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Assessing the NextGen Avionics Business Case from the Airline Perspective

The Implications of Airline Responses to Changes in Operational Performance

Felipe Moreno-Hines, Deborah Kirkman
Center for Advanced Aviation System Development
The MITRE Corporation
McLean, USA
fmhines@mitre.org
dkirkman@mitre.org

***Abstract*— The Next Generation Air Transportation System (NextGen) is expected to improve flight efficiency in the National Airspace System (NAS). However, some of these benefits will only be realized at the pace with which operators equip their fleets with the required enabling avionics. To accurately assess the prospects of voluntary equipage, policymakers must understand the value of NextGen improvements as seen from the airlines' perspective. Traditional cost-benefit valuation methods are not well suited for providing this perspective. The MITRE Corporation (MITRE) conducted research to better understand how airlines perceive NextGen, and how they internalize changes in flight performance in their operations. This understanding was pursued through interviews with airline managers and with regression analysis of historical airline operational data. We observe the pervasiveness of block time management in response to operational changes for a subset of airlines, and the impact of this response on various aspects of airline operations. The results of this research will be used to incorporate airline response into operational modeling and benefit valuation methodologies.**

Keywords- NextGen; equipage incentives; cost-benefit analysis; airline behavior; airline response; block time

I. INTRODUCTION

The Next Generation Air Transportation System (NextGen) is an ongoing, transformative change in Air Traffic Management (ATM) and operations. NextGen capabilities integrate new and existing technologies to enhance the safety of aviation, reduce its environmental footprint, and increase its operational efficiency by way of shorter, more predictable flight trajectories. These improvements are expected to more efficiently accommodate the projected growth and increased operational complexity of aviation demand [1].

More so than with previous infrastructure improvements funded by the Federal Aviation Administration (FAA), NextGen is predicated on large scale private investments in enabling cockpit avionics systems. This means that the expected societal benefits of key NextGen capabilities will only be realized if aircraft operators equip in sufficiently large numbers. Current equipage levels vary by operator and capability, and benefit projections typically assume comprehensive adoption through new aircraft deliveries (forward fit) and aggressive retrofitting of existing fleets [2]. For their part, most commercial operators will only invest in avionics under a compelling business case that considers their own situation-specific risks, benefits, and costs relative to competing uses of capital; and in light of impacts on current and projected competitive positioning.

To understand the prospects of voluntary aircraft equipage (particularly for retrofits), it is imperative that aviation policymakers understand how airlines perceive the NextGen value proposition. While operators are gradually modernizing their fleets through new deliveries, relatively low retrofit rates for some avionics packages are indicative of negative business cases in terms of operators' investment criteria and considerations. Even for specific NextGen capabilities with high existing and projected levels of fleet equipage, such as Performance Based Navigation (PBN), the business case may not close for some operators at levels needed to yield system-wide benefits. Thus, an understanding of the airline perspective is critical to inform the design of effective implementation strategies, and to accelerate adoption rates beyond the levels implied in existing long-term fleet acquisition plans. This prerequisite has been increasingly recognized by industry and academia, prompting efforts to develop innovative methods for conducting business case analysis [3, 4, and 5].

II. BACKGROUND

The conventional methodologies used to estimate the impact of investments in ATM are not well suited for understanding their value from the airline perspective. The Business Case and Performance Metrics Working Group (BCPMWG) of RTCA's NextGen Advisory Committee (NAC) cited this misalignment after surveying business case analytic methods and closure criteria [4].[1] Specifically, cost-benefit

[1] RTCA, Inc. is a private, not-for-profit corporation that develops consensus-based recommendations regarding communications, navigation, surveillance, and air traffic management (CNS/ATM) system issues.

analyses tend to be conducted at an aggregate, system-wide level without regard to individual decision-making entities. In addition, the scope of operational impacts evaluated is typically limited to average aircraft delays, and implicitly assume that airlines are static—that is, they do not adapt their operations to internalize postulated changes in flight performance. In practice, ATM system performance affects an airline's daily operations, which in turn affects schedules through the operations analysis feedback cycle [6]. Inasmuch as airlines modify their schedules over time in response to such changes, analyses of the potential benefits of air traffic system improvements may reflect unrealistic demand scenarios; and lead to different impact assessments than those projected by airlines in accounting for their 'consumption' of benefits [7]. Collectively, these practices can undermine the ability to understand the airlines' avionics equipage business case.

In Fiscal Year (FY) 2011, The MITRE Corporation's (MITRE) Center for Advanced Aviation System Development (CAASD) sponsored internally-funded research on potential operational mechanisms for incentivizing voluntary NextGen avionics equipage [8]. That work reinforced the need for different conceptual and analytical frameworks than those traditionally used to estimate and value operational benefits in cost-benefit analysis of ATM improvements. Thus, in FY 2012 MITRE extended the research to enhance our understanding of how airlines perceive and value prospective NextGen improvements. Specifically, this work sought to explore how airlines consume improvements in ATM-related flight performance; and to develop analytic tools to quantify the impact of such improvements on airline operational and financial performance, given airline response.

We pursued these objectives through discussions with airline managers, and with analysis of historical airline performance data aimed at linking operational performance to airline behavior. [2] As envisioned, the findings from this research will be used for two purposes. First, they will inform enhancements to CAASD's system performance modeling processes to reflect fundamental, observable airline behaviors. Secondly, they will assist in understanding and communicating the impact of ATM operational improvements in terms that resonate with airline stakeholders, through consensus-building forums such as RTCA's NAC.

