JOURNAL OF GUIDANCE, CONTROL, AND DYNAMICS
Vol. 32, No. 2, March–April 2009

Engineering Notes

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Short-Term National Airspace System Delay Prediction Using Weather Impacted Traffic Index

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DOI: 10.2514/1.38798

I. Introduction

THE National Airspace System (NAS) has been studied both for identifying the air traffic delay models and for improving the air traffic flow management efficiencies. Studies show that 70% of all delays in the NAS are related to weather and, of these, 60% are caused by convective weather [1]. For good weather days, factors other than weather, including air traffic demand–capacity imbalances, equipment outages, and runway conditions also have to be characterized. To guide flow control decisions and develop strategies to reduce delays, cancellations, and other costs during the day of operations in various weather conditions, it is useful to create a real-time delay prediction model and provide the delay prediction for several hours.

Efforts have been made in the past few years to identify the correlation between weather and delay on a daily basis both at the regional and the national level. The most promising concept is to use the weather impacted traffic index (WITI), which was first introduced by Callaham et al. [2]. Sridhar and Swei [3,4] and Chatterji and Sridhar [5] expanded the concept and built various daily NAS delay estimation models by linear regression. Furthermore, the NAS WITI has been combined with regional WITI and other nonlinear components. Klein [6] developed objective measures of the combined impact of traffic demand and weather on the air traffic system by further combining en route WITI, terminal WITI, and queuing delay to develop a new metric, the NAS weather index. Hansen and Xiong [7] developed models involving a relationship between observed airline delay and several causal factors, including traffic, airport weather, en route convective weather, and weather forecast accuracy. All of these models are static and provide a good correlation between weather and average air traffic delay on a daily basis. A dynamic model, which expands the level of detail to smaller time intervals, is lacking in the past research. Another variant of WITI can be developed using weather forecast products, which may increase the accuracy of the delay prediction. Klein et al. [8] studied a forecast WITI, named WITI-forecast accuracy, based on the collaborative convective forecast product (CCFP). Because the CCFP is updated every 2 h, it is not well suited for real-time air traffic delay prediction, which requires high update rates.

The Federal Aviation Administration (FAA) aviation system performance metrics (ASPM) reports actual delays at a sampling time interval of a quarter hour and up. The objective of this paper is to predict delays for the next 2 h using current and past information. The short-term delay prediction system uses WITI, predicted-WITI (P-WITI), and air traffic demand as inputs and provides estimates of NAS delay as outputs. The methodology used for WITI computation [3–5] is refined to generate both WITI and predicted-WITI based on the corridor integrated weather system (CIWS) [9] using the future air traffic management concepts evaluation tool (FACET) [10,11]. The predicted CIWS-WITI, which is updated every 5 min with 5-min forecast time steps, is more suitable for short-term delay prediction compared to the WITI based on CCFP, which is updated every 2 h with 2-h forecast time steps. Delay estimation models are limited to using convective weather information only due to the unavailability of suitable models for other weather conditions such as ceiling and visibility, high surface winds, and icing. As nonconvective weather models improve, they can be incorporated as additional variables in the estimation methods [12]. For good weather days, the delays are less related to the weather but more related to other factors including equipment outages, runway conditions, and air traffic demand–capacity imbalances. An adaptive scheme to switch between models based on weather conditions is implemented to provide both weather-related and non-weather-related delay predictions.

II. Factors Affecting Delay

This section describes and analyzes the traffic data, weather data, and delay observations available in the various databases that can be used to develop empirical models relating these variables.

A. Computation of WITI

WITI is an indicator of the number of aircraft affected by weather. The computation of WITI consists of 1) assigning a value of 1 to every grid cell $W_{i,j}$ of the weather grid W, where severe weather is indicated and zero elsewhere, 2) counting the number of aircraft in every grid cell $T_{i,j}$, and 3) computing the WITI at an instant of time k (typically at 1-min intervals) as follows:

$$\text{WITI}\,(k) = \sum_{j=1}^{m}\sum_{i=1}^{n} T_{i,j}(k)W_{i,j}(k) \tag{1}$$

where n is the number of rows and m is the number of columns in the weather grid.

