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Dynamic simulation model of air cargo demand forecast and terminal capacity planning

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ABSTRACT

This paper establishes an approach to forecast air cargo demand related to terminal capacity expansion. To balance capacity and demand, it is required to forecast the future demand based on optimistic and pessimistic projections to decide when and how much, the airport should expand the capacity. System dynamics simulation model can provide reliable forecast and generate scenarios to test alternative assumptions and decisions. It was found that GDP and FDI play an important role in fostering the demand. Terminal expansion would be required in 2018 based on the optimistic projection; meanwhile, based on pessimistic projection, the capacity can meet demand in 2030, which means no need to increase the capacity.

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1. Introduction

In line with world trade liberalization and global logistics operation, air cargo industry has been booming for the past decade. Transport by air cargo has become increasingly important, in consequence of the development of a leading global manufacturer. Manufacturing, especially in the high technology industries has a major contribution to air cargo volume. By value, 40% of global trade transactions are delivered by using aircraft [5]. Air freight is required for time-sensitive (high-value) commodities such as computers and cell phones which have a short marketing life and perishable products (fresh flowers, fruit, and live animals) because it offers speed, security and reliability. Growth in the use of just-in-time (JIT), where particular parts must arrive for assembly at specific times resulting manufacturers depend on air freight services for efficient just-in-time inventory management and to ensure their availability for final assembly. Air freighters enable the most economical sourcing of components and assemblies. Products that have high inventory carrying costs such as medical devices and jet engines are delivered via air freight to avoid critical time in transit [28]. Air cargo, trade, and GDP have a direct relationship and interdependent [26]. Gross domestic product (GDP) is the total market value of all final goods and services produced in a country in a given year, equal to total consumer, investment and government spending, plus the value of export, minus the value of imports. The demand of air cargo will increase as the trade volume and economic activity increase. The development of e-commerce will affect the growth in online retail sales that is also one of the key drivers that stimulate the air cargo growth. Air freight is required to deliver high value density goods such as microchips to other country to make sure that it would be competitive and viable for international business. Porter [22] has documented the correlation between air cargo and GDP growth. According to Porter and international business academicians, outward foreign direct

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investment (FDI) can generate a competitive strength to the nation's industry. Foreign direct investment (FDI) is investment of foreign assets directly into a domestic company's structures, equipment, and organizations.

Taiwan is the world's largest producer of computer components and now producing the telecommunications equipment [9]. Taiwan maintains partnerships with the US and Japan to integrate its domestic and international production to support its international manufacturing network. Air cargo is required for quick time delivery of high-technology components and goods that have high value and fragile.

In this paper, we developed model to forecast air cargo demand in the future to determine terminal capacity required to support long-term growth. For this study, we analyzed air cargo demand in Taiwan Taoyuan International Airport (TTIA) by utilizing system dynamics model. Although such analysis may differ from one airport to another, we keep the proposed model as generic as possible to facilitate its implementation in a wide spectrum of real-world cases. System dynamics framework is a method that can be used to analyze and to develop a model to forecast the air cargo demand and to evaluate some scenarios based on optimistic and pessimistic projections related to air cargo terminal capacity expansion.

System dynamics is a very powerful method if we compare to other conventional forecasting methods that present some problems, such as follows:

- It does not account for discontinuities in the external environment.
- Cause effect relationships between different parameters are not always correctly account, and might generate spurious correlations between variables, leading to inaccurate forecasts if one of the variables changes.

Conventional forecasting methods that rely on historical data might not predict the impact of major changes in strategy accurately. According to Senge [25], conventional forecasting methods are not suited for dealing with dynamic complexity with deep uncertainty: prediction of dynamic behaviors, model validity, and optimality may not be obtained. It might be harmful if there is a little time to solve or uncertainties cannot be reduced, and time-consuming [23].

System dynamics is more suitable in the context of the forecasting problem that has complexity with deep uncertainty, by modeling and simulating complex issues and analyzing the non-linear behaviors over time in order to develop and test the system behavior. System dynamics is an effective way to forecast the demand for air travel because of some advantages [16,24] such as:

1. System dynamics models offer the ability to incorporate expert knowledge in the model and the ability to model highly non-linear behavior.
2. System dynamics models are calibrated to historical data, and used to produce a forecast of the future demand. With the detailed and calibrated models, we will be able to accurately predict the demand volume based on demand scenario analysis. As a result, firms can avoid unnecessary capacity expansion because from the model output, it gives clear information on when the firm should expand the existing capacity to meet the future demand.
3. System dynamics models can provide more reliable forecasts than statistical models, allow user to determine key sensitivities, and therefore more robust sensitivities and scenarios.

This paper is organized as follows. Section 2 provides the previous related work. Section 3 describes the system dynamics modeling and validation. Section 4 demonstrates scenario planning for the next 20 years. Finally in Section 5, conclusion and further research required are presented.

2. Previous related work

The demand for air cargo transportation had shown enormous for the last several years, due to strength of economic growth, improvement of political stability and gradual free market environment through the open-skies policies. Globalization, digitization, aviation and time-based competition make the worlds of commerce and supply chain management rapidly changing. High technology products that typically small, light, compact, components and assembled products are increasingly shipped internationally by air in a fast and flexible manner. Air rights liberalization, improvement in customs quality, and reduction in corruption are three critical policy levers that affect the air cargo growth.

Gross domestic product (GDP) which represents the economic activity is the main driver of air cargo growth. World GDP growth rate was 3.5% in 2005, and achieved 4.0% in 2004 [2]. Global air cargo market will continue to grow based on a number of factors, such as economic growth in diverse areas of the world [3]. Today, Taiwan becomes a leading producer of high-technology products such as computers and mobile phones. The increasing importance of high-tech products in Taiwan's export and the growth of science-based industrial parks such as the one located in Hsinchu county is one of the key drivers of the economic development. Taiwan's principal export destinations are China, Hong Kong, USA. Trade between Taiwan and China grew in double digits annually in the 1990s [14].

Some researchers consider FDI and export have a relationship, which means that FDI can stimulate export [33]. There is an endogenous relationship between foreign direct investment and economic growth [32]. Love and Chandra [15] have analyzed that GDP, export, and the terms of trade are having relationship and co-integration. Other variable that has impact to export volume is foreign direct investment (FDI).

Foreign direct investment (FDI) is a good variable to be utilized in analyzing the emerging markets for the air freight traffic growth [8]. Frank and Chu [6] have developed an economic model to analyze the relations among foreign direct investment (FDI), export, and gross domestic product (GDP) as a proxy for economic growth. They found the causality relations among FDI, export, and GDP. GDP causes export and inward FDI also causes export.

Peng and Chu [21] have utilized six univariate forecasting models for the container throughput volumes in Taiwan's three major ports to search for a model that can provide the most accurate prediction of container throughput. The six univariate models include the classical decomposition model, the trigonometric regression model, the regression model with seasonal dummy variables, the grey model, the hybrid grey model, and the SARIMA model. By applying monthly data to these models and comparing the prediction results based on mean absolute error, mean absolute percent error and root mean squared error, they find that in general the classical decomposition model appears to be the best model for forecasting container throughput with seasonal variations.

