

# Management-Action-Embedded Sector-Demand Prediction Models

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**This paper describes a class of traffic flow management-action-embedded sector-demand prediction models. The models consist of the open-loop prediction, which is the prediction without management action, and the management-action model. The use of periodic autoregressive modeling approach enables the model to capture both the midterm (30 min to 2 h) trend based on the historical data and the short-term (less than 30 min) transient response based on recent observations. For severe weather days, both storm precipitation and echo tops were used to form a weather index to approximate the management actions due to reduced capacity. In addition to traditional trajectory-based sector-demand prediction methods, which predict only the open-loop behavior of the National Airspace System adequately for short durations of up to 20 min and are vulnerable to uncertainties, this class of models provides a reliable short- to midterm (both open- and closed-loop) sector-demand prediction that accounts for various traffic flow management actions. A combination of closed-loop and open-loop models provide decision-makers the full range of traffic behavior.**

## I. Introduction

TO ENSURE smooth air traffic flow and safety in the presence of disruptions caused by uncertainties, innovative modeling and design methods are needed in traffic flow management. One of the main functions of traffic flow management is to predict and resolve demand-capacity imbalances at the sector level. Thus, an accurate sector prediction model that can account for traffic flow uncertainty and weather impact is an essential component of traffic flow management.

Efforts have been made in the past to perform sector-demand predictions. Traditionally, models used in air traffic control and flow management are based on simulating the trajectories of individual aircraft. Deterministic forecasting of sector demand is routinely done within the enhanced traffic management system (ETMS), which relies on the computation of each aircraft's entry and exit times at each sector along the path of flight. Gilbo and Smith [1] proposed, acknowledging the uncertainty in the predictions, a regression model for improving aggregate traffic demand prediction in ETMS. A more recent traffic flow management simulation tool, the Future Automation Concepts Evaluation Tool (FACET) [2], was used to propagate the trajectories of the proposed flights forward in time and use them to count the number of aircraft in each sector for demand forecasting and establish confidence bounds on the forecasts [3]. These trajectory-based models predict the behavior of the National Airspace System adequately for short durations of up to 20 min and their accuracy is impacted by weather and trajectory prediction uncertainties [4–6]. In addition, these prediction models are open-loop, which means the traffic flow management (TFM) actions are not accounted in the models; therefore, the prediction does not reflect the actual sector demand after the TFM management actions.

The objective of this paper is to develop an empirical sector-demand prediction model that accounts for TFM actions, including

air traffic control and airline actions, and that accounts for both short-term (less than 30 min) and midterm (30 min to 2 h) predictions. The model consists of two parts: the open-loop prediction and the TFM action model. The open-loop predictions, similar to the traditional methods, are used to determine the possibility of demand-capacity imbalances at a future time, and help decide whether to activate the TFM action. The TFM action model simulates the demand reduction caused by the TFM actions. The closed-loop prediction represents the net result of the open-loop prediction and the TFM actions. The periodic autoregressive model and its variants [7,8] were used to build the model. The model considers both historical traffic flows to capture the midterm trend and flows in the near past to capture the transient response. In addition, for severe weather cases, the weather-impacted TFM action was modeled using weather forecast information. The proposed model provides both open- and closed-loop sector-demand predictions. Open-loop prediction is adequate for short durations. When looking at predictions for long durations, open-loop models produce large errors due to their inability to capture traffic initiatives and airline actions during the planning period. A combination of closed-loop and open-loop models provide decision-makers the full range of traffic behavior.

The remainder of the paper is organized as follows. Section II provides the sector-demand data and a description of the open- and closed-loop sector-demand prediction models. Next, in Sec. III, a weather factor is introduced and the TFM action model that considers weather is described. The results and performance of the models are demonstrated in Sec. IV. Finally, a summary and conclusions are presented in Sec. V.

## II. Data and Model

### A. Sector-Demand Data

The air traffic demand data were recorded from the Aircraft Situation Display to Industry (ASDI) data generated by the Federal Aviation Administration's ETMS. The ASDI data provide the locations of all aircraft at 1 min intervals. The sector demand, defined as the number of aircraft in each sector at a given time, can be computed using the ASDI data. Since traffic flow management decisions are made by comparing the peak number of aircraft in a sector during a 15 min interval with the sector's monitor alert parameter (MAP) value, the 15 min peak sector demand was used to build the models. A day is defined as a 24 h interval starting at 0400 hrs local time, since most of the aircraft departing on the previous day would have landed before 0400 hrs. The 15 min peak sector demand, denoted as  $d_k$ , where  $k = 1, \dots, 96$ .