This paper presents the results of an analysis that explored relationships between historical changes in actual and scheduled airline block (gate-to-gate) times and other airline performance metrics, so as to isolate and (where possible) value the impact of various airline response strategies. As the goal of this research was to lay a foundation for an enhanced modeling approach, neither the problem statement nor overall analytical methodology was wholly novel. That said, the main contributions of this work in the context of traditional modeling approaches include the differentiation among airlines (acknowledging the existence of vastly different operating models, and hence different responses to changes in performance); and the explicit treatment of airline response in estimating the value of ATM improvements (extending impacts beyond traditional valuation of flight time savings and associated direct operating costs, which assume static airline behavior).

[2] MITRE is currently conducting similar research relating to general aviation.

III. Approach

A. Airline Interviews

To gain insight into airline perspectives on NextGen improvements, the MITRE research team met with senior managers at several airline headquarters. These discussions included heads of scheduling, operations, finance, strategy, and other functional departments. Topics spanned investment analysis criteria and processes, performance measurement and reporting, operational responses to changes in performance, competitive positioning, and the role of corporate culture on strategic decisions, among others. The key findings from these meetings are discussed in [9].

A specific goal of these discussions was to appreciate the importance of the various factors required to close an airline's business case—particularly in the context of avionics equipage. The conceptual framework depicted in Fig. 1 was developed to generalize the motivating drivers behind airline investment decisions and assist in these discussions. [3] This framework postulates that individual airlines will be 'motivated' to invest if they have an understanding of the operational change in question; believe with some certainty that the changes will occur and can be exploited operationally; and value the operational and financial results of the investment. In this context, assumptions relating to airlines' dynamic response to changes in flight are depicted in the red chevron in Fig. 1.

At the same time, airline managers also emphasized the misalignment between aggregate-level, static, and delay-centric analyses used to communicate the impact of ATM improvements, and the airlines' investment analysis methodologies and considerations. Uncertainty aside, the operational benefits of NextGen were described as opportunities to 'do more with less'—that is, to increase the productivity of resources by applying operational efficiencies toward business objectives. The exact application (or consumption) of a flight performance improvement would depend on a multitude of situational factors, including current and forecasted demand environment, competition, network structure, and operational and resource constraints, among others.

[3] This framework was loosely based on the Expectancy Theory of Motivation, introduced in 1964 by Victor H. Vroom of the Yale School of Management to explain individuals' decision-making process [10]. Though the theory admittedly oversimplifies the internal dynamics of intra-organizational decision processes, its general principles can be applied to business decisions.

Figure 1. Airline Equipage Motivation Factors

All airlines interviewed identified the compression of scheduled block times from reduced flight times and variability as a major potential benefit of NextGen. Such schedule adjustments could increase passenger connectivity at hubs, with varying impacts depending on the relative importance of connecting itineraries to each airline's revenue structure. Airlines also validated the notion that reductions in scheduled block time could be used to enable additional flight segments with existing fleets; or, alternatively, to reduce the number of aircraft required to deliver a given schedule. However, such fleet utilization benefits were generally characterized as having less potential in terms of leveraging ATM operational improvements (perhaps merely a reflection of the aircraft utilization strategies of the airlines consulted, and the current low-growth environment).

As these benefits suggest, delay savings are but one relevant outcome when evaluating operational improvements. As it relates to the framework in Fig. 1, it suggests that *benefit estimation approaches that do not consider airline response may mischaracterize the value of such improvements from an airline perspective*. To the extent that this is true, the assumption of static airline schedules undermines policy-makers' ability to fully appreciate the incentivizing power of prospective performance changes.

This realization informed the design of a three-pronged effort to understand, model, and (where possible) value airlines' responses to changes in block time performance, given the emphasis that airlines placed on this behavior. The rest of this paper documents an analysis that relates historical scheduled block time changes to underlying block time performance at a system-wide level; and a set of airline-specific regressions that sought to correlate changes in scheduled block times with other operational and financial performance metrics.[4] A methodology to incorporate scheduled block response in National Airspace System (NAS) performance simulations was developed, but has not yet been implemented.

[4] While a market-specific analysis would align better with the airline decision-processes we were exploring, the airline data used in this research are only available at the system level.

B. Analysis of Block Time Trends in the NAS

NAS performance is one factor in airlines' production functions. Airlines interface with ATM through rules and procedures that impact how aircraft operate—including the time and predictability with which aircraft travel from 'gate-to-gate'. Airlines constantly internalize these aspects of flight performance through schedules that trade off operating costs with service-level business objectives in the pursuit of profits. As airlines detect changes in individual flight performance through monitoring and reporting processes, they can adjust schedules to maintain operational integrity or exploit new opportunities. Similarly, airlines can modify schedules to pursue different outcomes—such as to achieve higher on-time performance levels—even in the absence of changes in flight operational performance.

Nowhere is this behavior more evident than in the historical relationship between scheduled and achieved, or actual, block times—the elapsed time between gate pushback at the origin airport, to gate arrival at the destination airport. Fig. 2 illustrates the average actual (red) and scheduled (blue) block times per flight in the NAS between 1995 and 2012, for the subset of airlines that report Airline Service Quality Performance (ASQP) data on domestic operations to the United States (U.S.) Department of Transportation (DOT). These airlines currently account for over 85% of scheduled flights in the NAS, and serve over 340 airports. They are particularly representative of operational performance at larger airports.

