods that can be used to project workforce needs in the recovery year of 2024. Thus, there is a gap in the lack of research that combines a multi-model forecasting approach and DES to generate quantitative recommendations for personnel needs at Indonesian domestic cargo terminals.

The novelty of this research lies in the development of a predictive workforce model that simultaneously integrates forecasting and discrete-event simulation methods to determine cargo handling personnel needs in 2024. This integrative approach differs from previous studies that only simulated existing system conditions without considering future workload changes. This study uses three forecasting methods: Linear Moving Average, Double Exponential Smoothing Brown's, and Simple Linear Regression. The best method is then selected from the three methods based on the smallest error. The results are then used as direct input in the Arena simulation model. This is complemented by a highly detailed representation of the cargo process flow, from EMPU arrival, breakdown, X-ray and weighing, sorting, hoarding, outbound build-up, and the entire incoming process through the ULD. This is built using empirical time distributions from the Input Analyzer and time standards based on the Westinghouse method. Furthermore, this study specifically simulates post-pandemic recovery conditions in 2024. By incorporating ideal utilization criteria (< 80%), this study will generate recommendations for optimal personnel numbers, a level never previously developed in studies of air cargo handling in Indonesia.

This study has specific and measurable objectives to support the development of an accurate workforce evaluation model to address changes in workloads in 2024. First, this study aims to forecast incoming and outgoing cargo volumes using three forecasting methods and determine the best method based on MAD, MSE, and SDE values. The historical data used comes from a logistics company from 2009–2021. Second, this study builds a complete cargo handling process simulation model using Arena Software by incorporating actual operational data, time distributions, and time standards based on the Westinghouse method. Third, this study measures workforce utilization levels under existing conditions and a 2024 scenario to assess personnel capacity to handle increased cargo loads. Furthermore, this study tests several scenarios for adjusting the number of personnel in the AVSEC, Dispatcher, and Transporter positions to evaluate their impact on system performance. Ultimately, this study aims to generate recommendations for optimal personnel composition capable of processing all incoming and outgoing cargo without backlogs and with utilization levels within safe operational limits.

2. MATERIALS AND METHODS

Forecasting is an integral part of management's decision-making activity. An organization will always determine goals and objectives, predict environmental factors, and then choose actions likely to achieve these goals and objectives [24]. Forecasting methods are widely applied in transportation and logistics systems to estimate future demand and support operational capacity planning decisions [25], [26]. Then, simulation is a way to produce conditions from a situation in the sense of a model to be studied, tried, or trained.

Based on the handling of Cargo is grouped into two major groups, namely General Cargo and Special Cargo. In addition, based on the method of service and type of product, according to IATA AHM, Cargo is divided into General Cargo, Special Shipment (e.g., AVI, DG, LHO, HUM, VAL, VUN, PER, etc.), specialized cargo products (e.g., express Cargo, courier shipments, same day delivery). The following are several types of Cargo according to :

1. General Cargo is ordinary goods that do not require special handling but must still meet the requirements set out from a security perspective. This category includes household goods, office equipment, sports equipment, clothing (garments, textiles), etc.
2. Special Cargo is goods shipped that require special handling. This type of goods can be transported by air and must meet special requirements and handling per IATA regulations and the carrier. Goods that fall into this category are AVI, DG, PER, PES, PEM, HEA, etc.
3. Irregularity Cargo is a problem that occurs in cargo handling. In addition, irregularity can also be interpreted as irregularities in field services where the application does not follow the Standard Operating

Procedure. Types of Irregularity Cargo are Missing Cargo, Damage Cargo, Overload Cargo, and Found Cargo.

In general, the steps to be taken are to forecast the amount of Cargo to be loaded or unloaded at the logistic company in 2024, which is 2024 based on the background, is an optimal recovery year for national aviation. After forecasting is complete, simulating cargo handling with Arena software is analyzed to determine whether the simulation model created is optimal in determining the optimal model using the trial-and-error method. The simulation model is optimal if all cargo is not delayed/failed to depart, and the utility of cargo handling personnel is less than 80%.

The methods used in forecasting are the Linear Moving Average, Double Exponential Smoothing Brown's, and Simple Linear Regression, because based on the plotting of incoming and outgoing cargo data, they have exponential, seasonal, and linear patterns, the similarities of which can be seen in Eq. (1-13) [24].

1. Linear Moving Average

$$S_t' = \frac{X_t + X_{t-1} + X_{t-2} + \cdots + X_{t-(N+1)}}{N} \tag{1}$$

$$S_t'' = \frac{S_t' + S_{t-1}' + S_{t-2}' + \cdots + S_{t-(N+1)}'}{N} \tag{2}$$

$$a_t = S_t' + \left(S_t' - S_t''\right) = 2S_t' - S_t'' \tag{3}$$

$$b_t = \frac{2}{N-1}\left(S_t' - S_t''\right) \tag{4}$$

$$F_{t+1} = a_t + b_t m \tag{5}$$

where S_t' is the single moving average on the data t, S_t'' is a single moving average from $MA(N)_t$, N is the window width, α_t is constant, b_t is coefficients, m is the number of forecasted periods, and F_{t+m} is the forecast value of the next m period after X_t.

2. Double Exponential Smoothing Brown's

$$S_t' = \alpha X_t + (1-\alpha)S_{t-1}' \tag{6}$$

$$S_t'' = \alpha X_t + (1-\alpha)S_{t-1}'' \tag{7}$$

$$\alpha_t = S_t' + \left(S_t' - S_t''\right) = 2S_t' - S_t'' \tag{8}$$

$$b_t = \frac{\alpha}{1-\alpha}\left(S_t' - S_t''\right) \tag{9}$$

$$F_{t+m} = \alpha_t + b_t m \tag{10}$$

where S_t' is single exponential smoothing (for $S_t' = X_1$), S_t'' is double exponential smoothing (for $S_t'' = X_1$), α_t is constant, b_t is coefficients, m is the number of forecasted periods, and F_{t+m} is the forecast value of the next m period after X_t.