Houston et al. [10] have developed ARIMA model to compare forecasts of broiler production by econometric and physical models. They adopts a systematic analytical approach based on the economic principles of supply response functions to forecast the number of broilers in future years under the influence of changing economic variables. All economic variables tested were significant in one or more of the broiler production phases, reflecting the importance of incorporating economic variables. The study reflects no substantive difference between using structural and time series models for broiler water forecasting purposes, indicating that an appropriate lag structure can fully capture the information used in structural models, assuming no structural change.

Jiang et al. [11] have analyzed the future of air cargo demand in China and its implications for system infrastructure. Econometric methodology is used to determine the relationship between GDP and air cargo demand. GDP projections are obtained by trend analysis and the projections from China government and recognized institutions. By extrapolating current trends and evaluating government policies, China is projected to achieve sustained economic development over the next 20 years. The forecast projects air cargo traffic growth at 11.2% per annum, expanding more than seven fold by 2020 – resulting in an expected 27 million tonnes cargo throughput originating from China airports.

Ohashi et al. [20] have analyzed the trade-off between monetary cost and time cost of transshipment airport by utilizing two-stage least-squares estimation. Their results show that the choice of air cargo transshipment hub is more sensitive to time cost than the monetary costs. It is therefore important to reduce air cargo connecting time with adequate investment in capacity by increasing landing and airport charges. Karlaftis [12] developed Tobit models with GARCH errors/disturbances to forecast demand in regional airports. Their results reveal that the seasonal variations in demand might significantly affect demand predictions and by improving demand model specifications will obtain more accurate demand estimation. Matsumoto [18] has developed a basic gravity model consists of GDP, population, distance, and some dummy variables to examine air passenger and cargo flows in Asia, Europe and America. It was found that the air traffic density in some cities such as Seoul, Hong Kong, and Amsterdam, is growing at the extraordinary rate.

The air cargo volume throughput of the world has strongly linked to trade growth and has grown at between 1.5 and 2 times the rate of worldwide GDP growth [34]. There is an established relationship between air cargo growth and two key economic development factors such as GDP and inward foreign direct investment [13].

Lyneis [17] has analyzed the use of system dynamics models to "forecast" the behavior of markets. He claims that the structural orientation of system dynamics models provides more accurate depictions of short and mid-term behavior than statistical models, which often become skewed by "noise" in the system. Lyneis [16] has developed system dynamics model to forecast demand of commercial jet aircraft industry. Galvin [7] have utilized system dynamics to determine the future behavior of the principle components of the air traffic control (ATC) system over time.

We summarized all the previous researches in Table 1 to demonstrate all the key findings. We utilized these key findings as a basic knowledge to build the model. Even though there are some researches utilized statistical methods to prove the relationship of economics factors such as GDP and FDI to the demand of air traffic, but still very few researches that can

Table 1
Summary of previous research results.

Author (year)	Key findings
Porter (1990)	Outward foreign direct investment (FDI) can generate a competitive strength to the nation's industry
Xiaoying and Xiaming (2005)	There is an endogenous relationship between foreign direct investment and economic growth
Love and Chandra (2005)	GDP and foreign direct investment (FDI) have direct relationship to export
Graham (2002)	Foreign direct investment (FDI) is a good variable to be utilized in analyzing the emerging markets for the air freight traffic growth
Frank and Chu (2006)	There is a causal relationship among FDI, export, and GDP. GDP and inward FDI lead to export
Jiang et al. (2003)	There is a relationship between GDP and air cargo demand
Zhang and Zhang (2002)	The air cargo volume throughput of the world has strongly linked to trade growth and has grown at between 1.5 and 2 times the rate of worldwide GDP growth
Kasarda and Green (2005)	There is an established relationship between air cargo growth and two key economic development factors such as GDP and inward foreign direct investment
Lyneis (2000)	He claims that the structural orientation of system dynamics models provides more accurate depictions of short and mid-term behavior than statistical models, which often become skewed by "noise" in the system

relate between air traffic demand and terminal capacity expansion by considering the internal and external factors. System dynamics simulation model can provide a comprehensive study to accommodate the system complexity and to develop flexible long-plan strategies such as plan capacity expansion.

With high demand uncertainties, acquiring the right amount of air cargo terminal space has often been a major challenge for the airport authority. By forecasting the future demand of air cargo volume, a finite-horizon planning model is used to support the long-term capacity management. In this research, we utilize system dynamics to forecast and to develop several scenarios based on optimistic and pessimistic projection.

3. System dynamics modeling and validation

To develop the system dynamics model, first, we have to define the purpose of the model, which means that we should focus on a problem and narrow down the model. In this case, our aim is to develop a model to forecast air cargo demand in the future related with terminal capacity expansion to support long term growth. The second step, we should define the model boundary and identify the key variables, which means that we should select some significant components to generate the behavior of interest related with the model purpose. The next step is creating a diagram as the basic mechanisms of the system feedback loops.

3.1. Causal loop diagram

Causal loop diagram is a tool to represent the feedback structure of systems [27]. It consists of variables connected by arrows denoting the causal influences among them. Causal loop diagram for air cargo demand forecasting and terminal capacity expansion is given in Fig. 1. This causal loop diagram represents the relationship among GDP, FDI Growth, Air Cargo Export, Import, Transit, Demand, Terminal Capacity, Terminal Utilization, Desired Capacity, Additional Capacity, Excess of Capacity, Backlog, Delivery Delay, Competitor Utilization and Trade Volume Shift to Competitor. This diagram shows the cause and effect of the system structure. Each arrow represents a cause and effect relationship between two variables. The '+' and '−' signs represent the direction of causality. A '+' sign indicates can increase the result to destination variable. While the '−' sign indicates can decrease the result to the destination variable.

In line with the demand growth, it will generate more additional capacity that will decrease the terminal utilization. However, increasing terminal utilization will decrease the excess capacity. The higher the *Excess Capacity* will decrease the *Backlog* as well. *Backlog* will lead the *Delivery Delay* and the *Pressure to Expand Capacity. Pressure to Expand Capacity* depends on the *Perceived Delivery Delay* and *Normal Delivery Delay*. Meanwhile, *Desired Capacity* depends on the *Pressure to Expand Capacity* and *Additional Capacity*. In this case, *Backlog* will make the *Trade Volume Shift to Competitor* as long as the *Competitor's Utilization* less than the *Competitor's Capacity*. Additional capacity will generate low utilization in the beginning. However, the growth of demand will make the utilization higher.

Causal loop diagrams emphasize the feedback structure of the system, it can never be comprehensive. We have to convert the causal loop diagram into flow diagram that emphasizes the physical structure of the model. It has a tendency to be more detailed than causal loop diagram, to force us to think more specifically about the system structure.

