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An alternative methodology for planning baggage carousel capacity expansion: A case study of Incheon International Airport

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ABSTRACT

Intensifying competition for air transportation passengers has led airports to research optimal designs and determine the infrastructure expansion capacities of their terminals. As a result, many researchers have studied this subject from a variety of perspectives. In this study, we propose an alternative methodology of determining the expansion of baggage carousel capacity over a series of steps that includes both a simulation and a cost-benefit analysis. The methodology consists of three stages. In the first stage, we forecast the volume of arriving passengers (excluding transfer passengers) and aircraft traffic with an autoregressive integrated moving average (ARIMA) model. Next, we conduct an elaborate analysis to estimate passenger delay using a discrete event simulation model in which we consider the conveyor load and the baggage carousel allocation to aircraft rates. Finally, we determine a plan to expand baggage carousel capacity that accounts for expansion costs and passenger benefits. Construction and conveyor costs were applied to expansion costs, and capacity expansion leads to passenger benefits due to reduced waiting time. Using a real case with 23 candidate baggage carousels at Incheon International Airport during 2013–2015, our experiments demonstrate the strength of the proposed methodology in planning appropriate capacity expansion that reflects the operational flow of passengers within the airport based on the future trend of passenger demand. In particular, our results show that carousel no. 18 should be expanded during the first quarter of 2013, carousels no. 17 and no. 19 should be expanded in 2014, and carousel no. 5 should be expanded in 2015 to obtain optimal benefit-cost ratios of 1.65, 1.79, and 1.76 for each year, respectively.

1. Introduction

Since opening in 2001, Incheon International Airport has developed into a genuine world-class airport, ranking 2nd in international cargo traffic and 9th in international passenger traffic. Beginning in 2005, Incheon Airport has also been ranked 1st for nine straight years in the Airport Service Quality survey conducted by Airports Council International. The number of passengers at Incheon Airport has increased at a rate of approximately 7% from 2001 to 2013, on average (Fig. 1). In response to this growing demand, Incheon Airport is attempting to expand various types of infrastructure, including the expansion of the airport terminal, to maintain its current level of service.

Developing an analytical model of passenger flow in an airport terminal to determine the optimal infrastructure capacity in expansion planning is difficult due to the complexities of the terminal structure and demand uncertainty (Solak et al., 2009). Cause of this difficulty, several studies in this field has not considered passengers’ practical flow in the airport terminal. Nevertheless, it is important to determine whether the entire utilizable area is considered when planning for terminal capacity expansion. Solak et al. (2009) developed a maximum delay function in passageways and processing stations for calculating the maximum walking times by accounting for density, free-flow walking speeds (264 ft/min), and the length and width of passageways based on truncated Taylor series expansions (Rice, 1995); these authors suggested three approximations (triangular, parabolic and half-elliptical) to represent the shape of the peak for the processing stations. Suryani et al. (2010) calculated congestion with the M/G/1 queuing model that considers an arrival pattern of flights, service capacity, and runway capacity. Ronzani Borille and Correia (2013) incorporated arrival...
components into their simulation model and analyzed 720 scenarios that accounted for aircraft size, aircraft load factor, intervals between flights, passenger profiles, conveyor length, and differences in the arrival times of passengers and baggage at the conveyor belt.

However, the foregoing studies have certain limitations with respect to including various airport events in their calculations. For example, passenger waiting time at baggage claim is affected by equipment specifications and operation, such as conveyor loading and baggage carousel allocation to aircraft. Fig. 2 demonstrates that new luggage will not be loaded onto the conveyor when the total weight of the luggage on the conveyor is heavier than its maximum load capacity. After passengers remove luggage from the conveyor, luggage will begin to be loaded again. Such loading stoppages are components that increase passenger waiting time.

The basic premise of planning for the expansion of airport infrastructure capacity is to invest in improving the quality of service offered to passengers. The studies discussed above addressed passenger congestion and delay time to evaluate service levels after infrastructure capacity was expanded. However, according to Jorge and de Rusb (2004), it is necessary to evaluate the economic rationale of public investment decisions by applying analytical tools such as cost-benefit analyses.

The purpose of this paper is to determine the optimal expansion of baggage claim capacity at Incheon International Airport, considering future passenger arrival patterns and the operational aspects of baggage claim. For this determination, we propose a combination model that employs an autoregressive integrated moving average (ARIMA) model to forecast passenger demand, a simulation technique for estimating passenger waiting time and a cost-benefit analysis that uses expansion cost and passenger benefit. The proposed model is tested for facilitating its application to the real case of capacity expansion at Incheon International Airport.