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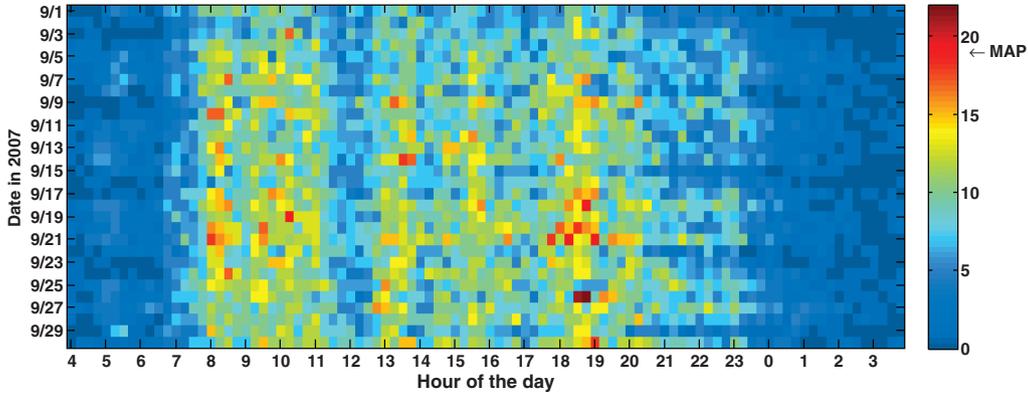


Fig. 1 Fifteen-minute peak sector demand at sector ZID93 in September 2007.

The average trend of sector demand on different days can be observed in Fig. 1, which shows the variation of 15 min peak sector demand in September 2007. In this figure, each horizontal strip represents one day of 15 min peak sector demand, and each vertical strip represents the peak sector demand at the same time of day during the entire month. As shown, the horizontal strips on 1 September, 8 September, 15 September, 22 September, and 29 September, which are Saturdays, have lower demands than the others. The blue vertical regions on the left and right show the offpeak traffic in the early morning and the late night. A vertical light blue region at around 1200 hrs divides the sector demand into a morning rush left of the region and an afternoon peak right of it. The sector-demand prediction model presented in the next section captures these variations in the demand.

**B. Demand Prediction Model**

Sector demand, defined as the number of aircraft in a sector, is the result of planned inflow and outflow and TFM actions. Figure 2a shows the block diagram of the current sector-demand system, where  $\mathbf{d}_k$  is the sector demand at the  $k$ th time step and  $\mathbf{d}_{k+p}$  is the sector demand at the  $(k + p)$ th time step. In the system, the traffic flow manager monitors the sector-demand prediction based on enhanced traffic management system (ETMS), denoted as  $\hat{\mathbf{d}}_{k+p}^{ETMS}$ ; if the prediction is high, TFM is activated to reduce the demand in the sector. The top half of the diagram, shown in the dashed box, is considered as an open loop; the bottom half, with the TFM action, is considered as a feedforward loop with negative gain. In the sector-demand prediction model, shown in Fig. 2b,  $f_{k,p}^{open}$  is the open-loop prediction model and  $\hat{\mathbf{d}}_{k+p}^{open}$  is the open-loop prediction, which is used to determine whether to activate the TFM action. When  $\hat{\mathbf{d}}_{k+p}^{open}$  is high, TFM is active.  $f_{k,p}^{TFM}$  is the model of the TFM action based on the open-loop prediction.  $\mathbf{d}_k^{open}$  is the actual open-loop sector demand, which is the sum of  $\hat{\mathbf{d}}_{k+p}^{open}$  and the open-loop prediction error,  $\mathbf{e}_k^{open}$ .  $\mathbf{e}_k^{TFM}$  is the error of the TFM action model. The model in Fig. 2b can be formulated as

$$\begin{aligned} \mathbf{d}_{k+p}^{open} &= f_{k,p}^{open}(\mathbf{d}_1 \dots \mathbf{d}_k) + \mathbf{e}_k^{open} \\ \mathbf{d}_{k+p} &= \mathbf{d}_{k+p}^{open} - (f_{k,p}^{TFM}(\mathbf{d}_{k+p}^{open}) + \mathbf{e}_k^{TFM}) \end{aligned} \quad (1)$$

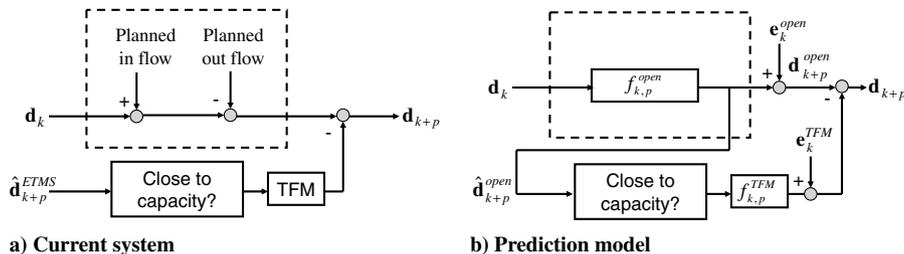


Fig. 2 Block diagram for sector-demand prediction and ATC action.

To implement the prediction model in Eq. (1),  $f_{k,p}^{open}$  and  $f_{k,p}^{TFM}$  need to be identified using historical data. In reality, it is not possible to identify the open-loop sector demand when TFM is in action because of the absence of data to verify the validity of the models during high demand. However, the open-loop model can be identified using data during low demand, since no TFM action is involved. With the assumption that the behavior of open-loop models are similar during low- and high-demand periods, the open-loop prediction model validated for low demand is also used during high demand.