3. Simple Linear Regression

$$f(x) = b_0 + b_1 x \tag{11}$$

$$b_0 = \frac{\sum Y}{N} - b_1 \frac{\sum X}{N} \tag{12}$$

$$b_1 = \frac{N\sum XY - (\sum X)(\sum Y)}{N\sum X^2 - (\sum X)^2} \tag{13}$$

where $f(x)$ is the response to predict, b_0 is intercept, b_1 is the slope, x is the independent variable (observation value on the x-axis), and y is the observation value on the y-axis.

The three methods will be compared using MAD, MSE, and SDE equations to determine the method that has the smallest error.

1. Mean Absolute Deviation

$$MAD = \sum_{t=1}^{n} \left|\frac{y_t - \hat{y}_t}{n}\right| \tag{14}$$

where y_t is the actual observed value in the period t, $\hat{y}_t$ is the forecast value in the period t, and n is the data observed.

2. Mean Square Error

$$MSE = \sum_{t=1}^{n} \frac{(X_i - F_i)^2}{n} \tag{15}$$

where X_i is the actual observed value in the period t, F_i is the forecast value in the period t, and n is the amount of data observed.

3. Standard Deviation Error

$$SDE = \sqrt{\sum_{t=1}^{n} \frac{(X_i - F_i)^2}{n-1}} \tag{16}$$

where X_i is the actual observed value in the period t, F_i is the forecast value in the period t, and n is the data observed.

The next step is to process the data that will be used as parameters in the simulation. The steps are:

1. Identifying the layout/view of the cargo handling system at logistic company
2. Calculating the cycle time and the amount of outgoing Cargo carried by EMPU officers, as well as the time and number of incoming Cargo carried by ULD aircraft to the terminal
3. Calculate each cargo group's cycle time at each location and resource using a stopwatch.
4. Testing the adequacy and homogeneity of standard time data [17] with Eqs. (17-21).

$$\alpha = 1 - P \tag{17}$$

$$S = \sqrt{\frac{\sum_{t=1}^{n} |x_i - \bar{x}|^2}{n-1}} \tag{18}$$

$$n' = \left(\frac{\left(Z\alpha/_{2}\right)s}{\left(\frac{re}{1+re}\right)\bar{x}}\right)^2 \tag{19}$$

$$BKA = \bar{x} + 3S \tag{20}$$

$$BKB = \bar{x} - 3S \tag{21}$$

where P is the confidence value (0.95 or 95% will be used in this study), α is the significance level, $Z\alpha/_{2}$ is the value obtained from the normal distribution table in the format ($t\infty, \alpha/_{2}$), $t\infty, \alpha/_{2}$ is the value obtained from the normal distribution table, re is the Relative Error, $\bar{x}$ is the average sample, x_i is the i-th observation sample, n is the initial sample size, s is the standard deviation, and n' is the required sample size.

5. Calculating normal time using the Westinghouse method and standard time [27] in handling each Cargo by Cargo handling personnel using Eq. (22-23)

$$W_n = \bar{W}_0 \,.\, Performace\ Rating \tag{22}$$

$$W_b = W_n \,.\, \frac{100\%}{100\% - \%allowance\ factor} \tag{23}$$

where W_n is the normal time, W_b is the standard time, $\bar{W}_0$ is the average observation time, the Performance rating is 1 ± Westinghouse performance rating, and the allowance factor is the working time allowance factor (percentage of rest time to total working time).

6. Determine the mathematical model of the distribution of time at stations that are not worked on by Cargo handling personnel, and determine the mathematical model of the distribution of cargo Coli arrivals per vehicle and ULD using the Input Analyzer menu.

7. Modeling a cargo handling simulation at logistic company, as well as verifying and validating the simulation model created by Eqs.(24-25) [28].

$$t = \frac{\bar{x}_{diff}}{S_{\bar{x}}} \tag{24}$$

$$S_{\bar{x}} = \frac{S}{\sqrt{n}} \tag{25}$$

where $\bar{x}_{diff}$ is the mean sample difference, n is the sample size, S is the standard deviation of the sample differences, and $S_{\bar{x}}$ is the estimated standard error of the mean.
8. Determine the number of Cargo handling personnel at PT. Optimal X in 2024 with a simulation model

Arena Simulation Software is a simulation software that uses the discrete event method to simulate most simulation efforts. In addition, ARENA has a user-friendly interface that makes it easier for users to build model views of complex systems and make various modifications to monitor future results [29].

3. RESULTS AND DISCUSSION

Cargo statistics are data records made by the airport management, integrated from the data of airlines with routes. The Airport Authority, as the supervisor of the implementation of airport activities, has the data records, which are then generally given to the Badan Pusat Statistik Indonesia for dissemination. For a logistics company, data is owned by the Badan Pusat Statistik Indonesia in its publication, " *STATISTIK TRANSPORTASI UDARA*". From these statistical data, it can be seen that the number of goods and Cargo that arrive or depart at the logistics company from 2009 to 2021. This data can be used to forecast incoming and outgoing cargo in 2024.

3.1. Forecasting

In processing incoming and outgoing cargo statistical data to forecast incoming and outgoing Cargo at a logistics company, the authors divide the forecasting data period into annual periods. The forecasting horizon of this forecasting period produces a horizon of 3 periods or 3 years. In forecasting, the methods used by the author are Linear Moving Average with a data width of 3, Double Exponential Smoothing Brown's with an α value of 0.2, and Simple Linear Regression. Forecasting is divided into two types: Cargo Incoming and Cargo Outgoing. By using Eqs. (1-13), the Incoming and Outgoing prediction results are obtained as in Table 1 and Table 2.