Currently, most WITI computations are done using the weather data, referred to as NOWRAD, provided by the Next Generation Weather Radar System [3–5]. NOWRAD weather data are provided as six discrete levels, 1–6, indicating light precipitation, light to moderate rain, moderate to heavy rain, heavy rain, very heavy rain with the possibility of hail, and very heavy rain and hail with the possibility of large hail. Level zero indicates absence of rain. Severe weather is indicated by level 3 or higher.

Since NOWRAD data are provided in a grid, the traffic counts derived from the aircraft position data have to be mapped to the same

Received 28 May 2008; revision received 5 August 2008; accepted for publication 7 August 2008.

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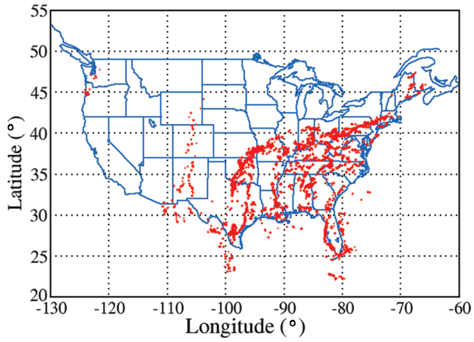
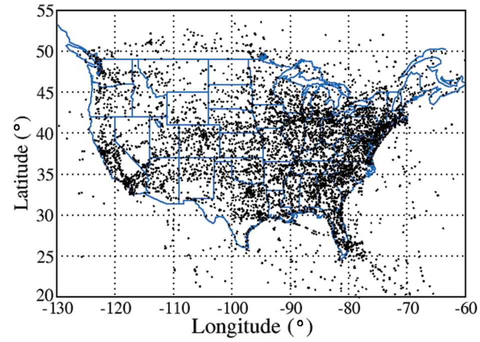


a) Weather



b) Expected traffic

Fig. 1 Regions of severe weather and expected traffic at 3:00 p.m. EST on 28 June 2007.

grid. This mapping is straightforward because aircraft position data are provided in terms of latitudes, longitudes, and altitudes. More details about traffic count generation can be found in [5].

Figure 1a shows the locations where severe weather is indicated at 3:00 p.m. Eastern Standard Time (EST), on 28 June 2007. The weather grid consists of 1837 rows and 3661 columns, which are approximately 1 n mile wide. Figure 1b shows the corresponding locations of aircraft in the weather grid based on historical demand. Finally, element-by-element multiplication of the two grids in Fig. 1 and summation in step 3 [see Eq. (1)] results in WITI at 3:00 p.m. on 28 June 2007. Observe from Eq. (1) that the unit of WITI is the number of aircraft since $W_{i,j}$ takes on values of 1 or zero. Thus, WITI is a weather weighted traffic count.

The weather information used in this paper is provided by the corridor integrated weather system. CIWS, created by the Massachusetts Institute of Technology Lincoln Laboratory, provides 2-h convective forecasts, every 5 min during the first hour and every 15 min during the second hour, updated every 5 min. Different contour levels indicate the level of weather severity. Although the CIWS does not cover the entire NAS, the coverage includes a major portion of the high traffic density eastern United States. The computation of WITI used in Eq. (1) has been modified to accommodate the CIWS weather formats [13]. The CIWS-WITI generation method has been integrated into the FACET [10,11].

The predicted-WITI is computed similar to the WITI. Instead of using the current weather information, the weather forecast along with the reference traffic is used to generate the predicted-WITI. The hourly WITI and predicted-WITI are shown in Fig. 2. In this case, at given hour h, the predicted-WITI provides an additional WITI forecast at the next hour, $h+1$. Even if there is some discrepancy due to the inaccuracy of the weather forecast, the additional information still may benefit the delay prediction, as discussed in the next section.