**C. Periodic Autoregressive Sector-Demand Model**

Autoregressive models have been used for short-term hourly air traffic delay prediction [9,10]. This research extends the delay prediction approach to open-loop sector-demand prediction. The TFM action model is incorporated in the prediction model and can be identified once the open-loop model is identified.

A 24 h period, starting at 0400 hrs local time, is divided into 96 15 min intervals. Given the observed 15 min peak sector demands for  $n$  days, the sector-demand data matrix is defined as

$$\mathbf{D} = \begin{bmatrix} d_{1,1} & d_{2,1} & \dots & d_{96,1} \\ \vdots & \vdots & \ddots & \vdots \\ d_{1,n} & d_{2,n} & \dots & d_{96,n} \end{bmatrix} \quad (2)$$

where  $d_{i,j}$  represents the 15 min peak sector demand at time step  $i$  on day  $j$ . For September 2007,  $\mathbf{D}$  has a dimension of 30 by 96, and Fig. 1 shows the image of the matrix  $\mathbf{D}$ . Letting  $\mathbf{d}_k$  be the  $k$ th column of  $\mathbf{D}$ , the  $p$ -step-ahead open-loop sector-demand prediction model at the  $k$ th time step can be described in the form of a first-order periodic autoregressive model:

$$\mathbf{d}_{k+p}^{open} = \alpha_{k,p} \mathbf{d}_k + \beta_{k,p} + \mathbf{e}_k^{open} \quad (3)$$

where  $\alpha_{k,p}$  and  $\beta_{k,p}$  are the coefficients that map the sector demand at time  $k$  to the open-loop sector demand at time  $k + p$ . For low-demand time periods, TFM is inactive; therefore, open-loop demand is the same as actual demand. A sector-demand threshold  $d_{threshold}$ , usually a small number lower than the sector MAP value, is used to define whether the demand is high or low. The demand is classified as high when  $d_{threshold} > 0$  and low when  $d_{threshold} \leq 0$ . Consider the sector demands that satisfy  $d_{k+p,j} \leq d_{threshold}$ , the least-squares

solution of  $\alpha_{k,p}$  and  $\beta_{k,p}$  that minimizes  $(\mathbf{e}_k^{\text{open}})^T \mathbf{e}_k^{\text{open}}$  can then be solved explicitly [11]. For high-demand cases, TFM action is active. The action is modeled as a negative linear feedforward gain based on the open-loop prediction and the threshold, formulated as

$$\mathbf{d}_{k+p} = \hat{\alpha}_{k,p} \mathbf{d}_k + \hat{\beta}_{k,p} - \gamma_{k,p} (\hat{\alpha}_{k,p} \mathbf{d}_k + \hat{\beta}_{k,p} - d_{\text{threshold}}) + \mathbf{e}_k \quad (4)$$

where  $\hat{\alpha}_{k,p}$  and  $\hat{\beta}_{k,p}$  are the least-squares solution of Eq. (3) using low-demand data,  $\gamma_{k,p}$  is the feedforward gain, and  $\mathbf{e}_k$  is the error of the model. Note that  $\gamma_{k,p}$  is equal to zero for low-demand cases. With  $\hat{\alpha}_{k,p}$  and  $\hat{\beta}_{k,p}$  known, the least-squares solution of  $\gamma_{k,p}$  for high-demand cases, denoted as  $\hat{\gamma}_{k,p}$ , can be solved explicitly using high-demand data.

On a day  $m$  other than the  $n$  days in the data set, the  $p$ -step prediction of the sector demand at the  $k$ th time step,  $\hat{d}_{k+p,m}$ , based on the observed sector demand,  $d_{k,m}$ , can then be expressed as

$$\begin{aligned} \hat{d}_{k+p,m}^{\text{open}} &= \hat{\alpha}_{k,p} d_{k,m} + \hat{\beta}_{k,p} \\ \hat{d}_{k+p,m} &= \hat{d}_{k+p,m}^{\text{open}} - \hat{\gamma}_{k,p} (\hat{d}_{k+p,m}^{\text{open}} - d_{\text{threshold}}) \end{aligned} \quad (5)$$

In the model,  $\hat{\alpha}_{k,p}$  and  $\hat{\beta}_{k,p}$ , identified from the historical data with low demand, capture the periodic features with no TFM action during a day; the observed sector demand  $d_{k,m}$  provides the transient information to the open-loop prediction;  $\hat{\gamma}_{k,p}$ , identified from the historical data with high demand, models the TFM actions. The model in Eqs. (4) and (5) is referred to as the periodic autoregressive (PAR) sector-demand prediction model.

As an example, peak sector-demand data in August 2007 were used to construct the data matrix in Eq. (2). Equations (3) and (4) were used to identify the model parameters  $\hat{\alpha}_{k,p}$ ,  $\hat{\beta}_{k,p}$ , and  $\hat{\gamma}_{k,p}$ , where  $k = 1, \dots, 96$  and  $p = 1$  for one step, or 15-min-ahead prediction. The peak sector demands on 3 September 2007 were predicted using Eq. (5). The prediction results for sector ZID93 are shown in Fig. 3. The black dots represent the sector demand in a 1 min interval, the blue line represents the 15 min peak sector demand, the green line represents the 15-min-ahead sector-demand prediction, and the red line is the MAP value. The root-mean-squared (rms) error between the actual peak sector demand and the 15 min demand prediction for the day is 1.96. The rms error during the hours that most aircraft fly, 0700 to 2300 hrs EDT, is 2.23. The rms error when the demand is great than 50% of the MAP value is 2.63.