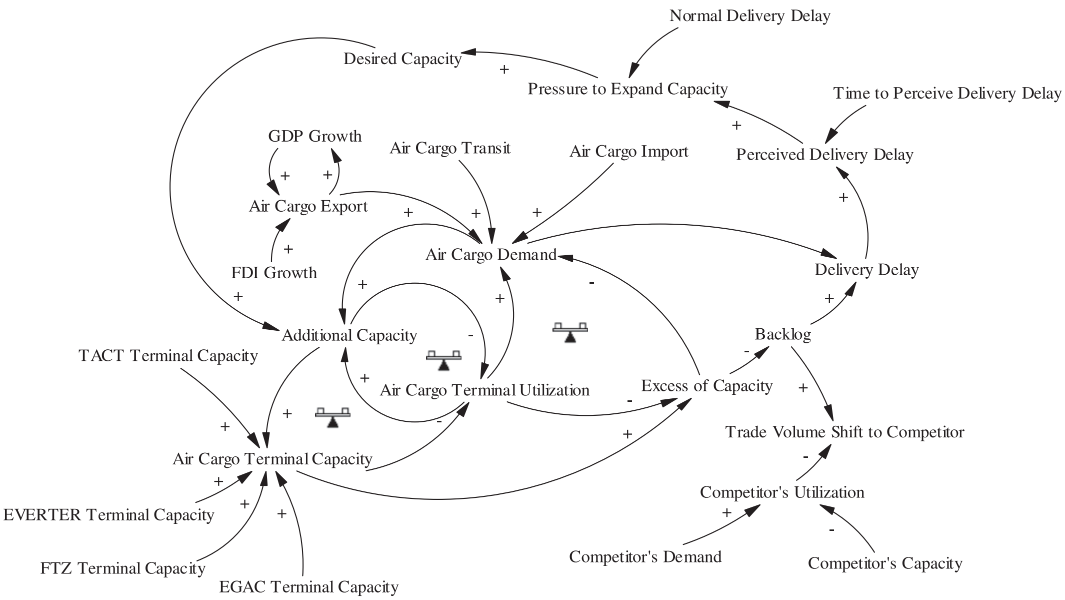

Fig. 1. Causal loop diagram for air cargo demand forecasting and terminal capacity expansion.

3.2. Air cargo demand based on existing condition (base model)

Air freight volumes are rising in response to gently accelerating economic growth as the impact of globalization and trade liberalization. Fig. 2 shows the flow diagram of air cargo demand based on existing condition. As we can see from Fig. 2, *Air Cargo Demand* is determined by *Air Cargo Export*, *Air Cargo Import*, and *Air Cargo Transit* (see Eq. (1)).

$$\text{Air Cargo Demand} = \text{Air Cargo Export} + \text{Air Cargo Import} + \text{Air Cargo Transit} \tag{1}$$

We classified the air cargo export as a level variable to accumulate the integrating rates of the export growth (see Eqs. (2), (3)).

$$\text{Air Cargo Export } (t) = \text{Air Cargo Export } (t - dt) + (\text{Export Rate}) * dt \tag{2}$$

$$\text{Export Rate} = \text{MAX}(\text{Effect of GDP Growth}, \text{Effect of FDI Growth}) * \text{Export Rate Adjustment} \tag{3}$$

Variable dt represents the time interval of simulation. In this study, we set dt parameter equals to 1 year. To accumulate the integrating rates of the import growth, we classified the air cargo import as a level variable (see Eq. (4)).

$$\text{Air Cargo Import } (t) = \text{Air Cargo Import } (t - dt) + (\text{Import Rate}) * dt \tag{4}$$

The transit volume at a certain time depends on the volume of transit at the previous time and the transit rate during the time interval of simulation (see Eq. (5)).

$$\text{Air Cargo Transit } (t) = \text{Air Cargo Transit } (t - dt) + (\text{Transit Rate}) * dt \tag{5}$$

There are four air cargo terminals in Taiwan, those are EGAC, EVERTER, TACT and FTZ. The utilization of the air cargo terminal is the proportion of air cargo demand (capacity at the terminal is being used) and the terminals capacity (see Eq. (6)). Excess of capacity will happen as long as the amount of capacity is greater than the demand (see Eq. (7)).

$$\text{Air Cargo Terminal Utilization} = \text{Air Cargo Demand}/\text{Air Cargo Terminals Capacity} \tag{6}$$

$$\text{Excess of Capacity} = \text{Air Cargo Terminals Capacity} - \text{Air Cargo Demand} \tag{7}$$

3.3. Parameter estimation

Parameter estimation is required to develop mathematical models by utilizing data or observation from the real system. The estimation of parameters can be obtained in some ways such as statistics data, published reports, and statistical methods [4]. The estimation result for total terminals capacity is given in Eq. (8). The capacity of each terminal (EGAC, EVERTER, FTZ, and TACT) and the initial values of the parameters are listed in Table 2. All these parameter values are obtained from

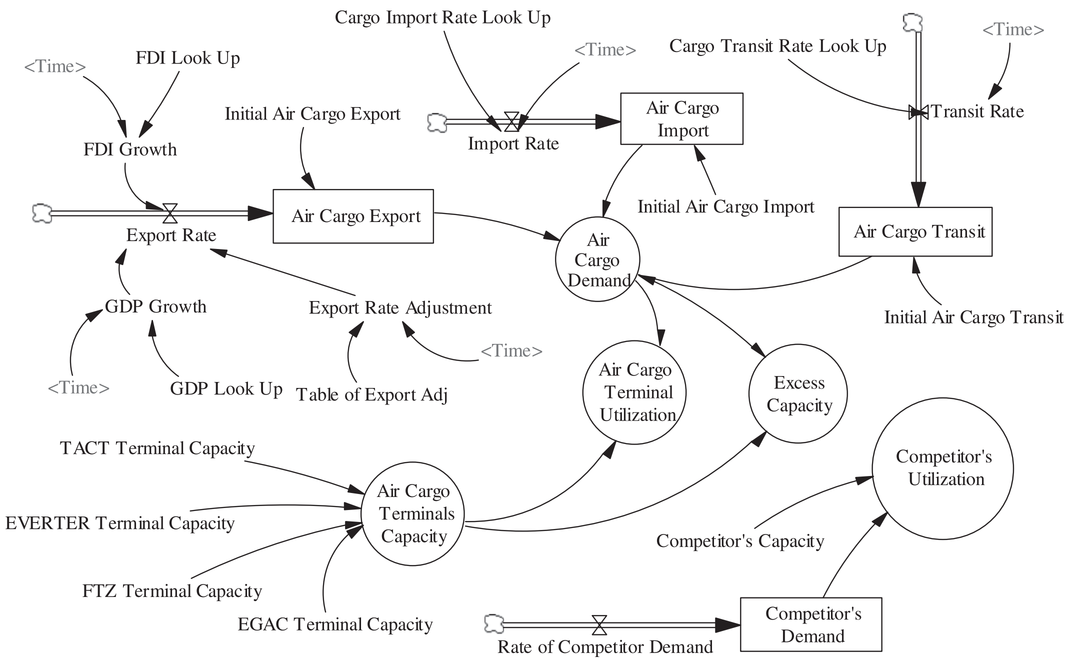

Fig. 2. Flow diagram of air cargo demand based on existing condition.

statistical data provided by Taiwan Taoyuan International Airport (TTIA). Initial values of parameters are required to define equation of level variables such as air cargo export, import, and transit.

$$\text{Air Cargo Terminals Capacity} = \text{EGAC Terminal Capacity} + \text{EVERTER Terminal Capacity} + \text{FTZ Terminal Capacity} + \text{TACT Terminal Capacity} \quad (8)$$

In this study, we set the simulation timing for 15 years starting from 1996 to 2010 based on consideration of learning the system behavior of air cargo demand before and after the terrorist attack on September 11, 2001 and the availability of the data. The simulation time step is one year. Fig. 3 demonstrates the air cargo export, import, and transit during 1996–2010. As we can see from Fig. 3, the average export rate was around 3.17%, average import rate was around 0.56% and average transit rate was around 20.36%. In 2010, export, import, and transit grew 21%, 30%, and 40% respectively, as the impact of GDP growth.