The calculation of monthly average block times per flight in ASQP controls for changes in fleet mix and airport-pairs over time to account for differences in aircraft performance and market distance, respectively. This is achieved by calculating frequency-weighted averages between each pair of contiguous months in the series, based on the common set of departure-arrival-aircraft triplets in each month. This method leverages the fact that the overall structure of airline operations changes little from month to month, such that normalized changes between periods are highly representative of underlying trends. The monthly changes are then connected and applied to an initial period to produce synthetic series that remove the effects of airport-pairs and fleet mix changes, but which may not necessarily match directly-computed statistics for individual periods.

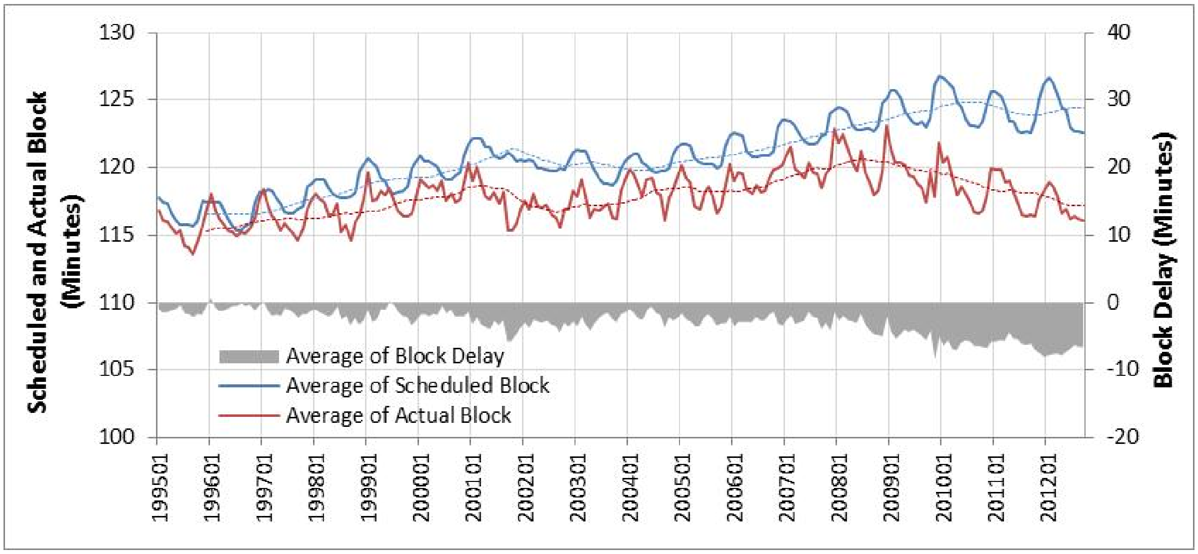

Figure 2. Monthly Historical Block Time Performance in the NAS (adjusted for changes in fleet mix and airport pairs)

In addition to a pronounced seasonal pattern—smoothed out by the dotted, 12-month moving averages—Fig. 2 clearly illustrates the airline practice of "padding" scheduled block times to accommodate actual performance (note the truncated y-axis to emphasize the point). Block delay (depicted in grey) is defined as the difference between actual and scheduled block times. It serves as an *indicator* of intended schedule padding (over expected performance), since actual performance in any period may deviate from the projections that informed the schedule-setting process.

Historically, airlines have set scheduled block times that preserve prevailing levels of negative block delay (i.e., flights take less time than scheduled, on average). We observe this during periods of block time increases, such as 1995 – 2000 and 2003 – 2008; and the interim period, during which block times dropped with demand (demand not shown). Beginning around 2008, scheduled padding increased to unprecedented levels as airlines did not reduce scheduled block times to match the downward trend in actual performance. This phenomenon reflects a comprehensive, concerted effort by airlines to improve on-time performance—in the words of one airline executive, airlines began "buying" on-time performance at the cost of higher schedule padding (though not necessarily longer scheduled block times, in absolute terms). This trend roughly coincides with the introduction of the Airline Passenger Bill of Rights Act of 2007, which established financial penalties for chronically late flights and reflected increased public focus on airline delays.

The effect of block time padding on average gate arrival delay—an indicator of on-time performance—is illustrated in Fig. 3. For any completed flight in ASQP, gate arrival delay equals the sum of gate pushback delay (measured against scheduled departure time) and block delay (defined previously as the difference between actual and scheduled block time). Thus, reductions in block delay—either from longer scheduled times, shorter actual times, or combinations of both—translate to reductions in gate arrival delay, all else equal. Fig. 3 highlights the reduction in average gate arrival delay from lower block delays starting around 2009, and continuing through 2012. In terms of this metric, the period from the end of 2011 to the start of 2012 produced the best continuous period in gate arrival performance since 1995.

