



Evaluating predictability based on gate-in fuel prediction and cost-to-carry estimation



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ABSTRACT

Predictability in the aviation system affects costs to airlines and passengers. We propose a predictability metric based on a flight's gate-in fuel (GIF) which can be directly measured and monetized by aviation stakeholders. We estimate GIF for six major U.S. airlines. Since GIF data are not directly available, we develop an estimation methodology to obtain GIF from pushback weight and fuel burn, including a conversion from passenger to weight payload based on an econometric model. The methodology accounts for aircraft operating empty weight and payload. We find that GIF varies across airlines and time of year, and is highest during the summer period. We monetize GIF through a cost-to-carry analysis as extra fuel loading results in additional fuel burn. Our estimates reveal that, in 2012, airlines spent an additional \$59 million to \$667 million on carrying GIF, with a total across all six airlines of \$1.46 billion.

1. Introduction

Improving system performance has long been the focus of many air navigation service providers (ANSP) worldwide. Developing key performance indicators (KPIs) which measure the eleven globally endorsed key performance areas (KPAs) by the International Civil Aviation Organization (ICAO) enables ANSPs to identify areas for improvement and take action to improve performance as well as communicate to stakeholders how actions can affect the performance of the system (CANSO, 2015). KPIs also help ANSPs measure the benefit of implementing various initiatives and programs such as precise navigation and others under the Next Generation Air Transportation System (NextGen). Among the eleven globally endorsed key performance areas (KPAs)¹ (ICAO, 2009), the concept of predictability in air traffic management has recently received considerable attention from the Federal Aviation Administration (FAA, 2012) and European Organisation for the Safety of Air Navigation (EUROCONTROL, 2015). Predictability, defined by International Civil Aviation Organization (ICAO), is the “ability of airspace users and ANSPs to provide consistent and dependable levels of performance” (ICAO, 2009). The FAA believes predictability is the way to assess and monitor the operational health of the U.S. aviation system (Hao and Hansen, 2014; Woodburn and Ryerson, 2014); leading them to explore new definitions of predictability as a

possible KPI or performance metric. A better understanding of how to measure predictability and how to assess the potential benefit of enhanced predictability are of great interest to various stakeholders as well as the academic community.

When the air traffic management system is not predictable, airlines and passengers are affected. A lack of predictability affects airlines both in the planning stages and the actual operations of flights. Airlines produce a flight plan, which charts the route of flight and estimates the amount of fuel that will be needed for the trip, roughly 2 hours before a flight; this flight plan, through the choice of route and the quantity of fuel loaded for contingencies (fuel loaded above what is required) reflects the airline's view of predictability. Airlines load extra fuel on flights in order to mitigate risks such as unexpected airborne delays or reroutes. Previous studies in this area confirm that the more uncertainty that airlines face, the more extra fuel they load (Ryerson et al., 2014, 2015); moreover, this additional fuel loading comes at a significant cost. Based on the estimation of one major U.S. airline data, the annual fuel burn cost to carry extra fuel is in the order of \$220 million (Ryerson et al., 2015). Besides the fuel loading aspect of airlines flight planning, predictability is also found to have significant direct impact on airline scheduling (Sohoni et al., 2011; Hao and Hansen, 2014; Kang and Hansen, 2017a), operating cost (Ball et al., 2010; Zou and Hansen, 2012) and passengers' level of service (ACRP, 2014), and indirect

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¹ The eleven KPAs include predictability, safety, security, environmental impact, cost effectiveness, capacity, flight efficiency, flexibility, access and equity, participation and collaboration, interoperability.

impact on the economy. From an ANSP's point of view, an informative performance metric should not only be able to accurately reflect the system performance, but also provide policy makers with a clear benefit link such that the benefit of adopting/improving this metric can be easily justified.

Towards defining and estimating predictability, we propose a novel metric that is based on the predictability metric called flight gate-in fuel (GIF), the amount of fuel left in the tank when a flight pulls into the destination gate (to be discussed in details in Section 2.2). We combine our previous work on monetizing the cost to carry excess fuel with recent U.S. legislation that mandates all airlines provide flight level fuel data to the FAA and make this publicly available.

The reminder of this paper is organized as follows: Section 2 establishes the link between predictability and fuel loading. Section 3 and 4 describes the data source and methodology used in developing GIF prediction model. Section 5 presents an application of the GIF prediction model to other airlines. The monetization of performance metrics is demonstrated in Section 6. Conclusions and discussions with respect to the new predictability metric are discussed in Section 7.

