A Fuzzy Logic Based Analog Forecasting System for Ceiling and Visibility

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Outline

Introduction

- Ceiling and visibility prediction
- Fuzzy logic
- Analog forecasting / k-nearest neighbors

Combining all of the above

Operational application: WIND-3
Ceiling and Visibility Prediction

Critical airport forecasts for: planning, economy, and safety. Ceiling height and visibility prediction demands precision in near-term and on local scale:

- Ceiling height, when low, accurate to within 100 feet.
- Visibility, when low, accurate to within 1/4 mile.
- Time of change of flying category should be accurate to within one hour.

Safety concern

“Adverse ceiling and visibility conditions can produce major negative impacts on aviation - as a contributing factor in over 35% of all weather-related accidents in the U.S. civil aviation sector and as a major cause of flight delays nationwide.”

Fuzzy Logic Definition

“Fuzzy logic a superset of Boolean logic dealing with the concept of partial truth – truth values between ‘completely true’ and ‘completely false’. It was introduced by Dr. Lotfi Zadeh of UCB in the 1960’s as a means to model the uncertainty of natural language.”

Analog Forecasting / $k$-nearest neighbors

- A basic statistical learning technique
- Analog forecasting contrasts with linear regression, two are complementary
- Linear regression →
- Solutions based on line which best discriminates between two classes
- Generally accurate but evidently locally wrong where effects are non-linear

Analog Forecasting / k-nearest neighbors

1. 1 nearest neighbor classifier →
2. Solutions based on single nearest neighbor
3. Generally more accurate than linear regression, but locally more unstable

Analog Forecasting / k-nearest neighbors

- 15 nearest neighbor classifier
- Solutions based on majority of 15 nearest neighbors
- Generally more accurate than linear regression, and less locally unstable than 1 nearest neighbor

Analog forecasting / \(k\)-nn complements Linear Regression

Compared to the linear model approach (basis of most statistical systems for C&V prediction):

1. The \(k\)-nearest neighbors technique has a relative lack of structural assumptions about data.

   “The linear model makes huge assumptions about structure and yields stable but possibly inaccurate predictions. The method of \(k\)-nearest neighbors makes very mild structural assumptions: its predictions are often accurate but can be unstable.”

2. \(k\)-nn is computationally expensive, but newly practical.

Both points borne out in ceiling and visibility prediction system…

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Ceiling and visibility articles since 1970

Using Multiple Linear Regression (MLR) and Multiple Discriminant Analysis (MDA)


Conditional climatology without MLR or MDA


Moore’s Law

The empirical observation that at our rate of technological development, the complexity of an integrated circuit, with respect to minimum component cost will double in about 24 months. ¹

Operational Application: Prediction System: WIND-3

WIND: “Weather Is Not Discrete”

Consists of three parts:

- **Data** – weather observations and model-based guidance;
- **Fuzzy similarity-measuring algorithm** – small C program;
- **Prediction composition** – predictions based on selected C&V percentiles in the set of $k$ nearest neighbors, k-nn.

**Data: what current cases and analogs are composed of**

- Past airport weather observations: 190 airports, 30 years of hourly obs, time series of ~ 300,000 detailed observations;
- Recent and current observations (METARs);
- Model based guidance (knowledge of near-term changes, e.g., imminent wind-shift, onset/cessation of precipitation).
## Data: Past and current observations, regular METARs

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<tr>
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### Data: Past and current observations

E.g., over 300,000 consecutive hourly obs for Halifax Airport, quality-controlled.

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Data: Computer model based guidance

Predictions of weather elements related to C&V, e.g. temperature, dewpoint, wind, weather, dp/dt.

1. Any available model output can be used.

Predicted weather sequence would suggest lifting C&V.
Algorithm: Collect Most Similar Analogs, Make Prediction

Archive search is like contracting hypersphere centered on present case. Axes measure differences weather elements between compared cases. Distances determined by fuzzy similarity-measuring functions, expertly tuned (for first approximation), all applied together simultaneously.