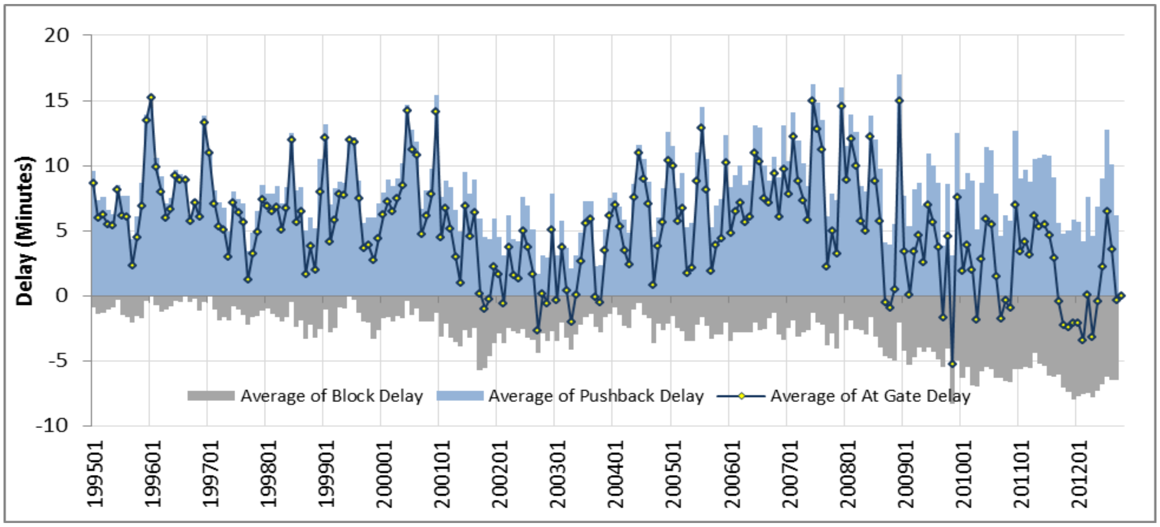

Figure 3. Monthly Historical Block Delay Performance in the NAS (adjusted for changes in fleet mix and airport pairs)

Fig. 4 quantifies the changes in average airline block performance over three historical periods. Note that from 2005 to 2010, a 4.25 minute decrease in average gate arrival delay was comprised primarily of a large reduction in block delay, which itself was driven almost exclusively by a 3.64 minute increase in average scheduled block times [Fig. 5].

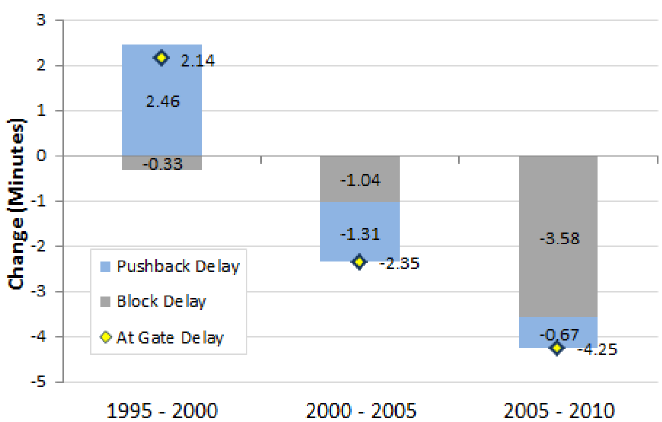

Figure 4. Change in Average Pushback, Block, and Gate Delays

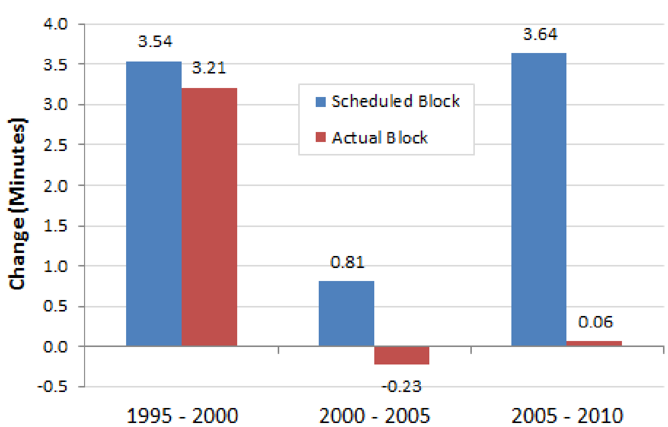

Figure 5. Change in Average Scheduled and Actual Block Times

As the historical data illustrate, block time scheduling is one way through which airlines internalize and actively manage flight performance toward business objectives. Airlines respond to changes such as those anticipated from NextGen with tactics that alter the structure of their operations and drive key performance outcomes. This dynamic behavior has implications for aviation policy analysis, including in the context of avionics equipage incentives. Specifically, it raises two related questions: 1) how might assumptions about airline response affect the modeled operational performance on which the business cases for various NextGen capabilities are predicated? and 2) what will be the impact of NextGen on airlines in light of their likely responses to operational improvements, and associated costs and benefits? The rest of this paper focuses on the latter.

C. *Analysis of Airline Block Time Response*

We investigated individual airline's responses to actual block time changes through regression analysis of operational and financial data.

1) Airline Value Chain Framework: We tested several hypothesized relationships in the context of a generic airline 'value chain' as informed by our discussions with airlines and prior research (Fig.6). This framework outlines various mechanisms by which changes in flight performance, once observed by an airline, are presumed to be exploited through explicit changes to its schedule. While not exhaustive, the possible mechanisms place airline performance (and corresponding impact metrics) in the proper context of a complex, dynamic aviation system. The highlighted paths correspond to the postulated causal relationships that we investigated through regression analysis, starting with the change in actual flight performance (darkly shaded box). From here, we hypothesize an observable response in average scheduled block time, which we recognize as one among various possible changes to the schedule structure which are not explicitly depicted.