B. Delay

The delay observations provided by the FAA ASPM are used in this paper. ASPM provides performance data for 75 domestic airports at two different sampling rates, hourly and quarter-hourly. Figure 3 shows the normalized NAS ASPM schedule arrival delay and the CIWS-WITI on 28 June 2007.

Next, the correlation between the ASPM scheduled arrival delay and CIWS-WITI is examined. Assume the hourly ASPM delay is $\{d(h)|h=1\cdots24\}$ and the CIWS-WITI is $\{w(h)|h=1\cdots24\}$ on 28 June 2007. There is a similarity between the shapes of the two curves in the figure. As a reference, the correlation coefficient between $d(h)$ and $w(h)$ is 0.93. This result suggests that the hourly WITI is highly correlated with the hourly ASPM delay and could be used to build a linear model for the delay prediction.

III. Prediction Model

Research done by Sridhar and Swei [3,4] and Chatterji and Sridhar [5] shows a strong linear correlation between air traffic delay and daily WITI. Unlike previous research, which is focused on the effect of weather on total delay during a day, this research correlates weather and delay on an hourly basis and uses the estimation model to predict delay for the next 2 h. The availability of certain types of weather data and actual past delay every 15 min is used in the development of the correlation. Several different estimation models are considered depending on the availability of past weather, forecast of future weather, past delay, and past and future air traffic demand. The weather and traffic data are translated into WITI and WITI forecast. Averaging procedures discussed in the previous section are used to smoothen the noise in the 15 min updates. Various linear autoregressive model structures with exogenous inputs (ARX) are used to perform the delay prediction [14–16]. At a given time t, all the

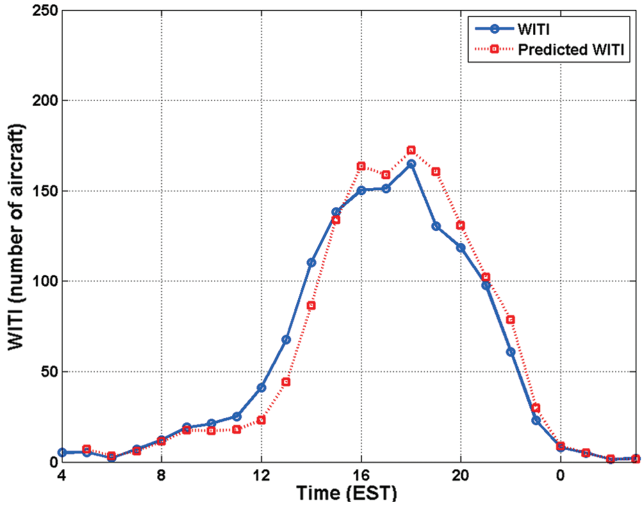


Fig. 2 CIWS-WITI and 1-h-ahead predicted-WITI on 28 June 2007.

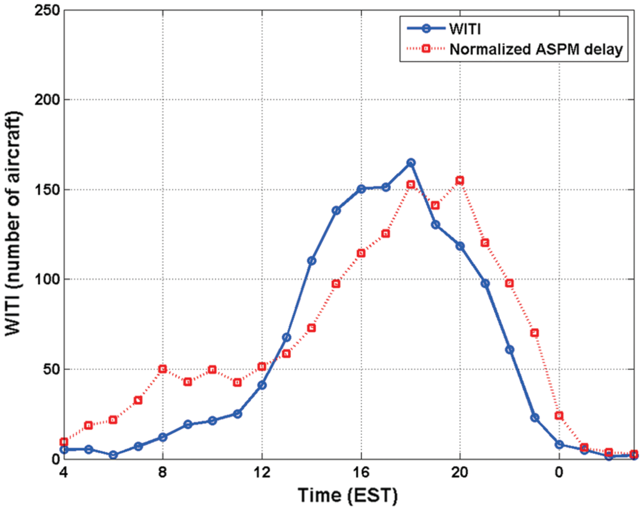


Fig. 3 The ASPM delay and CIWS-WITI on 28 June 2007.

available observations, which include the current and past WITI and delay, and the reference air traffic volume is used for delay prediction. Furthermore, the predicted CIWS-WITI up to 2 h ahead is used in the filtering ARX model to provide additional information. The rest of the section describes three specific estimation and prediction models.