Table 1. The incoming forecasting

Year	Linear Moving Average (kg)	Double Exponential Smoothing Brown's (kg)	Simple Regression Linear (kg)
2009	-	-	6,434,801
2010	-	-	6,526,920
2011	-	4,803,903	6,619,040
2012	-	5,237,122	6,711,159
2013	-	5,639,063	6,803,279
2014	6,784,420	6,117,666	6,895,399
2015	8,310,096	7,201,077	6,987,518
2016	9,464,606	7,952,669	7,079,638
2017	10,294,422	8,694,713	7,171,758
2018	10,674,711	9,696,363	7,263,877
2019	12,760,205	11,188,030	7,355,997
2020	10,296,023	10,254,566	7,448,116
2021	4,521,412	7,970,109	7,540,236
2022	-966,964	6,086,194	7,632,355
2023	-3,803,505	5,999,036	7,724,475
2024	-6,640,046	5,911,878	7,816,594

Table 2. The outgoing forecasting

Year	Linear Moving Average (kg)	Double Exponential Smoothing Brown's (kg)	Simple Regression Linear (kg)
2009	-	-	3,571,040
2010	-	-	3,856,143
2011	-	3,818,635	4,141,245
2012	-	3,578,295	4,426,348
2013	-	3,548,575	4,711,451
2014	3,800,429	3,796,912	4,996,554
2015	5,289,599	4,352,303	5,281,656
2016	5,925,138	4,693,779	5,566,759
2017	6,601,088	5,337,794	5,851,862
2018	6,876,650	5,941,291	6,136,965
2019	9,802,591	7,644,486	6,422,067
2020	1,0151,420	8,224,505	6,707,170
2021	7,809,483	7,470,559	6,992,273
2022	2,942,130	6,247,881	7,277,376
2023	1,503,126	6,352,286	7,562,478
2024	64,121	6,456,692	7,847,581

The forecasting results for incoming cargo show different prediction patterns among the three methods, as shown in Table 1. The Linear Moving Average method produces a drastic decline and even negative forecast values after 2021, indicating that this method is less suitable for capturing the long-term trend of cargo recovery after the pandemic. Meanwhile, Double Exponential Smoothing Brown's shows a more stable trend, but still predicts lower cargo growth. In contrast, the Simple Linear Regression method shows a consistent increasing trend and predicts incoming cargo in 2024 to reach 7,816,594 kg, reflecting the gradual recovery of domestic air cargo activities.

The forecasting results for outgoing cargo also indicate that the Simple Linear Regression method provides a more realistic upward trend compared to the other methods, as shown in Table 2. The Linear Moving Average method shows unstable predictions with a sharp decline after the pandemic period, while Double Exponential Smoothing Brown's produces more moderate growth values. The Simple Linear Regression method predicts outgoing cargo in 2024 to reach 7,847,581 kg, indicating that cargo demand is expected to recover and continue increasing in line with the projected normalization of domestic aviation operations.

By using Eqs. (14-16), the error value of the forecasting method used, both Incoming and Outgoing, is obtained. The error value can be seen in Table 3 and Table 4.

Table 3. The error of the incoming cargo forecasting method

Method	MAD	MSE	SDE
Linear Moving Average	2,170,258	1.00×10^{13}	3,385,457
Double Exponential Smoothing Brown's	2,429,705	9.31×10^{12}	3,200,555
Simple Regression Linear	2,055,612	6.70×10^{12}	2,695,932

Table 4. The error of the outgoing forecasting method

Method	MAD	MSE	SDE
Linear Moving Average	1,879,383	6.38×10^{12}	2,700,309
Double Exponential Smoothing Brown's	1,527,835	3.87×10^{12}	2,064,513
Simple Regression Linear	1,078,655	2.36×10^{12}	1,602,140

The Simple Linear Regression method in Table 3 produces the smallest MAD, MSE, and SDE values compared to the other forecasting methods for incoming cargo. These results indicate that Simple Linear Regression has the highest forecasting accuracy and is better able to represent the historical trend of incoming cargo volume at the logistic company. Therefore, this method was selected as the basis for forecasting incoming cargo demand in 2024 simulation scenario.

According to Table 4, the Simple Linear Regression method also provides the lowest error values for outgoing cargo forecasting, as indicated by the smallest MAD, MSE, and SDE values among all methods tested. This demonstrates that the method is more consistent and reliable in capturing the trend of outgoing cargo movement at logistic company. Therefore, the Simple Linear Regression method was chosen for forecasting outgoing cargo demand in the 2024 simulation scenario.

3.2. Simulation Modelling

This logistics company is a cargo service company that operates daily, with employees working hours starting at 05.00 – 20.00 WIB or the last flight. Then the employee's working hours are divided into the morning and afternoon shifts. The morning shift starts at 05.00 - 12.30 WIB, then the afternoon shift starts at 12.30 - 20.00 WIB. Each Shift consists of 6 Transporters, 2 Dispatchers, 2 Manifestors, one cashier, 1 AVSEC, and 1 Supervisor. In this model, cashiers, Manifestors, and Supervisors will not be counted because the workforce does not handle the Cargo directly.

Observation data on the number of coli upon the arrival of EMPU vehicles and the arrival of ULD. In addition to the data on the number of coli in a pallet, a data adequacy test will not be carried out because what will be taken is the average, while the arrival of the EMPU Vehicle and ULD is by the manifest, so it only needs to find the data distribution. Data for outgoing cargo service time results from observing processing time from each work station, starting from EMPU Vehicle Arrival, EMPU Vehicle Breakdown, X-Ray and Scales, Outgoing Sorting and Stockpiling, Waiting in the Outgoing Warehouse, and Outgoing Build Up. Meanwhile, the incoming cargo service time results from observing the processing time from each work station, starting from the Arrival of Incoming ULD, Breakdown of Incoming ULD, Incoming Sorting and Stockpiling, waiting at the Incoming Warehouse, and Handover with EMPU.

