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Air passenger demand forecasting and passenger terminal capacity expansion: A system dynamics framework

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ABSTRACT

This paper deals with how to develop a model to forecast air passenger demand and to evaluate some policy scenarios related with runway and passenger terminal capacity expansion to meet the future demand. System dynamics frameworks can be used to model, to analyze and to generate scenario to increase the system performance because of its capability of representing physical and information flows, based on information feedback control that are continuously converted into decisions and actions. We found that airfare impact, level of service impact, GDP, population, number of flights per day and dwell time play an important roles in determining the air passenger volume, runway utilization and total additional area needed for passenger terminal capacity expansion.

1. Introduction

Analyzing air travel demand is an integral part of an airport's plan that reflects the capacity utilization, which will be considered to make decisions. Regarding to the development of infrastructure facilities and to reduce the airport risk, it is important to evaluate and to forecast the volume of air passenger demand in the future. Peak demand in passenger flows at the airports, typically determined by seasonal and cyclical patterns. Therefore, it is essential to manage the facilities such as runway and passenger terminal capacity planning and design, to cover demand during the planning horizon. Runway utilization, terminal capacity and the availability of facilities to handle arrival and departure of passengers flow, are the main entities that will affect the required landside capacity.

According to Lyneis (2000), the air travel demand can be affected by two factors, e.g. external and internal factors. Assumption about future demand and performance are essential for business decisions. He considered airfare as the internal factor, and Gross Domestic Product (GDP) and population as the external factors. People play in a dominating role in the city life, the scale of population will determine the air travel demand (Jifeng, Huapu, & Hu, 2008).

Miller and Clarke (2007) have developed a model to evaluate the strategic value of air transportation infrastructure. They considered airfare impact and level of service impact as the internals variables that affect the air travel demand. These two variables were determining using the concepts of price and time elasticity, respectively.

According to Transportation Research Board (1987), landside elements in the passenger terminal can be classified into three classes, those are processing facilities that will process passengers and their luggage; holding facilities that passengers wait for some events such as check in and flight boarding; and flow facilities that passengers use them to move among the landside elements.

Brunetta, Righi, and Andreatta (2000) note that there are essentially three ways that have been used to analyze the flows and determine the amount of space and the number of servers required for the airports, those are queuing theory, graphical analyses using cumulative diagrams and computer simulations. According to their research, formal applications of pure queuing theory (Lee, 1966) have not proven efficient for design because the processes in airports are essentially never in a steady-state condition, they are almost always in transient condition. Graphical analyses of the cumulative arrivals and service (Newell, 1971) does not tie in well to the process of designing a complete terminal, since each major alternative is likely to change the pattern of flows into a particular activity area. Simulations provide the way of investigating the flows throughout an entire building. The airport landside capability is influenced by the terminal capacity that can be evaluated for each individual functional component of the airport landside.

In this paper, we developed model to analyze and to forecast air passenger demand in the future related with runway and passenger terminal capacity to support long-term growth. For this study, we analyzed air passenger demand in Taiwan Taoyuan International Airport (TTIA) by utilizing system dynamics model. System dynamics framework is a method that can be used to analyze

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and to develop a model to forecast the air passenger demand and to evaluate some scenarios of runway and passenger terminal capacity expansion related with the air passenger demand in the future. While the demand for air travel is difficult to forecast, it is important to utilize system dynamics for several reasons (Lyneis, 2000):

1. Forecasts come from calibrated system dynamics models, that are likely to be better and more informative than those from other approaches.
2. System dynamics model can provide more reliable forecasts of short- to mid-term trends than statistical models, and therefore lead to better decisions.
3. System dynamics model provide a means of determining key sensitivities, and therefore of developing more robust sensitivities and scenarios.

In general, there are two kinds of scenarios: the first one is parameter scenario, which means that the scenario is made by changing the value of the parameter. The second one is structure scenario, which means that the scenario is made by adding some feedback loops, adding new parameters, or by changing the structure of the feedback loops.

The simulation tool (Vensim) that we use allows us to conceptualize, document, simulate, and analyze the system dynamics model. The tool also provides a simple and flexible way to build simulation models from causal loops and flow diagrams. Under uncertain demand, industry players are forced to take a cautious approach towards capacity expansion, therefore the right information becomes critical in ensuring high level of service (LOS) availability. The focus of system dynamics framework is identifying the feedback loops that dominate the dynamics behavior of the system.

In the process we identify information flow(s) that provide the alternative policy for determining runway and terminal capacity expansion to meet the future demand. The information gathered from the system was used to analyze the structure and the behavior of systems to provide a scientific basis for decision making. Although such analysis may differ from one airport to another, we keep the proposed of the model as generic as possible to facilitate its implementation on a wide spectrum of real-world cases.

This paper is organized as follows. Section 2 provides the literature review and Section 3 presents the system dynamics model as a method for model development. Section 4 describes the base model development. Base model run results is provided in Section 5. Model validation is explained in Section 6. Section 7 demonstrates scenario development in terms of modifying the information structure and parameter values to design policy. Finally in Section 8, conclusion, the important aspect of system dynamics framework, and the successfulness of model, assumption we use in developing some scenarios are presented.

2. Literature review

The rapid growth of air transportation in Asia Pacific region has attracted considerable attention of researchers and academics. Increasing numbers of flights and volumes of traffic, make the demand analysis plays an important role in determining the adequacy of runway and passenger terminal capacity. Various studies have emerged to explain some factors that influence the air travel demand and airport capacity.

Poore (1993) has developed a study to test the hypothesis that forecasts of the future demand for air transportation offered by aircraft manufacturers and aviation regulators are reasonable and representative of the trends implicit in actual experience. He compared forecasts issued by Boeing, Airbus Industry and the International Civil Aviation Organization (ICAO) which have actual experience and the results of a baseline model for revenue passenger kilometers (RPKs) demand.

Inzerilli and Sergioc (1994) have developed an analytical model to analyze optimal price capacity adjustments in air transportation. From this study, they used numerical examples to analyze the behavior of the policy variables (and the resulting load factor) under different degrees of uncertainty.

Matthews (1995) has done measurement and forecasting of peak passenger flow at several airports in the United Kingdom. According to his research, annual passenger traffic demand can be seen as the fundamental starting point, driven by economic factors and forecasting. While forecasts of hourly flows are needed for long-term planning related with infrastructure requirements. Hourly forecasts are almost always based on forecasts of annual flows.

Bafail, Abed, and Jasimuddin (2000) have developed a model for forecasting the long-term demand for domestic air travel in Saudi Arabia. They utilized several explanatory variables such as total expenditures and population to generate model formulation. Another study for air travel demand forecasting has done by Grosche, Rothlauf, and Heinzl (2007). According to their research, there are some variables that can affect the air travel demand, including population, GDP and buying power index. He considered GDP as a representative variable for the level of economic activity.

Swan (2002) has analyzed airline demand distributions model. The model explains when the Gamma shape will dominate and when the Normal will determine the shape. From his study, he found that Gamma shapes are probably better for revenue management and Normal for spill modeling. Fernandes and Pacheco (2002) have analyzed the efficient use of airport capacity. According to their research, on the basis of passenger demand forecast, it was possible to determine the period when capacity expansion would become necessary to maintain services at standards currently perceived by passengers.

Hsu and Chao (2005) have examined the relationships among commercial revenue, passenger service level and space allocation in international passenger terminals. They developed a model for maximizing concession revenues while maintaining service level, to optimize the space allocation for various types of stores.

Svrcek (1994) has analyzed three fundamental measures of capacity, including static capacity that is used to describe the storage capability of a holding facility or area, dynamic capacity which refers to the maximum processing rate or flow rate of pedestrians and sustained capacity that is used to describe the overall capacity of a subsystem to accommodate traffic demand over a sustained period.

Yamaguchi et al. (2001) have analyzed the economic impact analysis of deregulation for airport capacity expansion in Japanese domestic aviation market. According to their research, deregulation and airport capacity expansion play significant roles in realizing full benefit of aviation market growth. In line of deregulation policy, airport capacity expansion was accelerated to meet the growth demand.

3. System dynamics model

System dynamics was developed by Forrester (1961) in Massachusetts Institute of Technology (MIT). This framework is focused on systems thinking, but takes the additional some steps of constructing and testing a computer simulation model. The main characteristics of this method is the existence of complex system, the change of system behavior from time to time and also the existence of the closed loop feedback. This feedback describes the new information about the system condition, that will yield the next decision. Sterman (2000) has developed some steps to create system dynamics model such as depicted in Fig. 1. Modeling is a feedback process that go through constant iteration and an iterative cycle. It is embedded in the larger cycle of learning and action constantly taking place in organizations:

Step 1: Problem articulation: in this step, we need to find the real problem, identify the key variables and concepts, determine the time horizon and characterize the problem dynamically for understanding and designing policy to solve it.

Step 2: Dynamic hypothesis: modeler should develop a theory of how the problem arose. It guides modeling efforts by focusing on certain structures. In this step, we need to develop causal loop diagram that explain causal links among variables and convert the causal loop diagram into flow diagram. This flow diagram consists of some variables such as depicted in Table 1.

Step 3: Formulation: to define system dynamics model, after we convert the causal loop diagram into flow diagram, we should translate the system description into level, rate and auxiliary equations. We need to estimate some parameters, behavioral relationships and initial conditions. Writing equations will reveal gaps and inconsistencies that must be remedied in the prior description.

Step 4: Testing: the purpose testing is comparing the simulated behavior of the model to the actual behavior of the system.

Step 5: Policy formulation and evaluation. Once modelers have developed confidence in the structure and model behavior, we can utilize it to design and evaluate policies for improvement. The interactions of different policies must also be considered, because the real systems are highly nonlinear, the impact of combination policies is usually not the sum of their impacts alone.

System dynamics can be applied to a wide range of problem domains such as strategy and corporate planning, public management and policy, business process development, biological and medical modeling, energy and the environment, theory development in the natural and social sciences, dynamic decision making, complex nonlinear dynamics, software engineering, and supply chain management.

Lyneis (2000) 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. According to Sterman (2000), the dynamic behavior of a system is said to arise from the interaction among the various system components over time. Lyneis (1998) has developed system dynamics model to forecast demand of commercial jet aircraft industry. James and Galvin (2002) have utilized system dynamics to determine the future behavior of the principle components of the air traffic control (ATC) system over time.

System dynamics has three important roles in developing the model. The first and the most important one is the system structure that will characterize its behavior. The second one is the nature of the structure where the mental models play an important role in dynamic behavior of the system. The third one is that significant change can be used to alter the structure (structure scenario). This structure can be represented by feedback loops.