This paper is organized as follows. Section 2 performs a literature review in terms of forecasting model, simulation model, and airport capacity expansion of airport. Section 3 presents the detailed procedures of our study. Section 4 describes the experimental results using real case of Incheon International Airport. Finally, in Section 5, the conclusion is presented.

2. Literature review

An accurate airport passenger demand forecast can help reduce airport risk regarding both short- and long-term planning for airport facility expansion and other decisions. Several approaches have been used in the literature to forecast air passenger volume. In its Airport Development Reference Manual (ADRM), the International Air Transport Association (IATA) (2004) defined airport capacity and described the relation between the capacity of passenger terminal facilities and an airport’s level of service. Scarpel (2013) applied an integrated mixture of local experts model (IMLEM) to forecast air passenger volume at São Paulo International Airport. The model was employed to address rapidly changing situations, i.e., when the time series presents turning points or any type of structural changes in the short term. Due to regional differences in input spaces, gross domestic product (GDP) growth was used as a leading indicator to forecast domestic passenger volume in the IMLEM. Mean absolute percentage error

![Fig. 1. The pattern of annually increasing passenger demand at Incheon International Airport.](image1)

![Fig. 2. The relevance of conveyor load capacity and baggage allocation to conveyor.](image2)
(MAPE) was used to estimate the accuracy of the forecast (2.82%). Several authors have argued that MAPE should be avoided as a measure of forecast accuracy because it may treat forecast errors above the actual observation differently from those below the observation value (Armstrong and Collopy, 1992; Makridakis, 1993).

Suryani et al. (2010) forecasted air passenger demand for Taiwan Taoyuan International Airport utilizing a system dynamics framework. According to this study, air passenger demand is affected by both external and internal factors; airfare and level of service were considered as internal factors, and GDP and population growth were the external factors in the model. Using the relationships among these factors, they developed optimistic and pessimistic scenarios based on GDP growth. Tsui et al. (2014) developed seasonal ARIMA (SARIMA) and ARIMA with exogenous input (ARIMAX) models to forecast the passenger volume for Hong-Kong International Airport from 11 principal originations using monthly time series data from the 1993–2010 period. These authors employed an intervention model to consider the effects of interventions and/or exogenous shocks (such as Severe Acute Respiratory Syndrome (SARS) and international oil price fluctuations) on their SARIMA model. In addition, the ARIMAX model was computed to consider internal and external factors and shock effects in the cause-effect time series regression model. Chen et al. (2009) forecasted monthly passenger arrivals to Taiwan from Japan, Hong Kong, and the United States with Holt–Winters, SARIMA, and Grey forecasting models and classified arriving passengers by their travel purposes, i.e., whether the passengers were traveling for tourist, non-tourist, or other reasons. These authors showed that the SARIMA model outperformed the Holt–Winters and Grey models with respect to forecasting tourism passengers. Kulendran and Witt (2003) compared the accuracy of several forecast models, including the error correction model (ECM), the structural time series model (STSM), the basic structural model (BSM), and various ARIMA models. They forecasted international business passenger demand for Australia from New Zealand, the United Kingdom, the United States, and Japan and showed that the ARIMA and BSM models outperformed other forecast models at short-term forecasting.

**Fig. 3.** Research procedure of baggage carousel expansion planning.
According to Solak et al. (2009), it is particularly difficult to build a holistic simulation model to analyze passenger flow in an airport terminal due to the complex structure of terminals and demand uncertainty. Most studies have either developed a generic model of the entire airport terminal or have narrowed their focus to an analysis of airport performance. Jim and Chang (1998) developed an airport passenger terminal simulation model using Simulation Language for Analogue Modeling II (SLAM II) and described passenger and baggage flows in the arrival and departure hall by considering a variety of input variables, such as aircraft type, domestic/international passengers and baggage, passenger group size, and passenger characteristics. Their model focused on an analysis of the general airport flow by including many elements of the entire terminal rather than analyzing details in a specific area. Freivalde and Lace (2008) analyzed the processes of check-in, security control, boarding control, and baggage sorting to find the bottleneck that was causing passenger congestion at the Riga International Airport. According to this study, the baggage sorting and security control areas were bottlenecks due to high passenger volume. The simulation model in this study employed an analysis time of approximately one hour and assumed that there were 100 passengers per flight and that passengers arrived regularly at baggage claim. Ronzani Borille and Correia (2013) compared Brazil's five airports using a service index that is calculated by using the available area around carousels, the number of arriving passengers at peak time, and the averaging waiting time; this study considered passenger profile, conveyor length, and inter-arrival time at baggage claim, as the main factors of influence when establishing operational activity-based scenarios.

