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# An Aggregate Air Traffic Forecasting Model subject to Stochastic Inputs

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**This paper introduces an aggregate air traffic model that calculates the number of aircraft in each Air Route Traffic Center in the United States at any time iteration. The algorithm has the feature of being able to compute the shortest path of an aircraft using future previsions. Weather perturbations and available resources are two main types of input that have a stochastic nature due to their uncertainties. Too often they result in last minute delays or flight cancellations. Thus when predictions are available, their integrations in the path computation modify the aircraft trajectories accordingly, generating robust flight plans. More importantly, this algorithm handles different aircraft types which fly at different cruising speeds, making the scenarios being tested more realistic. Three simple scenarios were tested to validate this aggregate model. A large scale example using historical traffic data of a typical day in the National Airspace System is also presented. The results in comparison with uncontrolled simulations performed in the Future Automation Concepts Evaluation tool show that the model constitutes a potential Traffic Flow Management strategy.**

## Nomenclature

| | |
|---|---|
| $A/C$ | Aircraft |
| $ASDI$ | Aircraft Situation Display to Industry |
| $ATM$ | Air Traffic Management |
| $NAS$ | National Airspace System |
| $MPC$ | Model Predictive Control |
| $FACET$ | Future Automation Concepts Evaluation Tool |
| *Subscript* | |
| $i$ | Variable index |

## I. Introduction

The Federal Aviation Administration and the United States Department of Transportation have announced in their latest forecast[1], a prediction of increased traffic from two to three times the current traffic by 2025-2030. In response to this, advanced research is being conducted to anticipate this growth and to prepare controllers and airlines to collaborate efficiently. Many previous studies have already covered airline operations. Gao et al developed a fleet optimization algorithm[2] integrating crew scheduling. Yen and Birge formulated a stochastic crew scheduling optimization model[3]. Yang addressed the hub location and flight route planning optimization in his model[4]. There have also been several algorithms developed for air traffic control. In 1993, Delahaye and Odoni investigated the use of a genetic algorithm on airspace partitioning[5]. More recently, Gianazza et al[6] applied optimal techniques to the sectorization problem and compared classical with stochastic methods. Delahaye and Odoni also addressed the airspace congestion reduction problem using a genetic algorithm[7]. Hansen and Mukherjee further researched that problem in their publication[8] focusing on the arrival flow management at Dallas Fort-Worth International airport under weather and reduced airport capacity. Almost $60,000$ flights are typically operated in the United States airspace everyday. There is a logical need for innovative and efficient traffic flow management (TFM) strategies that can handle more flights. Often times flights are subject to unexpected disruptions. It is necessary for stochasticity to be integrated in models so that they will help better reflect more real world situations.

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### A. Background on air traffic management

Air Traffic Management is a global research area and solutions developed for it consider both the airlines and the controllers. Incidents, unscheduled maintenance, unavailable resources (plane, gate, runway) and weather perturbations are the main sources of traffic disruptions. They often lead to delays (ground and air) or even often times, flight cancellations. These are non-deterministic events in nature and thus hard to predict. But they play an essential role in air traffic management models. Model Predictive Control (MPC) processes are multi variable control algorithms used to compute future change in variables of dynamic systems. Anticipating and predicting disturbances accurately is needed to simulate realistic scenarios. The more they are considered, the more accurate and realistic the output and simulations are. Due to the importance of traffic volume, their considerations add complexity that is hard to handle which induces most of the time excessive algorithm run time. The use of MPC simplifies the time prediction of a near horizon starting with historical data.

### B. Background on air traffic flow models

Many air traffic models have been developed focusing on different traffic aspects regardless of the data's nature (deterministic or stochastic). Two main kinds of formulation have been used to describe the air traffic. Trajectory-based formulations were derived by Kamgarpour[9], by Prete[10] and by Smith[11]. Those models generate similar individual aircraft routing strategies in the presence of weather and dense operations. This trajectory-based formulation usually leads to a large number of states as mentioned by Sridhar et al.[12], complicating the design of simple air traffic strategies. However, Sun et al[13] as well as Sridhar[12] derived aggregate flow models. This kind of formulation is volume-oriented and focuses on A/C counts. Depending on the geographic repartition of the centers or sectors considered, aggregate models calculate the number of flights in each defined region based on the flow conservation principle mentioned in Eq. (1) and follow aircraft volumes flying in the same direction. The number of aircraft in center $j$ at the next time $t+1$ can be computed from the number of aircraft in $j$ at $t$ via the difference between the inflow and the outflow of aircraft coming and leaving a neighboring center. Sun et al.[13] demonstrated that the aggregate formulation shows flexibility in handling larger flight sets as well as stochastic events.

$$x_j(t+1) = x_j(t) + dep_j(t) - arr_j(t) + \sum_{l=1, l\neq j}^{N} \beta_{lj} x_j(t) - \sum_{l=1} N\beta_{jl} x_j(t) \tag{1}$$

### C. Motivation and algorithm overview

Currently, air traffic flow is predicted by propagating forward in time the trajectories following the deposed flight plans. Due to the anticipated increase of air traffic, a common effort between American government, research agencies and the aerospace industry has led towards a Next Generation of Air Transportation System (NextGen) concept. The goal being to transform and modernize the current National Airspace System (NAS). Evaluation tools like the Future Automation Concepts Evaluation Tool (FACET) have been developed to predict the behavior of the NAS and to model air traffic flow for demand forecasting. However, they give accurate results only for a short timespan.

Based on the overall advantages and disadvantages of air flow models developed so far, this paper formulates a dynamic A/C count aggregate model. This model proposes a TFM strategy that addresses one of the NextGen needs and that can be used with a longer timespan. This paper uses the NAS and its 20 continental centers as the allowable flying zones. The architecture of the network is stored in a fixed-size matrix so that the complexity of the algorithm does not increase with the number of flights considered. This is the main strength of the algorithm. The algorithm calculates the shortest path using a dynamic formulation inspired by Dijkstra's method in combination with a MPC process. This model differs from the previous studies by addressing prior gaps and combining large scale and stochastic elements. Additional research is currently being performed to translate the aggregate model results into real traffic flow management policies. This work intends to simplify the tools used to handle large scale scenarios and reduce the complexity added by stochastic perturbations.