Basic idea, key to $k$-nn

$\sim 10^6$ points

weather states $\leftrightarrow$ ordered points in 12-D weather sequences $\leftrightarrow$ generally continuous loci weather variables tend to flow in certain directions

need an intelligent similarity measure

Analog ensemble

Forecast ceiling and visibility based on outcomes of most similar analogs.

Spread in analogs helps to inform about appropriate forecast confidence.
MSC aviation weather service reorganization
Two Canadian Meteorological Aviation Centres
CMAC-West in Edmonton, CMAC-East in Montreal
Products: TAFs, GFAs, SIGMETs, AIRMETs

CMAC-W
97 TAFs
39 forecasters
6-7 operational desks
CMAC-E
83 TAFs
33 forecasters
5-6 operational desks

For more information, contact Steve Ricketts,
Manager CMAC-W,
steve.ricketts@ec.gc.ca

New opportunities
- Develop software to assist forecasters to handle data, increase situational awareness, and write TAFs
- Increase follow-up on verification statistics
- Develop new products
Prediction

Probabilistic forecast: 10 $\text{%ile}$ to 50$\text{%ile}$ cig. and vis. from analogs
CSI = hits / (hits + misses + false alarms), IFR flying category ⇒ Ceiling < 1000 feet or Visibility < 3 miles.
Statistics are comprehensive for 190 Canadian airports for period from February - April 2005.
• TAF statistics are from the Aviation TAF Performance Measurement Web Site, http://performance.ec.gc.ca
• CVG-3 statistics from WIND forecasting system for ~350,000 24-hour forecasts made hourly.
WIND system forecasts ceiling and visibility using analog forecasting (data-mining and fuzzy logic).
• Data consists of current METARs, climatology (hourly obs from 1971-2004), and GEM-based MOS guidance (mainly for the 6-24 hour projection period) from CMC.
• For more details, visit: http://collaboration.cmc.ec.gc.ca/science/arma/bjarne/wind3
Questions?

E-mail: bjarne.hansen@ec.gc.ca

Webpage: www.cmc.ec.gc.ca/rpn/hansen
Key Points

Two technologies help to improve forecasting systems:
- Fuzzy logic is useful for making expert systems;
- Analog forecasting is effective for ceiling and visibility forecasting.

Forecasters using tools with this technology can:
- Increase the quality of forecast products;
- Increase the efficiency of forecast production.
... → “Conclusion”

By building expert systems that combine artificial intelligence (AI), large amounts of data (climatological and current, remotely sensed and ground based), currently available computing power, model based guidance, and forecaster expertise, we can:

→ Increase value of model output;
→ Increase value model-based and post-processing based weather forecast products;
→ Increase forecast quality, variety, and forecasting efficiency.
Ceiling and Visibility Prediction

Aviation weather forecasting that is very concerned with nowcasting. Ceiling height and visibility prediction demands precision in near-term and on local scale:

- Ceiling height, when low, accurate to within 100 feet.
- Visibility, when low, accurate to within 1/4 mile.
- Time of change of flying category should be accurate to within one hour.

**Safety concern**

C&V affect aviation safety.

“Adverse ceiling and visibility conditions can produce major negative impacts on aviation - as a contributing factor in over 35% of all weather-related accidents in the U.S. civil aviation sector and as a major cause of flight delays nationwide.”


R&D of techniques to improve C&V detection and forecasting could help to improve public and marine forecasting.

Lowered visibility due to fog, affects automotive safety.  

Fuzzy Logic

Use of fuzzy logic has increased exponentially over the past 30 years, based on the number of uses of the word “fuzzy” in titles of articles in engineering and mathematical journals. ¹

In meteorological systems, use of fuzzy logic began about ten years ago. ²

Prediction System – Data Structure and Case Retrieval

Compose present case: recent obs + NWP
Collect most similar past cases

Present Case

Recent past

Time zero

Future

Guidance

Similarity measurement

Past Cases

Traversing Case Base
Related MSC aviation weather related research

• **Nowcasting** with the Airport Vicinity Icing and Snow Advisor (AVISA), related to Alliance Icing Research Study (AIRS), www.airs-icing.org. For information about AIRS contact George Isaac, Senior Scientist, Meteorological Research Branch, george.isaac@ec.gc.ca.