Many studies have attempted to determine the optimal design and expansion capacities. However, most studies have only focused on a particular area of the terminal capacity problem in a single-period approach based on short-term demand forecasts and have critical limitation with respect to including the characteristics of airport terminals which have complex structures and uncertain demand. In reality, it is difficult to develop an analytical model of passenger flow that can assist capacity expansion planning. Solak et al. (2009) developed time functions to approximate maximum delays in passageways and processing stations inside the airport terminal and employed these delay functions to build a multi-stage stochastic programming model based on a multi-commodity flow network representation of the entire airport terminal. In this model, infrastructure capacities and the width of passageways were determined subject to a given deterministic demand scenario and a fixed budget constraint. Suryani et al. (2010) used a system dynamics model to balance capacity and demand over the long term and considered future demand forecasts based on optimistic and pessimistic scenarios to decide when and how much an airport should expand its infrastructure capacity. Jorge and de Rusb (2004) performed an economic evaluation of a major investment in transportation infrastructure. When a project such as capacity expansion is to be implemented, it is necessary to identify and measure the benefits and costs during the project period to evaluate economic realities. These authors divided the benefits of air-side and land-side investment into four categories: (i) reduced travel, (ii) improved service reliability, (iii) reduced operating costs, and (iv) increased traffic.

### Table 1
The rate of passengers on a daily basis in August (peak month) from 2001 to 2012.

| Variables | Day |
|-----------|-----|
| Mon. | Tue. | Wed. | Thu. | Fri. | Sat. | Sun. | Total |
| Passenger | 13.82% | 13.27% | 14.34% | 14.53% | 15.04% | 14.15% | 14.83% | 100% |
| Aircraft | 14.42% | 12.88% | 14.06% | 13.93% | 14.43% | 14.57% | 15.72% | 100% |

### Table 2
The hourly passenger rate for August (peak month) from 2001 to 2012.

| Hourly | Aircraft | Passenger |
|--------|----------|-----------|
| Arrival | Arrival | Arrival |
| 00:00–01:00 | 0.58% | 0.30% | 12:00–13:00 | 5.73% | 5.32% |
| 01:00–02:00 | 0.45% | 0.23% | 13:00–14:00 | 4.63% | 4.14% |
| 02:00–03:00 | 0.44% | 0.31% | 14:00–15:00 | 5.22% | 5.47% |
| 03:00–04:00 | 0.89% | 0.88% | 15:00–16:00 | 6.74% | 7.63% |
| 04:00–05:00 | 3.02% | 3.62% | 16:00–17:00 | 7.79% | 9.42% |
| 05:00–06:00 | 4.22% | 4.67% | 17:00–18:00 | 9.47% | 10.54% |
| 06:00–06:59 | 5.31% | 5.64% | 18:00–19:00 | 7.18% | 6.97% |
| 07:00–07:59 | 5.42% | 5.20% | 19:00–20:00 | 4.95% | 4.44% |
| 08:00–09:00 | 4.39% | 3.91% | 20:00–21:00 | 4.93% | 4.62% |
| 09:00–10:00 | 2.00% | 1.52% | 21:00–22:00 | 3.12% | 3.01% |
| 10:00–11:00 | 3.50% | 2.54% | 22:00–23:00 | 1.30% | 1.11% |
| 11:00–12:00 | 7.90% | 8.01% | 23:00–24:00 | 0.81% | 0.48% |

### Table 3
Summary of ADF tests for unit roots with the 1st differenced demand data.

| Variables | d | D | ADF test statistic | P-value | Results |
|-----------|---|---|--------------------|--------|---------|
| Passenger | 1 | 0 | -9.2575 | <0.01 | Rejected the null |
| Aircraft | 1 | 0 | -5.8396 | <0.01 | Rejected the null |

d: 1st difference, D: Seasonal difference.

### Table 4
Summary of ADF tests for seasonal unit roots with the 1st differenced demand data.

| Variables | d | D | ADF test statistic | P-value | Results |
|-----------|---|---|--------------------|--------|---------|
| Passenger | 1 | 0 | -1.4167 | 0.1411 | Fail to reject the null |
| Aircraft | 1 | 0 | -0.819 | 0.3083 | Fail to reject the null |

d: 1st difference, D: Seasonal difference.

### Table 5
Summary of ADF tests for seasonal unit roots with the 1st differenced and seasonal differenced demand data.

| Variables | d | D | ADF test statistic | P-value | Results |
|-----------|---|---|--------------------|--------|---------|
| Passenger | 1 | 1 | -12.944 | <0.01 | Rejected the null |
| Aircraft | 1 | 1 | -11.789 | <0.01 | Rejected the null |

d: 1st difference, D: Seasonal difference.