### D. Plan

Part II describes the aggregate flow model and an application example is given for its validation. Part III presents the overall architecture of the algorithm and analytic tools derived. In Part IV, historical air traffic data is used as the input for the model to create a real world scenario. This is then compared with a FACET simulation. Part V concludes the paper with remarks and future work.

# II. Aggregate flow model

The aggregate flow model developed in this paper focuses on finding the shortest route for aircraft from their origin to their destination. This dynamic model integrates different features that are described next, followed by examples of situations. These examples are used as references for the model validation.

## A. Description of the shortest-path model

The model computes the shortest path of a set of flights using time predictions of available future resources and weather predictions. This model is a dynamic, time-dependent algorithm based on Dijkstra's method. The main mathematical tool being used is a square matrix, whose size reflects the number of centers considered. Each element of the matrix is itself a row vector containing prediction information at different time periods. The number of time frames used can be adapted depending on the information available and the precision of the time frame being represented. The current version uses four sub-elements representing four time predictions. These predictions correspond to the state of the airspace from $t_{now}+1$ to $t_{now}+4$. The value being stored is a weighed sum (Eq. (2)) of three components $C_1$, $C_2$ and $C_3$. $C_1$ is a function of the distance between two neighboring regions. $C_2$ is a function of the data relative to the capacity of the centers and the availability of the resources. $C_3$ is a function of the available weather predictions. For the large scale scenario presented later, these values come partly from geographical positions of the centers and partly from historical data (August, 24th 2005).

$$cost = f(geographic\,proximity,\ available\,capacity,\ available\,ressources,\ weather\,prediction) \tag{2}$$

$$cost = \lambda_1 C_1 + \lambda_2 C_2 + \lambda_3 C_3$$

Equation (2): Cost function where $\lambda$s are scaling parameters

This formulation underlines that the size of the matrix is only dependent on the number of entities considered, such as the number of centers or the number of sectors. Thus, once the context has been defined, that matrix size is a constant throughout the iterations regardless of the number of flights studied. It allows the shortest path computation to have a time complexity of $\mathcal{O}(n^3)$, and a space complexity of $\mathcal{O}(n^2)$, where $n$ is the number of centers or sectors.

A feature of this model is the possibility to have different aircraft types flying at different speeds in the input set. For this preliminary study, three different categories are considered, each having a characteristic constant speed. This distinction is established based on a statistical analysis on a set of decoded ASDI data. An ASDI data decoder has been written in C++ to decode raw ASDI messages. Based on several aircraft types present in the data set, average cruise speeds are computed. Those are then considered as references for the different aircraft types. Then depending on that speed and the distance to fly, it will take more or less iterations for each plane to reach its destination. In the data available, the majority ($90\%$) of the aircraft considered are commercial airplanes (airliners and regional planes). In the airliner category two types of airliners can be defined. The first one is the wide-body jet airliner category such as the Boeing 777 or the Airbus 330 flying at cruise on average at $0.82 < Mach < 0.85$ ($550kts$). The wide-body jet airliners form the type 1 classification. The second type of aircraft considered is the narrow-body jet such as the Airbus 320 or the Boeing 737 flying on average at a cruise speed of $Mach = 0.78$ ($450kts$). It forms the type 2 classification. The third aircraft type considered is the regional plane such as the Embraer 190, Bombardier CRJ. On average they fly at a cruise speed of $Mach = 0.74$ ($420kts$). A few business jets are also present in this aircraft set such as the Dassault Aviation Falcon 900 or the Gulfstream V. These business jets are considered part of the type 1 classification due to their high speed. In reality they fly much higher than the airliners (FL410 compared to a FL360). So they do not interfere with commercial planes during cruise. Military aircraft like C-130 observed in the data set are not considered. Any aircraft flying less than $200kts$ is excluded, meaning any general aviation planes are not considered as well. The following Table 1 describes the aircraft classification (based on speed) being implemented with the average speed associated.

**Table 1. Aircraft classification**

| Aircraft type (model) | Category | Examples | Speed |
|---|---|---|---|
| 1 | wide-body jet airliner and business jet | A330/340, B747, B777 and F900, GV | $V_1$ |
| 2 | narrow-body jet airliner | A320 family, B737 family | $V_2$ |
| 3 | regional | CRJ100/200 | $V_3$ |

The speed is translated in the number of iterations within which an aircraft needs to fly from one center to another. For example, a type 1 aircraft would change centers every iteration whereas a type 3 would need four iterations. Additionally, it is assumed that on average, an aircraft of type $i$ spends $round(nbIt/2)$ in the take-off center and in the landing center, where $nbIt$ represents the number of type $i$ A/C iterations.

Figure1 illustrates the algorithm and its capability to handle stochasticity in its input file. The dynamism of the model resides in the way the construction of the shortest path is achieved. At every iteration, some predictions (more or less accurate) with different time frames are available and are used to compute the cost. Thus, some anticipation strategies for the A/C can be undertaken before the perturbation is completely established.

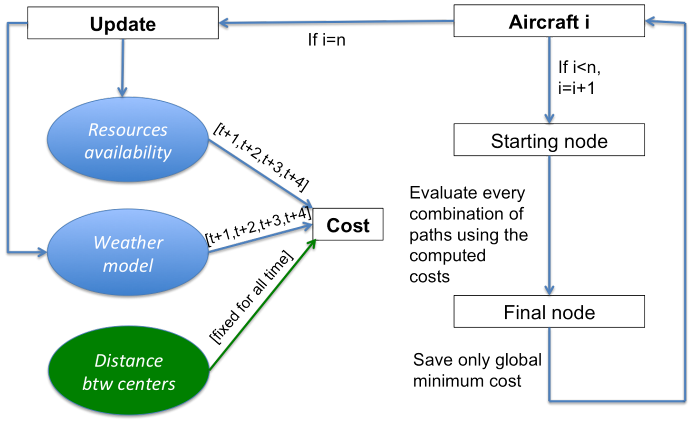


**Figure 1. Model block diagram representation**

## B. Scenario

To understand the algorithm functioning, a simple scenario context that is solvable by hand is presented in this section. The 20 United States centers are considered with a set of flights containing three aircraft. In order to show the functionalities and specificities of this model, three sub-cases are derived on the same context. For these three sub-cases, all aircraft take off from different centers but all three of them have the same destination. Each center is defined by a name and a maximum capacity. The cost matrix is then filled in with costs computed thanks to Eq. (2). All centers that are not physically connected by any geographic borders have an infinite cost to be reached. The geographic partition of the United States centers can be seen in Figure 2.