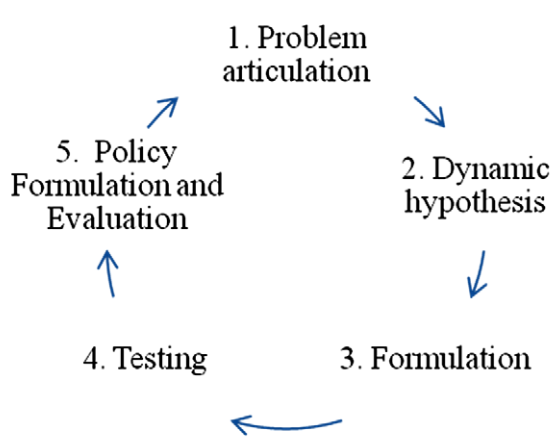

Fig. 1. System dynamics modeling process.

4. Base model development

In general, the demand for air passenger can be affected by two factors, those are external and internal factors. Some internal factors that affect the air passenger demand are airfare impact and level of service impact. While the external factors we consider *economic conditions* such as Gross Domestic Product (GDP) and *demographic factor*, e.g. population. Air transportation demand tends to evolve as a function of price changes and economic conditions (Department of Finance Canada, 2008). According to Seraj, Abdullah, and Sajjad (2001), there are several factors that affect the air travel demand, those are basically macroeconomic and demographic factor (population).

Fig. 2 represents the causal loop diagram of air passenger demand and passenger terminal capacity expansion. Causal loop diagrams have been used to describe basic causal mechanisms hypothesized to underlie the reference mode of behavior over time (Richardson, 1995; Sterman, 2000), to create a connection between structure and decisions that generate system behavior.

This causal loop diagram represents the relationship among *Population*, *GDP Growth*, *Level of Service Impact*, *Airfare Impact*, *Runway Utilization* and *Passenger Required Space*. 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. For example, increase *Population* can increase *Births*, but increase *Deaths* can decrease *Population*.

Each feedback loop has a polarity that will indicate the causality direction that implies how a change in any variables within the feedback loop. There are two kinds of feedback loop. The first one is reinforcing feedback loop, which means that feedback flows will generate exponential growth. The second one is balancing feedback loop, which means that feedback loop will maintain the system stability. The main causal loops in this model are depicted below:

Average number of flights per day $\xrightarrow{+}$ Congestion $\xrightarrow{+}$ Airline congestion cost $\xrightarrow{+}$ Airfare impact $\xrightarrow{-}$ Air passenger demand $\xrightarrow{+}$ Average number of flights per day

Average number of flights per day results in more congestion and airline congestion cost. As price elasticity has negative impact to airfare, the more airline congestion cost will cause airfare impact become more negative and decrease the demand of air passenger. Air passenger demand will increase in line with GDP growth and Population growth:

Table 1
Some variables in system dynamics.

Variable	Symbol	Description
Level	▭	A quantity that accumulates over time, change its value by accumulating or integrating rates
Rate	⧗	Change the values of levels
Auxiliary	○	Arise when the formulation of a level's influence on a rate involves one or more intermediate calculations, often useful in formulating complex rate equations, used for ease of communication and clarity

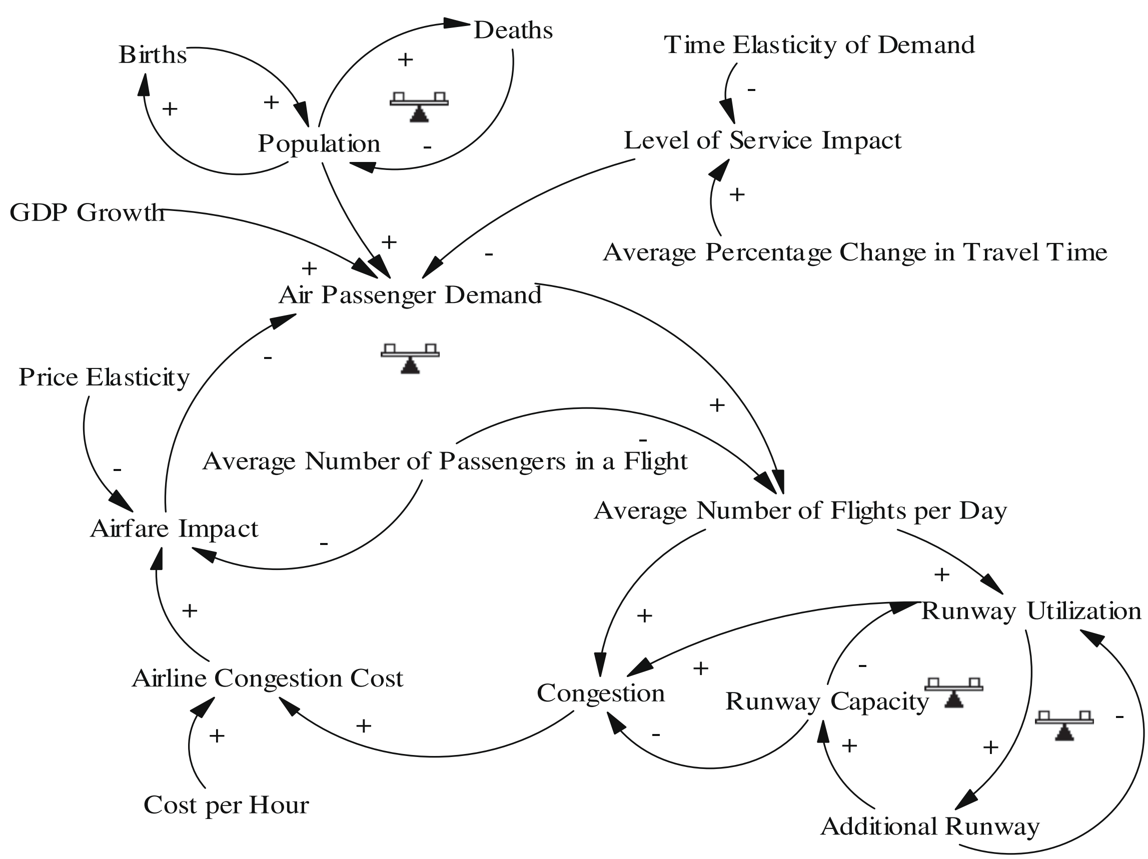

Fig. 2. Causal loop diagram of air passenger demand and passenger terminal capacity expansion.

> Average number of flights per day $\xrightarrow{+}$ Runway utilization $\xrightarrow{+}$ Additional runway $\xrightarrow{+}$ Runway capacity $\xrightarrow{-}$ Congestion $\xrightarrow{+}$ Airline congestion cost $\xrightarrow{+}$ Airfare impact $\xrightarrow{-}$ Air passenger demand $\xrightarrow{+}$ Average number of flights per day.

Average number of flights per day attracts more runways utilization and additional runway. The more additional runway, the larger the runways capacity will be and will decrease the runways utilization. Runways capacity has negative impact to congestion, airline congestion cost and will decrease the effect of negative airfare impact to air passenger demand. The more air passenger demand, the more average number of flights per day will be.

> Passenger required space $\xrightarrow{-}$ Dynamic capacity $\xrightarrow{+}$ Terminal space area $\xrightarrow{-}$ Terminal utilization $\xrightarrow{+}$ Passenger required space.

As the demand of air passenger increases, it generates more passenger required space. The growth of passenger required space will decrease the dynamic capacity and will need more terminal space area. However, increase the terminal space area will decrease the terminal utilization.

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 emphasize 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. 3 shows the flow diagram of air passenger demand and runway utilization (base model).

This model consists of five sub-models: airfare impact, level of service impact, GDP, population and runway utilization.

4.1. Airfare impact sub-model

Airfare represents the fare for transportation on a commercial airplane. The airfare impact on air passenger demand is determined by utilizing the concept of price elasticity of demand. Price elasticity of demand is defined as the percentage change in demand as the impact of 1% change in average airfare. While time elasticity of demand is the percentage change in total travel demand that occurs with a 1% change in travel time. In this study, airfare impact is the change in demand from a percentage change in average travel cost times price elasticity (see Eqs. (1)–(5)):

$$\text{Airface Impact} = \varepsilon_{\text{price}} * \Delta\text{Travel cost} \tag{1}$$

$$\Delta\text{Travel cost} = \frac{\text{Congestion Cost/Passenger}}{\text{Average Airface}} * \text{Transfer Cost} \tag{2}$$

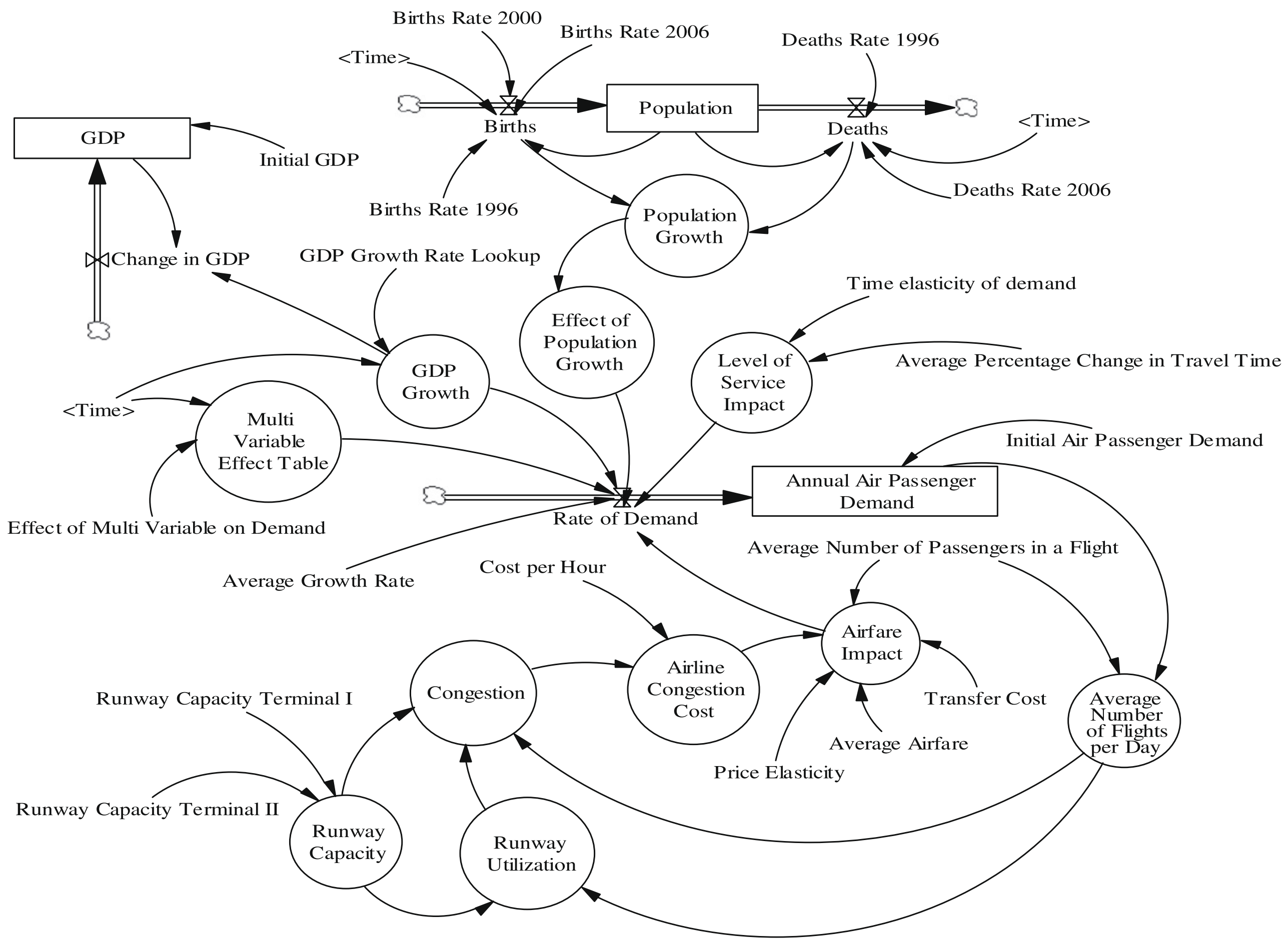

Fig. 3. Flow diagram of air passenger demand and runway utilization.