Determining the number of samples to be used in this research. A data adequacy test was carried out so that the sample used could represent the population of the system. In this study, a confidence level of 95% was used. Calculation of data adequacy test and data uniformity (17-21), with the results shown in Table 5.

Table 5. Data Adequacy and Uniformity Test

No	Process	Observation	Test Result	Data Adequacy	Uniformity
1	The Arrival EMPU Vehicle	40	8	Adequacy	Uniformity
2	Breakdown EMPU Vehicle	40	22	Adequacy	Uniformity
3	X-Ray and Scale	40	9	Adequacy	Uniformity
4	Sort and Hoarding Outgoing	40	16	Adequacy	Uniformity
5	Waiting in the Outgoing Warehouse	20	6	Adequacy	Uniformity
6	Build Up Outgoing	40	36	Adequacy	Uniformity
7	Arrival of ULD Incoming	19	4	Adequacy	Uniformity
8	Breakdown ULD Incoming	40	38	Adequacy	Uniformity
9	Sort and Hoarding Incoming	40	35	Adequacy	Uniformity
10	Waiting in the Incoming Warehouse	40	9	Adequacy	Uniformity
11	Handover with EMPU	40	22	Adequacy	Uniformity

The sample data is sufficient if the test results are less than the observations. In Table 5, for EMPU vehicle arrivals, the number is 8 < 40, so the data is sufficient. Likewise, for other processes, the test results are less than the observations. These results indicate that the sample data are sufficient to represent the actual operational conditions of cargo handling activities at the logistic company and can therefore be reliably used as input parameters for the simulation model.

Calculation of normal time and standard time is carried out for all time data from observations (except for the arrival time of EMPU Vehicles, incoming ULD arrivals, and waiting time at the outgoing Warehouse, as well as incoming) by calculating the Westinghouse performance rating method [27]. The results are categorized as Excellent Skill (B2), Good Effort (C2), Good Condition (C), and Poor Consistency (F), of which these ratings will produce a total Westinghouse performance rating of 1.08, which will be used to calculate normal time. The allowance factor used is 6.25%, with allowance components consisting of 2% personal needs, 3.5% fatigue, and 0.75% unavoidable obstacles. This allowance factor will be used to calculate the standard time. The following is the calculation of normal time (23) and standard time (24):

1. Breakdown EMPU Vehicle

$$W_n = (0.47)(1.08) = 0.50 \text{ minute}$$

$$W_b = \frac{0.50(100)}{100-6.25} = 0.53 \text{ minute}$$

2. X-Ray and Scale

$$W_n = (0.91)(1.08) = 0.98 \text{ minute}$$

$$W_b = \frac{0.98(100)}{100-6.25} = 1.04 \text{ minute}$$

3. Sort and Hoarding Outgoing

$$W_n = (2.14)(1.08) = 2.31 \text{ minute}$$

$$W_b = \frac{2.31(100)}{100-6.25} = 2.46 \text{ minute}$$

4. Build up Outgoing

$$W_n = (0.68)(1.08) = 0.73 \text{ minute}$$

$$W_b = \frac{0.73(100)}{100-6.25} = 0.79 \text{ minute}$$

5. Breakdown ULD Incoming

$$W_n = (0.73)(1.08) = 0.79 \text{ minute}$$

$$W_b = \frac{0.79(100)}{100-6.25} = 0.84 \text{ minute}$$

6. Sort and Hoarding Incoming

$$W_n = (0.71)(1.08) = 0.76 \text{ minute}$$

$$W_b = \frac{0.76(100)}{100-6.25} = 0.81 \text{ minute}$$

7. Handover with EMPU

$$W_n = (0.44)(1.08) = 0.47 \text{ minute}$$

$$W_b = \frac{0.47(100)}{100-6.25} = 0.50 \text{ minute}$$

The time distribution test was carried out on the observation time data, which did not include the standard time. In addition to that, the distribution test was also carried out on the number of coils that came to each EMPU and ULD vehicle. In the Arena simulation software, the distribution test is carried out using the analyzer input menu. The complete results of the distribution testing can be seen in Table 6.

Table 6. Distribution test

No	Process	Distribution
1	The Arrival Coli of the EMPU Vehicle	2.5 + 13 * BETA(1.11, 1.31)
2	Coli ULD Incoming	0.5 + GAMM(9.45,1.35)
3	The Arrival of EMPU Vehicle	12.5 + 4.5 * BETA(2.21, 1.67)
4	Waiting in the Outgoing Warehouse	15.2 + 3.8 * BETA(1.59, 1.26)
5	Arrival ULD Incoming	NORM(54.5, 2.58)
6	Waiting in the Incoming Warehouse	6.52 + 2.32 * BETA(1.64, 1.33)

Based on Table 6, each operational process and cargo arrival pattern follows a specific statistical distribution obtained from the Input Analyzer in Arena Software. Most processes are represented by Beta, Gamma, and Normal distributions, indicating variability in cargo arrivals and service times within the cargo handling system. These distribution models are important to accurately represent real operational conditions and improve the reliability of the simulation results.

After the distribution test has been completed, a simulation model is created based on all the previously calculated information, and a simulation of the model is run. In this analysis, the simulation model is run seven times a replication, where one replication is equal to 1 working day. The output results from the simulation and the initial model utilization rate can be seen in Table 7 and Table 8.