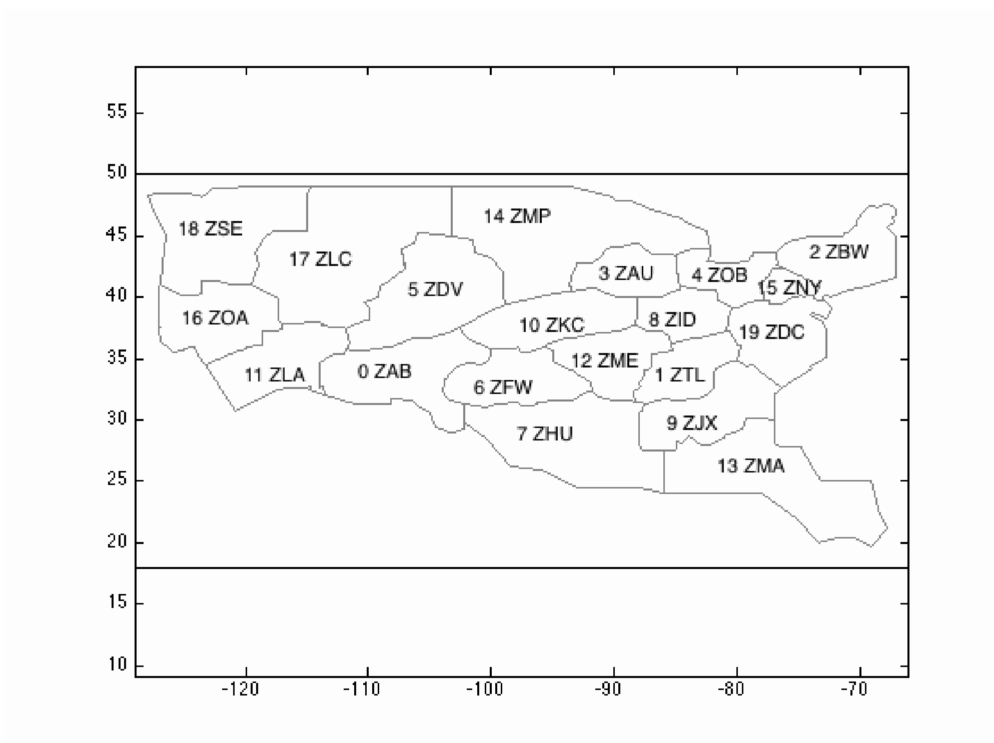


**Figure 2.** 20 **continental Unites States centers**

The following Table 2 gathers the centers' information for the context being defined and illustrated in Figure 2. The index number of the centers chosen (left column) is the one given out by simulations with FACET. The value of the maximum capacity of every center at all times is considered as a constant since this scenario's only purpose is to explicit the model presented. In reality, these numbers will differ throughout the day.

**Table 2. Scenario 1: United States centers definition**

| Center | Name | Max Capacity at all time |
|---|---|---|
| 1 | ZAB | 2 |
| 2 | ZTL | 2 |
| 3 | ZBW | 2 |
| 4 | ZAU | 2 |
| 5 | ZOB | 2 |
| 6 | ZDV | 2 |
| 7 | ZFW | 2 |
| 8 | ZHU | 2 |
| 9 | ZID | 2 |
| 10 | ZJX | 2 |
| 11 | ZKC | 2 |
| 12 | ZLA | 2 |
| 13 | ZME | 2 |
| 14 | ZMA | 2 |
| 15 | ZMP | 2 |
| 16 | ZNY | 2 |
| 17 | ZOA | 2 |
| 18 | ZLC | 2 |
| 19 | ZSE | 2 |
| 20 | ZDC | 2 |



### 1. *Scenario $i$: Same aircraft type - no weather*

The following Table 3 summarises the information inputted to calculate the shortest path of the aircraft set in scenario $i$.

**Table 3. Scenario $i$: Aircraft set**

| Aircraft | Flight ID | Departure center | Arrival center | AC Type |
|---|---|---|---|---|
| 1 | AIR1 | 0 | 3 | 1 |
| 2 | AIR2 | 1 | 3 | 1 |
| 3 | AIR3 | 2 | 3 | 1 |

### 2. *Scenario $ii$: Same aircraft type - weather*

For this second scenario, Table 3 gathers the information needed as input for the aircraft set. However, a weather perturbation is affecting centers that aircraft will cross during their journey. In this scenario, the weather model being implemented translates the presence of weather perturbations by decreasing the available capacity of centers affected. Centers altered by weather conditions will have an increased cost. In this scenario, the weather zone is moving from east to west. At each iteration, the cost matrix is updated according to the weather disturbances to show that the centers affected are harder to be flown over. The weather perturbation is described in Table 4. The column named "Centers affected at $t + 1$" presents which center is going to be affected by the weather perturbation with $100\%$ accuracy. The following columns show which center is predicted to be affected with respectively $80\%$ and $60\%$ accuracy.

Table 4. Scenario $ii$: Weather

| Time | Centers affected at $t+1$ | Prediction at $t+2$ | Prediction at $t+3$ |
|---|---|---|---|
| $t_1$ | 4-8-19 | 4-8 (still) and 1-3 | 1-3-8 (still) and 10-12 |
| $t_2$ | 1-3-4-8 | 1-3-8 (still) and 10-12 | 10-12 |
| $t_3$ | 1-3-8-10-12 | 10-12 (still) | none |
| $t_4$ | 10-12 | none | none |

#### 3. Scenario iii: Different aircraft type - no weather

This last scenario underlines the model's originality—it can consider different types of aircraft. Table 5 presents the aircraft set considered for scenario $iii$. This scenario does not consider any weather disturbances.