### Table 6
SARIMA models of monthly passenger and aircraft arrivals for Incheon International Airport.

| Explanatory variables | Air passenger arrivals | Aircraft arrivals |
|-----------------------|------------------------|-------------------|
| SARIMA (0,1,0)(2,1,0)12 | Coefficients | SARIMA (0,1,0)(2,1,0)12 | Coefficients |
| Constant | -0.00000291 | -0.00021 | |
| MA (1) | -0.17198 | -2.11 | |
| MA (2) | 0.28619 | 3.61 | |
| MA (3) | 0.29244 | 3.64 | |
| SAR (12) | -0.58972 | -7.54 | |
| SAR (24) | -0.48679 | -6.67 | |
| SMA (12) | 0.11236 | 7.69 | |
| AIC | 364.927 | 576.078 | |
| BIC | 350.551 | 567.452 | |
| MAPE (%) | 3.22% | 6.4% | |

Remark: ** and *** denote that the explanatory variable is significant at the 0.05 and 0.01 significance level, respectively. T-statistics are printed in parentheses.
3. Proposed architecture and methodology

This study addresses planning for expanded baggage carousel capacity targeting on Incheon International Airport. The architecture consists of an ARIMA forecasting model, a discrete-event simulation (DES) model capturing the detailed operational activities at the baggage claim, and a heuristic algorithm based on a cost-benefit analysis, as shown in Fig. 3. For application of DES, the models that can describe the operational activities at an airport infrastructure can be simulated using scientific programming languages such as C or C++. However, standard simulation packages, such as ARENA and ProModel, AutoMod etc., are also available; such packages facilitate the process of building models and provide support for output analysis and optimization. To advance the author’s knowledge of ARENA 14.0 (Kelton et al., 2002), that simulation package is chosen for modeling the baggage claim process and conducting the experiment, including the forecast demand, the allocation rate, and the condition of the conveyor.

We first forecasted the future arriving passenger demand and aircraft traffic volume with an ARIMA model by using historical monthly data from January 2001 to December 2012 that was obtained from Incheon International Airport. Next, the results of the forecast for the period from January 2013 through December 2015 were translated from monthly data into hourly data to use as input for simulation in the passenger flow analysis.

There are three stages for translating the monthly demand data forecasted by an ARIMA model into hourly simulation input data. First, the monthly dataset is translated into four identical weekly datasets. Indeed, the demand pattern at Incheon Airport is almost identical on a weekly basis. Second, we generate daily datasets from the weekly datasets that reflect each day’s relative ratio over total weekly demand (e.g., the Monday ratio = 13.83% of passenger traffic as shown in Table 1). To generate the hourly arrival dataset for both aircraft and passengers, the arrival pattern of aircraft and passengers is generated as the relative ratio by each hourly time slot (00:00–24:00) in Table 2.

We developed the baggage carousel simulation model based on conveyor conditions and the aircraft allocation to baggage carousel rates at Incheon International Airport to capture the dynamic behavior of baggage claim. This simulation was used to measure the
that redetermined the start time, location, and quantity of expansion claim. During planning to expand baggage carousel capacity, we waiting time for picking up passengers’ baggage at the baggage claim. During planning to expand baggage carousel capacity, we determined the start time, location, and quantity of expansion construction with a simulation-based heuristic search algorithm that reflected a cost-benefit analysis. In our search algorithm model, a baggage carousel is stopped for the duration of construction (3 months) after it is selected for expansion. Thus, although passenger waiting time decreases after construction, it increases at other baggage carousels during the construction period. Because of the fluctuation of demand and different aircraft allocation rates to each baggage carousel, it is important to consider the start time, location, and the quantity of expansion to answer the following key questions: 1) When is the proper period to expand a baggage carousel?; 2) Which baggage carousel should be expanded?; and 3) How many baggage carousels should we expand?

3.1. SARIMA model

ARIMA and SARIMA models have been widely used in forecasting air passenger demand. The ARIMA model is acknowledged to be an accurate forecast method over the short and medium terms (Coshall, 2009; Andreoni and Postorino, 2006; Chen et al., 2009). In this paper, we employed Incheon International Airport’s historical data from January 2001 to December 2012 to generate an ARIMA model to forecast Incheon International Airport’s monthly arriving passenger volume and aircraft traffic between January 2013 and December 2015.

To forecast the future demand pattern using our ARIMA model, the historic time series should meet the stationary conditions. In general, if the mean and variance of the data are non-stationary, natural logarithmic transformation and differencing is used to stabilize the data. The non-seasonal and seasonal unit roots are tested to identify the stationarity using the augmented Dickey–Fuller (ADF) test, which is the most notable and commonly used test. The unit root test is used to examine whether a time series is stationary. If the time series contains a unit root, then it is non-stationary and subsequently must be transformed into a stationary series by removing the unit root(s). This objective can normally be reached by differencing the series. In practice, most time series can become stationary series by replacing the original data with a first difference. In the case of seasonality, a time series can become stationary after taking d non-seasonal differences and D seasonal differences.