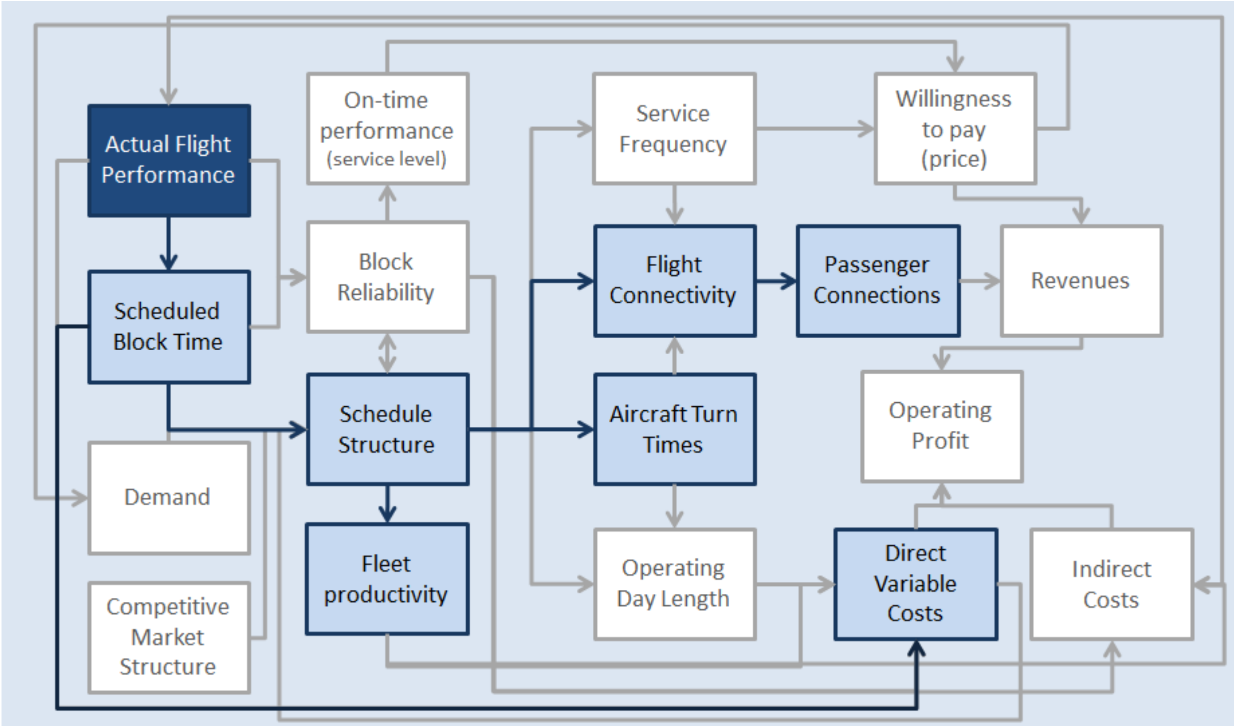

Figure 6. Generalized Airline Value Chain and Hypothesized Relationships for Regression Analysis (Highlighted)

We postulate that changes in scheduled block time inversely impact fleet productivity, flight and passenger (or network) connectivity, and aircraft turn times; and directly impact variable operating costs through higher pilot salary expenses, as explained in more detail under "Results". While the other hypothesized relationships illustrated in grey in Fig. 6 are not addressed explicitly in this paper, they reflect a qualitative understanding of secondary impacts which may serve as candidates for further analysis.

The goal of the regression analyses was to quantify observable, airline-specific, and statistically significant linear relationships that are consistent with this conceptual model (recognizing that in practice, these relationships may not be linear). In this way, the framework forced a degree of discipline on the statistical analysis, since the operational complexity, number of variables, aggregation of data, and inherent randomness could easily lead to the misinterpretation of non-intuitive, coincidental relationships as significant.

2) Data: The analysis dataset was fused from multiple sources collected and reported by the U.S. DOT. These consisted of the aforementioned ASQP, and Form-41 Airline Financial reports, which also include a vast array of airline operating metrics.[5] The latter was restricted to U.S. domestic operations so as to match the scope of the ASQP data. We analyzed quarterly, network-wide data for eight ASQP airlines for the period 1998 (Q1) through 2011(Q3), for a possible total of 55 periods per airline.[6] These airlines consisted of American Airlines, American Eagle, Delta Airlines, JetBlue Airways, Northwest Airlines, Southwest Airlines, United Airlines, and US Airways.[7] The resulting dataset contained over 60 continuous and categorical variables for each airline-period combination represented, most of which were ultimately excluded from analysis due to weak, unexplained, or otherwise unobserved explanatory relevance. The variables included in the final regressions are defined below.

- *Average actual block time*: Elapsed time between aircraft gate departure time and gate arrival time (minutes)
- *Average actual flight time*: Elapsed time between aircraft wheels-off at departure airport and wheels-on at arrival airport (minutes)
- *Average taxi-in time*: Elapsed time between aircraft wheels-on at arrival airport and gate arrival (minutes)
- *Average scheduled block time*: Elapsed time between aircraft scheduled gate departure time and scheduled gate arrival time (minutes)
- *Average scheduled aircraft turn time*: Elapsed time between scheduled aircraft gate arrival and next scheduled gate departure (minutes, intra-day flights)

[5] Form-41 quarterly reports were obtained from DataBase Products, based in Dallas, Texas.