$\varepsilon_{\text{price}}$ is the price elasticity of demand which represents the percentage change in air passenger demand as a result of a 1% change in travel cost due to the congestion costs. The price elasticity of demand has been estimated at approximately −1.6 for leisure passengers and −0.8 for business passengers (Belobaba, 2001).

In this study, congestion is defined as the waiting time (per peak hour of traffic) for each aircraft that's wants to land on the runway. According to Larson and Odoni (1981), the waiting time is obtained by utilizing M/G/1 queuing system such as depicted in Eq. (3):

$$\text{Congestion} = \frac{\lambda * \left(\left(\frac{1}{\tau}\right)^2 + \sigma_t^2\right)}{2 * (1 - \rho)} \tag{3}$$

$$\rho = \frac{\lambda}{\mu} \tag{4}$$

$$\text{Congestion Cost} = \text{Congestion} * \text{Cost per Hour} \tag{5}$$

where λ is the average number of flights for a specified of time determined by the Poisson distribution, σ_t is the standard deviation of service time and μ is runway capacity. While ρ can be defined as runway utilization.

4.2. Level of service impact sub-model

Level of service impact is the change in demand as the impact of the percentage change in average travel time times time elasticity (see Eqs. (6) and (7)):

$$\text{Level of service impact} = \varepsilon_{\text{times}} * \Delta\text{Travel Time} \tag{6}$$

$$\text{Travel Time} = 0.4 + ABS(0.01 * \text{RANDOM NORMAL}(\,)) \tag{7}$$

where $\varepsilon_{\text{times}}$ is the time elasticity of demand and ΔTravel Time is the percentage change in travel time. RANDOM NORMAL( ) is a function that provides a normal distribution of mean 0 and variance 1. Time elasticity of demand is the percentage change in total demand that occurs with a 1% change in travel time. We utilized ABS function to return to absolute value of RANDOM NORMAL( ). In this study, we assumed that the average percentage change in travel time was around 40% by considering that travel air kept a portion of its fleet in reserve (initially 40%, later much less) to resolve scheduling conflicts (Ingram, 2004).

4.3. Population sub-model

The growth of population can generate more travel demand. We classified the total population as the level variable, while birth rate and death rate as the auxiliary variables (see Eqs. (8)–(10)). Parameter dt represents the time interval of simulation. In this study, the time interval is 1 year. During 1996–1999, the births rate in Taiwan was ±13.2/1000 population, ±13/1000 population in 2000–2005 and ±11.14/1000 population in 2006. While for the deaths rate was ±6/1000 population during 1996–2005 and ±6.53 starting from 2006.

Based on these conditions, we utilize IF THEN ELSE function for the births and deaths formulation. 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. Condition must be a Boolean expression or an expression or variable that can be interpreted as Boolean. If condition is true, than the function evaluates and returns *true value*, otherwise *false value* is evaluated and returned:

$$\text{Population}(t) = \text{Population}(t - \mathrm{d}t) + (\text{Births} - \text{Deaths}) * \mathrm{d}t \quad (8)$$

$$\begin{aligned}\text{Deaths} = {} & \text{IF THEN ELSE}(\text{Time} < 2000,\ \text{Deaths Rate } 1996/1000 \\ & * \text{Population, IF THEN ELSE}(\text{Time} < 2006, \\ & \text{Deaths Rate } 2000/1000 * \text{Population}, \\ & \text{Deaths Rate } 2006/1000 * \text{Population})) \end{aligned} \quad (9)$$

$$\begin{aligned}\text{Births} = {} & \text{IF THEN ELSE}(\text{Time} < 2000,\ \text{Births Rate } 1996/1000 \\ & * \text{Population, IF THEN ELSE}(\text{Time} < 2006, \\ & \text{Births Rate } 2000/1000 * \text{Population}, \\ & \text{Births Rate } 2006/1000 * \text{Population})) \end{aligned} \quad (10)$$

4.4. GDP sub-model

GDP is chosen as a level variable, and change in GDP as a rate variable. Change in GDP depends on GDP growth (see Eqs. (11) and (12)). In this study, we utilize lookup or table function for GDP growth based on consideration that GDP growth is a nonlinear function. Lookup table represents the dynamic behavior of a physical system by mapping multiple inputs to a single output in a multidimensional data array. In the simpler two-dimensional case, lookup tables can be represented by matrices. Each element of a matrix is a numerical quantity, which can be precisely located in terms of two indexing variables (see Eqs. (13) and (14)):

$$\text{GDP}(t) = \text{GDP}(t - \mathrm{d}t) + (\text{Change in GDP}) * \mathrm{d}t \quad (11)$$

$$\text{Change in GDP} = \text{GDP Growth}/100 * \text{GDP} \quad (12)$$

$$\text{GDP Growth} = \text{GDP Growth Rate Lookup}(\text{Time}) \quad (13)$$

$$\begin{aligned}&\text{GDP Growth Rate Lookup}([(1996, -8) \\ &- (2007, 10)], (1996, 8.4), (1997, 6), (1998, 5.7), (1999, 5.8), \\ &(2000, -2.2), (2001, 3.2), (2002, 2.2), (2003, 5.2), (2004, 3.1), \\ &(2005, 4.7), (2006, 4.5), (2007, 4.5))\end{aligned} \quad (14)$$

4.5. Runway utilization sub-model

Runway capacity is the limiting factor that leads to congestion (Kessides, 1996). As demand for air travel increases, average number of flights requiring service on this runway also increases (see Eqs. (15)–(17)). If runway capacity is held constant, the increase in demand will lead to congestion, which raises the airline congestion cost. The higher airline congestion cost, the greater the airfare impact will be:

$$\begin{aligned}\text{Runway Utilization} = {} & \text{Average Number of Flights} \\ & \times \text{per Day/Runway Capacity}\end{aligned} \quad (15)$$

$$\begin{aligned}&\text{Average Number of Flights per Day} = \text{Annual Air Passenger} \\ &\times \text{Demand}/(365 * \text{Average Number of Passengers in a Flight})\end{aligned} \quad (16)$$

$$\begin{aligned}\text{Runway Capacity} = {} & \text{Runway Capacity Terminal I} \\ & + \text{Runway Capacity Terminal II}\end{aligned} \quad (17)$$

4.6. Main relationships of the model

Air passenger demand is very volatile and cyclical (Skinner, Dichter, Langley, & Sabert, 1999). In order to capture this nonlinear relationships, we utilized lookup or table functions. In this study, we consider multivariable effect table to accommodate the nonlinear relationships among demand, airfare impact, effect of population growth, GDP growth, level of service impact and multivariable effect (see Eqs. (18)–(21)). The general format can be described as follows:

$$\text{Table for effect of } X \text{ on } Y = (X1, Y1), (X2, Y2), \ldots, (Xn, Yn)$$

where (Xi, Yi) represents each pair of points defining the relationship. We set the time as Xi and the effect of interaction among variables as Yi. The other function that we used in this model is MAX function. The MAX function format is given as follows:

$$\text{MAX}(A, B)$$

This function means that returns the larger of A and B. In this study, we set A as the level of service impact and B as the airfare impact:

$$\begin{aligned}&\text{Annual Air Passenger Demand}(t) \\ &= \text{Annual Air Passenger Demand}(t - \mathrm{d}t) \\ &+ (\text{Rate of Demand}) * \mathrm{d}t\end{aligned} \quad (18)$$

$$\begin{aligned}&\text{Rate of Demand} = (\text{Effect of Population Growth} \\ &+ \text{MAX}(\text{Level of Service Impact}/100,\ \text{Airfare Impact}/100)) \\ &* \text{GDP Growth} * \text{Average Growth Rate/MultiVariable Effect Table}\end{aligned} \quad (19)$$

$$\begin{aligned}&\text{MultiVariable Effect Table} \\ &= \text{Effect of MultiVariable on Demand}(\text{Time})\end{aligned} \quad (20)$$

$$\begin{aligned}&\text{Effect of MultiVariable on Demand}([(1996, -100) \\ &- (2007, 100)], (1996, 12.83), (1997, -17), (1998, 3.2), \\ &(1999, 2.45), (2000, 10.5), (2001, 2.32), (2002, -0.34), \\ &(2003, 0.81), (2004, 1.7), (2005, 1.8), (2006, 3.3), (2007, 1))\end{aligned} \quad (21)$$

4.7. Parameter estimation

Parameter estimation is the process of utilizing data or observation from a system to develop mathematical models. The assumed model consists of a finite set of parameters, the values of which are calculated using estimation techniques. Parameter values can be drawn from all available sources, not merely from statistical analysis of time series. All information is admissible in the modeling process. The estimation of parameters can be obtained is some ways, e.g. statistics data, published reports and statistical methods. The coefficient estimation results for effect of population growth and population growth are given in Eqs. (22) and (23). Other values of coefficients of the base model are listed in Table 2:

$$\text{Effect of Population Growth} = \text{Population Growth}/100{,}000 \quad (22)$$

$$\text{Population Growth} = \text{Births} - \text{Deaths} \quad (23)$$

5. Base model run results

As mentioned above, this study has focused on air passenger demand, runway and passenger terminal capacity expansion. In the base model, we set the simulation timing for 12 years starting from 1996 to 2007 based on consideration of learning the system behavior of air travel demand before and after terrorist attack in 2001 and the availability of the data. The simulation time step is 1 year.