A. Predicting ARX Model with WITI

For real-time delay, or live prediction, the future delay is predicted based on the current and past information about the delay. Assume $d(t)$ is the delay, and $w(t)$ is the WITI, at a given time t, the available observation set consists of $\{d(i)|i = 1\cdots t\}$ and $\{w(i)|i = 1\cdots t\}$. The nth order, p-steps-ahead predicting ARX model can be formulated as

$$\widehat{d}(t+p) = \sum_{k=0}^{n-1} \begin{bmatrix} a_k & b_k \end{bmatrix} \begin{bmatrix} d(t-k) \\ w(t-k) \end{bmatrix} + d_0 + e(t) \tag{2}$$

where $\widehat{d}(t+p)$ is the delay prediction at time $t+p$, d_0 represents a delay offset which is not weather related, and $e(t)$ is the prediction error. The model coefficients a_k and b_k can be found by solving the least-square solution to the equation

$$\begin{bmatrix} d(t) \\ \vdots \\ d(n+1) \end{bmatrix} = \begin{bmatrix} d(t-p) & \cdots & d(t-p-n+1) & w(t-p) & \cdots & w(t-p-n+1) & 1 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ d(n) & \cdots & d(1) & w(n) & \cdots & w(1) & 1 \end{bmatrix} \begin{bmatrix} a_0 \\ \vdots \\ a_{n-1} \\ b_0 \\ \vdots \\ b_{n-1} \\ d_0 \end{bmatrix} \tag{3}$$

B. Filtering ARX Model with WITI and Predicted-WITI

The predicted-WITI can be used in the prediction model. At a given time t, in addition to $d(k)$ and $w(k)$ up to time t, the predicted-WITI $\{w_p(k)|k = 1\cdots t+p\}$ is also available. The nth order, p-steps-ahead filtering ARX model is described by the equation

$$\widehat{d}(t+p) = \sum_{k=0}^{n-1} \begin{bmatrix} a_k & b_k \end{bmatrix} \begin{bmatrix} d(t-k) \\ w_p(t-k+p) \end{bmatrix} + d_0 + e(t) \tag{4}$$

where $\widehat{d}(t+p)$ is the delay prediction at time $t+p$, d_0 represents a delay offset which is not weather related, and $e(t)$ is the prediction error. Note that $w_p(t+k) = w(t+k)$, when $k <= 0$. The model coefficients a_k and b_k can be found by solving the least-square equation

$$\begin{bmatrix} d(t) \\ \vdots \\ d(n+p) \end{bmatrix} = \begin{bmatrix} d(t-p) & \cdots & d(t-p-n+1) & w(t) & \cdots & w(t-n) & 1 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ d(n) & \cdots & d(1) & w(n+p) & \cdots & w(p) & 1 \end{bmatrix} \begin{bmatrix} a_0 \\ \vdots \\ a_{n-1} \\ b_0 \\ \vdots \\ b_{n-1} \\ d_0 \end{bmatrix} \tag{5}$$