Table 5. Scenario $iii$: Aircraft set

| Aircraft | Flight ID | Departure center | Arrival center | AC Type |
|---|---|---|---|---|
| 1 | AIR1 | 0 | 3 | 3 |
| 2 | AIR2 | 1 | 3 | 2 |
| 3 | AIR3 | 2 | 3 | 1 |



### C. Implementation and validation

The code has been written and implemented in C++ and ran on a 3.40 GHz INTEL i5 CPU, 6.00 GB RAM DELL workstation running LINUX.

#### 1. Implementation

The scenarios introduced last section are now implemented and an input file is generated. Due to the risky nature of the problem studied (safety, economical and environmental consequences of being delayed in the air), it is assumed that the air delay is twice as expensive as the ground delay.

#### 2. Expected results

Using the context defined and the geographic configuration of the United States centers, expected results can be drawn explicitly for each sub-case.

1. Scenario $i$

   In this scenario, it can be clearly seen that the third plane is going to be affected by a delay. Table 6 synthesizes the expected trajectory of all three aircraft.

Table 6. Scenario $i$: Expected results with no weather

| Aircraft | Flight ID | Departure center | Arrival center | Path | Delay |
|---|---|---|---|---|---|
| 1 | AIR1 | 0 | 3 | 0-10-3 | no |
| 2 | AIR2 | 1 | 3 | 1-8-3 | no |
| 3 | AIR3 | 2 | 3 | 2-2-4-3 | ground delay |

2. Scenario $ii$

   In the case of no weather on the three aircraft routes, the centers' capacity will be the only limitation. However if a perturbation is present on the centers that will be crossed then the cost will be re-adjusted, introducing rerouting and/or delay for the scenario tested. Since every aircraft of the set flies at the same speed, path modification and delay will influence their journey. Table 7 summarizes the expected trajectory of the aircraft when a weather perturbation is forming. Rerouting and ground delays are expected.

**Table 7. Scenario $ii$: Expected results with weather**

| Aircraft | Flight ID | Departure center | Arrival center | Path | Delay |
|---|---|---|---|---|---|
| 1 | AIR1 | 0 | 3 | 0-0-5-14-3 | ground delay |
| 2 | AIR2 | 1 | 3 | 1-12-10-14-3 | no |
| 3 | AIR3 | 2 | 3 | 2-2-2-2-4-3 | ground delay |

3. Scenario $iii$

   For this last case, since no weather affects the aircraft, it can be expected that AIR3 will reach its final destination first followed by AIR2 and AIR1. The results are presented in the following Table 8. No delay is expected since each aircraft flies at different speeds.

**Table 8. Scenario $iii$: Expected results with 3 aircraft types**

| Aircraft | Flight ID | Type | Departure center | Arrival center | Path | Delay |
|---|---|---|---|---|---|---|
| 1 | AIR1 | 3 | 0 | 3 | 0-0-0-10-10-10-10-10-3-3-3 | no |
| 2 | AIR2 | 2 | 1 | 3 | 1-1-8-8-8-3-3 | no |
| 3 | AIR3 | 1 | 2 | 3 | 2-4-3 | no |

### 3. *Validation*

When the simulation is ran, we export the output (results) file to Matlab to display the shortest paths found for each aircraft and each sub-scenario. The filling rate of each center is defined and computed in Eq. (3) and in Table 9 a color scale is established to characterize its respective filling level.

$$filling\ rate = \frac{maximum\ capacity\ of\ center\ i\ -\ current\ capacity\ of\ center\ i}{maximum\ capacity\ of\ center\ i} \quad (3)$$

**Table 9. Scenario 1: Color scale**

| Color | Filling rate $rate$ |
|---|---|
| white | $0 < rate < 0.5$ |
| yellow | $0.5 < rate < 0.8$ |
| orange | $0.8 < rate < 1$ |
| red | $rate = 1$ |

For now, an iteration represents a time period. For these small scenarios, the discretization is coarse and we assume that one iteration is 30 minutes. As mentioned before, the initial scenario was developed for preliminary introduction purposes. Thus a realistic time period will be computed for future simulations using historical air data.

1. Scenario $i$

   The first scenario implemented takes four iterations. The following set of plots in Figure 3 presents the aircraft count evolution throughout time.

   It can be seen in Iteration 2 that the maximum capacity of center 3 is reached. Thus, ground delay is generated as the less expensive solution for AIR3.