[6] The set was limited to eight airlines due to volume and processing constraints of the methods employed.

[7] Note that US Airways and America West began reporting DOT data as US Airways in October, 2007; and Delta and Northwest began reporting jointly as Delta in January, 2010.

- *Average daily flights per aircraft*: Number of flights per day / number of aircraft in quarter
- *Average distance per flight*: Total aircraft miles / number of flights in quarter
- *Average number of seats per flight*: A measure of aircraft size
- *Number of daily flights*: Daily domestic flights by airline
- *Network concentration index*: A measure of the distribution of an airline's operations over the airports it serves. Calculated as the Gini coefficient, ranging from 0 (uniformly distributed operations) to a theoretical maximum of 1 (perfect inequality).
- *Schedule bank index*: A measure of the "peakiness" of an airline's arrival schedule over the course of a day at its four largest airports. Used to distinguish between rolling-hub and pronounced bank operations. Measured by the degree of serial correlation between arrival counts in rolling 30-minute time periods (as calculated through a Durbin Watson statistic, where higher values indicate more "peaky" schedules).[8]
- *Daily possible aircraft connections*: Total number of possible airport arrival-departure aircraft combinations in schedule day within assumed connection window (between 30 and 240 minutes from scheduled arrival, as assumed for all airports in an airline's network.)
- *Quarterly connecting passengers*: Total number of multiple-coupon passenger itineraries from 10% ticket sample
- *Average pilot salary per available seat mile (ASM, real)*: Total pilot salary / total ASMs (inflation adjusted)

3) Airline Response Regressions: We performed multivariate, Ordinary Least Squares (OLS) regressions using JMP statistical software to model the impact of unit changes between operational variables of interest (i.e., to test the effect of changes in performance variables on dependent outcomes depicted in Fig. 6). All regressions initially took the linear form:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n + e \qquad (1)$$

where Y refers to the dependent operational performance variable in question, α is a constant, $X_{1\ldots}X_k$ are values for the explanatory variables, $\beta_1 \ldots \beta_k$ are the estimated coefficients, and e is an error term.

Though we performed regressions on a common set of dependent variables (Y) for all airlines, the set of explanatory variables (X) was allowed to vary by airline in recognition of their potentially different operating models and performance. The goal of each regression was to isolate the effect of a single operational variable by accounting for as much variability as possible explained by other variables. The main objectives in constructing each regression were:

- Intuitive direction of effects (signs) and causality (as reflected in Fig. 6)
- High explanatory power, as measured by adjusted R^2
- Significance of explanatory variables at the 0.05 level
- Low degree of correlation between explanatory variables (needed to meaningfully isolate the effect of unit changes in the operational variable of interest. As a general rule, correlation coefficients greater than 0.30 were deemed excessive, and were addressed by excluding the appropriate explanatory variables from the regressions.)
- Randomly distributed residuals, with no evidence of serial correlation.

Not surprisingly due to the time-series data, initial models exhibited high degrees of positive serial correlation, as evidenced by low Durbin Watson statistics. To remove potential estimation errors introduced by the presence of autocorrelation, we took the first difference of all variables, thus re-expressing each observation as the change over the value in the preceding period. The resulting regressions took the form:

$$\Delta Y_t = \beta_1 \Delta X_{1t} + \beta_2 \Delta X_{2t\ +\ldots} \beta_n \Delta X_{n1+\ldots} e \qquad (2)$$

where ΔY_t denotes the change in Y in period t, and $\Delta X_{1t\ldots} \Delta X_{nt}$ are the changes in the corresponding variables in period t. This effectively addressed serial correlation; but also significantly diminished the significance and explanatory power of many of the relationships tested in Fig. 6 using (1).[9] Since we presume that airline responses to persistent changes in performance lag observed data, it is highly likely that models with more tailored lag specifications could perform better. While several models were explored to test the hypothesized relationships, only those that demonstrated statistically significant results are presented in the following section.

4) Regression Results and Interpretation: Table 1 presents the significant regression coefficients between explanatory and dependent operational variables of interest, by airline.

[8] The choice of four airports was driven by computational limitations, but was deemed to reasonably capture each airline's main hubs. The 'rolling' nature of the time periods reduces the sensitivity of the metric to the 30-minute assumption (since much of the information in one period is included in the next).

[9] A lag of one period effectively removed the trend in the time series, thus enabling the use of cross-sectional analysis which requires independent observations.