Fig. 4 demonstrates Taiwan GDP during 1996–2007. As we can see from Fig. 4, average Taiwan GDP growth during 1996–2007

Table 2
Values of parameters of base model.

Parameter	Value	Unit
Average growth rate of demand	745,633	Passengers/year
Initial passenger demand	15,613,600	Passengers
Initial GDP	7,944,600	NT Million Dollar
Average airfare	140	$/one way
Average number of passenger in a flight	250	Passengers
Price elasticity	−0.8	–
Time elasticity of demand	−1.6	–
Cost per hour	6761	$/h
Runway capacity	420	Flights/day

was around 4.23% annually. The global slowdown in 2001 caused by terrorist attacks on the United States, made Taiwan GDP –2.2% decline. Recovery began in 2002, real growth of 3.16% was recorded. Taiwan's economy had been growing rapidly, starting from 2004. GDP bounced back and rose by 5.1% in 2004, 3.16% in 2005, 4.6% in 2006 and 4.5% in 2007.

Fig. 5 represents Taiwan population during 1996–2007. Population grew around 0.47–0.75%. In 2007, population was around 23.14 million people with average births rate −0.76% and average deaths rate 1.49%. Fig. 6 shows the airfare and airline cost congestion. Airfare impact became more negative in line with increase in airline cost congestion.

Fig. 7 represents the impact of level of service to the demand growth. As we can see from Fig. 7, level of service had negative impact to the air travel demand. It has fluctuated around −64% to −67% as the results of time elasticity and the percentage change in travel time.

Fig. 8 shows the annual air passenger demand during 1996–2007 in TTIA. Average growth of air passenger demand was around 4.32% as the impact of airfare, effect of population growth, GDP growth, level of service impact, and multivariable effect. The causal relationship among rate of demand, airfare impact, effect of population growth, GDP growth, level of service impact and multivariable effect is given in Fig. 9. As we can see from Fig. 9, airfare impact had a very significant contribution to the demand growth (rate of demand). Multivariable effect is restricted by internal variables (airfare impact and level of service impact) and external variables (GDP growth and effect of population growth).

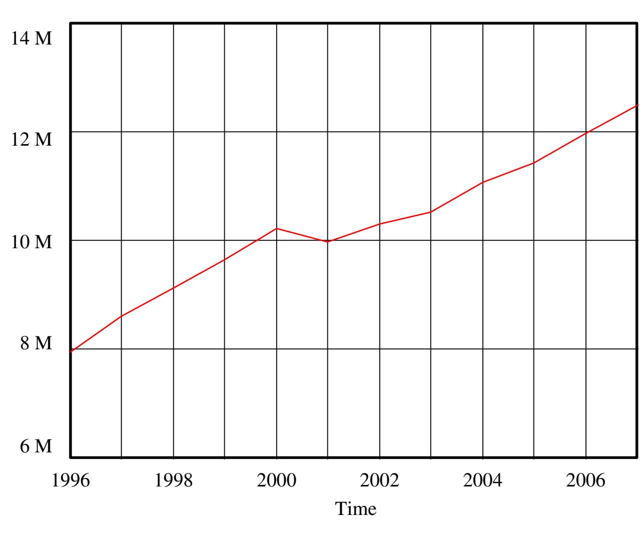

Fig. 4. GDP.

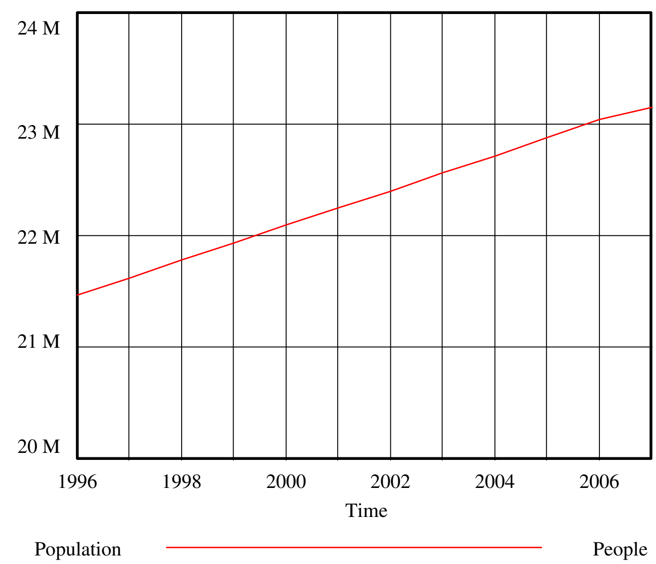

Fig. 5. Population.

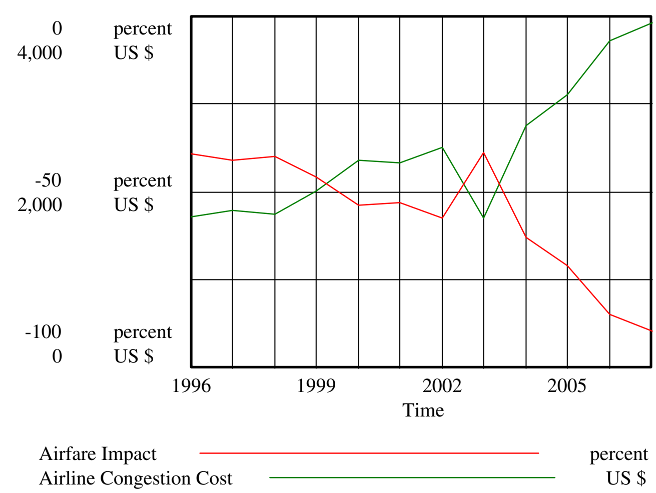

Fig. 6. Airfare impact and airline cost congestion.

Fig. 10 represents the average number of flights per day in TTIA. During 1996–2007, the average number of Flights per day was around 171–257 flights. With this condition, the runways utilization was 0.404 in 2003 and 0.6101 in 2007. Runway utilization during 1996–2007 is given in Fig. 11.

6. Model validation

Validation process is required to help build confidence in the model. The objective is to achieve a deeper understanding of the model. To do this process, we need historical data during the time horizon of simulation of the base model (1996–2007). According to Barlas (1994), a model will be valid if the error rate, less than 5% (see Eqs. (24)–(26)). Valid implies being supported by objective truth. The comparison between model and data of air passenger demand, GDP and population are given in Figs. 12–14, respectively (see Table 3),

$$\text{Errorrate} = \frac{|\bar{S} - \bar{A}|}{\bar{A}} \tag{24}$$

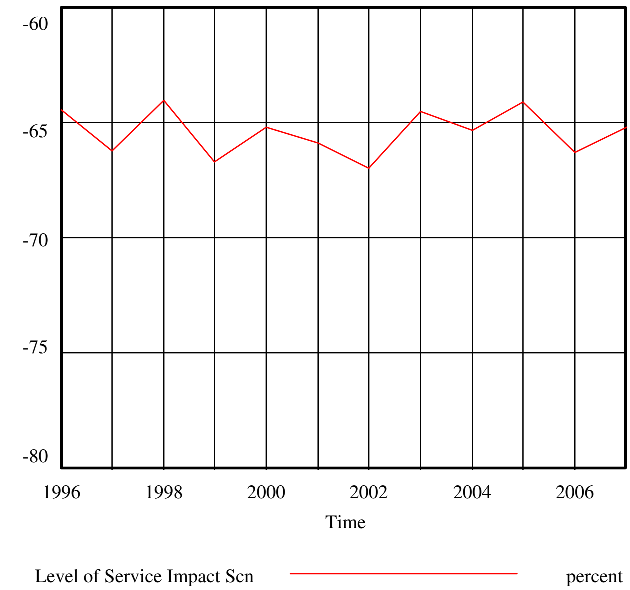

Fig. 7. Level of service impact.

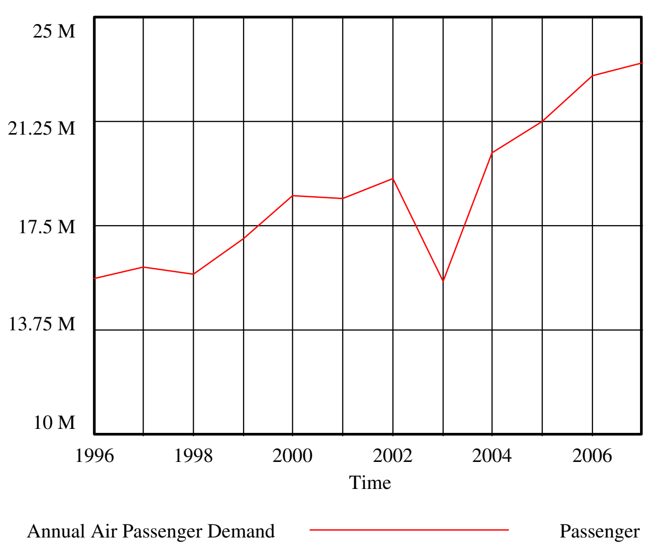

Fig. 8. Annual air passenger demand.

where

$$\bar{S} = \frac{1}{N}\sum_{i=1}^{N} Si \tag{25}$$

$$\bar{A} = \frac{1}{N}\sum_{i=1}^{N} Ai \tag{26}$$

7. Scenario development

In this section, we show how the system structure of a valid model can be exchanged by adding some feedback loops, adding new parameters, and changing the structure of the feedback loops (structure scenario) and how the parameter model can be changed to see the impact to other variables (parameter scenario). Scenario development is a prognosis method where the present data is used to develop various possible, often alternative future scenarios (Reibnitz, 1988). In this study, we developed some scenarios that demonstrate how a future situation can be regarded as a logical consequence of possible events occurring in the future. A scenario

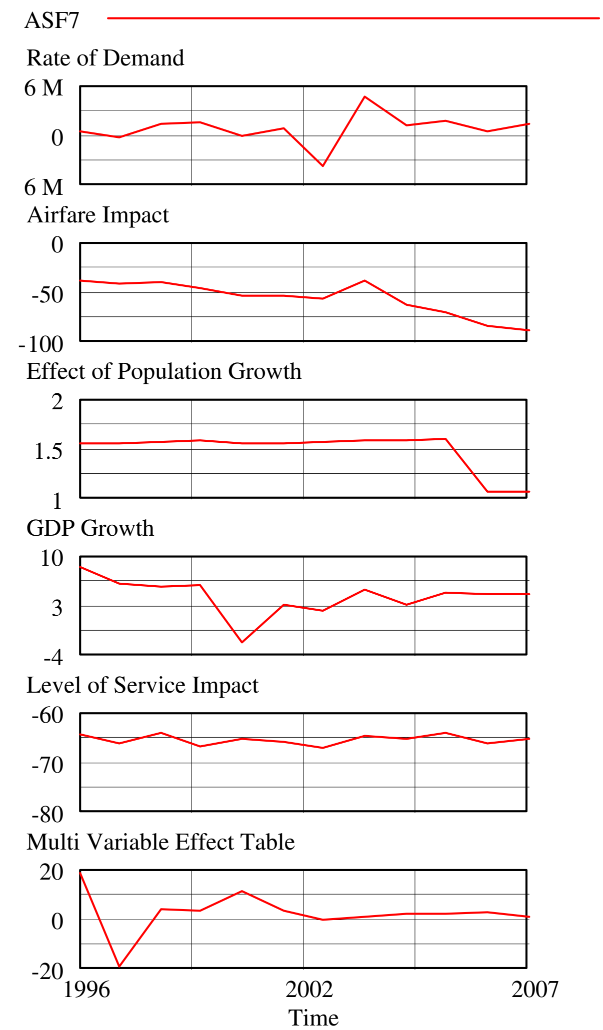

Fig. 9. Causal relationship among rate of demand, airfare impact, effect of population growth, GDP growth, level of service impact and multivariable effect.