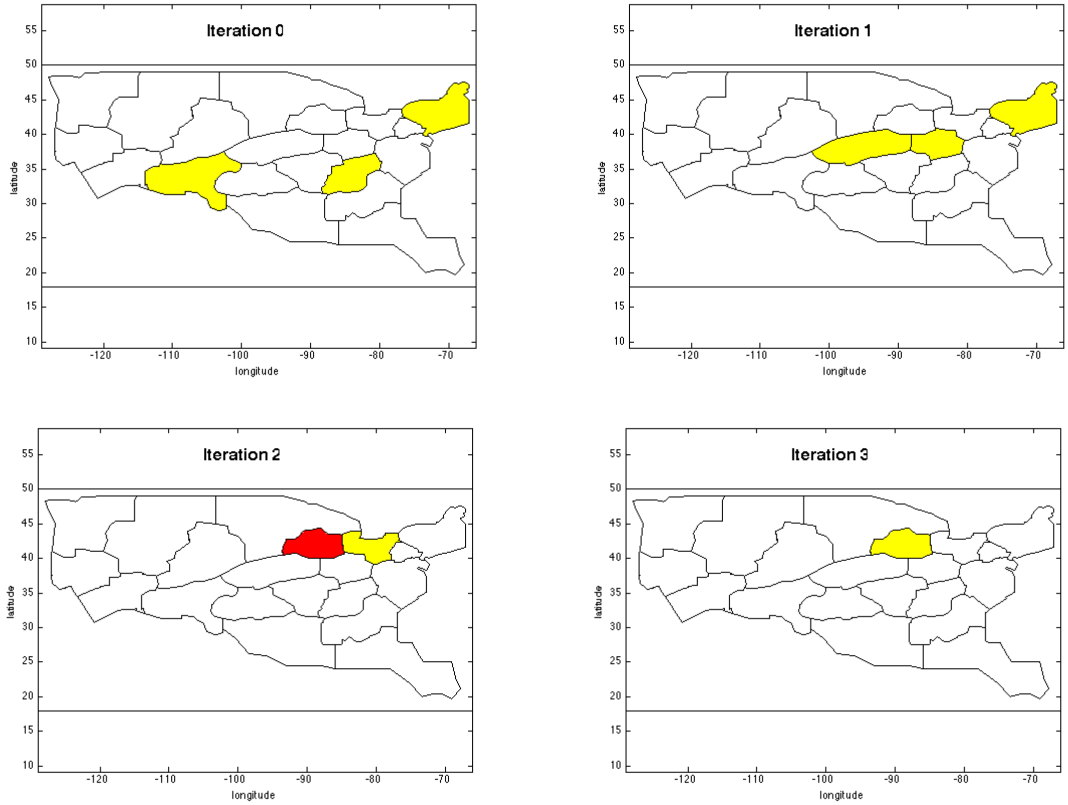


**Figure 3. Scenario i: United States centers filling evolution.**

2. Scenario $ii$

   The second scenario implemented takes six iterations.The following set of plots in Figure 4 presents the evolution of the aircraft count throughout time. The black cells illustrate the weather position. Once again, since the aircraft fly at the same speed the maximum capacity of centers $14$ and $3$ are reached. Some ground delays have also been generated due to a lower cost than rerouting or air delay.

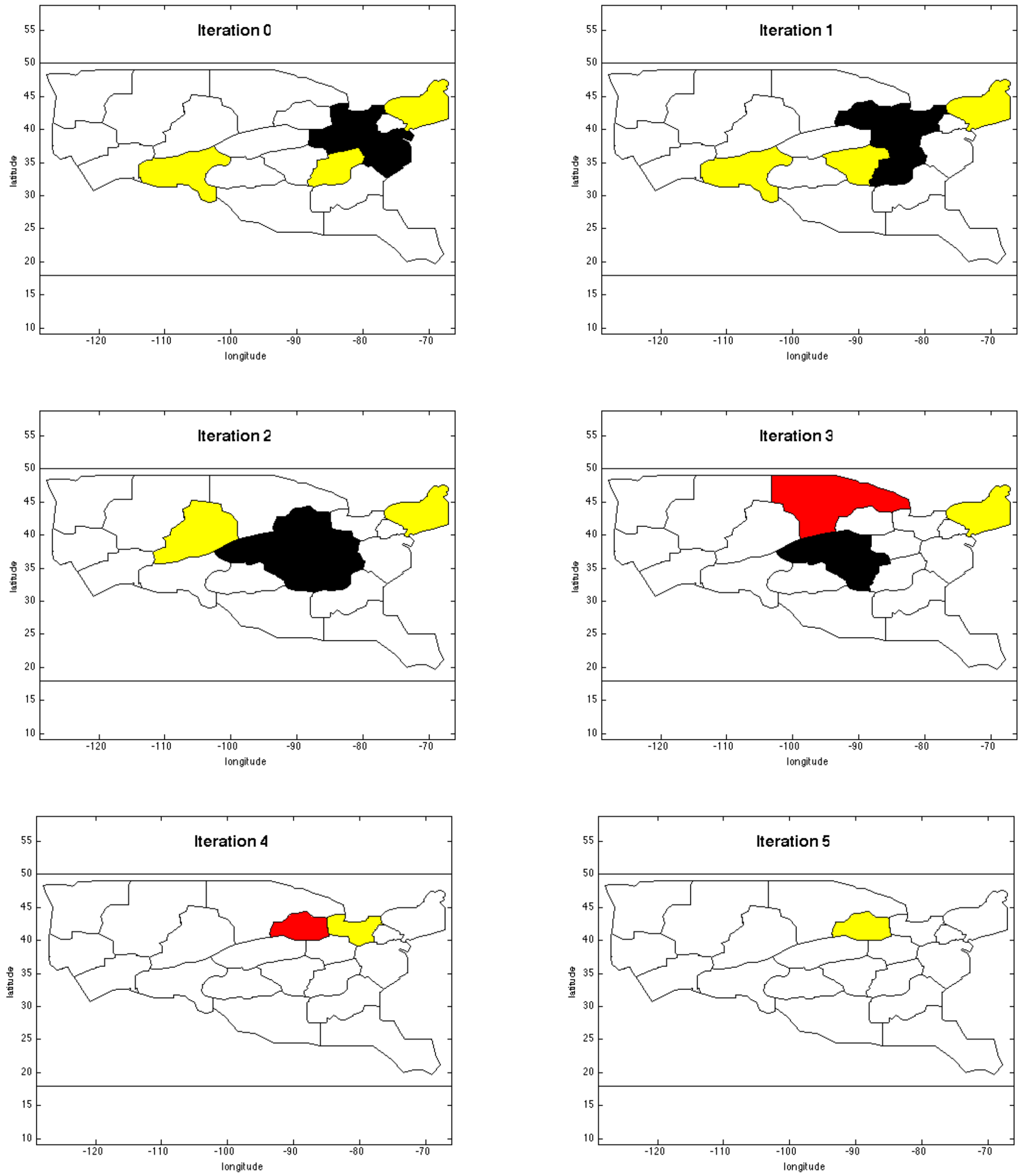


**Figure 4. Scenario ii: United States centers filling evolution when weather (black) is moving.**

3. Scenario $iii$

   The last and third scenario implemented uses 10 iterations. Since the three aircraft have three different speeds, they evolve independently. Thus there is no ground delay nor rerouting generated. The following set of plots in Figure 5 presents the aircraft count evolution throughout time. Iterations 3 and 4; 5 and 6; and 8, 9 and 10 are identical and will not be shown for clarity.