C. Filtering ARX Model with Air Traffic Volume

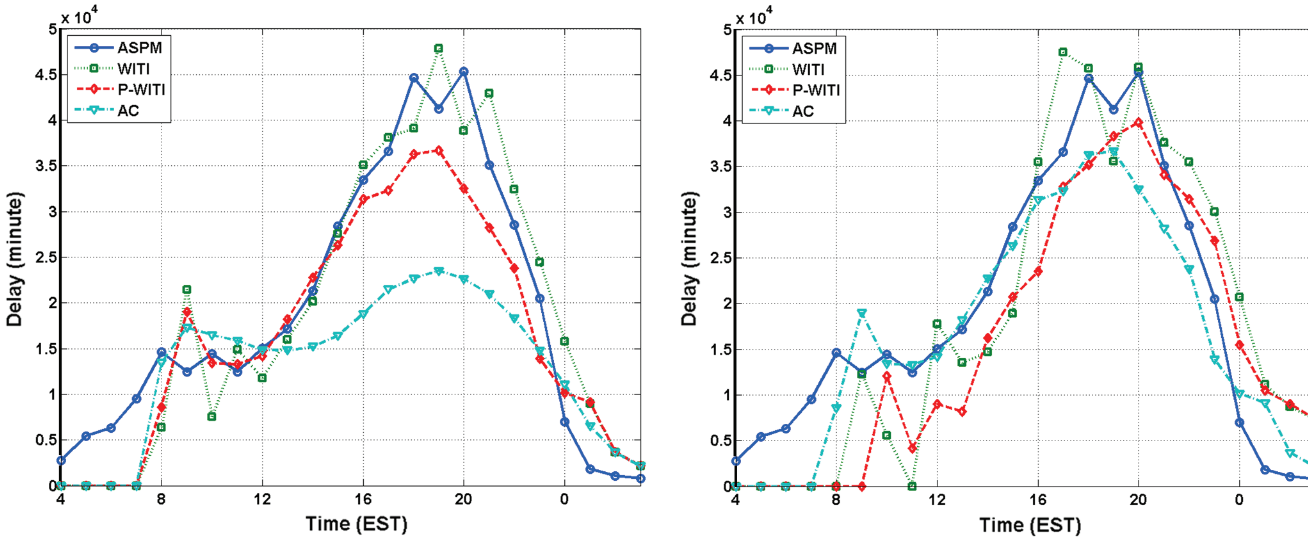
Not all the air traffic delays are weather related. WITI provides weather-related information and is best to predict the weather-related delay. The prediction model without the weather information is built to predict delay that is not correlated with the weather. Examining the air traffic delay during a day, it is evident that high delay usually appears during peak traffic times. In other words, air traffic volume is highly correlated with delay. The air traffic volume on the reference day is used for this model. The total number of aircraft at time t, $a_c(t)$, in the region covered by CIWS will be used to develop an air traffic volume prediction model. Note that $a_c(t)$ is a known quantity throughout the day. At a given time t, the observations of $\{d(i)|i = 1\cdots t\}$ and $\{a_c(i)|i = 1\cdots t+p\}$ are available. The nth order, p-steps-ahead filtering ARX model is formulated the same way as in Eq. (4), replacing $w_p(t)$ with $a_c(t)$. The model coefficients a_k and b_k can be found by solving the least-square Eq. (5), replacing $w(t)$ with $a_c(t)$. This model is referred to as the AC model in the rest of the paper.

IV. Results

Three prediction models, the predicting ARX model with WITI (WITI model), the filtering ARX model with predicted-WITI (P-WITI model), and the AC model, are described in the previous section. Next, these models are used with the data for 28 June 2007 at the sampling rate of 1 h. The delay prediction starts at the fifth data point, or 8:00 a.m. (EST) because at least four data points are needed to estimate the model coefficients. At a given hour h, the observations $\{w(i)|i = 1\cdots h\}$, $\{w_p(i)|i = 1\cdots h+2\}$, $\{a_c(i)|i = 1\cdots 24\}$, and $\{d(i)|i = 1\cdots h\}$ are available. For the 1-h delay prediction, the first order models are used and the results are shown in Fig. 4a. For the 2-h delay prediction, the second-order models are used and the results are shown in Fig. 4b.

The data for the months June, July, and August 2007 are used to compare the performance of delay prediction with the three models. Results show that for the 1-h prediction, the first-order WITI model performs well, and for the 2-h prediction, the second-order P-WITI model works well. It is reasonable to assume the predicted-WITI provides more information with further prediction. The AC model performs better than the others during most of the low delay days. Further, it was found that the WITI counts are low in these cases. When the WITI is low, the delay is more likely to be related to the air traffic volume than weather.

Using these trends, an adaptive scheme is developed that switches between the WITI/P-WITI model and the AC model based on the WITI/P-WITI value. At a given hour t, WITI values $w(t)$,



a) 1-hour prediction **b) 2-hour prediction**

Fig. 4 The NAS ASPM delay and prediction on 28 June 2007.