Table 2
Parameter values of the base model.

Parameter	Value	Unit
Initial Air Cargo Export	425,943	tonnes
Initial Air Cargo Import	292,538	tonnes
Initial Air Cargo Transit	63,877	tonnes
EGAC Terminal Capacity	500,000	tonnes
EVERTER Terminal Capacity	300,000	tonnes
FTZ Terminal Capacity	1.2e+006	tonnes
TACT Terminal Capacity	1.5e+006	tonnes

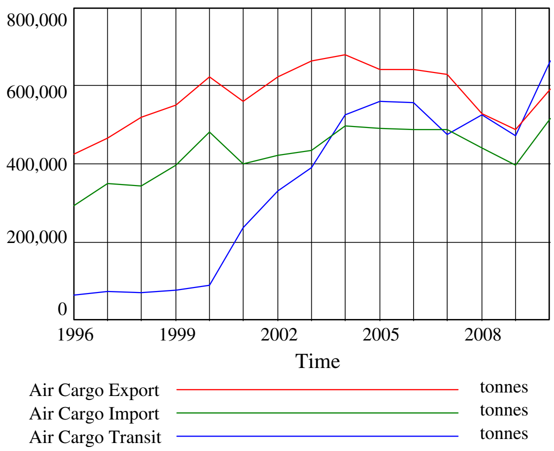

Fig. 3. Air cargo export, import, and transit.

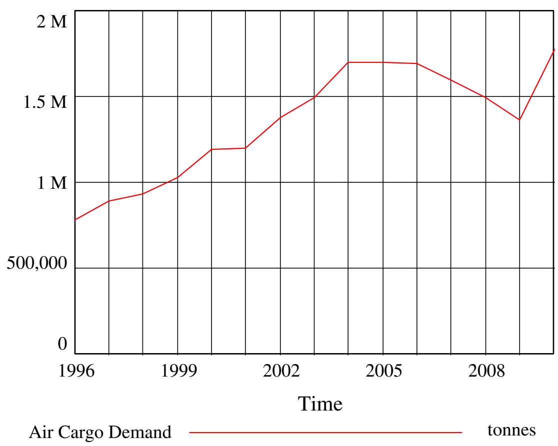

Fig. 4. Air cargo demand.

Table 3
The average value of simulation result ($\bar{S}$) and data ($\bar{A}$).

Variable	Average value of simulation ($\bar{S}$)	Average value of data ($\bar{A}$)
Air Cargo Demand	1,344,747 (tonnes)	1,352,983 (tonnes)

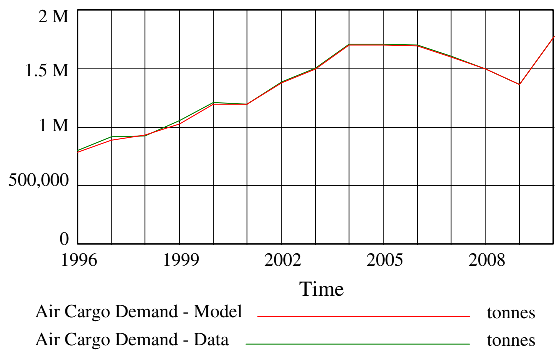

Fig. 5. Comparison between demand model and demand data.

Fig. 4 shows the *Air Cargo Demand* during 1996–2010. As we can see from Fig. 4, the average growth of air cargo demand was around 6.9% as the impact of air cargo export, import, and transit. With increasing globalization, in period 1996–2004, the demand grew between 8% and 15%, as the transport of air cargo has become increasingly important. The demand growths started to decline during the period of 2005–2009 in line with the worst economic crisis in decades, and start to grow in 2010.

3.4. Model validation

Validation is a process of evaluating model simulation to determine whether it is an acceptable representation of the real system. Historical data during the time horizon of simulation of the base model (1996–2010) is required (see Eqs. (20)–(22)). A model will be valid if the error rate is smaller than 5% [1]. From the base run results, we can obtain the average value of simulation ($\bar{S}$) of *Air Cargo Demand* = 1,344,747 tonnes. Meanwhile, the average value of historical data ($\bar{A}$) of *Air Cargo Demand* = 1,352,983 tonnes as depicted in Table 3. Error rate is defined in Eqs. (9)–(11).

$$Error\ rate = \frac{|\bar{S} - \bar{A}|}{\bar{A}} \tag{9}$$

where:

$$\bar{S} = \frac{1}{N}\sum_{i=1}^{N} S_i \tag{10}$$

$$\bar{A} = \frac{1}{N}\sum_{i=1}^{N} A_i \tag{11}$$

Based on these results, we can determine the error rate as follows:

$$Error\ rate\ of\ demand = \frac{|1,344,747 - 1,352,983|}{1,352,983} = 0.0061$$

According to the above result, the error rate is smaller than 5%, which means that our model is valid. The comparison between simulation result (model) and historical data of *Air Cargo Demand* is given in Fig. 5.

4. Scenario planning

Scenario is an approach to develop a set of stories that might happen in the future. Several alternative scenarios can be obtained from a valid model by adding some feedback loops, adding new parameters, and changing the structure of the feedback loops (structure scenario) or by changing the value of the parameter to see the impact to other variables (parameter scenario). In this study, we combined between structure scenarios and parameter scenarios to generate more robust sensitivity analysis. The scenario block diagram is given in Fig. 6. We set the time horizon of the scenario model for 20 years based on consideration of the learning behavior of the system. This time span will provide a better understanding of the system behavior of air cargo demand which will have an impact on the outputs and the policy alternatives to be developed.

4.1. Parameter scenario

In this scenario, we modify the value of the parameter based on optimistic and pessimistic projection related to terminal capacity expansion. Figs. 7 and 8 show the flow diagram of air cargo demand based on optimistic and pessimistic projections respectively.

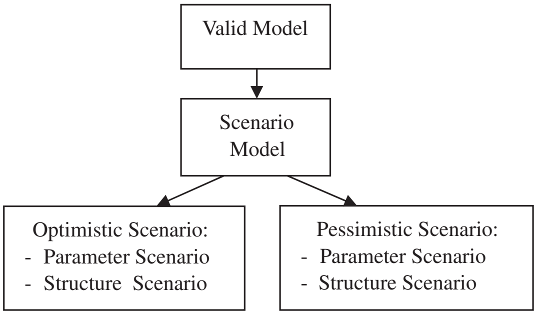

Fig. 6. Scenario block diagram.