The three solutions exposed in this section validate the model and its use in further scenarios since the results obtained after simulations coincide well with the expected results.

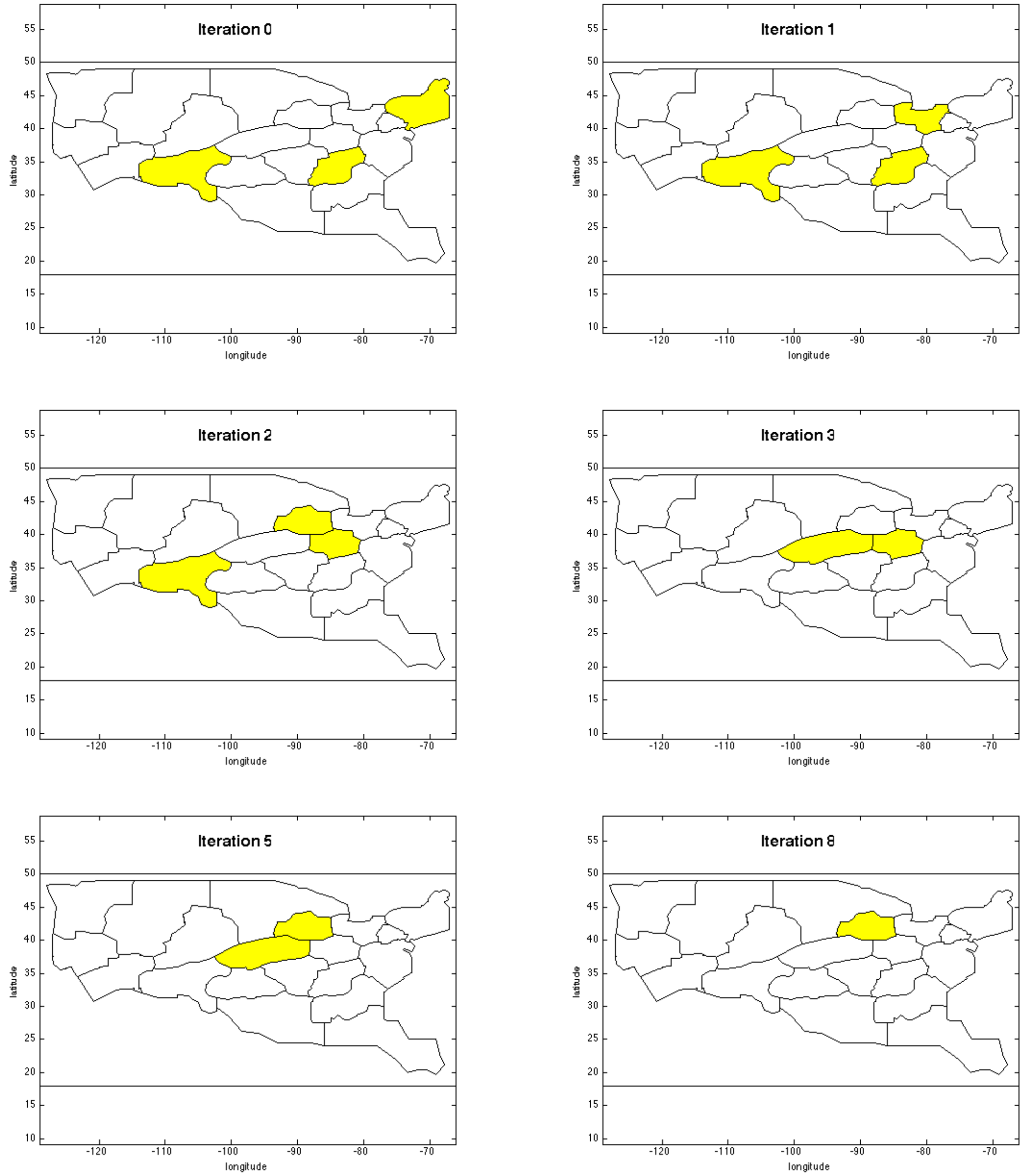


**Figure 5. Scenario iii: United States centers filling evolution.**

# III. Algorithm

Before entering in a real world example using historical air data, the author thinks that it is important for the reader to understand how the model (dynamic shortest path) is integrated in the algorithm. The following Figure 6 gives an overview of the algorithm architecture.

## A. I/O files

### *1. Input file*

In order to generate an input file for the code, raw ASDI messages are decoded by a decoder implemented in C++ by the author. Useful information such as the flight ID, the departure center, the arrival center and aircraft type are retained and ordered by takeoff times. This ordering system has been chosen for practical reasons and to be able to be compared with FACET playback mode simulations. The author is aware that the ordering choice might affect the efficiency of the model. Once the information is decoded, an input file using JSON formatting is then written and contains the necessary aircraft details. Departure center, arrival center and aircraft type are used to create a flight plan for each plane in the set. This input file also contains the ground and air delay costs as well as the neighbor matrix. This neighbor ma-

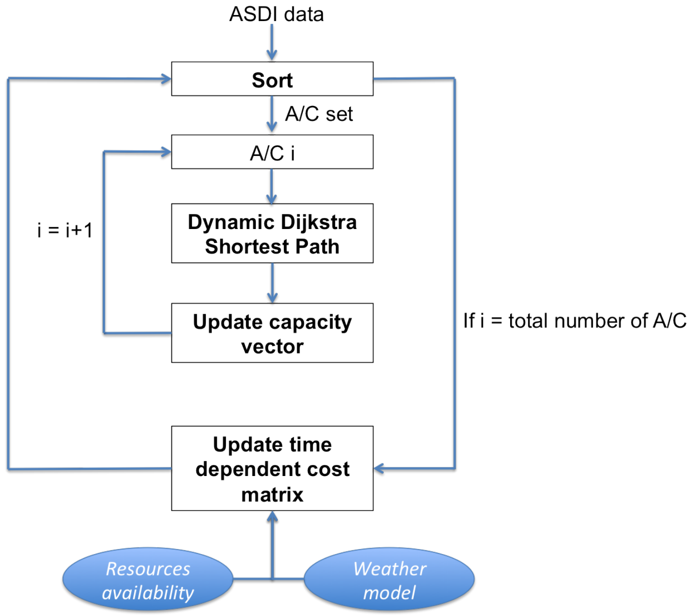


**Figure 6. Algorithm block diagram representation**

trix is built to define the graph of the centers where a connection between two centers represents geographic adjacency.