The model can be extended by using the cumulative sum of the past sector demands as an observation instead of using a single observation  $d_{k,m}$  in Eq. (5), since the sum includes more information than a single observation and has less noise compared with the single peak sector demand. Following the definition of the sector-demand matrix  $\mathbf{D}$  in Eq. (2), where  $\mathbf{d}_k$  is the  $k$ th column of  $\mathbf{D}$ , the cumulative  $p$ -step-ahead sector-demand model at time step  $k$  can be described in terms of the cumulative sum of  $q$  past sector demands as

$$\begin{aligned} \mathbf{d}_{k+p} &= \alpha_{k,p} \sum_{i=k-q+1}^k \mathbf{d}_i + \beta_{k,p} \\ &- \gamma_{k,p} \left( \alpha_{k,p} \sum_{i=k-q+1}^k \mathbf{d}_i + \beta_{k,p} - d_{\text{threshold}} \right) + \mathbf{e}_k \end{aligned} \quad (6)$$

where  $\alpha_{k,p}$  and  $\beta_{k,p}$  are the coefficients that map the cumulative sector demand at the  $k$ th time step to the sector demand at the  $(k+p)$ th time step, and  $\gamma_{k,p}$  is the TFM action gain. Once the least-squares solution of coefficients  $\alpha_{k,p}$ ,  $\beta_{k,p}$ , and  $\gamma_{k,p}$  are identified, the  $p$ -step prediction of the sector demand at the  $k$ th time step for a day  $m$ ,  $\hat{d}_{k+p,m}$ , based on the observed cumulative sector demand,

$$\sum_{i=k-q+1}^k d_{i,m}$$

can be expressed as

$$\begin{aligned} \hat{d}_{k+p,m}^{\text{open}} &= \hat{\alpha}_{k,p} \sum_{i=k-q+1}^k d_{i,m} + \hat{\beta}_{k,p} \\ \hat{d}_{k+p,m} &= \hat{d}_{k+p,m}^{\text{open}} - \hat{\gamma}_{k,p} (\hat{d}_{k+p,m}^{\text{open}} - d_{\text{threshold}}) \end{aligned} \quad (7)$$

### III. Weather Factor

Weather has a big influence on air traffic sector demand and the uncertainty in weather may cause error in the predictions [5,12]. If a severe storm blocks a sector or regions near it, the sector capacity may drop dramatically, causing the TFM in action to reduce the sector demand [13,14]. A weather factor that models the TFM action on severe weather days in the sector-demand prediction is derived in this section.

To model the weather impact on TFM action, an accurate weather forecast product with a high update rate is required. In addition, to capture the impact on all low, high, and superhigh sectors, the storm echo tops information is useful. The weather data used in this paper was provided by the Corridor Integrated Weather System (CIWS) [15], which provides both accurate precipitation and echo tops data and is updated every 5 min. In addition, CIWS provides precipitation and echo tops forecasts at 5 min intervals up to 2 h in the future.

The weather factor used to model the TFM action was chosen to be the sector weather index, defined as the percentage of area covered by the storm with precipitation vertically integrated liquid (VIL) level 3 and above. Only storms with the echo tops above the lower boundary of the sector are considered. The sector weather index at time  $k$  is formulated as

$$w_k = \frac{A_k^w}{A} \quad (8)$$

where  $A$  is the area of the sector and  $A_k^w$  is the area of the sector covered by storms with the echo tops at or above the lower bound of

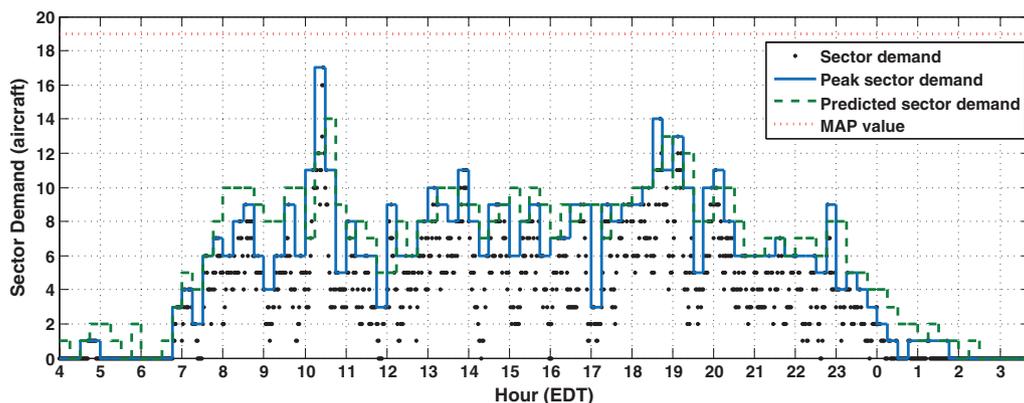


Fig. 3 Sector demand and peak sector demand at sector ZID93 on 3 September 2007.