Table 7. The output from initial simulation

No	Result	Unit	Amount (average per day)
1	Arrival EMPU Vehicle	Unit	48
2	Coli every vehicle	Coli	357
3	Departure cargo	Coli	357
4	Arrival ULD	Unit	13
5	Cargo taken by EMPU	Coli	161
6	Coli every ULD	Coli	161

Table 8. Early model resource utility

No	Resource	Work Station	Utility (%)
1	AVSEC	X-Ray and Scale	38.68
2	Dispatcher 1	Build Up Outgoing 1 and 2	29.38
3	Dispatcher 2	Breakdown ULD Incoming 1 and 2	14.09
4	Transporter 1	Breakdown EMPU 1, Sorting and Hoarding Outgoing 1	55.41
5	Transporter 2	Breakdown EMPU 2, Sorting and Hoarding Outgoing 2	55.78
6	Transporter 3	Build Up Outgoing 1, Breakdown ULD Incoming 1	22.05
7	Transporter 4	Build Up Outgoing 2, Breakdown ULD Incoming 2	21.42
8	Transporter 5	Sorting and Hoarding Incoming 1, Handover with EMPU 1	10.65
9	Transporter 6	Sorting and Hoarding Incoming 2, Handover with EMPU 2	11.32

The initial simulation model can represent the daily operational activities of cargo handling at a logistics company, including the arrival of EMPU vehicles, ULD arrivals, and the flow of incoming and outgoing cargo, as shown in Table 7. The simulation results indicate that the number of departing cargo units is equal to the number of incoming and outgoing cargo units, showing that the existing system is still capable of handling current operational demand under normal conditions.

It can be seen in Table 8 that the level of utilization, which is also the level of activity of each Cargo handling workforce resource at the logistics company, is not too busy, with the highest percentage being 55.78 percent owned by Transporter 2. This can still be said to be a reasonable limit because it is still below 70 percent [30], so it can be said that the current number of personnel is still sufficient and able to handle the loading and unloading of Cargo at the logistic company.

This verification aims to guarantee the correctness of the model. This model verification includes checks to ensure that all elements in the model represent the real system. To verify the cargo handling model itself, what is verified is the number of resources or labor directly related to the Cargo to be handled, how many processes occur, and how many personnel are involved in the process. The following is a verification model of cargo handling at a logistics company in Table 9.

According to Table 9, it can be seen that the number of processes and the number of personnel involved between the real system using the initial model of the simulation start to occur, so it can be said that the simulation model can describe the processes in the real system.

Table 9. Model verification

No	Condition	Real	Simulation	Explanation
1	The number of AVSEC	1	1	suit
2	The number of dispatchers	2	2	suit
3	The number of Transporters	6	6	suit
4	The number of the whole process	11	11	suit
5	The number of arrival personnel EMPU vehicle	0	0	suit
6	The number of Breakdown personnel EMPU vehicle	2	2	suit
7	The number of personnel in the Scale and X-ray	1	1	suit
8	The number of personnel sorting and Hoarding Outgoing	2	2	suit
9	The number of personnel waiting in the Outgoing Warehouse	0	0	suit
10	The number of personnel Build Up Outgoing	3	3	suit
11	The number of personnel arriving ULD	0	0	suit
12	The number of personnel Breakdown ULD	3	3	suit
13	The number of personnel sorting and Hoarding Incoming	2	2	suit
14	The number of personnel waiting in the Incoming Warehouse	0	0	suit
15	The number of personnel handover with EMPU	2	2	suit

Testing the validity of the research data was carried out using the Paired T-test method, which compared the output produced by the real system with the simulation model. The results of the initial model validation of the real system in a logistics company can be seen in Table 10.

Table 10. Model Validation

Replication to	Real	Simulation	Difference
1	617	565	52
2	588	571	17
3	500	535	-35
4	540	478	62
5	495	500	-5
6	580	497	83
7	491	480	11
The Average Difference			26.42

Based on Table 10, the differences between the real system output and the simulation results are relatively small, with an average difference of 26.42. It is possible to validate the initial simulation model of the logistic company by using Eqs. (24-25):

$$S = \sqrt{\frac{\sum_{i=1}^{n} |x_i - \bar{x}|^2}{n-1}} = \sqrt{\frac{\sum_{i=1}^{40} |x_i - (-26.42)|^2}{7-1}} = 41.24$$

$$S_{\bar{x}} = \frac{S}{\sqrt{n}} = \frac{41.24}{\sqrt{7}} = 15.58$$

$$t = \frac{\bar{x}_{diff}}{S_{\bar{x}}} = \frac{26.42}{15.58} = 1.69$$

The t-table value in the normal distribution table with a confidence level of 95% and $\alpha = 0.05$ is 1.943 or -1.943, with a t-count = 1.69, then the value of t-table ≤ t-count ≤ t-table, so that the hypothesis is accepted. The results state that there is no significant difference between the simulation output and the real system output, and this simulation model is declared valid.

The 2024 cargo handling simulation model is a data simulation model about the conditions under which domestic flights in Indonesia will experience a recovery, like before the pandemic in 2024. Based on the forecast results in 2024, incoming Cargo is as much as 7,816,594.9 kg of Cargo, while outgoing Cargo amounted to 7,847,581.01 kg of Cargo. Based on the results of observations, the average weight of 1 Coli of Cargo is 25 kg. It is 312,663 coli of incoming Cargo per year, which equals 26,055 coli of Cargo per month and 868 coli of Cargo per day. Then for outgoing Cargo, 313,903 coli of Cargo per year equals 26,158 coli of Cargo per month and 872 coli of Cargo per day.

To adjust the number of coli that had been predicted previously, namely 868 coli per day for incoming and 872 coli per day for outgoing, a condition was created by increasing the number of coliforms arriving in the initial simulation model data. Each data point at the Arrival EMPU Vehicle workstations was doubled, and each data point at the Arrival ULD workstations was changed to 7 times. This was done to ensure the number of outgoing and incoming packages matched the forecast results. Then, a mathematical model of random numbers was found for each workstation. Then a simulation of conditions in 2024 was run using the initial model. The simulation output results and the utilization rate can be seen in Table 11 and Table 12.