TABLE I. SUMMARY OF REGRESSION RESULTS BY AIRLINE

Δ in Dependent Variable	Δ in Explanatory Variable of Interest	American Airlines	American Eagle	Delta Airlines	JetBlue Airways	Northwest Airlines	Southwest Airlines	United Airlines	US Airways
Avg. Scheduled block time	Avg. Actual block time	**0.75** [3; 0.73]	**0.75** [1; 0.66]	**0.91** [2; 0.67]	**0.90** [1; 0.86]	**0.80** [2; 0.74]	**0.78** [2; 0.76]	**0.62** [2; 0.58]	**0.89** [1; 0.81]
Avg. Scheduled block time	Avg. Actual flight time	**0.96** [2; 0.81]	**0.99** [2; 0.74]	**1.12** [2; 0.78]	**0.96** [2; 0.90]	**1.26** [2; 0.81]	**0.70** [2; 0.76]	**0.70** [2; 0.66]	**1.05** [2; 0.90]
Avg. Daily flights per aircraft	Avg. Scheduled block time	**-0.02** [3; 0.33]		**-0.02** [2; 0.38]		**-0.05** [2; 0.40]		**-0.02** [2; 0.34]	
Avg. Scheduled aircraft turn time	Avg. Scheduled block time			**-0.15** [2; 0.17]					
Avg. Daily flights per aircraft	Avg. Scheduled aircraft turn time	**-0.02** [3; 0.33]	**-0.11** [2; 0.33]		**-0.03** [2; 0.20]	**-0.08** [2; 0.40]		**-0.03** [2; 0.34]	**-0.05** [2; 0.26]
Daily possible aircraft connections	Avg. Scheduled block time		**-491.31** [2; 0.86]	**-2016.21** [2; 0.76]			**-545.75** [2; 0.93]		
Quarterly connecting passengers	Daily possible aircraft connections	**4.8** [2; 0.61]	**5.6** [2; 0.46]	**18.7** [2; 0.69]	**32.9** [2; 0.46]	**10.3** [3; 0.73]	**58.0** [1; 0.33]	**7.4** [3; 0.83]	
Avg. Pilot salary per available seat mile (real)	Avg. Scheduled block time	**6.4E-5** [1; 0.13]				**8.2E-5** [2; 0.13]	**6.7E-5** [1; 0.11]		

The relationships are sorted from most direct (i.e. between flight performance variables and scheduled block time) to secondary, downstream effects in the airline value chain in Fig. 6. Note that some variables—most notably, the change in average scheduled block time—are used as both dependent and explanatory variables in different regressions. Each cell in Table 1 presents the regression coefficient for the variable of interest (in bold), atop the total number of explanatory variables in the model, and the model adjusted R^2 (in brackets). Empty cells indicate that a statistically significant linear relationship was not established at the 0.05 level. Thus, Table 1 summarizes the results of 64 attempted models (8 relationships explored for each of 8 airlines).

a) Scheduled block time: The first two rows in table 1 characterize the historical linear relationships between two metrics of actual block time performance and scheduled block time. On average, one minute increases in actual block time tend to be correlated with between 0.6 and 0.9 minute increases in scheduled block time. By comparison, one minute increases in actual flight time (that is, excluding taxi components) are associated with larger increases in scheduled block time, with the exception of Southwest airlines. Though not tested explicitly, this suggests relatively weaker relationships between taxi times and block schedules. The coefficients and high adjusted R^2 across airlines for the first two models listed highlight the pervasiveness of schedule padding as a performance and resource management tool—even with a model specification that does not account for a lag in the planning horizon. The relationships that follow quantify the impact of network-level changes in scheduled block times on other operational variables under the airlines' control.

b) Aircraft utilization: Increases in scheduled block time are historically achieved at the expense of daily aircraft utilization, as measured by average daily flights per aircraft. This tradeoff was observed with four airlines—notably, the four largest hub-and-spoke networks. While coefficients of -0.02 daily flights seem operationally insignificant, over networks averaging close to 400 aircraft operating 3.6 flights per day, this represents a loss of 8 flights per day and 2,920 flights a year.[10] Assuming 2010 representative values for flight distance (1,060 miles), seats per flight (162), and revenue per available seat miles (RASM, \$0.106), this translates to an annual revenue loss of over \$52 million per airline, all else equal.[11] For additional perspective, compare this result to a simple valuation of the underlying 1.3 minute increase in actual block time needed to generate the assumed, one minute increase in scheduled block time (1/0.75). Valuing fuel consumption at a nominal \$32 per actual block minute[12], the same fleet and network would impose an additional fuel expense of approximately \$22 million per airline. (Note that this figure should be compared to the lost operating profit on the \$52 million in revenues calculated above, to account for the non-incurred operating costs.) This simple calculation suggests that the observed impact of scheduled block time increases on aircraft utilization is small, though not insignificant, relative to

[10] The interpretation of the reduction in aircraft utilization as a loss assumes a causal relationship with changes in scheduled block time.

[11] This estimated revenue impact is presented for perspective, and was not tested empirically.

[12] 2010 value for the airlines in this analysis.

a directly-incurred increase in fuel expense from an underlying change in actual block time. This finding is not inconsistent with anecdotes from our discussions with airlines. If we assume scheduled block time increases to 'buy' on-time performance (with no changes in actual block performance), these fleet productivity losses would, in principle, be offset by gains related to service quality and schedule integrity improvements. Such effects were not modeled in this analysis.

c) Aircraft turn times: At least two airlines described the operational trade-off between scheduled block time and scheduled aircraft turn time. Intuitively, more time between gate departure and arrival should translate to less time at the gate, all else equal. However, only a weak inverse relationship was observed for Delta Airlines, through a regression that explained only 17% of the historical variance in average turn times.