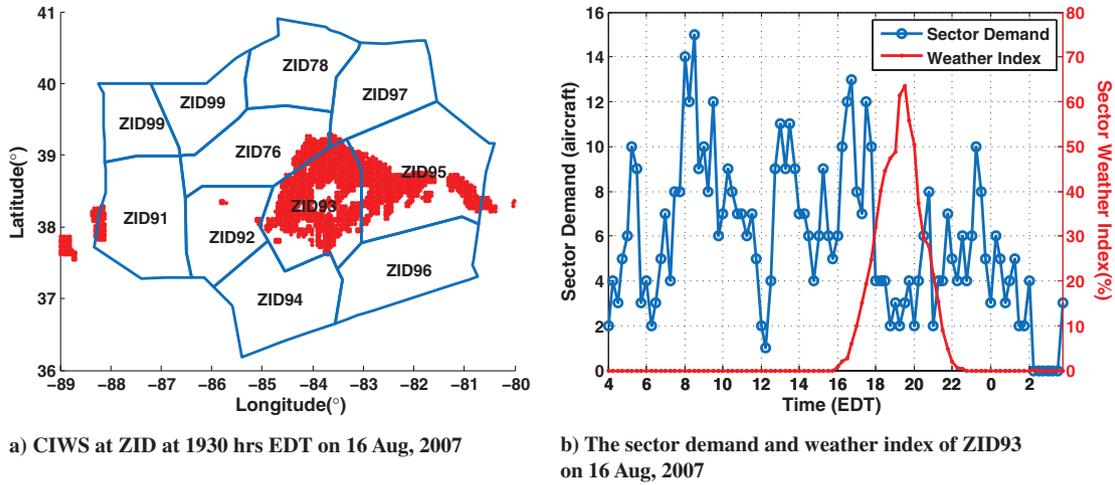


Fig. 4 Weather data, sector demand, and weather index on a severe weather day.

the sector. The sector weather index is a number between 0 and 1 and is often expressed in terms of a percent in the figures in this paper. Note that if time  $k$  is a future time, the weather forecast is used to determine  $A_k^w$ . It is possible to use other definitions of a sector weather index [13,14].

Figure 4a shows a snap shot of the CIWS data for the high-altitude sectors at Indianapolis center (ZID) on a severe weather day. The red spots indicate the storms with VIL level 3 and above, and the echo tops at 35,000 ft. As shown in this figure, most of the sector ZID93 is covered by the storm. The sector weather index for ZID93 on 16 August 2007 is shown in the red curve in Fig. 4b. Also shown is the actual sector demand on the same day in the blue curve. Note that the sector weather index is greater than 30% from 1800 to 2000 hrs Eastern Daylight Time (EDT), and the sector demand clearly drops during the same period.

Traffic reduction due to weather impact can be modeled in many different ways [16]. In this research, the open-loop prediction was first estimated, and then the prediction was adjusted by the TFM

action based on the sector weather index. Assume that the TFM action is active when the sector weather factor exceeds  $w_{low}$ , and TFM blocks out the entire sector when the weather factor reaches  $w_{high}$ . The sector-demand reduction rate is modeled as the power law distribution,  $1 - ((w_k - w_{low}) / (w_{high} - w_{low}))^\lambda$ , where  $\lambda$  is the power of the distribution. To reflect the thresholds, the sector weather index in Eq. (8) is redefined as

$$w_k = \begin{cases} w_{low} & \text{if } A_k^w / A \leq w_{low} \\ A_k^w / A & \text{if } w_{low} < A_k^w / A < w_{high} \\ w_{high} & \text{if } w_{high} \leq A_k^w / A \end{cases} \quad (9)$$

To model the TFM action on the sector-demand prediction model, the weather forecast is used to compute the predicted sector weather index. Assume at time  $k$ , the predicted sector weather index at time  $k + p$  is  $w_{k+p}$ , the PAR sector-demand prediction model in Eq. (7) can be rewritten as