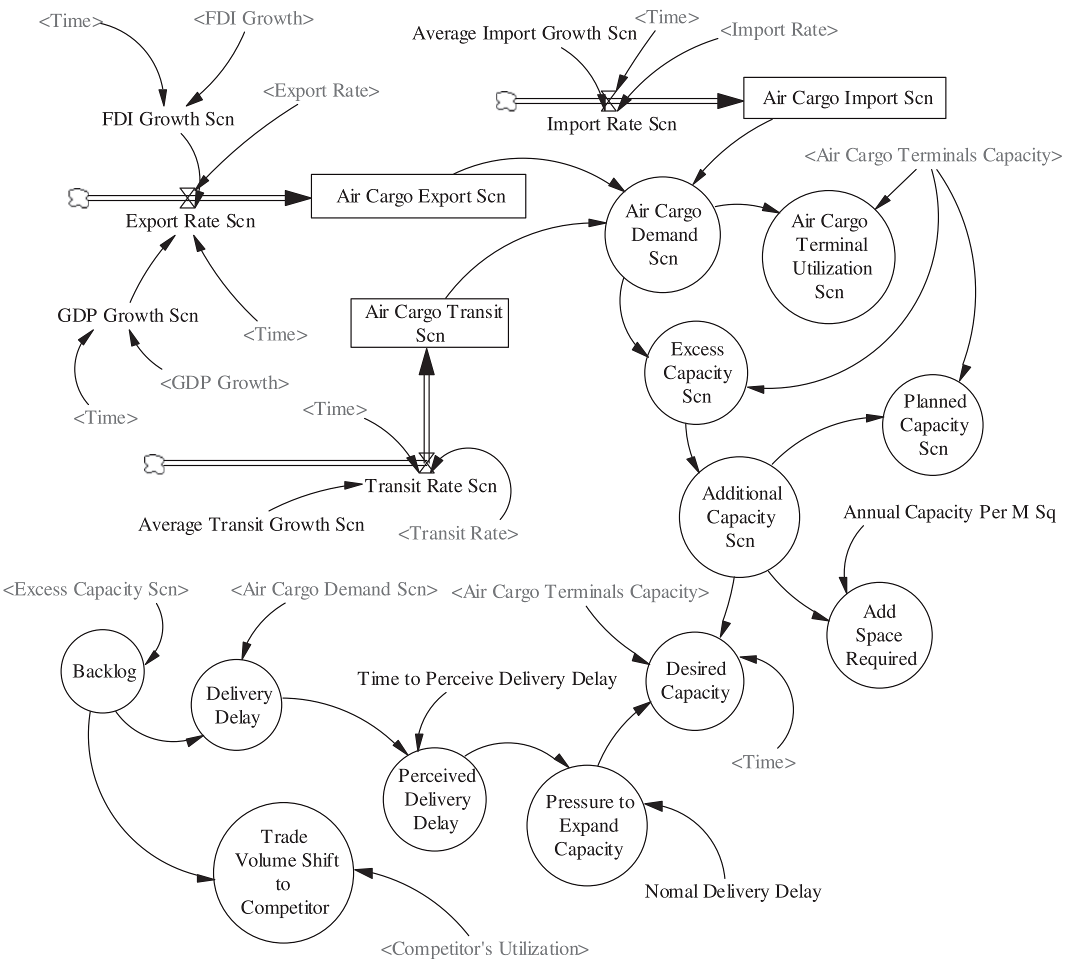

Fig. 7. Flow diagram of air cargo demand optimistic scenario.

4.1.1. Optimistic parameter scenario

This scenario is made to check the air cargo terminal capacity to meet the future demand if GDP is predicted to grow with average growth rate 6% annually. This assumption is made by considering Taiwan government prediction. Based on this prediction, the average economic growth will achieve 6% annually [29]. In this research, we utilized variance–covariance method with VaR 1% to predict the GDP growth and FDI growth rates. We assumed that GDP growth rates are normally distributed with average growth rate (μ_P) 6% and standard deviation (σ_P) of 1% (see Eq. (12)). Meanwhile, FDI growth rates are projected to grow 15.6% and standard deviation of 1% by considering the average growth rates of Taiwan FDI during 1996–2010 (see Eq. (13)).

$$\text{GDP Growth Rate Opt. VaR}_{1\%} = \mu_{P\ (\text{GDP Growth})} - 2.33\sigma_{P\ (\text{GDP Growth})} \tag{12}$$

$$\text{FDI Growth Rate Opt. VaR}_{1\%} = \mu_{P\ (\text{FDI Growth})} - 2.33\sigma_{P\ (\text{FDI Growth})} \tag{13}$$

Some reasons that will affect the FDI growth rates are international cost competitiveness of production in the affected countries due to devaluations, has made these countries more attractive as sites for export-oriented investments and liberalization of government policy has made FDI easier [30]. GDP growth and FDI growth are the key factors that will affect the export rate (see Eq. (14)).

$$\text{Export Rate Opt. Scn} = \text{FDI Growth Scn} * \text{GDP Growth Scn}/1000 \tag{14}$$

Air cargo import is projected to grow with average 12.9% (μ_P Optimistic) and standard deviation of 1% (σ_P Optimistic) based on Hong Kong outward to Taiwan in 2001 and 2004 (see Eq. (15)).

$$\text{Average Growth Rate of Import Opt. VaR}_{1\%} = \mu_P \text{ Optimistic} - 2.33\sigma_P \text{ Optimistic} \tag{15}$$

Freight transit is expected to grow with annual average growth rate 14% (μ_P Optimistic) and standard deviation of 1% (σ_P Optimistic) based on the transshipment data of Hong Kong transshipment outward during 2002–2004 (see Eq. (16)).

$$\text{Average Transit Growth Opt. VaR}_{1\%} = \mu_P \text{ Optimistic} - 2.33\sigma_P \text{ Optimistic} \tag{16}$$

4.1.2. Pessimistic parameter scenario

This scenario is made to check the existing air cargo terminal capacity whether it can meet the future demand if *GDP* is predicted to grow with average growth rate 2.8% annually. This assumption is made by considering that *global GDP* growth rate would be only 1% and for *developing countries* would be around 4.5% [35]. We set the average GDP growth rate at around 2.8% by considering the global GDP growth rate and the developing countries growth rate.

Variance–covariance method with VaR 1% is utilized to predict the GDP growth rates and FDI growth rates based on consideration that GDP growth rates are normally distributed with average growth rate (μ_P) 2.8% and standard deviation (σ_P) of 1% (see Eq. (17)). Meanwhile, based on pessimistic projection, FDI growth rates are projected declined to be around −20% (μ_P) and standard deviation (σ_P) of 1% based on the FDI growth in 2009–2010 (see Eq. (18)).

$$\text{GDP Growth Rate Pes. VaR}_{1\%} = \mu_{P\ (\text{GDP Growth})} - 2.33\sigma_{P\ (\text{GDP Growth})} \tag{17}$$

$$\text{FDI Growth Rate Pes. VaR}_{1\%} = \mu_{P\ (\text{FDI Growth})} - 2.33\sigma_{P\ (\text{FDI Growth})} \tag{18}$$