2. Overview of predictability literature

2.1. Defining predictability

Previous studies have considered predictability in the aviation system but stopped short of directly developing, estimating, and monetizing a metric. Table 1 summarizes various metrics used in existing studies associated with predictability. Generally speaking, system predictability can be categorized into three groups: facility-oriented (e.g. airport), human-related, and flight-oriented. Facility-oriented predictability metrics can track performance changes of airfield facilities. One example is an airport-specific capacity profile, also known as declared called rates. Hourly or quarter-hourly fluctuation of capacity (flights that can be handled at an airport over a unit of time) indicates the predictability of an airport in terms of handling flights. Human-related predictability usually refers to the consistency of flight controllers' operating decisions. However, there is little research in developing human-related predictability metrics. The main research body is currently centering on flight-oriented predictability which is also the focus of this paper.

Flight predictability can also be viewed in strategic and tactical dimensions (CANSO, 2015). Strategic predictability metrics reflect aspects of performance that flight operators can know months in advance

when they plan flight schedules. For instance, scheduled block time adjustment (Kang and Hansen, 2017a) reflects airlines' strategic responses to system predictability. Tactical predictability metrics, including actual block time variability, flight plan variability, on-time performance, focus on day-of-operations. More details could be found in Table 1.

However, most of the predictability metrics in Table 1 cannot be directly monetized, which motivates us to propose a novel metric that is monetizable. In the next section, we will discuss in detail the link between predictability and our proposed GIF metric and the GIF monetization framework.

2.2. Impact of predictability on fuel consumption

The link between flight predictability and airline fuel loading and consumption is a matter of physics and economics: loading extra fuel results in additional fuel burn and burning fuel costs money. It is, however, not simple that fuel loaded (or uplifted) is an indicator of predictability.

Fuel is the second largest single operating cost item for many airlines, and the contribution of fuel consumption to global warming is also of increased concern (BTS, 2015; Kang and Hansen, 2017b). However, in order to better understand the context of this study, we need to look at the general fuel planning process. Airlines rely on flight dispatchers to perform the duty of flight planning including fuel planning and loading. US Federal Aviation Regulations (E-CFR, 2015) (FARs) require a domestic commercial flight to uplift enough fuel to complete the flight to the intended destination airport (mission fuel), as well as fly from the destination airport to the alternate airport (if required based on the weather forecast at the scheduled time of arrival) and hold in the air for 45 min at normal cruising speed (reserve fuel). These quantities are automatically calculated by the airline's flight planning system after the dispatcher chooses a route of flight among several possible routes. Even if it is not required by the FARs, on top of mission fuel and reserve fuel, airline dispatchers may uplift contingency fuel to be on the aircraft to hedge against various uncertainties (e.g. weather uncertainty, traffic congestion uncertainty, traffic control uncertainty etc.) to ensure flight safety. Contingency fuel uplift is based on a combination of corporate fuel policies and airline dispatchers' own judgment. It reflects the airline dispatcher's assessment of the "downside" risks that may lead to additional fuel burn beyond what is projected by the flight plan. Fuel uplifted for alternate airports that are not required can serve much the same purpose as contingency fuel if the

Table 1
Summary of predictability metrics.

Category	Items	Metrics	Source
Facility-oriented	Capacity variability	Difference between 85th and the 15th percentile of airport declared called rates	CANSO (2015); Performance Review Commission and FAA-ATO (2014)
Flight-oriented	Schedule reliability	Departure delay Arrival delay (on-time performance)	Performance Review Commission and FAA-ATO (2014) CANSO (2015); Performance Review Commission and FAA-ATO (2014); Millner et al. (2012)
	Block time variability	Difference between 85th and the 15th percentile of flight time for each flight phase Difference between scheduled and actual block time Flight time variability or effective flight time variability for each flight phase	CANSO (2015); Performance Review Commission and FAA-ATO (2014) Woodburn and Ryerson (2014) CANSO (2015), ICAO (2013), Hao and Hansen (2014), Liu et al. (2014), Zou and Hansen (2012), ACRP (2014)
Flight plan variability	Flight plan variability	Trajectory prediction accuracy	Tobaruela et al. (2014)
		Different percentiles of actual block time distribution	Hao and Hansen (2014)
		Change in scheduled block time	Kang and Hansen (2017a)
Pre-departure sequence variability	Pre-departure sequence variability	Travel time difference between last pre-departure flight plan and last amended flight plan	CANSO (2015)
		Trajectories difference between last pre-departure flight plan and last amended flight plan	CANSO (2015)
		Correlation between the queue entry and the aircraft take-off roll in pre-departure phase	Liu et al. (2014)

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