Table 11. The output from initial simulation in 2024

No	Result	Unit	Amount (average per day)
1	Arrival EMPU Vehicle	Unit	48
2	Coli every vehicle	Coli	900
3	Departure cargo	Coli	569
4	Arrival ULD	Unit	13
5	Cargo taken by EMPU	Coli	898
6	Coli every ULD	Coli	895

Table 12. Early model resource utility in 2024

No	Resource	Work Station	Utility (%)
1	AVSEC	X-Ray and Scale	97.5
2	Dispatcher 1	Build Up Outgoing 1 and 2	46.88
3	Dispatcher 2	Breakdown ULD Incoming 1 and 2	78.28
4	Transporter 1	Breakdown EMPU 1, Sort and Hoarding Outgoing 1	99.84
5	Transporter 2	Breakdown EMPU 2, Sort and Hoarding Outgoing 2	100
6	Transporter 3	Build Up Outgoing 1, Breakdown ULD Incoming 1	63.01
7	Transporter 4	Build Up Outgoing 2, Breakdown ULD Incoming 2	62.14
8	Transporter 5	Sort and Hoarding Incoming 1, Handover with EMPU 1	60.68
9	Transporter 6	Sort and Hoarding Incoming 2, Handover with EMPU 2	61.37

The simulation results for the 2024 scenario indicate a significant increase in cargo volume compared to the initial conditions, particularly in the number of incoming and outgoing cargo coli per day, as shown in Table 11. However, the number of departing cargo units is lower than the total arriving cargo units, indicating that the existing system is unable to fully process the increased workload and that some cargo remains unhandled under the current personnel configuration.

Table 12 shows that several resources in the 2024 simulation scenario show utilization levels exceeding the ideal operational limit of 80% [28], particularly AVSEC and Transporters in the outgoing cargo process. Transporter 2 reaches 100% utilization, indicating that the resource is operating at maximum capacity and has become a bottleneck in the system. The simulation results also show that 331 coli arriving from the EMPU Vehicle, as shown in Table 11, cannot be handled by the existing outgoing cargo personnel. These findings indicate that the current number of personnel is insufficient to accommodate the projected increase in cargo volume in 2024, making it necessary to add cargo handling personnel, especially for AVSEC, Transporter 1, and Transporter 2 positions.

The initial simulation model for conditions in 2024 has a high level of resource utilization, and several items cannot be handled. A more optimal model is made from the trial-and-error results, whose output and utility levels can be seen in Table 13 and Table 14.

Table 13. Output of the simulation model for proposed conditions for 2024

No	Result	Unit	Amount (average per day)
1	Arrival EMPU Vehicle	Unit	48
2	Coli every vehicle	Coli	900
3	Departure cargo	Coli	900
4	Arrival ULD	Unit	13
5	Cargo taken by EMPU	Coli	900
6	Coli every ULD	Coli	900

Table 14. Proposed model resource utilities year 2024

No	Resource	Work Station	Utility (%)
1	AVSEC 1	X-Ray and Scale 1	49.38
2	AVSEC 2	X-Ray and Scale 1	48.12
3	Dispatcher 1	Build Up Outgoing 1 and 2	48.75
4	Dispatcher 2	Breakdown ULD Incoming 1 and 2	51.93
5	Dispatcher 3	Build Up Outgoing 3 and Breakdown ULD Incoming 3	52.14
6	Transporter 1	Breakdown EMPU 1, Sort and Hoarding Outgoing 1	69.62
7	Transporter 2	Breakdown EMPU 2, Sort and Hoarding Outgoing 2	73.10
8	Transporter 3	Breakdown EMPU 3, Sort and Hoarding Outgoing 3	69.89
9	Transporter 4	Breakdown EMPU 4, Sort and Hoarding Outgoing 4	67.70
10	Transporter 5	Build Up Outgoing 1, Breakdown ULD Incoming 1, Sort and Hoarding Incoming 1, Handover with EMPU 1	52.07
11	Transporter 6	Build Up Outgoing 2, Breakdown ULD Incoming 2, Sort and Hoarding Incoming 2, Handover with EMPU 2	51.87
12	Transporter 7	Build Up Outgoing 3, Breakdown ULD Incoming 3, Sort and Hoarding Incoming 3, Handover with EMPU 3	53.79

The proposed simulation model for 2024 is capable of processing all incoming and outgoing cargo without any unhandled cargo remaining in the system, as shown in Table 13. The number of departing cargo units becomes equal to the number of arriving cargo units, indicating that the addition of personnel successfully improves system capacity and operational performance under the projected cargo demand conditions.

The simulation results show that the addition of 1 AVSEC, 1 Dispatcher, and 1 Transporter can improve the performance of logistic company's cargo handling system in the 2024 scenario, as shown in Table 14. This performance improvement is primarily due to reduced bottlenecks at critical workstations, particularly X-Ray and Scales, as well as the breakdown EMPU and sort & hoarding outgoing processes, which initially showed very high utilization rates (>80%), as shown in Table 12. The literature states that utilization approaching maximum capacity increases the risk of queues, delays, and service failures in air cargo systems [7], [13], [14]. Similar findings have been emphasized, showing that excessive resource utilization in cargo terminals significantly increases congestion risk and reduces service reliability [31].

Adding personnel increases service capacity and balances inbound and outbound process flows. With the addition of dispatchers, coordination between processes becomes more effective, thus minimizing workload imbalances. This aligns with the findings of Kierzkowski et al. [6] and Drljača et al. [14], which emphasize that cargo handling efficiency is strongly influenced by the appropriateness of personnel to the actual workload, not solely by process acceleration.