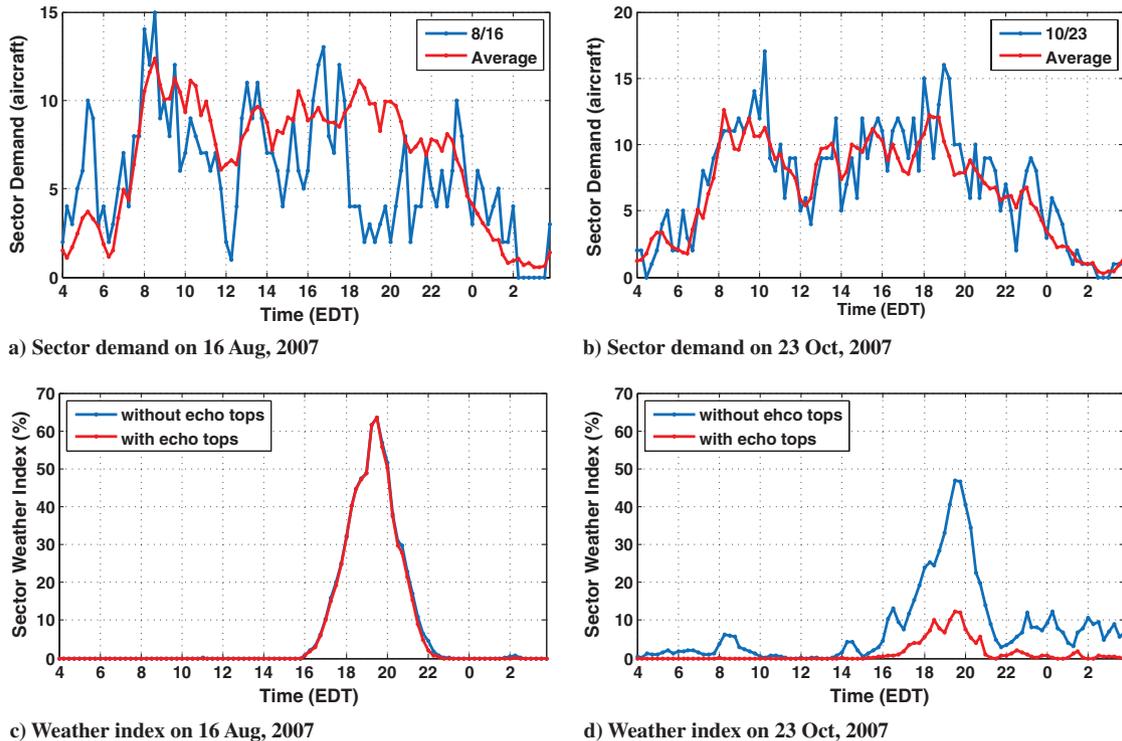


Fig. 5 Sector demand and weather indices with and without echo tops information on 16 August and 23 October 2007.

$$\hat{d}_{k+p,m}^{\text{open}} = \hat{\alpha}_{k,p} \sum_{i=k-q+1}^k d_{i,m} + \hat{\beta}_{k,p}$$

$$\hat{d}_{k+p,m} = \hat{d}_{k+p,m}^{\text{open}} - \left( \frac{w_{k+p} - w_{\text{low}}}{w_{\text{high}} - w_{\text{low}}} \right)^{\lambda} (\hat{d}_{k+p,m}^{\text{open}}) \quad (10)$$

Using the echo tops information provides a more representative weather index, especially for the high sectors. If there are storms with low echo tops located at some high sectors, the weather might have minimal impact on the sector demand. The sector demand and weather index for sector ZID93 on two different days is shown in Fig. 5. Both days have severe storms, but one has high echo tops, while the other has low echo tops. The sector demands on severe weather days were compared with the average sector demand on the rest of the days in the same month. In Fig. 5a, the sector demand on 16 August 2007 is lower than the average between 1800 and 2000 hrs EDT because of the high weather index during the period, as indicated in Fig. 5c. The blue line in Fig. 5c shows the weather index considering the area covered by storms without the echo tops information, and the red line is the weather index considering the echo tops at 35,000 ft and above. In this case, the two lines are close. This suggests that there are severe storms in the area and most of the echo tops are higher than the lower bound of sector ZID93. On the other hand, on 23 October 2007, there is no demand reduction compared to the average of the other days in October 2007 during 1800 and 2000 hrs EDT, shown in Fig. 5b, even though there are storms in the sector during the period, as shown in Fig. 5d. The red line in Fig. 5d is substantially lower than the blue line, which means even though there are storms in the sector, most the echo tops are lower than the low boundary of the sector and have minor impact on the sector demand. In the next section, the sector weather index refers to the index with the echo tops information.

#### IV. Results

The sector demands of 25 high and superhigh sectors in ZID were investigated in this research. The sector demands for the month of August 2007 were used to build the PAR sector-demand prediction model, described in Eqs. (2) and (4). The time step used in the models is 15 min. Once the parameters were identified, Eq. (7) was used to perform the sector-demand prediction for the month of September 2007. Starting from the 15 min prediction model, up to 2 h prediction model were built and evaluated. The results of four superhigh sectors ZID91, ZID92, ZID93, and ZID94, and four high

**Table 1 Sector-demand prediction errors of the PAR model in September 2007 (the unit is the number of aircraft)**

Sector Name	MAP	Average prediction rms error from 0700 to 2300 hrs EDT					
		15 min	30 min	45 min	60 min	90 min	120 min
ZID81	17	2.20	2.30	2.31	2.31	2.29	2.31
ZID82	16	1.77	1.82	1.84	1.77	1.80	1.82
ZID83	16	1.81	1.83	1.84	1.83	1.84	1.85
ZID84	16	2.09	2.13	2.10	2.12	2.10	2.07
ZID91	19	2.34	2.42	2.43	2.39	2.43	2.46
ZID92	17	1.92	1.98	1.95	1.96	1.98	1.99
ZID93	19	2.44	2.55	2.54	2.52	2.59	2.56
ZID94	17	2.19	2.26	2.27	2.23	2.24	2.23

sectors ZID81, ZID82, ZID83, and ZID84 in the southwest region of ZID were presented.