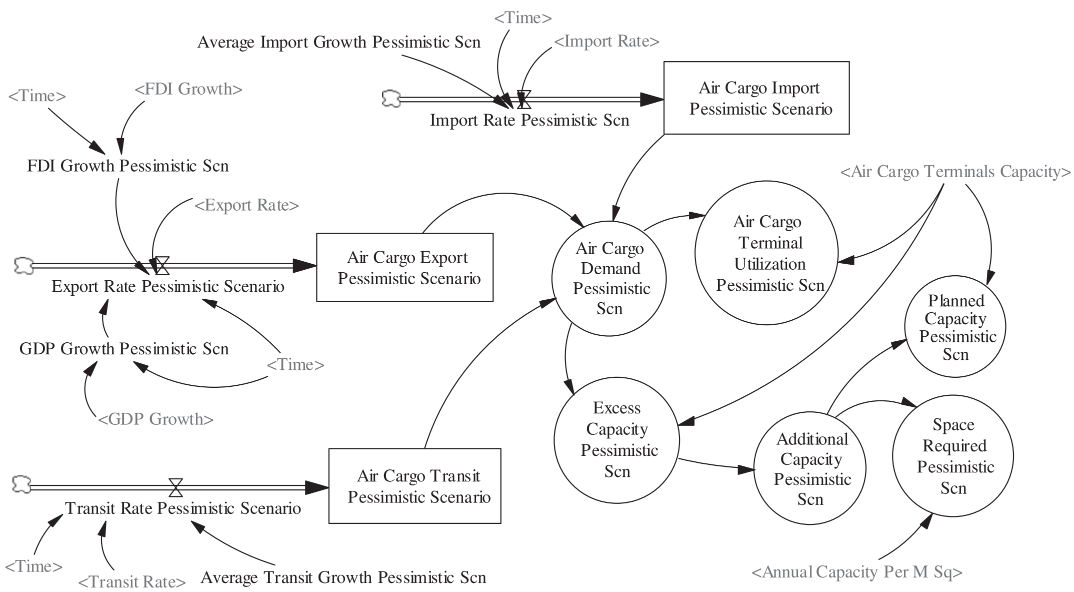

Fig. 8. Flow diagram of air cargo demand pessimistic scenario.

Table 4
Projected demand based on some experiments of the growth of GDP, FDI, import, and transit.

GDP growth	FDI growth	Import growth	Transit growth	Projected demand in 2030 (million tonnes)
Optimistic	Optimistic	Optimistic	Optimistic	10.80
Optimistic	Optimistic	Optimistic	Pessimistic	5.94
Optimistic	Optimistic	Pessimistic	Optimistic	8.01
Optimistic	Optimistic	Pessimistic	Pessimistic	2.88
Optimistic	Pessimistic	Optimistic	Optimistic	10.67
Optimistic	Pessimistic	Optimistic	Pessimistic	5.55
Optimistic	Pessimistic	Pessimistic	Optimistic	7.61
Optimistic	Pessimistic	Pessimistic	Pessimistic	2.48
Pessimistic	Optimistic	Optimistic	Optimistic	10.75
Pessimistic	Optimistic	Optimistic	Pessimistic	6.12
Pessimistic	Optimistic	Pessimistic	Optimistic	8.38
Pessimistic	Optimistic	Pessimistic	Pessimistic	3.11
Pessimistic	Pessimistic	Optimistic	Optimistic	10.01
Pessimistic	Pessimistic	Optimistic	Pessimistic	5.85
Pessimistic	Pessimistic	Pessimistic	Optimistic	8.11
Pessimistic	Pessimistic	Pessimistic	Pessimistic	2.84

Export Rate Pessimistic Scenario is restricted by *GDP Growth Pessimistic Scn* and *FDI Growth Pessimistic Scn* (see Eq. (19)).

$$\text{Export Rate Pessimistic Scenario} = \text{FDI Growth Pessimistic Scn} * \text{GDP Growth Pessimistic Scn}/1000 \tag{19}$$

Import growth and transit growth rates are projected to grow with average 4.5% (μ_P Pessimistic) and standard deviation (σ_P) of 1% by considering UNCTAD forecast [31] (see Eqs. (20) and (21)).

$$\text{Average Growth Rate of Import Pes. VaR}_{1\%} = \mu_P \text{ Pessimistic} - 2.33\sigma_P \text{ Pessimistic} \tag{20}$$

$$\text{Average Transit Growth Pes. VaR}_{1\%} = \mu_P \text{ Pessimistic} - 2.33\sigma_P \text{ Pessimistic} \tag{21}$$

To investigate the effects of several factors such as GDP growth, FDI growth, import growth, and transit growth on the volume of air cargo demand, in this research, we utilize 2^k factorial design. Factorial designs are widely use in experiments involving several factors where it is necessary to study the joint effect of factors on a response [19]. The projected demand of air cargo in 2030 with some experiments of the four factors are listed in Table 4. As we can see from Table 4, GDP growth has a very strong effect to the demand of air cargo compared to other factors such as *FDI Growth*, *Import Growth*, and *Transit Growth*.

4.2. Structure scenario

In this scenario, we add a new structure to the base model to check the air cargo terminal utilization and excess capacity related to the demand forecast based on optimistic and pessimistic projection.

4.2.1. Optimistic structure scenario

Air Cargo Terminal Utilization Scn depends on *Air Cargo Demand Scn* and *Air Cargo Terminals Capacity* (see Eq. (22)). *Excess Capacity Scn* is the difference between *Air Cargo Terminals Capacity* and *Air Cargo Demand Scn* (see Eq. (23)). Additional capacity would be required if excess capacity is less than zero. We utilized IF THEN ELSE function for *Additional Capacity Scn* to accommodate the value changes when additional capacity is required (see Eq. (24)). This function has general format *IF THEN ELSE (condition, true value, false value)* which means that returns first value if condition is true, second value if condition is false. Pressure to expand capacity is the ratio of the perceived delivery delay compared to normal delivery delay (see Eq. (25)–(28)). Desired capacity depends on the Pressure to Expand Capacity and the Additional Capacity Scn (see Eq. (29)).

$$\text{Air Cargo Terminal Utilization Scn} = \text{Air Cargo Demand Scn}/\text{Air Carg Terminals Capacity} \tag{22}$$

$$\text{Excess Capacity Scn} = \text{Air Cargo Terminals Capacity} - \text{Air Cargo Demand Scn} \tag{23}$$

$$\text{Additional Capacity Scn} = \text{IF THEN ELSE}(\text{Excess Capacity Scn} < 0, 7.5e+006, 0) \tag{24}$$

$$\text{Backlog} = \text{IF THEN ELSE}(\text{Excess of Capacity Scn} < 0, \text{Excess of Capacity Scn}, 0) \tag{25}$$

$$\text{Delivery Delay} = \text{ABS}(\text{Backlog}/\text{Air Cargo Demand Scn}) \tag{26}$$

$$\text{Perceived Delivery Delay} = \text{SMOOTH}(\text{Delivery Delay}, \text{Time to Perceive Delivery Delay}) \tag{27}$$

$$\text{Pressure to Expand Capacity} = \text{Perceived Delivery Delay}/\text{Nomal Delivery Delay} \tag{28}$$

$$\text{Desired Capacity} = \text{Pressure to Expand Capacity} * \text{Additional Capacity Scn} \tag{29}$$

Planned Capacity Scn represents the total air cargo terminal capacity after the capacity expansion (see Eq. (30)). In this study, we assumed that annual capacity per meter square (*Annual Capacity per M Sq*) would be around 10 tonnes/m^2 based on consideration of the annual capacity of TACT (1,500,000 tonnes) and the TACT area (146,425 m^2) (see Eq. (31)).

