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A new direct demand model of long-term forecasting air passengers and air transport movements at German airports

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ABSTRACT

The German Aerospace Center has developed and applied a “classical” four-step model of forecasting passenger and flight volume at German airports for many years. However, it has become increasingly difficult to update and verify the model because of a lack of specific data. We have therefore developed a more versatile model based upon co-integration theory, which directly forecasts passenger and flight volume at German airports. The paper describes the model approaches and discusses the advantages and disadvantages of both the classical and new model approaches. The model includes demand shocks and estimated GDP-elasticity is 1.31. The model has been employed to estimate the effects of Brexit on traffic volume at German airports for the years 2016–2018.

1. Introduction

It is generally understood that forecasts are estimates which should be based as far as possible on causal relationships, with input data, hypotheses, and methods stated and described in a retrievable way for those who use them. In contrast to prophecies, forecasts yield “if-then” results, the validity of which is typically limited because of the scarcity of data, lack of methodological quality, and uncertainty about the occurrence of influencing factors and premises. In spite of the conditionality of the results, there is a general demand for pre-thinking future alternatives in order to realise the future, in line with Saint-Exupery, who stated that one should not want to foresee the future but make the future feasible.

Air transport politics, infrastructure planning, and research and development of transport technologies need estimates of future demand for transport services and their potential to change as a consequence of alternative developments in the air transport environment. As long as states pursue demand-oriented planning of the transport infrastructure by following established political objectives, especially that of free choice of the mode, having solid expectations of that demand is a prerequisite for realising such a transport policy. In addition, for long range planning of a transport system it is useful to know the future transport requirements for different socio-economic scenarios, on the one hand, and for transport strategic options, on the other.

The forecasting task does not make statements about the development and volume of transport demand in order for the participants of the planning process (i.e. the public affected by projects) to believe them or otherwise, but rather to elaborate on relationships, i.e. functions or chains of arguments, between demand and influencing factors, and to evaluate them and the significance of the results.

The fact that political decisions about investment projects are increasingly debated again in legal proceedings shows the public's growing interest in knowing about the arguments which have led to these project decisions. There is a growing tendency for the public to question the validity of forecasts and take a sceptical attitude towards forecasting and ‘forecast experts’.

There is no unique solution to the problem of how to bridge the discrepancy between the risk and uncertainty of forecasting and the necessity of making forecasts available for planning purposes (forecast dilemma). One possibility for reducing the burden of the task is to regard forecasting as a continuous effort and thus take into account the newest developments in data and methodology (Airports Commission, 2013). The German Aerospace Center (Deutsches Zentrum für Luft- und Raumfahrt e.V., DLR) developed a “classical” four-step model to forecast passenger demand and flight volume at German airports several decades ago. This is described briefly in the following paragraphs (for more details see Wilken et al., 1981). Although this model has been refined over time and cannot be regarded as obsolete in general, various circumstances have led to the need to develop a new model which is more versatile and responds better to contemporary forecast questions than the former one. The main factor has been the lack of the specific data needed for updating the demand generation models.

While a major strength of complex four-step models is versatility and analysis of travel behaviour in detail, the main objective of this paper was to develop a rather parsimonious model aimed at producing sound forecasts of a specific variable. The new model, which relies on

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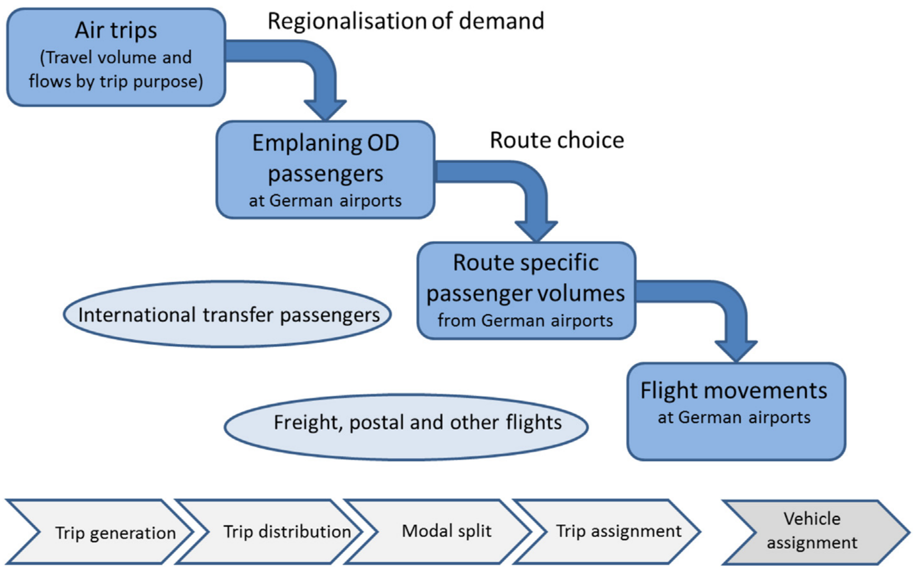

Fig. 1. Classical four-step model of DLR passenger demand forecast of Germany.

statistical data being readily available, will be described in detail after a broad description of the four-step model, followed by a brief case study on the effects of Brexit on German air traffic volume, and a discussion of the benefits and drawbacks of both models.