• **WIND System** - Automated analog forecasting, could be combined with AVISA to make a future airport weather prediction system.

• **Comprehensive Fog Modeling Team** - a new initiative to coordinate several lines of fog-related research (e.g., AVISA, WIND, Lunenburg Project, NWP modeling, and detection from satellite) in a long-term research program aimed at satisfying user needs. Users include aviation, Search and Rescue, military, shipping, industry and the public. For information, contact Stewart Cober, Chief of Cloud Physics and Severe Weather Research Division, stewart.cober@ec.gc.ca.
Fuzzy Logic Applications

Fuzzy logic is used in expert systems in hundreds of domains:

- transportation, automobiles, consumer electronics, robotics,
- pattern recognition, classification, telecommunications,
- agriculture, medicine, management, education. ¹

Fuzzy logic models uncertainty inherent in descriptions of continuous, real-world systems. There are many fuzzy logic based systems that deal with environmental data:

- agriculture, climatology, ecology, fisheries, geography, geology,
- hydrology, meteorology, mining, natural resources, oceanography,
- petroleum industry, risk analysis, and seismology. ²

Fuzzy Logic at Research Applications Program, NCAR

According to Richard Wagoner, Deputy Director at Research Applications Program ("Technology Transfer Program"), NCAR:

- NCAR / RAP is now a “continuous set theory” [fuzzy set theory] development center.
- Over 90% of systems developed use fuzzy logic [FL] as the intelligence integrator.
  
  [ … P.S. It is now 100% ]

- [FL offers] unprecedented fidelity and accuracy in systems development.
- Automatic FL-based systems now compete with human forecasts.

For description of how fuzzy logic works in nowcasting systems, see:


Case-Based Reasoning

Meteorological view: CBR = analog forecasting

AI view: CBR = retrieval + analogy + adaptation + learning

CBR is a way to avoid the “knowledge acquisition problem.”

CBR is very effective in situations “where the acquisition of the case-base and the determination of the features is straightforward compared with the task of developing the reasoning mechanism.”

CBR and analog forecasting recommended when models are inadequate, e.g., for ceiling and visibility, sub-NWP-grid scale, which are strongly determined by local effects.

**k-Nearest Neighbor(s) Technique: k-nn**

Definition: “For a particular point in question, in a population of points, the $k$ nearest points.” ¹

Intuition: The closer the neighbors, the more useful they are for prediction.

“It is reasonable to assume that observations which are close together (according to some appropriate metric) will have the same classification. Furthermore, it is also reasonable to say that one might wish to weight the evidence of a neighbor close to an unclassified observation more heavily than the weight of another neighbor which is at a greater distance from the unclassified observation.” ²

k-nn is a basic CBR method. Commonly used to explain an observation when there is no other more effective method. ²

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Fuzzy k-Nearest Neighbor(s) Technique: fuzzy k-nn

Definition: “Nearest neighbor technique in which the basic measurement technique is fuzzy." ¹

Two improvements to $k$-nn technique by using fuzzy $k$-nn approach: ¹

- “Improve performance of retrieval in terms of accuracy because of avoidance of unrealistic absolute classification.”
- “Increase the interpretability of results of retrieval because the overall degree of membership of a case in a class that provides a level of assurance to accompany the classification.”

“Weather Prediction 101” (for “data miners”)

Two basic methods to predict weather: ¹

- **Dynamical approach** - based upon equations of the atmosphere, uses finite element techniques, and is commonly referred to as computer modeling or numerical weather prediction (NWP).

- **Empirical approach** - based upon statistical theory and often, implicitly, the “analog principle”: similar weather situations lead to similar outcomes

In practice, hybrid methods are used to predict weather.