Table 3 summarizes the results of the unit root test for the 1st order differenced variables. The ADF statistics for the 1st difference variables are all significant at the 5% significance level, which demonstrates that these are stationary.

In general, when the time series plots of the original and 1st differenced variables appear to have seasonality, the seasonal unit root test is required to prove it scientifically. Tables 4 and 5 demonstrate the results of unit root tests for the 1st differenced variables and 1st differenced and seasonally differenced variables, respectively. Table 5 demonstrates that ADF statistics of variables after seasonal difference are significant at the 5% significance level.

Both the ACF and PACF correlations are used to identify the orders of the AR and MA components for all the stationarity time series. The best-fit SARIMA models are identified based on the lowest BIC and AIC test results. To confirm the adequacy of the selected models, the ACF and PACF diagnostic and the Ljung—Box Q statistics verified that the residual series have ‘white noise’ characteristics.

Table 6 presents the results of the ARIMA model’s evaluation of SARIMA (0,1,3)(0,1,1)12 for passenger arrival and SARIMA (0,1,0)(2,1,0)12 for aircraft arrival. As a result, the two models are suitable for forecasting because they estimate proper coefficients and satisfy the hypothesis of white noise independence.

The results of forecasting passenger demand patterns and aircraft traffic are shown in Fig. 4. The MAPE test verifying forecast accuracy was 3.32% for air passengers and 6.4% for aircraft.
According to Lewis (1982), when the MAPE value is $\leq 10\%$ for a forecasting model, its forecasting performance is considered to be acceptable.

3.2. Description of the discrete event simulation model

3.2.1. Transformation of forecasting data for application of simulation schedule data

We first transformed the monthly data into hourly data for use as simulation input data. As shown in Fig. 5, the monthly data forecasted from Jan. 2013 to Dec. 2015 are translated into hourly arrival scheduling data by using information for average daily and hourly arrival rates during the peak month (August). Table 7 shows hourly schedule data on a Monday in August between 2013 and 2015. The average daily and hourly arrival rates were calculated using average daily passenger arrival numbers and aircraft traffic from 2001 through 2012 at Incheon International Airport. We employed the hourly schedule as our simulation schedule data.

3.2.2. Simulation approach for estimating passenger delay time at baggage claim

The simulation model captures the detailed passenger flow at baggage claim and estimates passenger delay time. To describe the real baggage claim of Incheon Airport, we modeled 23 baggage carousels that are allocated to 6 gates and each baggage carousel has a conveyor that is 90 m long, travels at a speed of 40 m/min, and can bear 100 kg/m for max load.

Based on the current flight status of Incheon Airport,\(^1\) we generated average allocation rate for each of the gates, such that (A) = 8.5%, (B) = 25.59%, (C) = 18.33%, (D) = 15.83%, (E) = 22.71% and (F) = 9.04%. Furthermore, we estimated the rate allocated by each baggage carousel to gates using average hourly aircraft arrival data from Monday to Sunday between March 2012 and March 2013. Such results are shown in Fig. 6.

In the simulation model, the baggage claim operations of the airport are represented individually. The detailed operational requirements of passengers and baggage flow at a baggage carousel are as shown in Fig. 7.

- Passengers arrive at the baggage carousel before their baggage
- Baggage arrives at the baggage carousel when more than 60% of the passengers from each aircraft have arrived at the baggage claim.
- There are two passenger types: passengers with no bags (20% of passengers in an aircraft) and passengers with one bag (80% of passengers in an aircraft).
- Baggage weight is between 20 and 50 kg and the sum of a bag’s width, length, and height is less than 1580 mm\(^2\)
- A baggage carousel’s waiting space is divided into four parts (starting area, ending area, central area I, and central area II)
- 20% of passengers wait at the starting area and ending area, 40% wait at central area 1, and 40% wait at central area 2, according to Ronzani Borille and Correia (2013).
- If the total baggage weight on the baggage carousel is greater than 70% of the conveyor’s max load, the staff will stop putting baggage onto the carousel. The rest of the baggage is put on the baggage carousel after 50% of the baggage on the carousel is claimed by passengers or otherwise removed from the carousel.
- Passengers wait for their baggage in four areas: A, B, C and D. In Fig. 7, baggage continues rotating on the conveyor and is searched by passengers at each area. If the baggage is claimed by a passenger, waiting time is recorded and the baggage leaves the system.