2. Literature review

As can be seen in Fig. 1, the DLR-Demand Model uses the phases of trip generation, trip distribution, modal split and trip assignment to follow the traditional four-step algorithm of models used for simulating and forecasting traffic, see Manheim (1979) or Ortuzar and Willumsen (2011). This methodological approach had originally been developed for modelling urban and regional traffic, however, it has also been extended to long distance travel (Wilken, 1977).

For trip generation, (linear) regression or gravity models are typically employed, however, gravity models may also cover the first two steps simultaneously, i.e. trip generation and trip distribution. Discrete choice models, e.g. the multinomial logit model, are typically used in steps two to three, i.e. trip distribution, model split and trip assignment. There is some kind of “methodological overlap” in the classical four-step procedure and the precise design depends on the application case. Furthermore, many models do not cover all four steps to study a special case or a particular problem.

The gravity models employed in air transport research can be traced back to Harvey (1951), who analysed airline traffic patterns in the US. A brief overview of contemporary gravity models for modelling origin-destination (O-D) demand in air transport can be found in Grosche et al. (2007) and in Tsui and Fung (2016). Grosche et al. (2007) developed gravity models based on variables describing general economic activity and geographical characteristics to forecast the air passenger volume of city pairs without any air service currently existing. Tsui and Fung (2016) analysed network developments between 2001 and 2012 at Hong Kong International Airport (HKIA) and, thus, focused their research work on a single airport. On the other hand, Matsumoto (2004) and Shen (2004) followed a network approach. Matsumoto (2004) developed a gravity model for passenger and cargo flows between a number of selected large cities such as Tokyo, London, Paris and New York. Shen (2004) estimated a gravity model to analyse inter-city airline passenger flows in a pre-defined 25-node US network. Examples of studies which focused on a very special research topic include Bhadra and Kee (2008), Endo (2007) and Hazledine (2009).

A brief overview of discrete choice models for steps two to three, in particular airport choice (step 2), can be found in Gelhausen (2007) and de Luca and Di Pace (2012). One of the first airport choice models based on discrete choice theory (Domencich and McFadden, 1975) was developed by Kanafani et al. (1975). Models that focused exclusively on airport choice comprise Skinner (1976), Harvey (1987), Ashford and Bencheman (1987), Ozoka and Ashford (1989), Innes and Doucet (1990), Windle and Dresner (1995), Basar and Bhat (2004), Hess and Polak (2006) and de Luca (2012). Examples of studies that focused on joint choices, such as airport and access mode choice, comprise Bondzio (1996), Gelhausen (2007) and Pels et al. (2003). Furuichi and Koppelman (1994) modelled the joint choice of airport and destination choice, whereas the studies of Hess et al. (2007), Pels et al. (2001, 2009) and Suzuki (2007) modelled departure airport and airline choice. Finally, Ndoh et al. (1990) and Yang et al. (2014) developed models for airport and route choice. A sophisticated four-step model for airport demand forecasting, mainly based on discrete choice theory, can be found in OECD (2016).

With regard to steps three and four and finally the vehicle assignment, Wilken et al. (2016) estimated a model to forecast segment specific passenger volumes in intercontinental travel based on a given O-D demand structure. Kölker et al. (2016) developed a statistical model approach to derive a typical fleet mix and growth of aircraft movements on segments which are based on a given passenger growth as input.

Table 1 arranges selected “landmark models” within the hierarchy of the four-step procedure and characterises them in terms of their number of variables and their model fit, i.e. goodness of fit. Some papers included various models, e.g. for different market segments. In these cases, the number of variables and goodness of fit measures lie within a certain range. Most models covered steps one or two of the four-step procedure and there are only a few models that covered route choice (Yang et al., 2014). Forecast efficacy was evaluated by R^2 for models that were estimated by ordinary least squares (OLS) and ρ^2 for models that were estimated by maximum likelihood (ML). However, goodness of fit was typically evaluated only in-sample by most authors and is thus only an imprecise predictor of out-of-sample forecast efficacy. The number of variables is generally rather high (especially if we consider that each model covers only one or two steps in the four-step procedure) and goodness of fit is rather mixed. Actual out-of-sample forecast accuracy is expected to be lower than the in-sample goodness of fit measures reported in Table 1. We therefore concluded that such complex models are rather unwieldy to use and explain, and offer only incremental improvements in forecasting compared to a more parsimonious approach. However, we have to keep in mind that model