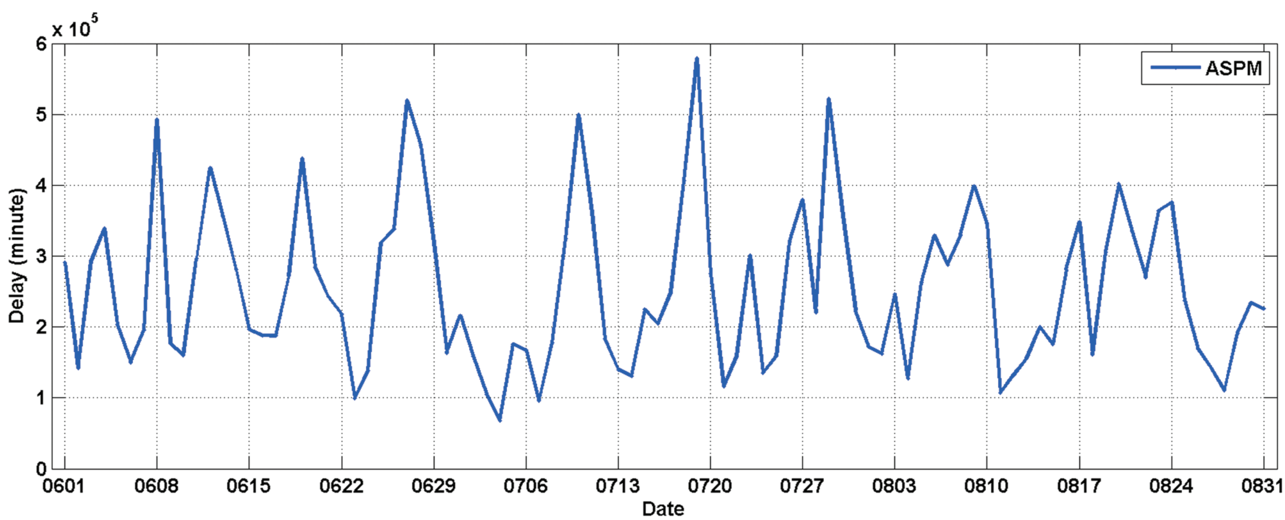


Fig. 5 ASPM delay during summer 2007.