The prediction results for the eight sectors are summarized in Table 1. Only the errors from 0700 to 2300 hrs were computed. The results include open-loop predictions on low-demand days, when TFM is inactive, and closed-loop predictions when TFM is activated. Note that the errors of the PAR model are not sensitive to the look ahead time. In general, the errors are larger with longer look ahead time, but only slightly. The errors of the 120 min prediction is 2.97% larger than the 15 min prediction on average. For all the high and superhigh sector in ZID, the results are similar. The errors are between 1.77 and 2.44 for the 15 min prediction, and between 1.82 and 2.56 for the 120 min prediction. Even though the differences between the errors are small, the same trends hold for the majority of sectors tested.

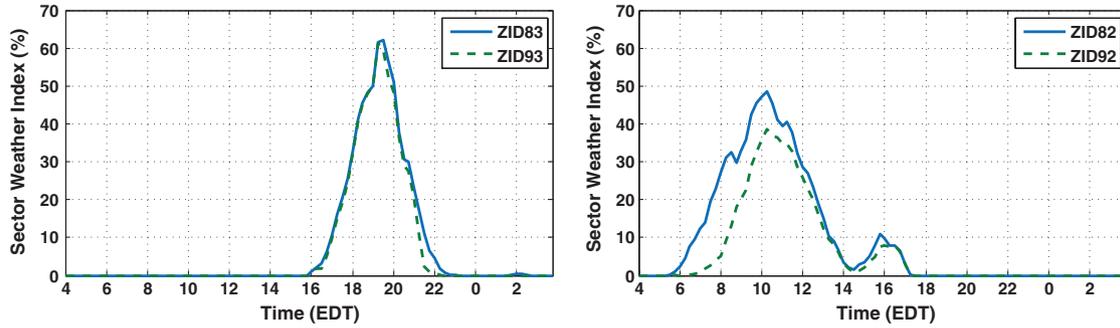
When the predicted sector-demands are lower than the demand threshold  $d_{\text{threshold}}$ , defined as sector MAP value subtracted by 4, the TFM actions are inactive so the model is open-loop. When the predicted demand is higher than  $d_{\text{threshold}}$ , TFM actions are activated so the closed-loop predictions are computed. Among the sectors tested, the TFM actions in the model are more active in ZID81 and ZID93, as more occurrences of TFM actions were triggered. The prediction errors of open-loop predictions on low-demand days, and closed-loop prediction at ZID81 and ZID93 are summarized in Table 2.

The sector-demand prediction for bad weather days uses the weather factor described in the previous section to model the TFM action, formulated in Eqs. (9) and (10), with  $w_{\text{low}} = 0$ ,  $w_{\text{high}} = 1$ , and  $\gamma = 1$ . The days with peak weather factors greater than 30% are considered bad weather days. For the days and sectors tested, there are four cases of severe weather periods: ZID83 on 16 August 2007 between 1600–2200 hrs EDT, ZID93 on 16 August 2007 between 1600–2200 hrs EDT, ZID82 on 21 August 2007 between 0600–1400 hrs EDT, and ZID92 on 21 August 2007 between 0800–1400 EDT, shown in Fig. 6. Since all these cases happened in August 2007, the model is built using data for July 2007. Two types of weather-impacted TFM action models are built: one uses the actual weather information and the other uses the forecast weather information. Using the actual weather information represents the cases with perfect weather forecast. It is used to evaluate the impact of weather forecast accuracy on the model.

The average closed-loop prediction errors of the four severe weather periods in August 2007 are shown in Fig. 7. It is noted that in all four cases, both the model using actual weather information (red dashed line) and the model using forecast weather (green dashed-dotted line) produce smaller errors than the open-loop model (blue solid line). The model using forecast weather performs as well as the model using actual weather when the prediction time is small (less than 30 min). However, with longer prediction time (more than 60 min), the performance starts to decay and the errors are closer to the open-loop model. As an example, in Fig. 7b, the closed-loop sector-demand prediction model using actual weather information improves the 15 min prediction over the open-loop model by 36%, the 60 min prediction by 43%, and the 120 min prediction by 41%. For the model using forecast weather, the improvement is 37% for the 15 min prediction, 44% for the 60 min prediction, and down to 23% for the 120 min prediction. This suggests that with longer prediction time, the forecast inaccuracy might effect the performance of the TFM action model, resulting in larger error in the prediction model.