Through a simulation run, we measured passenger numbers, total wait time, and average wait time. Table 8 shows the quarterly simulation results for each baggage carousel in 2013. Passengers’ average wait time was approximately 14.64 min, and normally showed the third quarter with the highest wait time because of the peak period of August.

3.3. Expansion planning of baggage carousel

3.3.1. The building conditions involved in baggage carousel expansion

The planning conditions for baggage carousel expansion is defined as shown in Fig. 8. While the existing conveyor (length: 90 m) is being replaced by the expanded conveyor (length: 110 m),

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\(^{1}\) To get information, access the following website: http://airport.kr/airport/flightinfo/IhArrStatusList.ia?gubun=E.

\(^{2}\) Based on the IATA ADRM standards, baggage weight is between 10 and 60 kg and the sum of a bag’s width (150–300 mm), length (450–900 mm), and height (400–750 mm) is less than 1950 mm.
and is out of service for three months, the allocation rate of such a carousel is equally distributed and added to those of other baggage carousels in the same gate. For example, Fig. 9 shows an example of expansion construction for baggage carousel 2: if baggage carousel 2 were to be expanded during the second quarter of 2015, baggage carousel 2’s aircraft allocation rate is added to the allocation rate of baggage carousels 1 and 3 in the same gate during the construction period.

Due to different allocation rates by each gate (gate: 8.5–25.59%, carousel: 15.3–36.6%) and fluctuations of hourly arrival patterns, and because demand fluctuates during all periods in terms of passenger benefits that we will detail in Section 3.3.2, the determinations of what, when, and how much should be expanded are important and interesting. The main challenges we face are to determine optimal expansion planning based on the three key objectives mentioned above.

3.3.2. Identification of benefits from baggage carousel expansion

To quantify passenger benefit from baggage carousel expansion resulting from improvement of services, we use the “income approach” methodology.

Generally, the income approach is used to calculate the value of work that is obtained when personal travel time saved by road building or improvement projects is converted into working time. Based on such an approach, we assume that reducing passenger time finding baggage at baggage claim can be allocated to passenger working activities in a value-added approach. Thus, the benefit of the time saved by the baggage carousel expansion project is calculated by Equations (1) and (2).

Total reduction waiting time in Equation (1) was measured by passengers’ over-waiting time, which means the passengers’ waiting time that exceeds baggage claim service time standards (Correia and Wirasinghe (2010)).
Passenger Benefit = Total reduction waiting time × time value of passenger \[ (1) \]

Time value of passenger = \( \frac{\text{average annual earnings}}{\text{average annual working hours}} \) \[ (2) \]

Passenger benefit was calculated under a formulation from the transportation facility investment evaluation guidelines (2011) that is published by Ministry of land, infrastructure and transport (MOLIT) in Korea. We considered the value of time for each passenger as $30.83 per hour. Because there is little difference between that figure and the $34.26 per hour suggested by Jorge and de Rusb (2004), our results should be workable and meaningful.

The costs considered in our work consist of the costs of construction, such as design costs, supervision charges, power supply costs, control equipment costs, etc., and conveyor installation costs that have been previously applied as real proposal costs by conveyor installment companies. On the basis of the above analysis, total investment in the expansion, as shown in Table 9, amounts to $398,887 for a 90 m conveyor belt and $473,098 for a 110 m conveyor belt. Table 9 displays the cost of each type of conveyor and its proportion of total costs.

### 3.3.3. The heuristic algorithm of baggage carousel expansion

In Fig. 10, our heuristic algorithm is designed to determine the optimal expansion period, location and quantity of baggage carousels by maximizing benefit over cost in each period in the planning horizon. The details of each step are the following:

1. **(Step 1) Initialize input parameters and variables:** In Step 1, we set the initial expansion quantity (= 1) and the planning horizon (= 3 years).

2. **(Step 2) Determine the expansion period and location through a simulation-based heuristic search:** We determine the period and the type of conveyor that should be expanded by using the