- Statistical methods infer estimated expected distributions under specified conditions. Theoretical distributions are fit to sparse data.

- Resampling methods are an option when data sets are large, and when condition specification is deferred to the last minute (run time, time-zero).

**Resampling**

“Resampling techniques are computationally expensive techniques that reuse the available sample to make statistical inferences. Because of their computational requirements these techniques were infeasible at the time that most of ‘classical’ statistics was developed. With the availability of ever faster and cheaper computers, their popularity has grown very quickly in the last decade.”

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**Applicability for aviation forecasting**

Rather than pre-compile probabilities of future weather categories based on outcomes of pre-selected categories of past weather cases, assuming that the pre-selected categories will closely resemble actual future weather cases, at run-time, compile probabilities of future weather values based on the outcomes of specific past cases most similar to the specific present case, and weight each similar past cases according to its degree of similarity with the present case.

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Motivation for fog prediction research: Increase safety

Crash of Air Canada Flight 646 ¹

- 23h48, 16 Dec. 1997, Fredericton
- Weather: wind calm, visibility ¼ SM in fog, vertical visibility 100 feet, temperature -8°C, dew point -8°C, remarks 8/8 sky coverage in fog.
- **Fog complicated landing and delayed rescue.**
- 39 passengers and 3 crew members, 9 were seriously injured and the rest received minor or no injuries.

Motivation for fog prediction research: Increase safety

Crash of Air Canada Flight 646

Flight delay causes

- Weather: 70%
- Volume: 13%
- Runway: 9%
- Other: 6%
- Equipment: 2%

Weather-related delays

- In some places, fog is main cause of weather-related delays.  
- At one airport alone, fog-related delays caused over $3M US in annual operating expenses.

### Average number of days with fog at Canadian airports

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<th>City</th>
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Aviation forecast service client needs

Clients need accurate forecasts to intelligently – strategically and safely and economically – manage air traffic and to determine amounts of fuel to load aboard individual airplanes.

- Low ceilings and visibility reduce landing rates at airports. When low conditions are forecast, extra fuel is loaded, to extend range, in case a plane must divert from destination to alternate airport. Flight plans must include “alternates.”

- Carrying extra fuel is expensive: transporting the fuels costs money, and the weight of the extra fuel reduces the amount of cargo that can be transported.

- Accuracy of forecasts is mainly determined by ceiling and visibility, and fog often causes reduced visibility.
Aviation forecast service client needs

Every 1% increase in TAF accuracy would result in $1M per year of value to the air traffic system in Canada – estimating conservatively, and assuming increase relative to recently measured levels of TAF accuracy. ¹ Savings would result from:

- Reduced fuel burn or payload substitution,  
  ~ 60% of the total potential saving;
- Fewer diversions, ~ 30% of the total benefit;
- Fewer fuel stops, ~ 10 percent of potential saving.

¹ Assessment of Aerodrome Forecast (TAF) Accuracy Improvement, NAV CANADA, May 2002, pg. 22.
Search and Rescue concern: “Where is the fog?”  

- The majority of military aviation operating out of Greenwood consists of Maritime Patrol and SAR activities, primarily using large turbo-prop aircraft, and to a lesser extent helicopters. Fog has a significant impact on each phase of these operations, often in a way that's somewhat different than commercial passenger operations.

- Both the Patrol and SAR activities spend a significant part of many missions at low level over the water. They need to be able to see, both for the visual aspects of identifying vessels and surface activity, and simply the safety of operation. Missions may be 6-10 hours in length and cover relatively large areas. Although for “operational” missions they may have little option as to the area over which they operate, they spend a lot of time training and can often select an area based on weather and other factors. Aircraft time is very expensive so they need to make maximum use of resources. Thus they have a strong interest in the extent of fog, changes in its coverage over time and space etc.

Search and Rescue concern: “Where is the fog?”