**Table 2 Open- and closed-loop sector-demand prediction errors of the PAR model in September 2007 (the unit is the number of aircraft)**

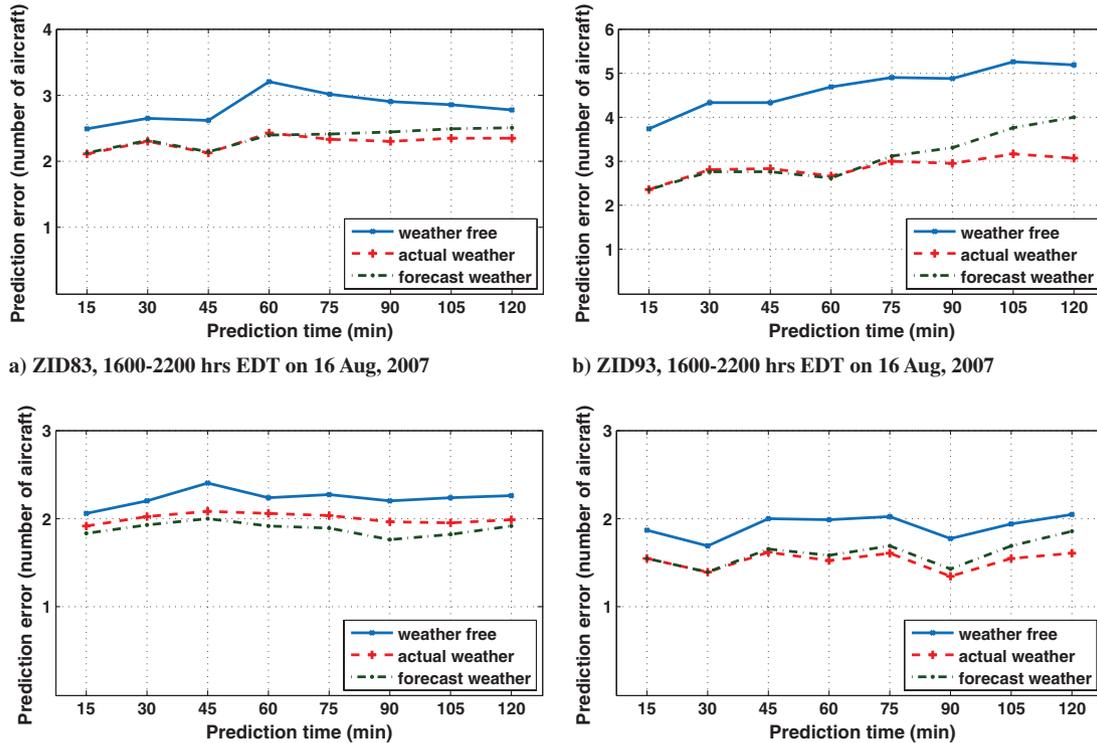
Sector Name	MAP	Sector Type	Average prediction rms error from 0700 to 2300 hrs EDT					
			15 min	30 min	45 min	60 min	90 min	120 min
ZID81	17	Open	2.20	2.30	2.33	2.32	2.30	2.25
ZID81	17	Closed	2.20	2.30	2.31	2.31	2.29	2.31
ZID93	19	Open	2.39	2.50	2.50	2.50	2.53	2.56
ZID93	19	Closed	2.44	2.55	2.54	2.52	2.59	2.56



a) ZID83 and ZID93 on 16 Aug, 2007

b) ZID82 and ZID92 on 21 Aug, 2007

Fig. 6 Sector weather indices on severe weather days in August 2007.



a) ZID83, 1600-2200 hrs EDT on 16 Aug, 2007

b) ZID93, 1600-2200 hrs EDT on 16 Aug, 2007

c) ZID82, 0600-1400 hrs EDT on 21 Aug, 2007

d) ZID92, 0800-1400 hrs EDT on 21 Aug, 2007

Fig. 7 Average prediction errors during severe weather periods.

**V. Conclusions**

A class of periodic autoregressive (PAR) models with management-action-embedded for sector-demand prediction is used for predicting air traffic demand in a sector between 15 min and 2 h in the future. The open-loop model was first identified using low-demand data, assuming no traffic flow management (TFM) action, then the TFM action model was identified using high-demand data. The closed-loop model is the net result of the open-loop and the TFM action models. The proposed PAR model captures both the midterm trend based on the historical data and the short-term transient response based on the near-past observation. For the sectors tested, the model provides the demand predictions with an average root-mean-squared (rms) error between 1.77 and 2.44 in the 15 min prediction and between 1.82 and 2.56 in the 120 min prediction. The performance of the prediction only decays slightly as the prediction interval is increased from 15 min to 2 h, with an error increase of 2.97%. For the sector-demand prediction in the presence of severe weather, the paper introduced the concept of a weather factor to model the TFM actions. For severe weather days, the model uses the storm precipitation and echo tops to form the TFM action model using the weather factor and then adjusts the open-loop prediction. The model improves the closed-loop sector-demand prediction by as

much as 37% for the 15 min prediction, 44% for the 60 min prediction, and 23% for the 120 min prediction on the days and sectors tested. In addition to traditional trajectory-based sector-demand prediction methods that predict only the open-loop behavior of the National Airspace System adequately for short durations of up to 20 min and are vulnerable to weather uncertainties, the management-embedded PAR models provide a reliable short- to midterm (both open- and closed-loop) sector-demand prediction that accounts for non-weather- and weather-impacted TFM actions. A combination of closed-loop and open-loop models provide decision-makers with the full range of traffic behavior.

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