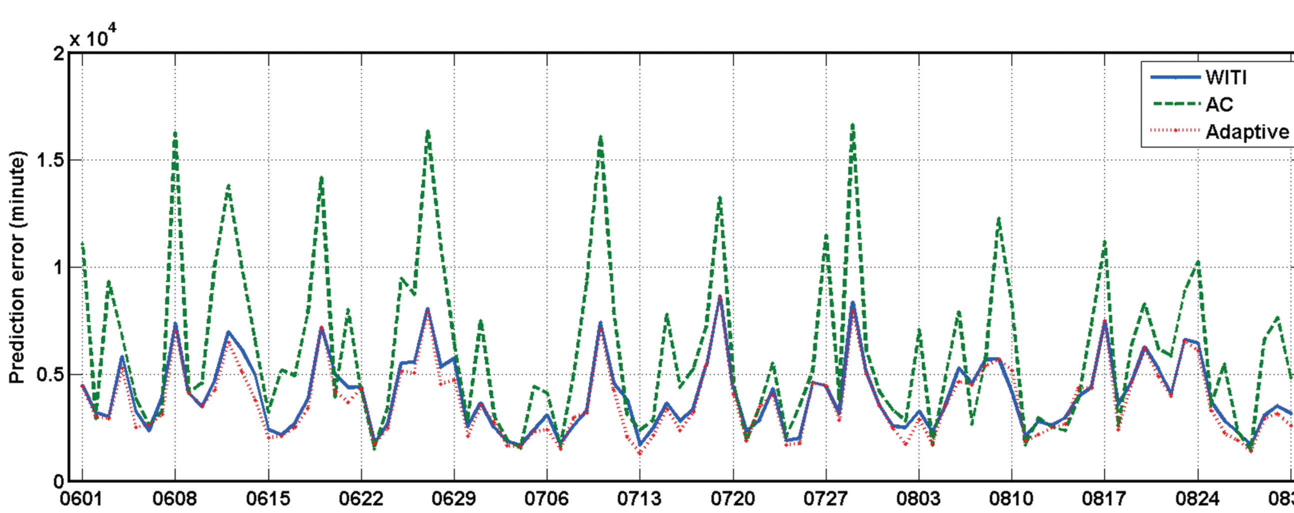


Fig. 6 One-hour delay prediction error for summer 2007.

$w(t+1), \ldots,$ and $w(t+p)$ are examined. If the WITI and predicted-WITI values are below a certain number δ, then the AC model is used for predicting the delay for the next hour. Otherwise, either WITI or the P-WITI model is used for predicting the delay for the next hour. A value of $\delta = 200$, which is based on historical WITI variations for this region, is used in the adaptive scheme. The prediction error of the new WITI and AC hybrid model (WITI-AC model) and P-WITI and AC hybrid model (P-WITI-AC) are significantly lower than the other models. The relative prediction error is defined as

$$e_{\mathrm{rms}} = \sqrt{\frac{\Sigma_{i=5}^{24}(d(i) - \widehat{d}(i))^2}{20}} \tag{6}$$

where $d(i)$ is the actual delay, and $\widehat{d}(i)$ is the predicted delay. Note that the prediction starts at the fifth data point, which is at 8:00 a.m. (EST). The root-mean squared errors, in minutes, for the prediction models for 28 June 2007 are 1) for 1-h prediction, WITI $= 5336$, P-WITI $= 5254$, AC $= 10,879$, and adaptive $= 4557$, and 2) for 2-h prediction, WITI $= 9295$, P-WITI $= 8583$, AC $= 12,388$, and adaptive $= 8384$.

The total daily delay during the period, June to August 2007, varies from a low of 70,000 min to a high of 580,000 min. For each day during the three-month period, Fig. 5 shows the total ASPM delay in the centers covered by the CIWS weather data. Figure 6 shows the results of the 1-h prediction using three different models, namely, the ARX model using WITI (WITI), the ARX model using air traffic volume (AC), and the adaptive model (adaptive) for summer 2007. In most cases, the WITI model performs better than the AC model, and the adaptive model has the least error. The cases where the adaptive model does not produce the least error, the magnitude of the errors produced by all the three models is small and close to each other (within 10%). The performance of the models for the 2-h delay prediction is similar to the 1-h prediction. In both cases, the adaptive models provide better prediction than the others. However, as expected, the magnitude of the errors for the 2-h prediction is higher than that for the 1-h prediction. The average error, in minutes, for the prediction models for summer 2007 are 1) for 1-h prediction, WITI $= 4024$, AC $= 6119$, and adaptive $= 3743$, and 2) for 2-h prediction, P-WITI $= 6205$, AC $= 7096$, and adaptive $= 5851$.

V. Conclusions

This paper presents a method to develop short-term delay prediction models for time intervals of up to 2 h. Various linear autoregressive model structures were implemented to perform the delay prediction with WITI, predicted-WITI, and reference traffic volume as exogenous inputs. The refined methodology for generating the WITI and predicted-WITI, together with the high-update-rate CIWS weather product is well suited for short-term delay prediction. An adaptive method was implemented to provide both weather-related and nonweather-related delay predictions depending on the weather and air traffic condition. The models are compared using traffic and weather data for the summer months of 2007. The results show that WITI provides the most useful information for the 1-h prediction, whereas the best 2-h predictions rely on both WITI and predicted-WITI. The reference air traffic volume provides nonweather-related information, which is useful on nonconvective weather days. This paper is the first to study short-term real-time air traffic delay prediction using WITI and predicted-WITI. The study should help traffic flow management in guiding flow control decisions and in identifying the strategies to reduce delays, cancellations, and costs during the day of operations in various weather conditions.

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