### 2. *Output file*

When the simulation is done, an output file using JSON formatting is written. It contains the filling rate information of each center at each iteration. This output file is used for post-processing and the results are displayed with Matlab.

## B. Body of the algorithm

At time $t$, once this input file is read, the model computes the shortest path of aircraft one at a time. It uses the four time prediction periods available at that time. The algorithm evaluates the cost to arrive at every center using different paths and different numbers of hops. The difference with the traditional Dijkstra algorithm resides in the eventual aircraft delay, and also that the cost of going from one node to another depends on the number of hops already flown. This inner-loop predicts the shortest path of each aircraft at time $t$. When the algorithm reaches the end of that loop, every aircraft of the set has a valid shortest path computed for that time. This shortest path anticipates the perturbation events predicted for the next time periods. The information contained in the cost matrix is then updated using the available predictions. This is how the stochastic nature of the input is handled. This update corresponds to the time-dependent outer-loop.

## C. Algorithm termination

The algorithm stops when every aircraft from the initial set of flights reaches its final destination.

**Algorithm 1** Aircraft count algorithm

```
Require: ASDI data
  Assume set of data ordered to create aircraft set
Require: geographic context

  procedure SHORTEST PATH(aircraft information, neighbor cost matrix)
Require: list of unvisited nodes to save the costs
Require: list of visited nodes to save path and number of hops
      for all unvisited nodes do
          for all neighbors do
              for all possible paths to current node do
                  compute cost
                  if new minimum per number of hops then
                      save cost
                      save predecessor
                      if predecessors list is empty for this number of hops then
                          add extra paths to unvisited node
                      end if
                  end if
              end for
          end for
      end for
      procedure CONSTRUCT PATH
          Find the number of hops that gives the minimum cost from origin to destination
          Read back from the predecessors the path
      end procedure
  end procedure
```

# IV. Application to a large scale scenario

This section exposes the preliminary results for a large scale scenario simulation. The goal of this simulation is to show that the model is able to handle a large set of aircraft and compute their shortest path throughout the day while following the air traffic trend of the day selected.

## A. Simulation setup

In order to present the results obtained, two simulations are performed in parallel, one with the aggregate model and one with FACET.

### *1. Aggregate model simulation setup*

Air data from August 24th, 2005 is selected to be a representative set of a typical day of air traffic operations.

A 30 minute iteration time step is set up in the aggregate model.

$1248$ flights are ordered within a 19 minutes takeoff time frame. So that it is expected that all aircraft will take off during the first iteration of the simulation, unless centers of the NAS have no available capacity to host the flights.

Using the air data, a preliminary statistical analysis is performed in FACET to estimate the maximum capacity of every center at every iteration. Once these values are estimated, they are incorporated into the model. Thus limiting the number of aircraft being able to take off and/or fly in the same center at the same time. These estimations are also added to the time prediction matrix so that at every current iteration, the model anticipates departures or routes flown by the aircraft reroutes them if necessary to avoid any air delay.

No weather model is applied to the historical air data since they are used for their natural trends. The model will read the aircraft set ordered by takeoff times and assign them a route based on first-come, first-serve according to the available capacity in the centers. Thus the estimations of the maximum capacity values reflect the day studied. One might have chosen another air traffic day and obtained different estimation characteristics for that day.

### *2. FACET simulation setup*

The same data set is used as input in FACET. The time interval is fixed with a 30 minutes time frame. The aircraft are ordered by takeoff time.

## B. Results

Once the simulation is ran, the aircraft counts per center per iteration are extracted. The current capacity of every center at every time period is computed. Figure 7 shows the results of the simulation. Clearly, the airspace modeled in our model is under-used due to the selection of only $1248$ flights in the data set (containing $27,000$ flights). The available capacities are much larger than the one necessary to route the aircraft selected. Thus no delay is generated throughout the iterations. Iterations $0$ and $3$ to $5$ present under-used capacity results, the filling rate of the centers is less than $20\%$. Thus they are not shown.

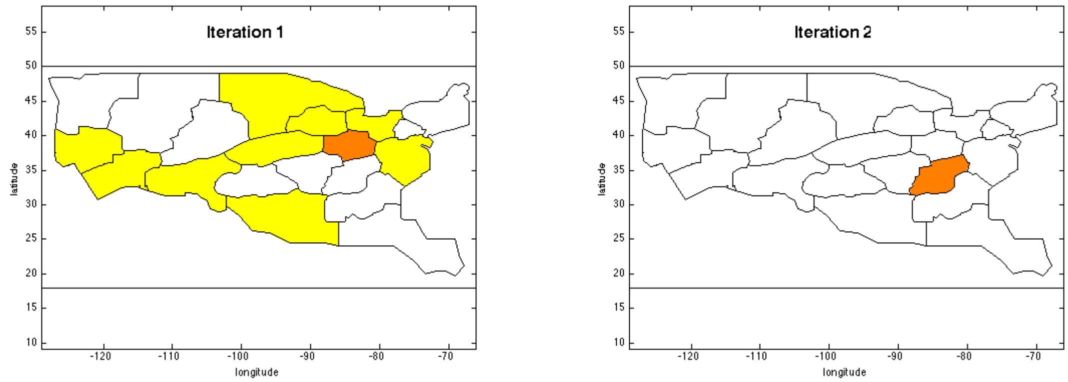


**Figure 7. Large Scale scenario evolution. Iteration $1$ and $2$**

Only the filling rates of the centers in Iterations $1$ and $2$ are shown because they are representative of the algorithm functioning.

Table $10$ summarizes the number of aircraft taken care of during each iteration of the simulation. At time $0$, every aircraft is considered in the model for a shortest path computation. Due to the aggregate aircraft selection, the takeoff times of the aircraft are very close to one another. Most of the aircraft have an $1$ to $1.5$ hour travel time implying a trajectory crossing only two or three centers. Thus due to the coarse time interval, most of the aircraft reach their destination early in the simulation.