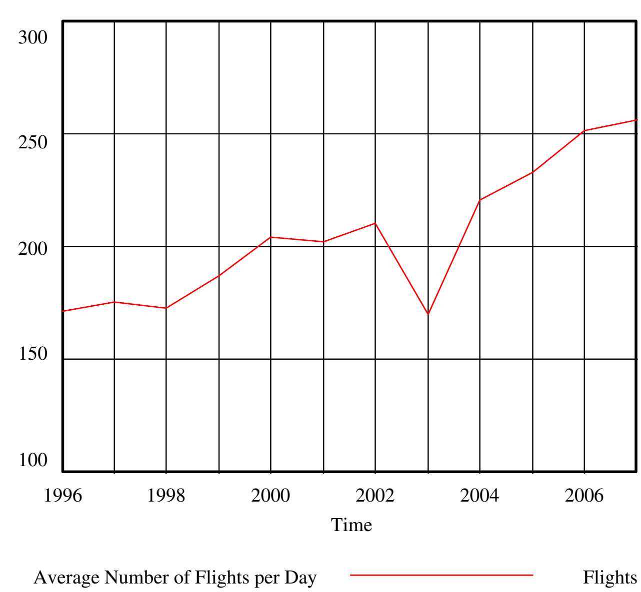

Fig. 10. Average number of flights per day.

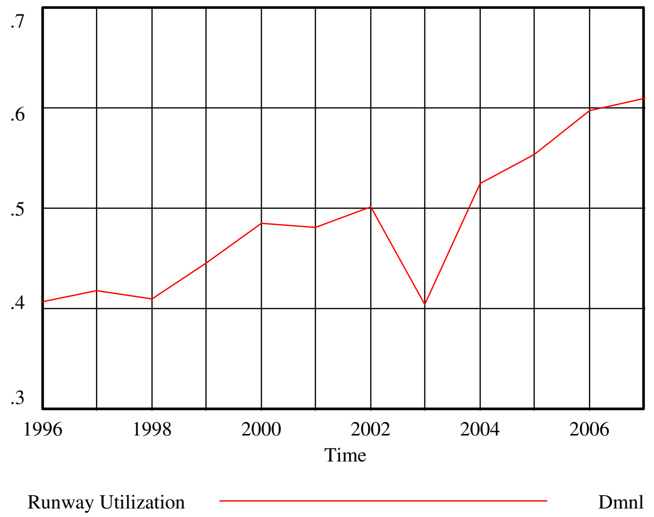

Fig. 11. Runway utilization.

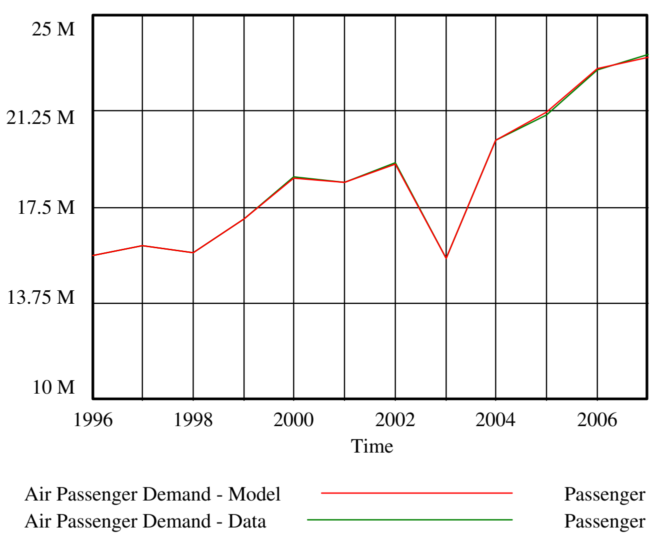

Fig. 12. Comparison between model and data of air passenger demand.

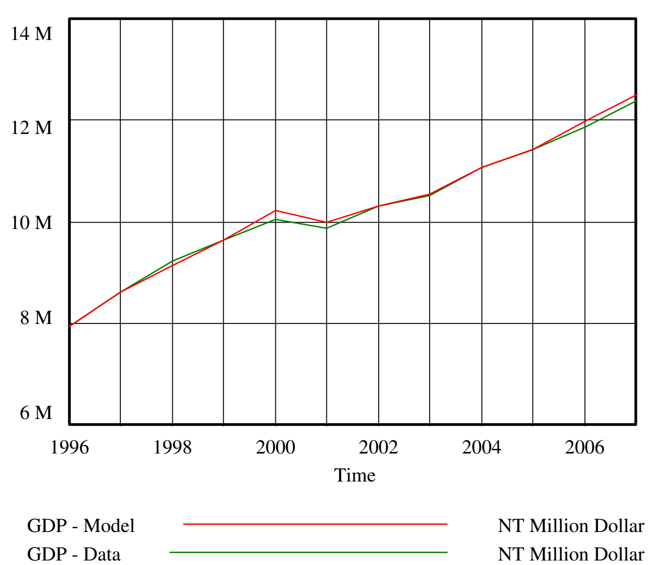

Fig. 13. Comparison between model and data of GDP.

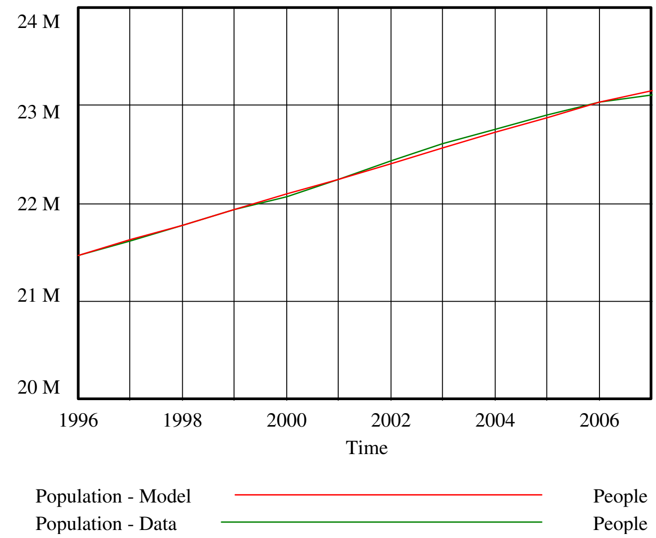

Fig. 14. Comparison between model and data of population.

Table 3
Comparison of model outputs with data.

Variable	Simulation ($\bar{S}$)	Data actual ($\bar{A}$)	Error rate
Demand	18,637,500	18,644,669	0.00038
GDP	10,272,916.7	10,239,629.3	0.003251
Population	22,317,500	22,325,320	0.000350253

can be seen as a movie, rather than as a photograph. We combined between structure scenario and parameter scenario to generate more robust sensitivity analysis. The scenario block diagram is given in Fig. 15.

7.1. Structure scenario

In this scenario, we modified the structure of airfare impact and add new structure to determine the flow of passenger in terminal building. In line with inflation rate, we assumed that airline congestion cost, average airfare and transfer cost will increase. We defined cost per hour, average airfare, and transfer cost as level variable, while average inflation rate will generate change in cost per hour, change in average airfare and change in transfer cost.

The flow of passenger depends on the air passenger demand, departure dwell time and arrival dwell time. We set the departure dwell time parameter = 1 h and arrival dwell time = 0.5 h based on our observation in TTIA. This passenger flow, will determine the excess of capacity of the terminal building. Additional daily capacity is required when excess of capacity is less than zero (see Eq. (34)). Total additional area for the terminal building is restricted by excess of capacity and the type of level of service of the standard area that will be utilized by the airport.

7.2. Parameter scenario

As parameter scenario, we developed optimistic and pessimistic scenarios to predict the future of air passenger demand related with runway and passenger terminal capacity expansion by utilizing 'A' level of service (LOS) area.

According to IATA (1981), the level of service can be divided into six levels (A, B, C, D, E and F). The best of LOS is 'A 'LOS which represents excellent service level and the worst is 'F' LOS which

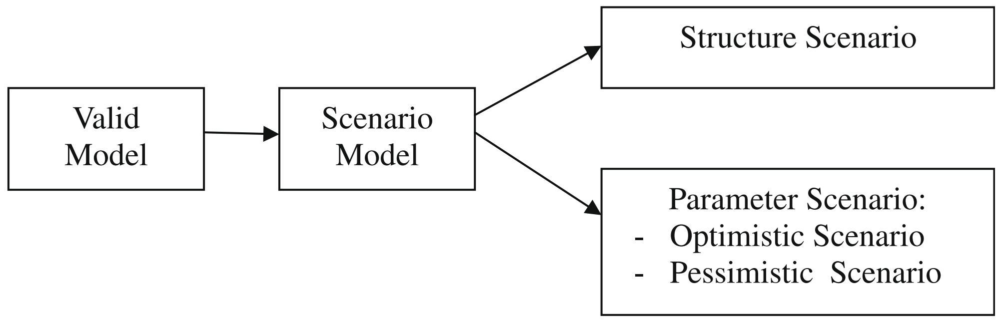

Fig. 15. Scenario block diagram.

represents unacceptable service level. Every LOS has different area requirement, such as depicted in Table 4.