### Table 8
Simulation results for 2013: Wait time per passenger in baggage carousels (1–23).

| Year | Quar. | Variables | Gate 1 | Gate 2 | Gate 3 |
|------|-------|-----------|-------|-------|-------|
|      |       | Gate 1    | Gate 2 | Gate 3 | Gate 4 | Gate 5 | Gate 6 |
|      |       | Conv. #1  | Conv. #2 | Conv. #3 | Conv. #4 | Conv. #5 | Conv. #6 | Conv. #7 | Conv. #8 | Conv. #9 | Conv. #10 | Conv. #11 |
| 2    | 1/4   | 138,060   | 221,940 | 227,520 | 429,900 | 450,960 | 316,050 | 238,200 | 264,780 | 297,900 | 224,760 | 184,500 |
|      |       | 14.8      | 14.7    | 14.4    | 14.5    | 14.5    | 13.9    | 14.9    | 15.1    | 14.6    | 14.7    | 14.4    |
| 0    | 1     | 31617.9    | 54314.6 | 54655.3 | 103782.2 | 109,001 | 73404.7 | 65667.2 | 72730.5 | 55219.6 | 44321.8 |
|      |       | 13.8      | 14.7    | 14.4    | 14.5    | 14.5    | 13.9    | 14.9    | 15.1    | 14.6    | 14.7    | 14.4    |
| 3    | 2/4   | 120,120   | 164,530 | 160,680 | 415,140 | 412,080 | 365,310 | 217,290 | 271,530 | 261,090 | 223,710 | 251,280 |
|      |       | 14.1      | 14.6    | 13.9    | 14.7    | 14.1    | 14.1    | 14.3    | 14.6    | 14.2    | 14.1    | 14.7    |
| 3/4  |       | 28175.5   | 40098.2 | 37288.8 | 101989.9 | 109,001 | 73404.7 | 59070.6 | 67222.2 | 72730.5 | 55219.6 | 44321.8 |
|      |       | 14.1      | 14.6    | 13.9    | 14.7    | 14.1    | 14.1    | 14.3    | 14.6    | 14.2    | 14.1    | 14.7    |
| 4/4  |       | 315210    | 40184.5 | 38732.9 | 104822.5 | 113,000 | 81567.2 | 58739.7 | 66722.2 | 73723.7 | 55219.6 | 44321.8 |
|      |       | 14.1      | 14.6    | 13.9    | 14.7    | 14.1    | 14.1    | 14.3    | 14.6    | 14.2    | 14.1    | 14.7    |

Quar: Quarter/Conv: Conveyor.

**Fig. 8.** Conditions of baggage carousel expansion.

### Table 9
The cost of type of conveyor and its proportion of total costs.

| Year | Quar. | Variables | Gate 4 | Gate 5 | Gate 6 |
|------|-------|-----------|-------|-------|-------|
|      |       | Conv. #12 | Conv. #13 | Conv. #14 | Conv. #15 | Conv. #16 | Conv. #17 | Conv. #18 | Conv. #19 | Conv. #20 | Conv. #21 | Conv. #22 | Conv. #23 |
| 2    | 1/4   | 146,640   | 190,050 | 267,990 | 265,620 | 169,680 | 301,830 | 377,580 | 411,000 | 143,970 | 150,690 | 95,700 | 54,630 |
|      |       | 14.4      | 14.1    | 14.4    | 14.4    | 14.2    | 14.1    | 14.1    | 14.5    | 14.7    | 14.1    | 13.9    | 20.6    |
| 0    | 1     | 35148.0   | 46759.9 | 64751.0 | 63681.7 | 40027.7 | 71174.6 | 91399.6 | 109937.9 | 34233.6 | 35009.5 | 32925.2 | 13182.4 |
|      |       | 14.4      | 14.1    | 14.4    | 14.4    | 14.2    | 14.1    | 14.1    | 14.5    | 14.7    | 14.1    | 13.9    | 20.6    |
| 3    | 2/4   | 201,900   | 178,800 | 264,540 | 271,920 | 208,860 | 258,720 | 442,890 | 392,610 | 189,450 | 143,340 | 87,930 | 94,830 |
|      |       | 15.7      | 15.7    | 15.4    | 14.8    | 14.8    | 15.1    | 14.8    | 14.8    | 15.1    | 15.0    | 14.8    | 15.2    |
| 3/4  |       | 49572.6   | 41086.5 | 64753.2 | 67298.3 | 48746.8 | 61464.2 | 126113.7 | 92572.6 | 46838.3 | 35786.1 | 20160.9 | 22495.1 |
|      |       | 14.7      | 13.8    | 14.7    | 14.8    | 14.0    | 14.3    | 17.1    | 14.1    | 14.8    | 15.0    | 13.8    | 14.2    |
| 4/4  |       | 190,290   | 231,150 | 283,800 | 274,980 | 176,370 | 324,390 | 502,800 | 404,520 | 170,610 | 219,000 | 119,190 | 46,770 |
|      |       | 13.5      | 14.6    | 14.6    | 15.1    | 14.9    | 14.4    | 15.6    | 14.7    | 14.5    | 15.1    | 15.1    | 15.9    |
|      |       | 36537.6   | 45463.4 | 62795.2 | 60334.4 | 51625.6 | 62560.5 | 100382.1 | 107058.6 | 33427.2 | 39501.8 | 29001.9 | 19,320.6 |

Quar: Quarter/Conv: Conveyor.
simulation-based search algorithm within a solution space consisting of a combination of periods and conveyor types. (Step 3) Terminating condition check: Terminating condition is used to determine whether a new solution is searching according to the following condition: If the Benefit-Cost (B/C) ratio of the current solution is greater than 1, move to Step 2 by adding the expansion quantity one more. Otherwise, go to Step 2 for searching the solution in the next period. If the current period is the end period of the planning horizon, the algorithm ends.