- Helicopters with their limited range can face particular challenges. For SAR operations at extended distance from shore, the helicopter crew may opt to use Sable Island or an oil platform for refuelling on the return trip. Even though they have electronic navigation aids to help them find that refuelling point, they still need to see the last few tens or hundreds of feet in order to land. **If unexpected fog prevents them from finding the refuelling spot in time they could run out of fuel or collide with an object on the surface while attempting to land.**

- There have been instances in which a SAR helicopter was tasked to lift a sick or injured crewman from a vessel operating in fog and, with the help of the meteorologist looking a satellite image, was **able to direct the vessel to a clear spot where the two could meet visually.** Obviously a knowledge of movements or changes in fog areas is of considerable interest in these kinds of missions.

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Search and Rescue concern: “Where is the fog?”

- Fog impacts takeoff and landing in a way somewhat similar to commercial operations. If fog reduces visibility to below required limits for takeoff but there is improvement anticipated, the aircraft will often start and hold near the end of the runway a little before the expected improvement. Obviously this uses fuel, adds to crew fatigue and impacts on the available time for training or the operational mission. **If improvement is early, a potential window of good training or mission time may be lost. If improvement is significantly late, resources are likewise wasted in waiting.**

- Just like commercial aircraft, military crews dislike having to land at a location other than the one originally planned. The cost of a night away from home for an aircraft and 10-person crew is significant, and the aircraft is not available for use in other training or operations. So diverting due to unforecast fog is a very negative occurrence, and crews will go to considerable lengths to avoid it.

Motivation for ceiling and visibility prediction research

Economics and Efficiency

• The commonest cause for TAFs needing to be amended is the occurrence of unforecast categories of cloud ceiling and visibility. ¹

• Production of TAF’s accounted for about $5M per year in revenue to Environment Canada from Nav Canada in 1999. ²

• The NWS estimates that a 30 minute lead-time for identifying cloud ceiling or visibility events could reduce the number of weather-related delays by 20 to 35 percent and that this could save between $500 million to $875 million annually. ³

• “The economic benefit of a uniform, hypothetical increase in TAF accuracy of 1% is approximately $1.2 million [Australian] per year for Qantas Intl. flights into Sydney.” ⁴

Motivation for AI-based ceiling and visibility prediction research

Scientific and Engineering Challenge

- Ceiling and visibility are sub-grid scale, “not resolvable” with NWP.
  “Unfortunately, cloud cover is the most difficult of meteorological variables for numerical models to predict. [MOS] output for predictions of ceiling and visibility is heavily dependent on the most recent station observations rather than the output of the numerical model. Consequently, the quality of ceiling and visibility forecasts has not increased as it has for other forecast variables. For 3- and 6-hour forecasts, several studies have shown that local forecasters could not do better and often did worse than persistence. MOS forecasts were not clearly better than those of the local forecaster for time frames of 9 hours or less.”

- Classical statistical (non k-nn) C&V prediction systems R&D since ± 1970, but none are used operationally (unlike for, e.g., temperature forecasts),
  based on review of ~ 80 articles;
  US and Netherlands have new “semi-operational” systems.

3. Thomas Hicks, Ted Crawford, and Matthew Wilson, 2003: A fuzzy logic system for automated short term aviation weather forecasts, 3rd Conference on Artificial Intelligence, American Meteorological Society.
Limitation in Current Objective Ceiling and Visibility Forecasting Systems

Assumption that present weather can be adequately described by using preselected samples and memberships of attributes in predefined categories.

Current systems, both analog based and rule based, are based on the assumption that airport weather data can only be represented and processed indirectly according to categories. Current systems use: ¹

- Prior probability based treatment of situations;
- Category based treatment of variables.

Prior probability based treatment of situations

- Limits specificity of the situation description. Not practical to calculate prior probabilities of outcomes of a specific situation such as:
  
  *July 10th, 6 am, ceiling height 100 feet, wind southerly 5 km/h, wind shift three hours hence to westerly 15 km/h*

  - Too many possible combinations to account for before the actual event.

Category based treatment of variables

- Does not intuitively reflect degree of similarity between cases;
- Attempt to compensate by using finer categories may result in yield “no past event” upon which to base a prediction.
Climatological information from specific airports.