**Table 10. Number of aircraft considered per iteration**

| Iteration | Number of aircraft |
|---|---|
| 0 | 1248 |
| 1 | 900 |
| 2 | 357 |
| 3 | 130 |
| 4 | 29 |
| 5 | 2 |

The runtime is $0.44$s.

## C. Comparison with FACET simulation

The results (aircraft count) of the equivalent FACET simulation are aggregated every 30 minutes for intelligible comparison purposes with our model. They are illustrated in the following histograms in Figure 8.

The figures present the evolution of the capacity during both simulations for two different centers (ZAB and ZDV). Clearly, it can be seen that the centers behave in a similar fashion in the two runs. They follow the same capacity trend. However, the aggregate model seems to release the aircraft sooner than FACET and seems to use less time periods to balance the traffic.

## D. Discussion

The following points justify the decisions made during the simulation setup.

1. 30 minute time period: this preliminary study uses a coarse temporal discretization to observe the model behavior and its reaction when handling a large set of A/C taking off shortly after one another. This time period will be reduced in future work to observe smaller aircraft set behaviors over longer periods of time.

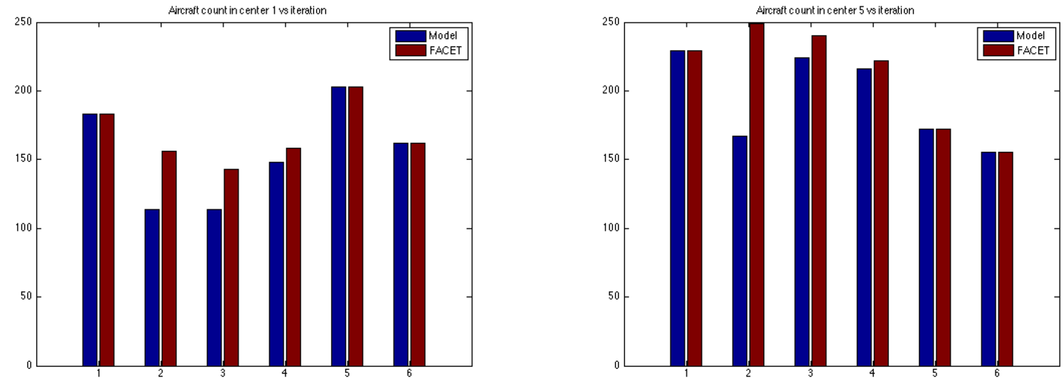


**Figure 8. Histograms. Center 0: ZAB (Left). Center 5: ZDV (Right. Model capacity $<=$ FACET capacity)**

2. The travel time between two centers does not take into account the difference of size between centers. A simulation closer to the reality of the geographical characteristics of the NAS is needed to show the disparities.

3. Total number of flights: $\sim$ 1300 flights were chosen to illustrate a busy part of the day (around 9 AM). Also, this set was used as a test to understand how predictions can balance the number of aircraft per center in the effort of reducing the number of controller interventions.

4. No delay is observed as the centers are not used at their maximum capacity.

The comparison of the results and the under-use of the centers during the simulations indicate the potential room for considering more traffic. It will help to highlight the delay control measures established in case of too many flights overlapping the current available center capacities.

# V. Conclusion and future work

This paper introduces a preliminary study of an A/C count aggregate model using stochastic inputs to forecast air traffic. The scenario and associated sub-cases developed and presented in this paper show encouraging results that can be improved furthermore with future research and modifications to the code.

## A. Concluding remarks

The algorithm produces expected results with respect to its design. The simulated results of the three small scale scenarios coincide with the expected results. The simulated results from the large scale simulation present a comparable trend with the results from FACET simulations. The use of a simple tool and mathematical formulations make the code understandable and flexible enough to handle more features. The results compared with FACET simulations give confidence in its future use.

## B. Future work

Several assumptions were made in order to simplify this first version of the code. Further improvements will be investigated in detail.

1. More A/C options

   Classifying aircraft with only three categories does not exactly reflect the whole fleet mix present in current aircraft sets. During cruise phase, planes can fly at speeds defined in a range and the assumption made to take their average reduces the realistic interpretation of the results. However, it serves as a preliminary study on how to handle planes flying at different speeds, which is too often lacking in existent models. Thus it has been thought that in the near future, cruise speed from ASDI messages will be conserved and stored with the information needed for the input file. From these speeds and distances between the neighboring centers, travel link times will be computed. Thus if travel link times are less than an iteration time then the A/C studied will stay in its current center. The iteration time will then be fixed and independent of the A/C speeds.

2. Sector level

   Since the current setup of the algorithm is implemented using a 20x20 matrix representing the continental United States centers, it does not highlight the complexity of the air traffic at the sector-level. Thus, to switch the code at the sector level, the size and the content of the matrix will have to be adjusted. The size of the matrix will represent the number of continental United States sectors and the content will be evaluated in the same way that the centers are, using the equation mentioned earlier in this paper but adjusted with sectors' values. Moreover, the maximum capacity vector will be updated listing all the sectors each having a maximum number of A/C that can be handled at the same time.

3. Push the model towards control strategies

   Additional research will focus on the translation of the aggregate results obtained after simulation into actual flight management strategies and policies regarding aircraft scheduling, routing and delay. By reducing the allowable maximum capacity of the centers, one can see how the model generates delay rules illustrating the available control procedures for the traffic flow.

4. Towards a stochastic optimization model

   A literature review on stochastic optimization for large scale ATM simulations has been written by the author. The main takeaway is that stochasticity has to be considered and integrated into models because its use will help to represent realistic scenarios. However, no matter the tool nor algorithm type used there is always a limitation on the number of flights that can be simulated at the same time. Stochasticity adds undeniable complexity to the analysis. Considering stochasticity in the input set and designing a model able to anticipate perturbations based on predictions is a step towards simulating more realistic air traffic situations. The next step of this algorithm is to include more of the stochasticity nature of the air traffic inside the model and not just in the input set.

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