Fuel Burn Estimation Modeling for ATM Benchmark Applications
Perspectives from an International Collaboration

Gabriele Enea, Ph.D. Engility Corporation*
Jesper Bronsvoort, Ph.D., Airservices Australia
Hartmut Fricke, Ph.D., TU Dresden
Almira Ramadani, Mike Paglione, FAA
Christian Seiß, Judith Rosenow, Ph.D., GfL

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*Currently with The MITRE Corporation’s Center for Advanced Aviation System Development
Background

• International institutions need to evaluate the benefits of new operational concepts both before and after they are implemented in the field.

• One of the main benefits that they need to quantify is the fuel burn reduction.

• Per flight, the fuel burn savings compared to legacy operations can be small.

• Therefore, the ATM community needs accurate fuel burn estimation models both from recorded and synthesized 4D trajectories.
Overview

1. Preliminary interviews and models classification
2. Fuel burn models
3. Models evaluation and results
4. Models discussion and international examples
5. Conclusions
Preliminary Interviews
Questionnaires Results

• List of questions circulated among relevant institutions:
  • What is your institution’s need for fuel burn estimation models from recorded 4D trajectories?
  • What type of studies do you perform with such models?
  • What type of input/output data do you need to run these models?
  • What are the challenges in using and validating these models?
  • Are there any features that your model doesn’t currently have that would be desired to have?

• Results helped to:
  • Identify best practice in fuel burn modeling
  • Identify input data necessary for accurate fuel burn modeling
  • Identify capability gaps in the state of the art
Fuel Burn Models

1. **Surveillance Data**
   - Quality of surveillance data strongly impacts accuracy

2. **Determine Airspeed from Navigation Equations**
   - Meteorological Forecast

3. **Determine Configuration (TOW)**
   - User Preferences Model

4. **Determine Drag**
   - Aircraft Performance Model

5. **Determine Thrust from Equations of Motion**

6. **Integrate**

7. **Determine Fuel Flow**

8. **Fuel Burn Estimate**

Not all the models include this step.

APM accuracy also strongly impacts accuracy results e.g. BADA 3 vs 4.
Models Classification Approach

• Each fuel estimation model was classified based on the following characteristics:
  1. Inputs/Outputs
  2. Wind models used
  3. Phases of flight covered
  4. Aircraft Performance Model
  5. BADA Version
  6. Accuracy level
  7. Validation
  8. Weight estimation technique
  9. Key results/applications
  10. Ability to run large data sets
Fuel Burn Models
Fuel Burn Models for Evaluation

1. FAA Tech Center AFEST
2. TU Dresden ETAS
3. FAA AEDT
4. FAA NextGen Office in-house model
5. Airservices Australia Dali’
Models evaluation
Sample Scenario for Comparison

• All the institutions involved in the fuel models comparison expressed interest in running a sample of flights
• Although, limitations on the number were presented for time/resources constraints
• Hence, a limited sample of 111 flights was selected
• Variability in the sample was provided by flights with:
  • Variable length
  • Different O-D pairs
  • Various aircraft types
  • Different day of the month*

*The complete data set of about 35,000 flights is from the month of June 2015
Sample Scenario for Comparison

Final sample of 60 flights with meaningful data for estimated TOW and fuel from all the models

Distribution of aircraft types

Summary:
- 13 days in June 2015
- 39 O-D pairs
- 9 aircraft types
- 5 airlines
- Shortest flight DCA-EWR of 220 Nmi
- Longest flight LAX-EWR of 2,495 Nmi

Most common reason for failure was a miss-match between internal aircraft database and aircraft type in the sample
Results
Fuel Estimation Models Data

1. FAA Tech Center AFEST
   a) Unknown TOW
   b) Known TOW

2. TU Dresden ETAS

3. FAA AEDT
   a) TAS
   b) Ground speed

4. FAA NextGen Office in-house model

5. Airservices Australia Dali’
   a) BADA 3
   b) BADA 4
Fuel Burn Estimation Results
Models with Known Initial TOW

<table>
<thead>
<tr>
<th>Fuel Burn Error [%]</th>
<th>AFEST TOW</th>
<th>FAA NextGen</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>-22.7</td>
<td>-26.3</td>
</tr>
<tr>
<td>25th percentile</td>
<td>-13.5</td>
<td>-13.9</td>
</tr>
<tr>
<td>Median</td>
<td>-9.5</td>
<td>-5.7</td>
</tr>
<tr>
<td>75th percentile</td>
<td>-5.2</td>
<td>-2.1</td>
</tr>
<tr>
<td>Maximum</td>
<td>18.8</td>
<td>33.2</td>
</tr>
</tbody>
</table>
Models with Unknown Initial TOW

<table>
<thead>
<tr>
<th>Fuel Burn Error [%]</th>
<th>AFEST NO TOW</th>
<th>ETAS</th>
<th>AEDT</th>
<th>Dalí</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>G. Speed</td>
<td>TAS</td>
<td>BADA 3</td>
<td>BADA 4</td>
</tr>
<tr>
<td>Min</td>
<td>-27.3</td>
<td>-31.2</td>
<td>-31.3</td>
<td>-27.3</td>
</tr>
<tr>
<td>25th perc.</td>
<td>-17</td>
<td>-18.5</td>
<td>-17.2</td>
<td>-16.5</td>
</tr>
<tr>
<td>Median</td>
<td>-13.1</td>
<td>-11.8</td>
<td>-8.6</td>
<td>-12.1</td>
</tr>
<tr>
<td>75th perc.</td>
<td>-8.5</td>
<td>-0.8</td>
<td>-0.2</td>
<td>-2.4</td>
</tr>
<tr>
<td>Max</td>
<td>13.3</td>
<td>46.9</td>
<td>26.3</td>
<td>25.2</td>
</tr>
</tbody>
</table>
TOW Estimation Results
Models with Unknown Initial TOW