Input:
- wind speed - 3 categories
- wind direction - 8 directions
- precipitation type - 3 types
- season - 4 seasons

288 bins
Predictions based on about 0.3% most similar cases

Output: Probabilities of pre-selected ceiling and visibility categories.

| Input: Station: St. John’s, Date: Jan. 15, Wind 045/15, Weather: Snow |
|-----------------------------|----------------|----------------|----------------|----------------|----------------|
| Output: Ceilings           |   C0-C1 |   C2-C4 |   C5-C9 |   C10-C24 |   C25-     |
| Ceilings                   |   0.7%  |   19.3% |   52.1% |   21.7%  |   6.2%      |
| Vsbys                       |   0-3/8 | 1/2-3/4 | 1-21/2 |    3-5   |    6-       |
|                           |   4.7%  |   26.0% |   30.9% |   14.6%  |   23.8%     |

Note: U-shaped distribution

Fuzzy similarity-measuring function

Three types of fuzzy operations designed to measure *degree of similarity* between three types of attributes.

1. **Continuous.** (e.g., wind direction, temperature, etc.)

\[ \mu^c (x_1 - x_2) \]

Design tight fit for critical elements, such as wind direction, relatively loose fit for others, such as temperature.

An expert forecaster suggests values that correspond to varying degrees of similarity.
Expertly configured similarity-measuring function

Expert specifies thresholds for various degrees of *near*

<table>
<thead>
<tr>
<th>Attribute</th>
<th>slightly near</th>
<th>near</th>
<th>very near</th>
</tr>
</thead>
<tbody>
<tr>
<td>date of the year</td>
<td>60 days</td>
<td>30 days</td>
<td>10 days</td>
</tr>
<tr>
<td>hour of the day</td>
<td>2 hours</td>
<td>1 hours</td>
<td>0.5 hours</td>
</tr>
<tr>
<td>wind direction</td>
<td>40 degrees</td>
<td>20 degrees</td>
<td>10 degrees</td>
</tr>
<tr>
<td>dew point temperature</td>
<td>4 degrees</td>
<td>2 degrees</td>
<td>1 degree</td>
</tr>
<tr>
<td>dry bulb temperature</td>
<td>8 degrees</td>
<td>4 degrees</td>
<td>2 degree</td>
</tr>
<tr>
<td>pressure trend</td>
<td>0.20 kPa (\cdot) hr(^{-1})</td>
<td>0.10 kPa (\cdot) hr(^{-1})</td>
<td>0.05 kPa (\cdot) hr(^{-1})</td>
</tr>
</tbody>
</table>
Fuzzy similarity-measuring function

2. Magnitude. (e.g., wind speed)

Fuzzy Decision Surface

Calm to lights wind speeds require special interpretation.
### Fuzzy similarity-measuring function

#### 3. Nominal. (e.g., precipitation)

**Fuzzy Relationships**

<table>
<thead>
<tr>
<th></th>
<th>Nil</th>
<th>Drizzle</th>
<th>Showers</th>
<th>Rain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nil</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drizzle</td>
<td>0.02</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Showers</td>
<td>0.03</td>
<td>0.50</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Rain</td>
<td>0.01</td>
<td>0.50</td>
<td>0.75</td>
<td>1.00</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

Different types of weather have different perceived degrees of similarity.
Prediction

To synthesize probabilistic forecasts, we make 11 series of deterministic forecasts based on percentiles of C&V in analogs (0, 10, 20, ..., 100): 0%ile is the lowest C&V, 50%ile is the median, 100%ile is the highest.

Using MSC / Nav Canada performance measures, experiments showed that the series in the 20 to 40 range verified fairly well.