4. Experimental results

The baggage carousel expansion planning results for 3 years are shown in Table 10. Twenty-three baggage carousels at Incheon International Airport were considered the candidate group for expansion from 2013 through 2015. As a result, baggage carousel no. 18 was expanded during the first quarter of 2013, baggage carousels no. 17 and no. 19 were expanded during the first quarter of 2014 and baggage carousel no. 5 was expanded during the first quarter of 2015.

In 2013, the total over-waiting time after expanding baggage carousel no. 18 (TO-BE) was approximately 28,778,730 h, and the total over-waiting time before expanding the baggage carousel (AS-IS) was approximately 2,913,143 h. The passenger benefit after expanding the baggage carousel was calculated by multiplying the decrement of over-waiting time by the value of passenger time. The passenger benefit was $779,071.31 and the expansion cost was $473,098.33. Therefore, the B/C ratio of expanding no. 18 in 2013 is 1.65. Then, when we considered that baggage carousel no. 5 was added in 2013, the B/C ratio of expanding baggage carousels no. 5 and no. 18 at that time was 0.653. Thus, baggage carousel no. 18 was determined as the expansion carousel for 2013.

In 2014, we first analyzed one baggage carousel expansion based on the AS-IS total over-waiting time of the expansion plan of 2013. Expanding baggage carousel no. 19 was the optimal solution, and the B/C ratio was approximately 2.41. We then used the AS-IS total over-waiting time (2,951,139.48 h) of the optimal expansion plan of one baggage carousel in 2014 to test the expansion test for two baggage carousels. The result was that the expansion of baggage carousels no. 17 and no. 19 was possible in

| Year | 2013 | 2014 | 2015 |
|------|------|------|------|
| Gate | Conveyor | 1/4 | 2/4 | 3/4 | 4/4 | 1/4 | 2/4 | 3/4 | 4/4 | 1/4 | 2/4 | 3/4 | 4/4 |
| 1 | | | | | | | | | | | | | |
| 2 | | | | | | | | | | | | | |

**Table 9** The costs of baggage carousel expansion.

| Conveyor length | Construction cost | Conveyor cost | Total cost |
|-----------------|-------------------|---------------|------------|
| 90 m            | US$ 259,740.26    | US$ 139,146.57 | US$ 398,886.83 |
| 110 m           | US$ 315,398.89    | US$ 157,699.44 | US$ 473,098.33 |

Fig. 9. A sample of expansion construction on baggage carousel 2 in 2015.
2014 (the B/C ratio = 1.79) and no. 5 in 2015 (B/C ratio = 1.76), respectively.

According to the results, the expanded baggage carousels are included in gates with a high arrival rate and have a high allocation rate of baggage carousels. The allocation rate of baggage carousel no. 5 in gate B (25.59%) is 30.17%, and the allocation rate of baggage carousels nos. 17, 18, 19 in gate E (22.71%) is 22.22%, 30.64%, and 31.82%, respectively. Regarding expansion periods, all expansions occurred within a particular quarter of each year, and these periods had a relatively low passenger demand level. Therefore, expanding baggage carousels with high allocation rates during the relatively low demand period is more likely to produce good results for the plan to expand capacity at Incheon International Airport.

5. Conclusion

The goal identified for this study is to propose an efficient methodology in determining the planning for baggage carousel expansion at Incheon International Airport, considering the future passenger arrival pattern and operational aspects of the baggage claim process. The proposed methodology is divided into three stages: passenger demand forecasting with the SARIMA model, simulation modeling and analysis for estimating passenger delay time reflecting detailed operational activities, and a simulation-based heuristic algorithm for maximizing benefit over cost. We conducted experiments to demonstrate the application of our approach in the real case of Incheon International Airport.

As a results, the optimal capacity plan is to expand no. 18 in 2013, nos. 17 and 19 in 2014, and no. 5 in 2015. Comparing between the as-is scenario (no expansion in 2013–2015), the B/C ratio is 1.65 in 2013, 1.79 in 2014, and 1.76 in 2015, respectively.

This study has made significant contributions to several subjects, including the following: (1) interfacing between forecasting and simulation modeling and analysis, (2) creating integrated schemes for efficient expansion planning between simulation analyses and cost-benefit analyses, and (3) extending the availability of the methodological aspects, technological aspects and applications of real cases in similar research areas.
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