7.2.1. Optimistic scenario

This scenario is made to check the runway and passenger 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 (The China Post, 2008). We utilized RANDOM NORMAL to generate the GDP growth fluctuation. RANDOM NORMAL provides a normal distribution of mean 0 and variance 1. In this study, we set the *GDP Growth Scn* = 6 + RANDOM NORMAL( ) to provide *GDP Growth* with a normal distribution of mean 6% and variance 1% (see Eq. (27)). *Population* is expected to grow around 0.48% annually based on the births rate (11.14/1000 population) and deaths rate (6.53/1000 population) by considering the existing condition:

$$\text{GDP Growth Scn} = 6 + \text{RANDOM NORMAL}(\,) \tag{27}$$

$$\text{Cost per Hour Scn}(t) = \text{Cost per Hour Scn}(t - \mathrm{d}t) + (\text{Change in Cost Per Hour}) * \mathrm{d}t \tag{28}$$

$$\text{Average Airfare Scn}(t) = \text{Average Airfare Scn}(t - \mathrm{d}t) + (\text{Change in Average Airfare}) * \mathrm{d}t \tag{29}$$

$$\text{Transfer Cost Scn}(t) = \text{Transfer Cost Scn}(t - \mathrm{d}t) + (\text{Change in Transfer Cost}) * \mathrm{d}t \tag{30}$$

$$\text{Average Inflation Rate Scn} = 1 + \text{RANDOM NORMAL}(\,) \tag{31}$$

$$\text{Percentage Change in Travel Time Scn} = 30 + \text{RANDOM NORMAL}(\,) \tag{32}$$

All cost components such as *Cost per Hour Scn*, *Average Airfare Scn*, *Transfer Cost Scn* will increase as the impact of Inflation (*Inflation Rate Scn*) (see. Eqs. (28)–(30)). We assume that the inflation rate will grow with average 1% annually by considering the average inflation rate for the last 4 years (see Eq. (31)). Percentage change in travel time will be less than the existing condition in the base model, we assume that the percentage change in travel time will be around 30% (see Eq. (32)).

Table 4
LOS parameters.

LOS area (sq. m.)	A	B	C	D	E
Baggage claim	2.00	1.80	1.60	1.40	1.20
Flow space	20.00	25.00	40.00	57.00	75.00
Check in	1.80	1.60	1.40	1.20	1.00
Holding area	2.70	2.30	1.90	1.50	1.00
Generic area	1.40	1.20	1.00	0.80	0.60

Fig. 16 shows the flow diagram of demand and passenger terminal capacity expansion optimistic scenario. As we can see from Fig. 16, annual demand forecast will determine passenger required space optimistic scenario. We can utilize this scenario model to check the runway utilization and passenger terminal capacity whether they can accommodate the forecast demand. In this study, arrival and departure dwell time have significant impact to passenger required space. If runway utilization is greater than one, means that the runway should be expanded in order not to make congestion longer (see Eq. (33)). If excess of capacity is strictly less than zero, means that they should expand the terminal capacity (see Eq. (34)):

$$\text{Additional Runway Scn} = \text{IF THEN ELSE}(\text{Runways Utilization Scn} \geqslant 1, 350, 0) \tag{33}$$

$$\begin{aligned}\text{Additional Daily Capacity Scn} &= \text{IF THEN ELSE}(\text{Excess of Capacity Opt Scn} \leqslant 0 : \text{AND} \\ &: \text{Excess of Capacity Opt Scn} > -1.7\text{e}+007, \\ &(1.7\text{e}+007/365), \text{IF THEN ELSE } (\text{Excess of Capacity Opt Scn} \\ &< -1.7\text{e}+007, (3.4\text{e}+007/365), 0))\end{aligned} \tag{34}$$

7.2.2. Pessimistic scenario

This scenario is made to check the runway and passenger terminal capacity to meet the future demand if *GDP* is predicted to grow with average growth rate 2.8% annually by considering that global GDP growth rate would be only 1% and 4.5% for developing countries (Zoellick, 2008). We utilized RANDOM NORMAL to generate the GDP growth fluctuation. In this study, we set the *GDP Growth Scn* = 2.8 + RANDOM NORMAL( ) to provide GDP growth with a normal distribution of mean 2.8% and variance 1% (see Eq. (35)).

By setting the average GDP growth around 2.8%, we expect that the scenario run result of GDP growth will be around 1–4.5%. For LOS impact and population, we adopt the variables from the base model, the percentage change of travel time will be around 40% and the population will grow with average growth rate around 0.48%. We assume that annual inflation rate will be around 2% based on Taiwan central bank prediction (Taipei times, 2008) (see Eq. (36)):

$$\text{GDP Growth Pessimistic Scn} = 2.8 + \text{RANDOM NORMAL}(\,) \tag{35}$$

$$\text{Average Inflation Rate Pessimistic Scn} = 2 + \text{RANDOM NORMAL}(\,) \tag{36}$$

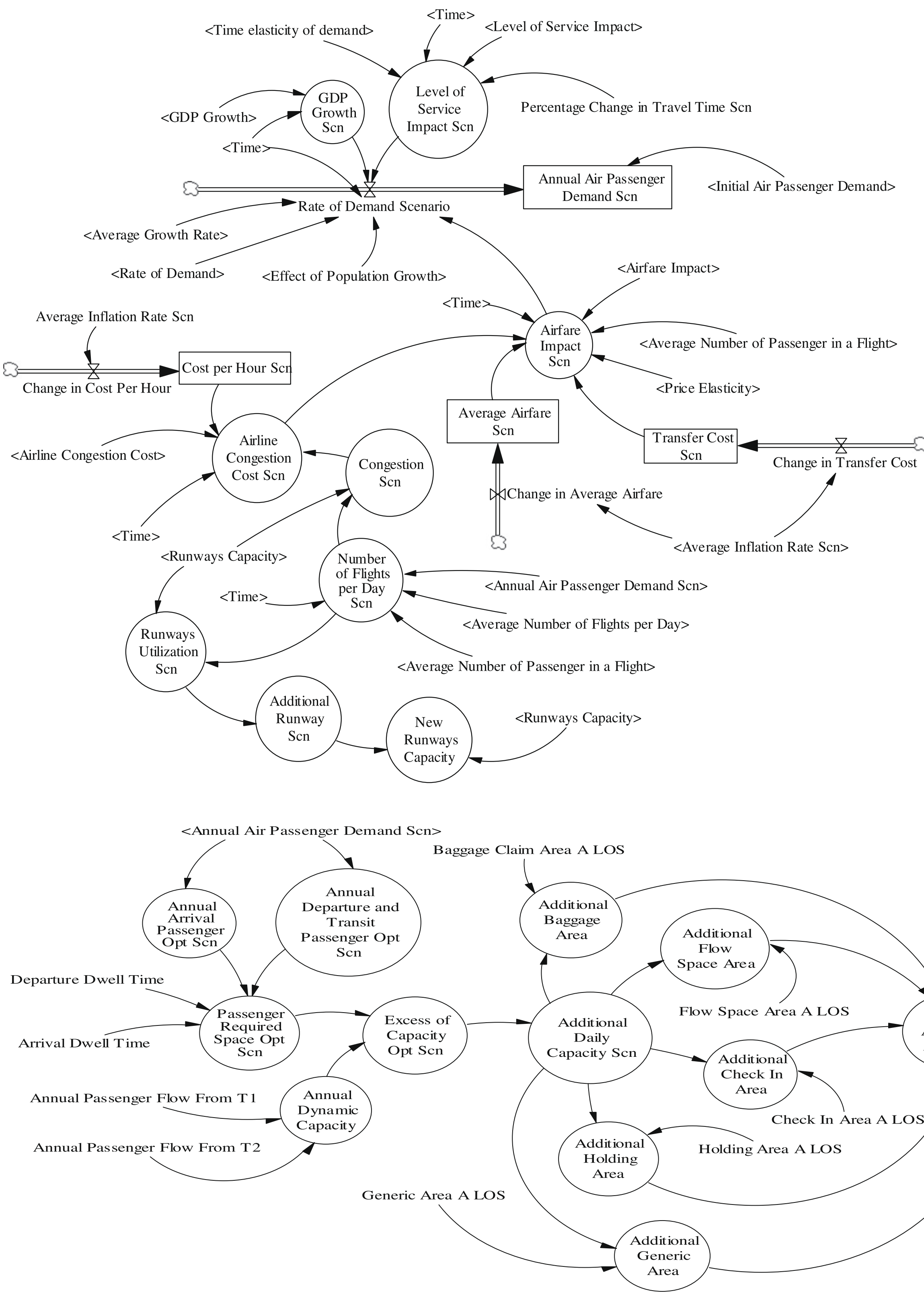

Fig. 16. Flow diagram of demand and passenger terminal capacity expansion optimistic scenario.

Fig. 17 shows the flow diagram of air passenger demand and passenger terminal capacity expansion pessimistic scenario. We can utilize this pessimistic scenario model to check the runway utilization and passenger terminal capacity whether they can accommodate the forecast demand in pessimistic condition. Average inflation rate will determine all components cost, e.g. average airfare, transfer cost and cost per hour (see Eqs. (37)–(39)):