Be aware of systematic tradeoffs between Frequency of Hits, False Alarm Ratio, and Probability of Detection, e.g.,

\[ \uparrow \text{IFR} \implies \uparrow \text{POD} \, \smiley \quad \text{and} \quad \uparrow \text{FAR} \, \frown \]

\[ \uparrow \text{VFR} \implies \downarrow \text{POD} \, \frown \quad \text{and} \quad \downarrow \text{FAR} \, \smiley \]
Prediction

Forecast: ceiling and visibility based on 30\%ile of analogs
Results

Forecasts are competitive with persistence and official TAFs in 0-to-6 hour range based on FOH, FAR, POD, CSI of alternate and VFR forecasts, using ADSB performance measurement technique. ¹

First impressions and forecaster feedback:

Probabilistic forecasts of C&V informative, high “glance value”.

WIND runs in **real-time** for climatologically different sites. Data-mining/forecast process takes about **one second**.

---

Forecaster Feedback

1. *WIND* forecast blizzard conditions to improve to VFR after one hour.
   Analog ensemble used to base predictions on was too large, as blizzards are a relatively rare event. Made a few changes to the code and then *WIND* forecast blizzard conditions more intelligently.

2. *WIND* often provides very good timing of significant category changes.
   Owe some credit to model guidance in many cases as, if wind shifts and precipitation are well forecast by the model, *WIND* benefits directly, and forecasts ceiling and visibility accordingly.

3. *WIND* highlights the possibility of rare and significant events, such as chance of ice fog in winter.
Forecaster Feedback

4. **WIND** provides reasonable values for the 6-to-24 hour period which could help in writing TAFs. Forecasting ceiling and visibility in this time period is presently difficult for forecasters because nowcasting techniques, such as persistence and extrapolation, are unreliable.

5. **WIND** generated TAF for CYYT on May 29th and 06 & 12Z worked quite well. It was an increasing southeasterly flow bringing in low stratus and fog. I believe the **WIND** had it going very low at 18Z while in fact it was about 19Z. This morning's (30/06Z) TAF had the visibility a bit more variable than it really was. So again we see some success in the process with stuff moving in farther in the future. However once the stuff is there, it remains to be seen what the success rate will be.

For nowcasting, persistence is hard to beat.
Verification Method

Each forecast verified using standard method according to the average accuracy of forecasts in the 0-to-6 hour and the 0-to-24 hour projection period of significant flying categories, e.g.,:

<table>
<thead>
<tr>
<th>Ceiling (m)</th>
<th>Visibility (km)</th>
<th>Flying category</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 200</td>
<td>&lt; 3.2</td>
<td>below alternate</td>
</tr>
<tr>
<td>≥ 200</td>
<td>≥ 3.2</td>
<td>alternate</td>
</tr>
<tr>
<td>≥ 330</td>
<td>≥ 4.8</td>
<td>VFR</td>
</tr>
</tbody>
</table>

Counted three sorts of events:

**OBSERVED**

<table>
<thead>
<tr>
<th>FORECAST</th>
<th>YES</th>
<th>NO</th>
</tr>
</thead>
<tbody>
<tr>
<td>hit</td>
<td>false alarm</td>
<td></td>
</tr>
<tr>
<td>miss</td>
<td>(non-event)</td>
<td></td>
</tr>
</tbody>
</table>

Statistics

Four statistics are calculated:

- Frequency of Hits (Reliability),\[ FOH = \frac{\text{hits}}{\text{hits} + \text{false alarms}} \]
- False Alarm Ratio,\[ FAR = \frac{\text{false alarms}}{\text{hits} + \text{misses}} \]
- Probability of Detection,\[ POD = \frac{\text{hits}}{\text{hits} + \text{misses}} \]
- Critical Success Index (Threat Score),\[ CSI = \frac{\text{hits}}{\text{hits} + \text{misses} + \text{false alarms}} \]

FOH and FAR for the 0-to-6 hours are routinely tracked for Nav Canada. However, CSI is more descriptive, more comprehensive, because it accounts for three possible significant outcomes.\(^1\)

Statistics: Caveats

Following statistics are only suggestive of forecast accuracy and value, may be misleading when verifying rare events, such as “below alternate”. Would be more meaningful to verify forecasts with Heidke Skill Score (HSS), or with a cost-based scheme.
Statistics: Caveats