After the addition of personnel, the utilization rate of all resources remained within a safe range (±50–75%), which, according to O'Loughlin [30] and Tamizhinian and Pillai [7], is optimal for maintaining smooth operations and accommodating demand variability. This condition allows all incoming and outgoing cargo to be processed without delays or failed departures.

From a managerial perspective, these results demonstrate that personnel size determination needs to be based on a quantitative approach that integrates demand forecasting and discrete event simulation. Additional personnel should be viewed as a strategy to improve operational reliability, efficiency, and safety, not simply as a cost increase. Therefore, the developed simulation model can be used as a decision-support tool in human resource planning, particularly in addressing the dynamics of cargo volumes during the post-pandemic recovery period. This finding is consistent with Ferreira et al. [32], who emphasized that simulation-based workforce planning enables organizations to determine staffing requirements more accurately under uncertain operational demand conditions.

4. CONCLUSION

This research successfully developed a forecasting and simulation model for cargo handling at a logistics company. Forecasting results using a simple linear regression method indicate that in 2024, incoming cargo volume is estimated to reach 7,816,594.9 kg and outgoing cargo volume to 7,847,581.01 kg. Based on discrete event simulation results using Arena software, existing conditions indicate resource utilization levels exceeding ideal limits at several critical workstations, potentially leading to delays and service failures. The addition of one AVSEC personnel, one dispatcher, and one transporter has been shown to improve system performance, as evidenced by the processing of all cargo without delay and a resource utilization level within a safe and efficient range.

This research has several limitations. The simulation model is based on historical data and assumes normal operating conditions, so it does not fully represent unforeseen disruptions such as weather variations, operational disruptions, or changes in security policies. Furthermore, this research does not integrate labor cost analysis and does not differentiate service characteristics based on cargo type, which could potentially impact processing times and resource requirements. Therefore, further research is recommended to develop the model by incorporating labor costs and productivity, more detailed cargo type classifications, uncertainty scenarios, and seasonal variations. This development is expected to produce more comprehensive and applicable human resource planning recommendations for air cargo terminals in Indonesia.

REFERENCES

[1] K. Dube, "Emerging from the COVID-19 pandemic: Aviation recovery, challenges and opportunities," *Aerospace*, vol. 10, no. 1, p. 19, 2023, doi: 10.3390/aerospace10010019.

[2] T. T. İnan, "Post-covid air transport recovery: A multidimensional analysis of European airports under eurocontrol," *Case Stud. Transp. Policy*, vol. 20, p. 101444, 2025, doi: 10.1016/j.cstp.2025.101444.

[3] A. Karam, A. E. E. Eltoukhy, I. A. Shaban, and E.-A. Attia, "A review of COVID-19-related literature on freight transport: Impacts, mitigation strategies, recovery measures, and future research directions," *Int. J. Environ. Res. Public Health*, vol. 19, no. 19, p. 12287, 2022, doi: 10.3390/ijerph191912287.

[4] Badan Pusat Statistik Indonesia, "Statistik transportasi udara 2020," *Badan Pusat Statistik Indonesia*, 2021.

[5] G. Gunawan *et al.*, "Analisis standar jumlah personel penanganan pengangkutan barang berbahaya di Bandar Udara Adisutjipto," *Angkasa: Jurnal Ilmiah Bidang Teknologi*, vol. 8, no. 1, pp. 93–104, 2017, doi: 10.28989/angkasa.v8i1.135.

[6] A. Kierzkowski, T. Kisiel, P. Uchroński, and A. Vidović, "Simulation model for sustainable management of the air cargo screening process," *Energies (Basel).*, vol. 16, no. 21, 2023, doi: 10.3390/en16217246.

[7] A. Tamizhinian and V. M. Pillai, "Performance evaluation of cargo warehouse operations of an indian airline using discrete event simulation: A case study," in *Recent Advances in Operations Management Applications*, A. Sachdeva, P. Kumar, O. P. Yadav, and M. Tyagi, Eds., Singapore: Springer Nature Singapore, 2022, pp. 335–350. doi: 10.1007/978-981-16-7059-6_25.

[8] J. Karnon, J. Stahl, A. Brennan, J. J. Caro, J. Mar, and J. Möller, "Modeling using discrete event simulation: A report of the ISPOR-SMDM modeling good research practices task force–4," *Medical Decision Making*, vol. 32, no. 5, pp. 701–711, 2012, doi: 10.1177/0272989X12455462.

[9] J. I. Vázquez-Serrano, R. E. Peimbert-García, and L. E. Cárdenas-Barrón, "Discrete-event simulation modeling in healthcare: A comprehensive review," *Int. J. Environ. Res. Public Health*, vol. 18, no. 22, p. 12262, Nov. 2021, doi: 10.3390/ijerph182212262.

[10] S. AlKheder, A. Alomair, and B. Aladwani, "Hold baggage security screening system in Kuwait International Airport using arena software," *Ain Shams Engineering Journal*, vol. 11, no. 3, pp. 687–696, 2020, doi: 10.1016/j.asej.2019.10.016.

[11] R. Jain, H. Bedekar, K. Jayakrishna, K. E. K. Vimal, and M. Vijaya Kumar, "Analysis and optimization of queueing systems in airports–Discrete event simulation," in *Advances in Applied Mechanical Engineering*, H. K. Voruganti, K. K. Kumar, P. V. Krishna, and X. Jin, Eds., Singapore: Springer Singapore, 2020, pp. 1189–1194. doi: 10.1007/978-981-15-1201-8_125.

[12] C. Amiguet and A. Schiper, "Discrete-event simulation in ADA," *Proceedings of the 1987 Annual ACM SIGAda International Conference on Ada, SIGAda 1987*, pp. 133–140, 1987, doi: 10.1145/317500.317518.