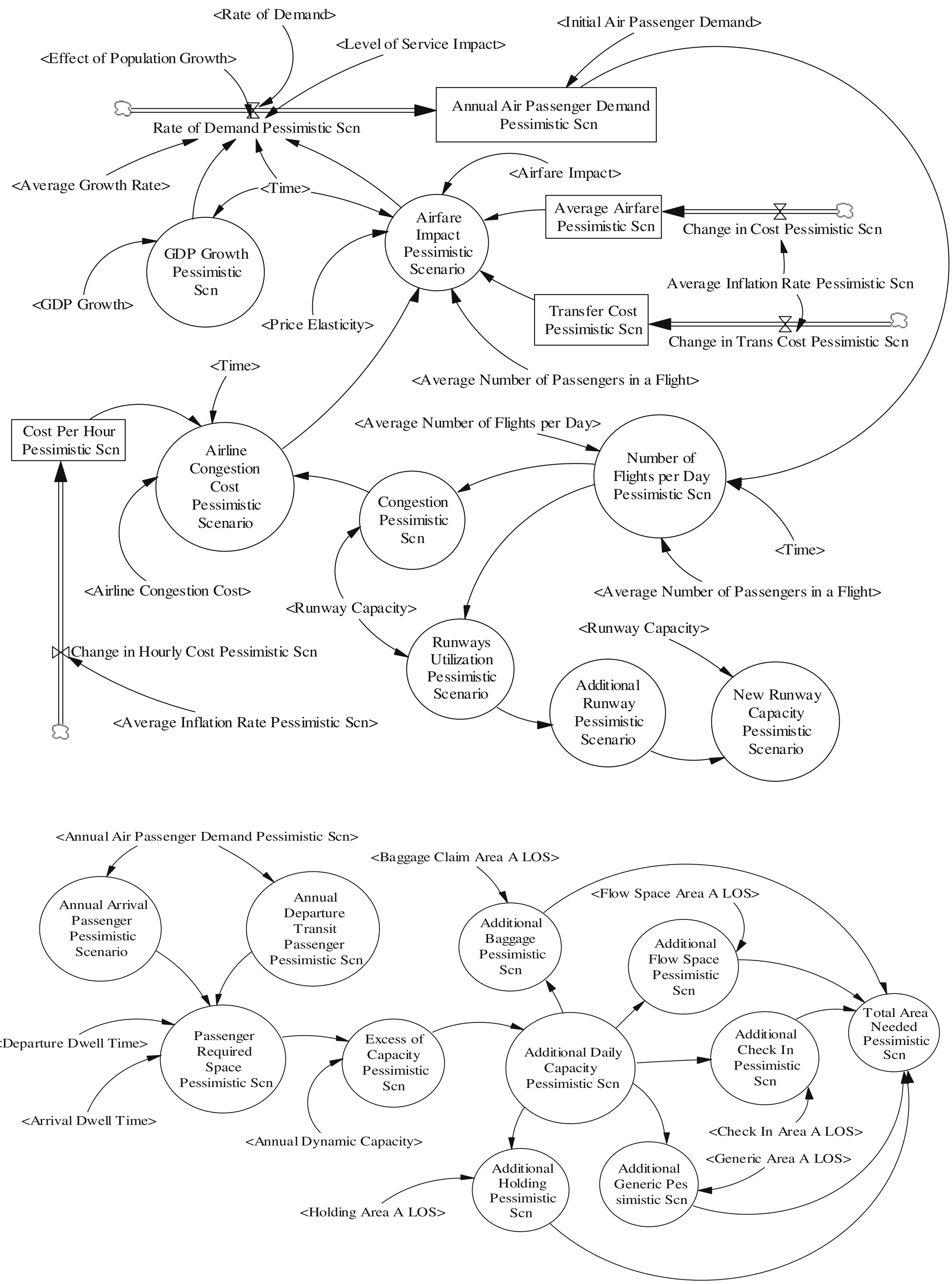

Fig. 17. Air passenger demand and passenger terminal capacity expansion pessimistic scenario.

$$\text{Cost Per Hour Pessimistic Scn}(t) = \text{Cost Per Hour Pessimistic Scn}(t-\mathrm{d}t) + (\text{Change in Hourly Cost Pessimistic Scn}) * \mathrm{d}t \quad (37)$$

$$\text{Average Airfare Pessimistic Scn}(t) = \text{Average Airfare Pessimistic Scn}(t-\mathrm{d}t) + (\text{Change in Cost Pessimistic Scn}) * \mathrm{d}t \quad (38)$$

$$\text{Transfer Cost Pessimistic Scn}(t) = \text{Transfer Cost Pessimistic Scn}(t - dt) + (\text{Change in Trans Cost Pessimistic Scn}) * dt \quad (39)$$

7.3. Scenarios run results

As we can see from Fig. 18, GDP will grow around 4.35–8% in optimistic condition and around 1.44–3.96% in pessimistic condition. *Level of Service Impact* that represents the change in demand from a percentage change in travel time has negative impact to the demand growth. Fig. 19 demonstrates level of service impact in optimistic and pessimistic condition. As we can see from Fig. 19, by reducing the percentage change in travel time, it will affect the level of service impact. Level of service impact become more positive and it will generate more air travel demand.

Fig. 20 demonstrates the airfare impact in optimistic and pessimistic condition. As we can see from Fig. 20, airfare impact also has negative impact to the demand growth in line with increase in all price components such as cost per hour, average airfare and transfer cost as the impact of inflation rate. Airfare impact in optimistic condition will be more negative than pessimistic condition as the impact of congestion. The greater the demand for air travel will increase the runway utilization and will lead to congestion. Population is predicted will grow ±0.48% annually. So, by the year 2028 the population will be around 25.48 million people.

Fig. 21 represents the annual passenger demand in optimistic and pessimistic condition. Demand will grow with average growth rate 6.6% annually in optimistic condition and 3.12% in pessimistic condition. So, by the year 2028, the air travel demand will achieve ±84.09 million passengers in optimistic condition and ±44.41 million passengers in pessimistic condition.

Fig. 22 shows the number of flights per day in optimistic and pessimistic condition. Average number of flights per day will be around 424 flights in 2013 and will achieve 922 flights in 2028 in optimistic condition. While for pessimistic condition, Average number of flights per day will be around 430 flights in 2024 and will achieve 487 flights in 2028.

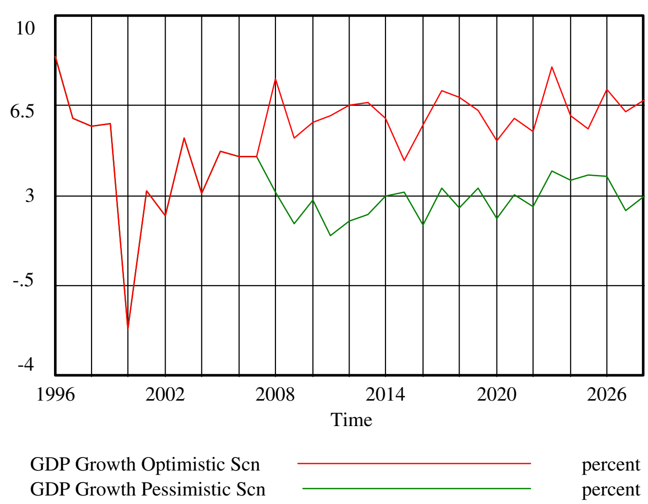

Fig. 18. GDP growth optimistic and pessimistic scenario.

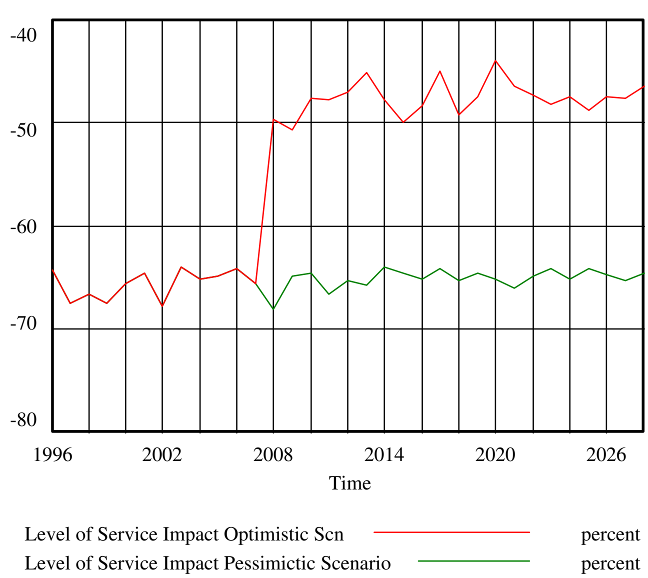

Fig. 19. Level of service impact optimistic and pessimistic scenario.

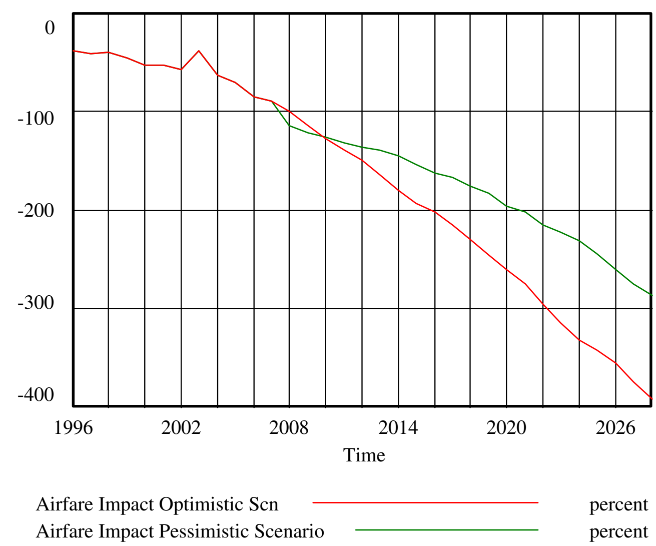

Fig. 20. Airfare impact optimistic and pessimistic scenario.

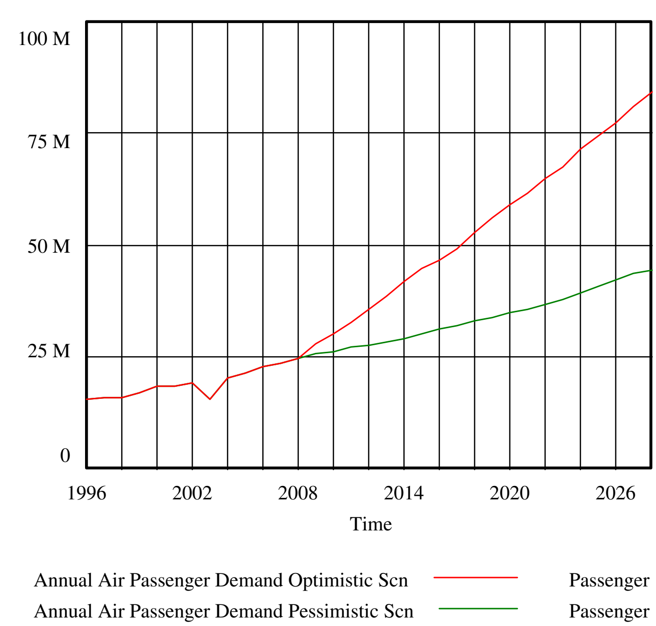

Fig. 21. Annual air passenger demand optimistic and pessimistic scenario.

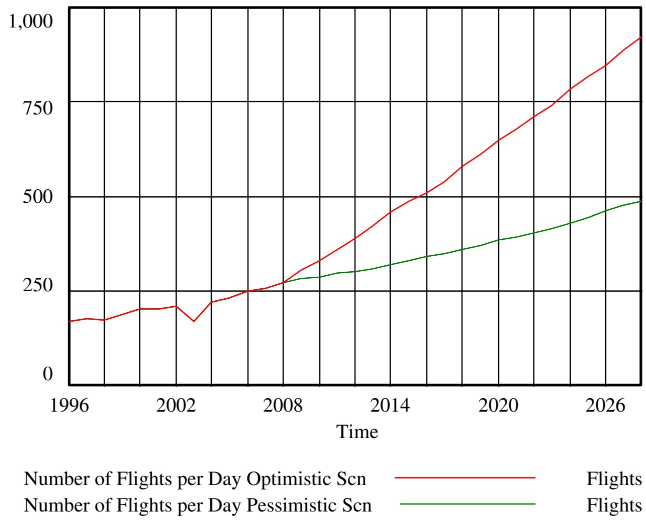

Fig. 22. Number of flights per day optimistic and pessimistic scenario.