<table>
<thead>
<tr>
<th>TOW Errors [%]</th>
<th>AFEST NO TOW</th>
<th>ETAS</th>
<th>AEDT Both Runs</th>
<th>Dalí</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BADA 3</td>
<td></td>
<td>BADA 4</td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>-16.1</td>
<td>-28.3</td>
<td>-24.6</td>
<td>-8.5</td>
</tr>
<tr>
<td>25th perc.</td>
<td>-10.1</td>
<td>-8.2</td>
<td>-18.5</td>
<td>-3.4</td>
</tr>
<tr>
<td>Median</td>
<td>-8.1</td>
<td>-3.5</td>
<td>-9.9</td>
<td>-1.3</td>
</tr>
<tr>
<td>75th perc.</td>
<td>-5.2</td>
<td>-0.2</td>
<td>-6.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Max</td>
<td>2.7</td>
<td>12.5</td>
<td>7.1</td>
<td>7.9</td>
</tr>
</tbody>
</table>
Models Discussion
ATM Modeling Needs

- **Baseline modeling** to characterize current operations prior to any change with recorded actual tracks.
- **Predictive modeling** to provide a pre-implementation assessment of the benefit or impact of a proposed change with synthesized predicted tracks.
- **Retrospective modeling** to provide a post-implementation assessment of the benefit or impact of an implemented change with recorded actual tracks.
Modeling Based on Actual Tracks

- **Unknowns:**
  - Aircraft weight
  - Airframe specific characteristics

- **Errors:**
  - Meteorological forecast
  - Aircraft performance
  - Noisy surveillance data

\[
\text{Estimated fuel burn scenario A} - \text{Estimated fuel burn scenario B} \]
\[
\text{Fuel burn impact scenario change} + \text{Track data errors} + \text{Forecast data errors} + \text{Aircraft weight errors} + \text{Aircraft performance errors} + \text{Actual wind changes} +... 
\]

- Actual change in fuel burn is contaminated because of errors resulting from the models applied and by changes in the actual conditions between the times when the two scenarios were observed.
- Difficult to find a statistically significant change that can be confidently attributed to the change in scenarios being assessed.
- Could be better to assess the difference in flown track miles, flight time, or level-offs, which in general can be measured more accurately, and transform these to fuel savings.
Modeling Based on Predicted Tracks

• Most of variables can be controlled (i.e. determined as part of the modeling process)

• When two predictive scenarios are being compared, most modeling errors cancel against one another (assuming a fairly linear process)

\[
\text{Estimated fuel burn scenario A} - \text{Estimated fuel burn scenario B} = \text{Fuel burn impact scenario change} + ... \\
\]

• The difference can be confidentially attributed to the assessed change being modelled

• A predictive assessment is only valid if the modelled trajectories are representative of actual operations

• Difficult to model tactical ATC and flight crew behavior
Comparative Modeling

- Use both predicted and actual tracks
- Compare the estimated fuel burn over a surveillance track, to a predicted reference trajectory for that flight based on the associated flight plan
- For both computations, the same forecast information, estimated take-off mass and aircraft performance models are used
- By subtracting the reference fuel burn from the estimated fuel burn over the surveillance track, biases and constant components of the error cancel out
- If the estimated fuel burn is subsequently expressed as a percentage of the reference fuel burn, some linear components of the error cancel out as well, provided the reference is adequate for the operation
Considerations from Airservices

• To support informed decision making in the ATM Airspace Concept Development Process, we need a capability to:
  
  • **Measure and monitor** the efficiency of operations to improve reporting and identify problem areas
  
  • **Model** the impact of proposed airspace changes on flight efficiency
Considerations from TU Dresden (1)

- Create a pseudo surveillance track based on aircraft & engine specific FDM data for that timeframe, model weather replacing NOAA data
- Calibrate APM for engine (Fuel flow as \( f(\text{TAS}, \text{Ma}, \text{T}, \text{p}, \text{GM}) \)) and airframe (\( c_D, c_L \) as \( f(\text{Ma}, \text{p}) \) from first principal data) until the Fuel Burn difference is < 0.1% (polynomial aerodynamic fitting):
Considerations from TU Dresden (2)

• Adopt calibrated APM to other aircraft of same type and engine by considering the tail-sign specific Performance Deviation Factor as stored in the FMS
• Execute calibration for a set of at least 5 GM cases per aircraft
• Best: APM should allow for analytic modelling of both the engine and the airframe in-/output (as does EJPM replacing BADA 4.0 in ETAS)
• Fuel burn calculation quality increases further and significantly when assuming weather error as constant and known along the flight track
Conclusions
Conclusions

• To fully support the design, implementation and review of ATM performance improvement initiative or airspace change, predictive modeling is also required to assess the impact of changes pre-implementation
• With different levels of complexity, the accuracy of the models is not always adequate to the changes that model users want to observe
• Even the highest fidelity model underperform with low quality input data
• Fuel burn metrics must be used carefully
Conclusions

• The limitations of these models and applied input data must be understood and transparent upon application
• The model’s level of complexity must be adequate for the objective of the study being performed
• Fuel burn savings should be normalized to control for factors not related to procedural changes
• Fuel burn is not always the most appropriate performance indicator for flight efficiency
• Modeling fuel burn from recorded 4DTs is a complex problem, therefore international collaboration can be very beneficial
Questions?

genea@mitre.org