Based on the optimistic projection, the demand of air cargo in 2030 is projected to be around 10.8 million tonnes, therefore backlog would be around 7.3 million tonnes. Spaced required depends on Additional Capacity Scn and Annual Capacity Per M Sq (see Eq. (32))

$$\text{Planned Capacity Scn} = \text{Additional Capacity Scn} + \text{Air Cargo Terminals Capacity} \tag{30}$$

$$\text{Annual Capacity Per M Sq} = 10 \tag{31}$$

$$\text{Space Required} = \text{Additional Capacity Scn}/\text{Annual Capacity Per M Sq} \tag{32}$$

4.2.2. Pessimistic structure scenario

Air Cargo Terminal Utilization Pessimistic Scn depends on *Air Cargo Demand Pessimistic Scn* and *Air Cargo Terminals Capacity* (see Eq. (33)). *Excess of Capacity Pessimistic Scn* is the difference between *Air Cargo Terminals Capacity* and *Air Cargo Demand Pessimistic Scn* (see Eq. (34)). We utilized IF THEN ELSE function for *Additional Capacity Pessimistic Scn* to accommodate the value changes when additional capacity is required (see Eq. (35)). *Space Required Pessimistic Scn* depends on *Additional Capacity Pessimistic Scn* and *Annual Capacity per M Sq* (see Eq. (36)). *Planned Capacity Pessimistic Scn* is the summation of *Additional Capacity Pessimistic Scn* and *Air Cargo Terminals Capacity* (see Eq. (37)).

$$\text{Air Cargo Terminal Utilization Pessimistic Scn} = \text{Air Cargo Demand Pessimistic Scn}/\text{Air Cargo Terminals Capacity} \tag{33}$$

$$\text{Excess Capacity Pessimistic Scn} = \text{Air Cargo Terminals Capacity} - \text{Air Cargo Demand Pessimistic Scn} \tag{34}$$

$$\text{Additional Capacity Pessimistic Scn} = \text{IF THEN ELSE(Excess of Capacity Pessimistic Scn} < 0, 750000, 0) \tag{35}$$

$$\text{Space Required Pessimistic Scn} = \text{Additional Capacity Pessimistic Scn}/\text{Annual Capacity Per M Sq} \tag{36}$$

$$\text{Planned Capacity Pessimistic Scn} = \text{Additional Capacity Pessimistic Scn} + \text{Air Cargo Terminals Capacity} \tag{37}$$

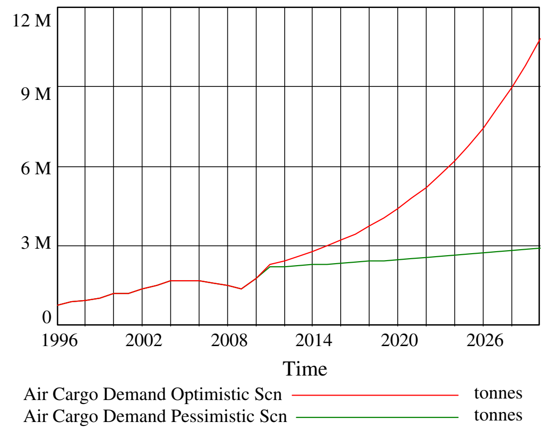

Fig. 9. Air cargo demand optimistic and pessimistic scenarios.

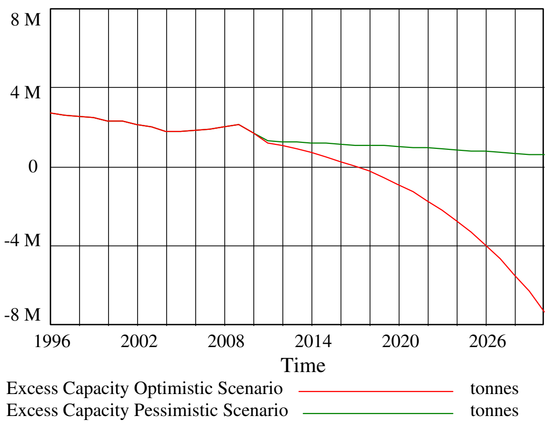

Fig. 10. Excess capacity optimistic and pessimistic scenarios.

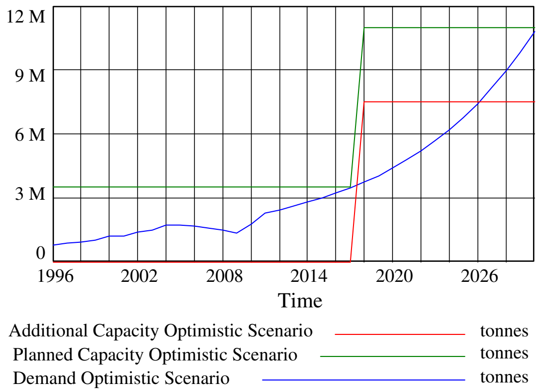

Fig. 11. Additional capacity, planned capacity and demand optimistic scenario.

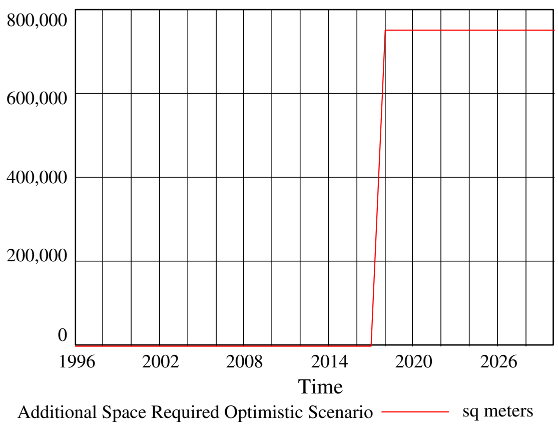

Fig. 12. Additional space required optimistic scenario.

Fig. 9 represents the air cargo demand in Taiwan during 1996–2030 based on optimistic and pessimistic projections. Based on the optimistic projection, demand is projected to grow with average growth rate 8% and would reach 10.8 million tonnes in 2030. Export would contribute 7%, import 10.6%, and transit 11.8% to the demand volume in optimistic projection. Meanwhile, according to the pessimistic projection, demand is projected to grow with average growth rate 2.5% and would only reach 2.84 million tonnes in 2030. Based upon this pessimistic projection, export, import, and transit would contribute 3.3%, 2.1%, and 2.5% respectively to the demand volume.

Fig. 10 shows the excess capacity during the period of 1996 to 2030 in optimistic and pessimistic projections. Based on our optimistic projection, there would be shortage capacity around 0.23 million tonnes starting from 2018, would reach 7.31 million tonnes in 2030. Meanwhile, under pessimistic projection, the existing capacity will meet the future demand until 2030.

Fig. 11 shows the additional capacity, planned capacity, and demand related to optimistic projections. Based on this optimistic projection, demand would reach 10.8 million tonnes in 2030. Because the existing capacity is only 3.5 million tonnes, there would be shortage capacity starting from 2018, and therefore additional capacity around 7.5 million tonnes is required to meet the future demand in 2030. With this expansion, the new design capacity (*Planned Capacity Optimistic Scenario*) would reach 11 million tonnes. Spaced required for the expansion would be around 750,000 m^2 (see Fig. 12).

Fig. 13 demonstrates the terminal capacity, demand, and excess capacity based upon pessimistic projection. Based on this projection, the terminal capacity can meet the demand in 2030, there will be no need to expand the capacity.