Though we were not able to establish statistical relationships between scheduled block and aircraft turn times for most airlines, we did find (intuitive) inverse relationships between scheduled turn time and daily aircraft utilization. Here, the impact of an additional minute of scheduled turn time was similar in magnitude to the incremental effect of scheduled block time (for airlines with statistically significant coefficients for both measures). While not established in this analysis, to the degree that future efforts can identify or reasonably assert an inverse link between schedule block time changes and aircraft turn times, there is quantitative, empirical basis for estimating the impact on aircraft utilization (as discussed previously).

d) Network connectivity: The related trade-off between scheduled block time and aircraft hub connectivity, as referenced by one airline, proved more evident in the data—albeit indirectly. In principle, reduced scheduled block times in the form of earlier scheduled arrivals at hubs can enable more passenger connection itineraries given constant minimum and maximum connect times. We defined the dependent variable as the daily number of possible aircraft connections on an airline's network (i.e., excluding regional code-sharing partners) for a representative schedule day in each month.[13] Note that this metric is merely an indicator of potential connectivity, without regard to the commercial marketability of each arrival-departure aircraft pair. Thus measured, the coefficients for aircraft connections enabled by a one minute reduction in scheduled block time for American Eagle, Delta Airlines, and Southwest Airlines in Table 1 represent 0.94%, 1.34%, and 0.44% of their 2010 levels, respectively (2010 levels are not shown in Table 1). These models achieved adjusted R^2 of 0.75 or greater, with much of the variance in aircraft connections explained by the number of flights in each airline's network (the other explanatory variable in each model referenced in Table 1).

While we established statistical relationships between scheduled block time and possible aircraft connections for only three airlines, all but one airline exhibited positive relationships between aircraft connections and the number of actual, or observed quarterly passenger connections. Taking Delta Airlines as an example, the estimated 2,016 aircraft connections enabled from a network-wide one-minute *decrease* in average scheduled block time translates to an estimated 37,681 additional domestic passenger connections per quarter (2,016 x 18.7 passengers). This represents less than 1% of Delta's 5.6 million connecting passengers averaged per quarter in 2010. Though small in relative terms, these coefficients allow future studies modeling or directly measuring schedule changes to estimate the impacts on connecting passenger traffic.

e) Pilot expenses: conventional benefit valuation methods generally assume that increases in scheduled block times translate to higher pilot salary expenses, in recognition of the fact that some airlines pay pilots based on the greater of scheduled and actual block times. We observed a direct statistical relationship between scheduled block time and inflation-adjusted pilot salary per ASM for only three airlines (the dependent variable is normalized by unit of output). The significant coefficients, which ranged from 6.4×10^{-5} to 8.2×10^{-5}, need to be placed in context for interpretation. Relative to their inflation-adjusted 2010 reference values, one minute increases in scheduled block time represent 1.9%, 1.6%, and 1.3% of real pilot salary expense per ASM for American, Northwest, and Southwest Airlines, respectively. That said, our regressions only achieved adjusted R^2 of around 0.12 in each case, implying that little of the quarter-to-quarter variance in pilot unit expense is explained by variations in scheduled block time. This finding is consistent with anecdotal insight from former airline personnel describing impacts on pilot salaries as small, if any, due to crew duty time constraints. This would point to the number of employed pilots as a better measure of the impact of changes in scheduled block time; however, this statistic is only reported annually, and was therefore not used as a dependent variable.

IV. CONCLUSIONS

The regression analyses presented in this paper were part of a broader effort to understand and quantify airlines' responses to systemic and lasting changes in ATM performance, such as those anticipated from NextGen. They were informed by a conceptual understanding of airline perspectives and behavior based on prior research, and enriched through candid discussions with senior airline managers and executives. An understanding of how airlines generically and specifically 'consume' operational performance changes is critical for evaluating the prospects of voluntary investments in enabling avionics. This has important implications on the adequacy of traditional modeling and valuation approaches for assessing impacts on airlines, as most implicitly assume static airline behavior even in the face of significant operational performance changes.

MITRE is contemplating enhancements to its modeling capabilities that will facilitate inclusion of some of the most fundamental and pervasive forms of airline response, including block time scheduling. The relationships quantified in this paper underscore these behaviors and provide a basis for the next phase of research and development. They also highlight

[13] We used the third Thursday of each month, averaged by quarter.

real differences between airline business models, affirming that a given set of operational improvements may present vastly different value propositions to different stakeholders. To this end, the analysis also highlights real limitations in the ability to observe complex, dynamic operational trade-offs from quarterly, network-level data.

At the same time, aviation analysts and policy-makers should also appreciate the role of improved benefits-estimation methods (and greater operational benefits) as necessary but insufficient in the broader context of airline motivating factors. The significant policy, implementation, and operational risks perceived by airlines are equally important challenges; but they require different tools and solutions.

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AUTHOR BIOGRAPHY

Felipe Moreno-Hines holds a B.A. in Economics with a Certificate in Markets and Management Studies from Duke University (Durham, NC, 1999), and a Masters in Business Administration from the Robert H. Smith School of Business, University of Maryland (College Park, MD, 2007). He is currently a Principal Economics and Business Analyst and Group Leader at The MITRE Corporation's Center for Advanced Aviation System Development in McLean, VA.

Deborah Kirkman holds an MS in Electrical Engineering from Stanford University (1980) and a BS in Electrical Engineering from the University of Virginia (1979). She co-chairs the Business Case and Performance Metrics Working Group of the RTCA NextGen Advisory Committee and is presently serving as the Architect for NAS Performance and Metrics at the MITRE Corporation's Center for Advanced Aviation System Development in McLean, VA.

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