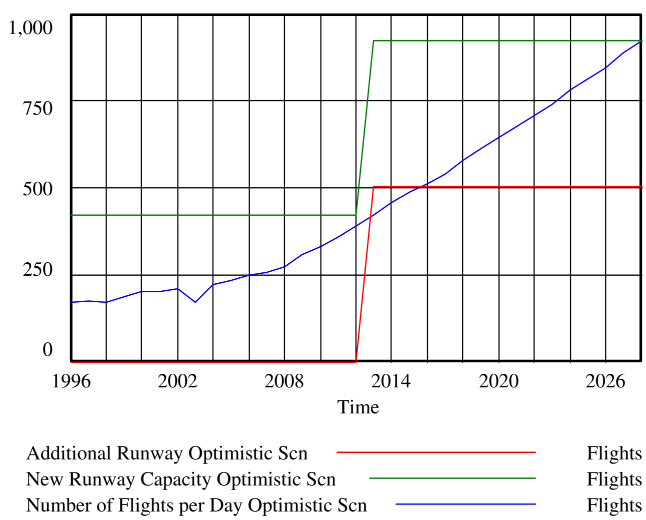

Fig. 23. Additional runway, new runway capacity, number of flights/day optimistic scenario.

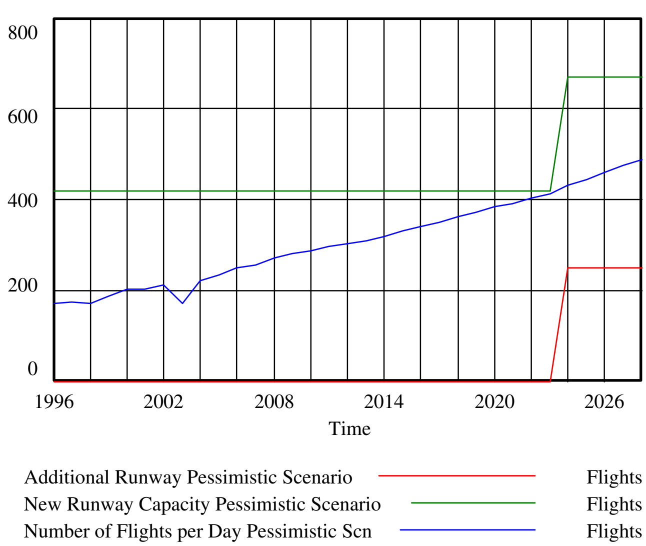

Fig. 24. Additional runway, new runway capacity, number of flights per day pessimistic scenario.

As we can see from Fig. 23, the airport needs additional runway that can provide ±500 flights starting from 2013 to cover demand

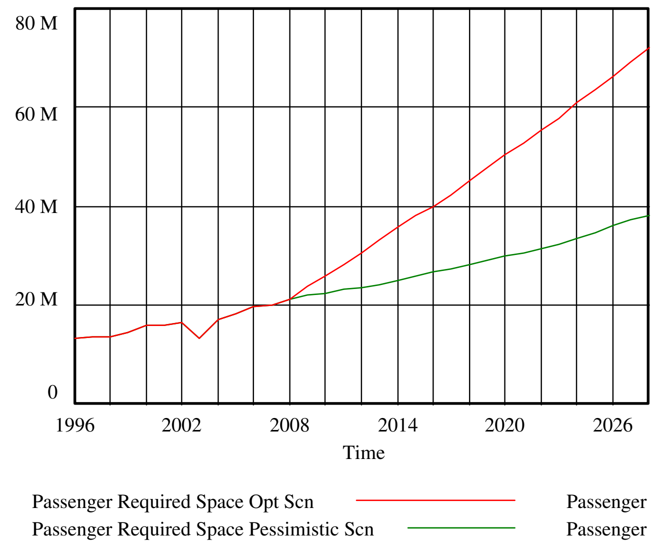

Fig. 25. Passenger required space optimistic and pessimistic scenario.

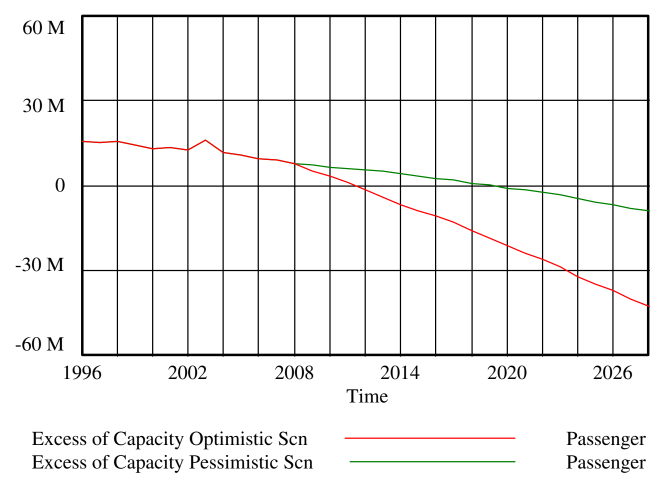

Fig. 26. Excess of capacity optimistic and pessimistic scenario.

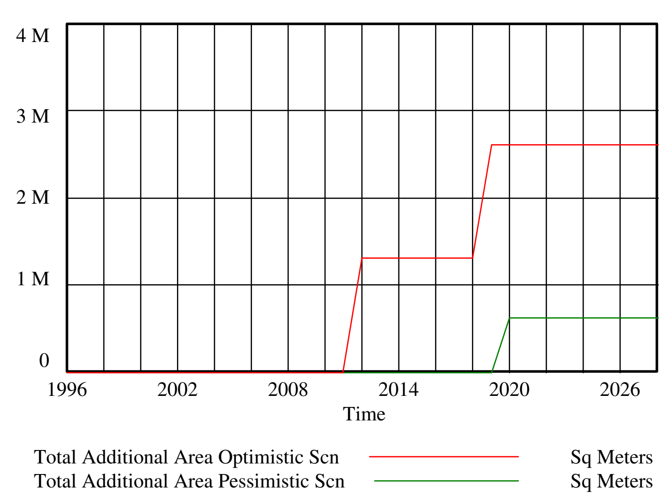

Fig. 27. Total additional area optimistic and pessimistic scenario.

Table 5
Scenario results summary.

Scenario	Average demand growth (%)	Runway expansion		Passenger terminal expansion	
		Year	Volume (F)	Year	Volume (sq. m)
Optimistic Average GDP growth = 6% Average inflation rate = 1% Average % change in travel time = 30%	6.6	2013	±500	2012 2019	1.3 million sq. m → 17 million pax 1.3 million sq. m → 17 million pax
Pessimistic Average GDP growth = 2.8% Average inflation rate = 2% Average % change in travel time = 40%	3.12	2024	±250	2020	614,258 sq. m → 9 million pax

until 2028. Runway utilization will be greater than 1 starting from 2013 in optimistic condition. While Fig. 24 shows the additional runway, new runway capacity and number of flights per day in pessimistic scenario. Runway utilization will be greater than 1, starting from 2024, therefore it is better to expand/ build a new runway capacity that can accommodate ±250 flights to cover demand until 2028.

The other consideration, besides, runway capacity, is terminal building related with baggage claim, flow space, check in, holding and generic area. Fig. 25 represents the passenger required space in optimistic and pessimistic condition. The passenger required space is made to check the dynamic flow of the passengers in terminal area. As we can see from Fig. 25, passenger required space in optimistic condition will be greater than in pessimistic condition in line with increase in air travel demand for optimistic condition.

Fig. 26 shows the excess of capacity in optimistic and pessimistic condition. The lack of capacity of passenger terminal area in optimistic condition would be happened starting from 2012 and from 2020 for pessimistic condition. The lack of capacity would be around 1.4 million passengers in 2012 and will achieve 42.9 million passengers in 2028 for optimistic condition. While in pessimistic condition, the lack of capacity would be around 0.9 million passengers in 2020 and will achieve 9 million passengers in 2028. It would be better that the airport authority expand the terminal area starting from the year 2012 in optimistic condition and from the year 2020 in pessimistic condition.

Fig. 27 demonstrates the total additional area needed in optimistic and pessimistic condition. As we can see from Fig. 27, for optimistic condition model, by adding 17 million pax such as the dynamic capacity in Terminal II of TTIA, total requirement for the terminal area will be around 1.3 million square meters to cover demand until 2018.

Starting from 2019, again the airport authority needs to expand their terminal capacity to cover demand for the next future in optimistic condition. Because the demand for air travel in pessimistic condition are lower than in optimistic condition, they only need to expand the terminal area to cover 9 million of passengers in 2028, so the total area requirement in pessimistic condition will be around 614,258 square meters to cover the future demand. We summarized all these scenario results in Table 5.

8. Conclusion

This paper presents a method for developing model to forecast air passenger demand and some scenarios related with runway and passenger terminal capacity expansion to meet the future demand from system dynamics point of view. As demand for air travel is difficult to forecast, it is important to utilize system dynamics based on consideration that forecasts come from calibrated system dynamics models, that are likely to be better and more informative than other approaches to develop more robust sensitivities, in order to lead better decisions.

From the base model and scenario development, we summarized that airfare impact, level of service impact, GDP, population, number of flights per day and dwell time play an important roles in determining the air passenger volume, runway utilization and total additional area needed for passenger terminal capacity expansion. It is important to forecast air travel demand in order to support long-term planning to meet the future demand during the planning horizon. Specification of *Level of Service* standards has a significant impact in determining the terminal space, since every LOS standard has different area requirement. We assume that demand for air travel will grow as general economic trends were positive for the airline industry. Rapid growth in air travel demand will force the airport authority to expand the runway and the passenger terminal facilities, e.g. baggage claim, flow space, check in, holding and generic area.

The important aspect of system dynamics framework is that it focuses on information feedback control to organize the available information into computer simulation model. By using a feedback structure, the existing conditions of the system can lead to decisions that will change the surrounding conditions and will influence the next decisions. In creating system dynamics model, information is used as the basic building blocks of a model. The successfulness of model depends on a clear identification of important purpose and objective. The model should help us to organize information in a more understandable way, and should link the past into present condition and extent the present into alternative futures through several scenarios development.

This study could be considered as a pilot study to decide when the airport should expand the runway capacity, passenger terminal capacity and to determine the total area needed to meet the future demand. Furthermore, it is obvious that further research is required to analyze revenue and performance management if the airport expands the runway and passenger terminal facilities, e.g. aprons, gates and ground service facilities.

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