4.3. Evaluative comparison

An evaluative comparison of air cargo *demand* forecast is made between the system dynamics results (optimistic and pessimistic projection) and statistics results by utilizing *lease squares method* and *Holt's model.*

4.3.1. Least squares method

Least squares method is a method of fitting a curve to data points so as to minimize the sum of the squares of the distances of the points from the curve. We utilized least squares to obtain the best fit to generate the data model. Least square

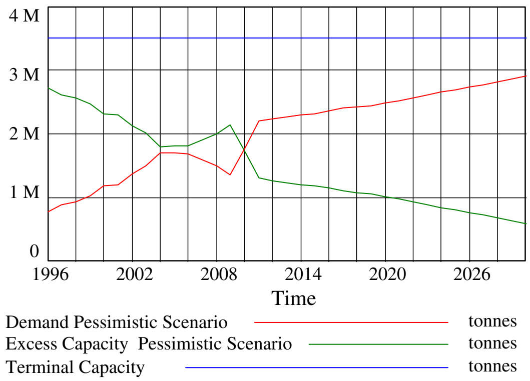

Fig. 13. Terminal capacity, demand, and excess capacity pessimistic scenario.

can be used as an approach to estimate the parameters of the equation in an approximate sense. The least square formulations are presented as follows (see Eqs. (38)–(40)).

$$Y = a + bx \tag{38}$$

where

$$a = \bar{y} - b\bar{x} \tag{39}$$

$$b = \frac{\sum xy - n\bar{x}\cdot\bar{y}}{\sum x^2 - n\bar{x}^2} \tag{40}$$

a is the demand intercept (tonnes) = 722539.19 tonnes, b the slope of the line (tonnes) = 89882.59 tonnes, $\bar{y}$ the average of all demand over time = tonnes, $\bar{x}$ the average of all time period = years, x the time period = year, y the demand value over time = tonnes, n the number of data, and Y is the value of the demand variable computed with the regression equation = tonnes.

4.3.2. Holt's model

For other comparative evaluation, Holt's model is utilized to compare the results from system dynamics framework based on consideration that air cargo demand has a level and a trend in the systematic component but no seasonality. Forecast for future period is expressed in Eq. (41):

$$F_{(t+n)} = L_{(t)} + nT_{(t)} \tag{41}$$

where $L_{(t)}$ is the estimate of level at period t, $T_{(t)}$ the estimate of trend at period t, and n is the number of periods for air cargo demand.

After observing air cargo demand for period t, it is required to revise level and trend as follows (see Eq. (42) and (43)):

$$L_{(t+1)} = \alpha D_{(t+1)} + (1-\alpha)(L_{(t)} + T_{(t)}) \tag{42}$$

$$T_{(t+1)} = \beta(L_{(t+1)} - L_{(t)}) + (1-\beta)T_{(t)}) \tag{43}$$

where α is the smoothing constant for the level = 0.1, β the smoothing constant for the trend = 0.2, and D is the demand at period t.

All the results of least squares method, Holt's model, optimistic and pessimistic scenarios can be plotted in one chart such as depicted in Fig. 14. As we can see from Fig. 14, the result of pessimistic projection is close to the result of lease squares

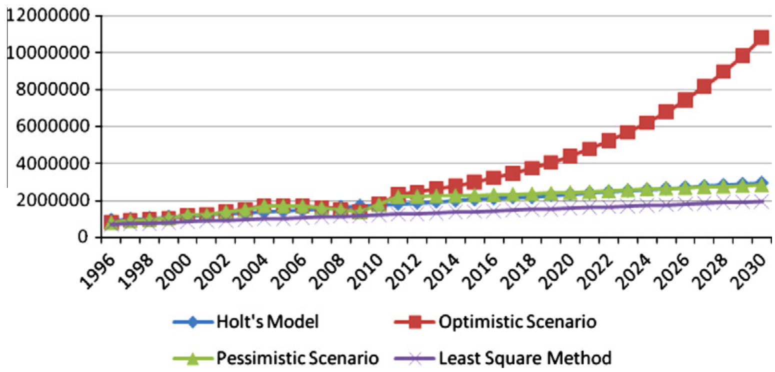

Fig. 14. Projected demand based on Holt's model, lease squares method, optimistic, and pessimistic scenarios.

Table 5
Mean Absolute Percentage Error (MAPE) for least square and Holt's model.

Year	Least square	Holt's model	Data	MAPE for least square	MAPE for Holt's model
1996	681,480	920135.708	796460	0.144	0.155
1997	718,753	967129.764	913520	0.107	0.029
1998	756,026	1026491.49	932053	0.063	0.034
1999	793,299	1085853.22	1057237	0.062	0.007
2000	830,572	1145214.94	1208838	0.063	0.011
2001	867,845	1204576.67	1189873	0.045	0.002
2002	905,118	1263938.4	1380748	0.049	0.012
2003	942,390	1323300.12	1500071	0.046	0.015
2004	979,663	1382661.85	1701020	0.047	0.021
2005	1,016,936	1442023.58	1705318	0.040	0.015
2006	1,054,209	1501385.3	1698807	0.034	0.011
2007	1,091,482	1560747.03	1605681	0.027	0.002
2008	1,128,755	1620108.76	1493120	0.019	0.007
2009	1,166,028	1679470.48	1358304	0.010	0.017
2010	1,203,301	1738832.21	1767075	0.021	0.001

method which means that the probability of occurrence of pessimistic projection might be higher than the probability of occurrence of optimistic projection.

4.3.3. Validation of least squares method and Holt's model

Mean Absolute Percentage Error (MAPE) is required to measure the accuracy of least squares method and Holt's model. Mean Absolute Percentage Error is the average of absolute error as a percentage of demand, such as depicted in Eq. (44). The values of MAPE at each period (n) are listed in Table 5.

$$\mathrm{MAPE}_n = \frac{\sum_{t=1}^{n}\left|\frac{F_t - D_t}{D_t}\right|}{n} \tag{44}$$

where F_t is the demand forecast and D_t is the demand data.

All the above results are based on long-range planning that might have some of potential limitations such as depicted below:

- Long-range planning forecast are based upon estimates. Many conditions we expect might be changed.
- One of the most important is that any model is in fact a subsystem cut from a general societal system. This implies that the distinction between endogenous and exogenous variables is unclear and thus the (sub) model is often unreliable as a tool for forecasting.
- The structure of a model reflects the structure of society. Changing societal structures requires models with changing structures and coefficients. Specific limitations are the instability of the functional form of relations, uncertainty about functional forms, and variability of parameters. Some attention is paid to the decrease in the risk of wrong forecasts.

5. Conclusion and further research

This paper has established a method for developing model to foreceast air cargo demand and scenarios related to planned capacity expansion to meet the future demand based on optimistic and pessimistic economic projections. From the results of some experiments of 2^k factorial design, we can conclude that GDP Growth has a very strong effect to air cargo demand compared to other factors such as FDI, import, and transit growths.

According to the optimistic projection, demand would exceed the existing capacity starting from 2018, it is therefore capacity expansion would be required. Based on this projection, capacity shortage would be around 7.3 million tonnes in 2030. Additional area of around 750,000 m^2 is required for the expansion. Meanwhile, based on pessimistic projection, the existing capacity would accommodate demand in 2030 and no need to expand the capacity. The probability of the occurrence of pessimistic projection might be higher than the probability of the occurrence of optimistic projection based on the comparison of system dynamics results and statistical forecasting model such as least squares method and Holt's model (see Fig. 14).

These models provide a powerful basis for learning and understanding the system behavior and alternative futures which would accommodate new developments through scenarios planning development (see Section 4). We can consider this study as a pilot study to decide when to expand the air cargo terminal capacity and to determine the total area needed to meet the future demand. Further research is required to analyze air cargo revenue and performance management due to specific characteristics of cargo inventory, cargo business, and cargo booking behavior.

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