[13] A. L. Nsakanda, M. Turcotte, and M. Diaby, "Air cargo operations evaluation and analysis through simulation," in *Proceedings of the 2004 Winter Simulation Conference, 2004.*, IEEE, 2004, pp. 1790–1798. doi: 10.1109/WSC.2004.1371531.

[14] M. Drljača, I. Štimac, A. Vidović, and S. Petar, "Sustainability of the air cargo handling process in the context of safety and environmental aspects," *J. Adv. Transp.*, vol. 2020, no. 1, p. 1232846, 2020, doi: 10.1155/2020/1232846.

[15] M. D. Al-Tahat, A. A. Alrousan, M. Z. Mistarihi, F. Al Shalabi, and S. Abu-Bajah, "Simulation modelling and analysis for improving the performance of production case study: Jordanian vehicles manufacturing company," *Acta Logistica*, vol. 8, no. 3, pp. 229–236, 2021, doi: 10.22306/al.v8i3.225.

[16] A. L. Tau, E. I. Edoun, C. Mbohwa, and A. Pradhan, "Product dispatch work process line improvement using arena simulation and modeling: A case study," in *Proceedings of the First Australian International Conference on Industrial Engineering and Operations Management, Sydney, Australia, December 20-21, 2022*, 2022. doi: 10.46254/au01.20220115.

[17] S. Park, J. Hwang, H. Yang, and S. Kim, "Simulation modelling for automated guided vehicle introduction to the loading process of ro-ro ships," *J. Mar. Sci. Eng.*, vol. 9, no. 4, p. 441, 2021, doi: 10.3390/jmse9040441.

[18] J. Ryczyński, A. Kierzkowski, and A. Jodejko-Pietruczuk, "Air cargo handling system assessment model: A hybrid approach based on reliability theory and fuzzy logic," *Sustainability*, vol. 16, no. 23, p. 10469, 2024, doi: 10.3390/su162310469.

[19] Y. Wulandari, T. Wahyudi, R. Rahmahwati, S. Uslianti, and F. Prima, "Simulation of queue system of retirement fund retrieval at the sanggau post office during the covid-19 pandemic using arena software," *OPSI*, vol. 14, no. 1, p. 89, Jun. 2021, doi: 10.31315/opsi.v14i1.4776.

[20] R. Setyaningrum and P. N. Sari, "Organic waste management based on supply chain management using arena simulation and macro ergonomics approach," *OPSI*, vol. 16, no. 2, p. 217, Dec. 2023, doi: 10.31315/opsi.v16i2.11325.

[21] Y. D. Astanti, I. Soejanto, and I. Berlianty, "Simulasi alur pelayanan rawat jalan (poliklinik) di rumah sakit menggunakan software promodel," *OPSI*, vol. 13, no. 1, p. 1, Jun. 2020, doi: 10.31315/opsi.v13i1.3223.

[22] Y. D. Astanti, B. D. Rahmawati, A. T. Akbar, and A. P. Rysnalendra, "Evaluation of waiting time for outpatient services at Respira Hospital Yogyakarta using discrete system simulation," *OPSI*, vol. 16, no. 2, p. 267, Dec. 2023, doi: 10.31315/opsi.v16i2.11536.

[23] R. Skapinyecz, "Recent trends in the optimization of logistics systems through discrete-event simulation and deep learning," *Algorithms*, vol. 18, no. 9, p. 573, 2025, doi: 10.3390/a18090573.

[24] S. G. Makridakis, S. C. Wheelwright, and V. E. McGee, *Forecasting: Methods and applications. 2nd Edition*. New York: John Wiley & Sons, INC., 1983.

[25] S. Turgay, R. Demir, and M. Kavacik, "A monte carlo-based approach to demand forecasting and stochastic optimization in supply chains," *Supply Chain Analytics*, p. 100210, 2026, doi: 10.1016/j.sca.2026.100210.

[26] M. Prastuti, I. N. Pujawan, E. Widodo, and H. Kuswanto, "A predictive analytics method for multiregional supply chain demand forecasting with spatial time series and machine learning," *Decision Analytics Journal*, p. 100706, 2026, doi: 10.1016/j.dajour.2026.100706.

[27] S. Wignjosoebroto, "Teknik tata cara dan pengukuran kerja," *Jakarta, Penerbit Guna Widya*, 1992.

[28] Kent State University, "SPSS tutorials: Paired samples t test," Kent State University. Accessed: Mar. 20, 2022. [Online]. Available: https://libguides.library.kent.edu/spss/pairedsamplesttest

[29] A. S. Hashemi and J. Sattarvand, "Application of arena simulation software for evaluation of open pit mining transportation systems − A case study," in *Proceedings of the 12th International Symposium Continuous Surface Mining - Aachen 2014*, C. Niemann-Delius, Ed., Cham: Springer International Publishing, 2015, pp. 213–224. doi: 10.1007/978-3-319-12301-1_20.

[30] E. O'Loughlin, "Resource utilization: What small businesses are doing wrong (and how to fix it)," Capterra. Accessed: Mar. 25, 2022. [Online]. Available: https://www.capterra.com/resources/optimal-resource-utilization-for-smbs/

[31] J. Karmelić, M. Jović Mihanović, A. Perić Hadžić, and D. Brčić, "Liner schedule reliability problem: An empirical analysis of disruptions and recovery measures in container shipping," *Logistics*, vol. 9, no. 4, p. 149, 2025, doi: 10.3390/logistics9040149.

[32] V. H. Ferreira *et al.*, "Two-phase optimization approach for maintenance workforce planning in power distribution utilities," *Electric Power Systems Research*, vol. 211, p. 108236, 2022, doi: 10.1016/j.epsr.2022.108236.

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