Slight differences between how the Aviation and Defence Services Branch (ADSB) statistics and the WIND and persistence statistics are calculated:

- ADSB statistics account for every minute in the 0-to-6 hour period, whereas the WIND and persistence statistics only account for accuracy at one-hour intervals.
- ADSB verification handles TEMPO forecasts by dividing results into two bins (e.g., 60% hit, 40% miss).
- ADSB statistics verify both regular and amended forecasts together, whereas WIND and persistence statistics only verify regular forecasts. Because amendments often occur when unforecast IFR weather occurs, and because forecasters have a tendency to hedge during such events (e.g., IFR TEMPO VFR), ADS scores might suffer as a result (?).
- ADSB forecasts and the WIND forecasts have different start times (WIND forecasts are made at 00, 06, 12, and 18 UTC).
Statistics: Caveats

Statistics are summaries of statistics at these airports: CYEG, CYFB, CYHZ, CYOW, CYQB, CYUL, CYVR, CYWG, CYXE, CYYC, CYYT, CYYZ, and CYZF.

Each airport's statistics are given equal weight, as is done in the ADS monthly regional statistical summaries. When the statistics for individual airports are considered, other patterns appear.

Legends in the graphs refer to 20, 30, and 40%ile. These refer to three series of forecasts produced by WIND-2, with ceiling and visibility (C&V) based on the 20th, 30th, and 40th percentile of C&V among retrieved analogs. The lower the percentile, the lower the forecast of C&V – it's like tending to pessimistically forecast the “worst-case scenario.”
Direction of Future Work: WIND-3

• Upgrade WIND-2 so that it can provide probabilistic ceiling visibility for 190 Canadian airports (180 civilian and 10 military), at 1-hour resolution, updated each hour, using data from Canadian operational models, surface observations and a long-term climatic data base.

• Create a visual presentation program to display results to operational users.

• Develop comprehensive performance measurement verification system and real-time application.

• Transfer system technology to Canadian Meteorological Centre and/or regional offices to be implemented as an operational product for the Canadian aviation forecasting community.
Conclusion

By building expert systems that combine artificial intelligence (AI), large amounts of data (climatological and current, remotely sensed and ground based), currently available computing power, model based guidance, and forecaster expertise, we can:

→ Increase value of model output.

→ Increase value model-based and post-processing based weather forecast products.

→ Increase forecast quality, variety, and forecasting efficiency.

Acknowledgements – thanks for many contributions to:

- **M.Comp.Sci. Thesis Committee**: Qigang Gao, Mohammed El-Hawary, Denis Riordan
- **NRL Colleagues**: David Aha, Richard Bankert, Michael Hadjimichael
- **RAP/NCAR Colleagues**: Paul Herzegh, Gerry Wiener
Future: Possible Additions and Improvements

**Partnerships:** exploring ways to collaborate with the Research Applications Program (RAP), NCAR and the Aviation Weather Research Program (AWRP) to leverage limited funds, achieve mutual benefits, and realize following improvements more quickly.

**Links to other software:** enable WIND to help with weather watch, proactive alerting of impending problems. For example, combine with MultiAlert to enable a smart alert, and thus help forecasters to increase situational awareness.

**Data fusion:** exploit all available data and employ data fusion techniques \(^1\) to improve nowcasting systems, by intelligently integrating of output of various models \(^2\) (e.g., various CMC models and Updatable MOS, or UMOS), forecaster input, and objective nowcasts of precipitation (based on systems under development), and moving cloud areas seen / detected on satellite images.

**Graphic user interface:** let expert forecasters guide the data-mining to test "what-if" weather scenarios based on various possible conditions.

---

2. Shel Gerding and William Myers, 2003: Adaptive data fusion of meteorological forecast modules, 3rd Conference on Artificial Intelligence Applications to Environmental Science, AMS.
Future: Possible Additions and Improvements

**Fuzzy rule base:** make WIND more of an expert system, to make it systematically act more "intelligently", as we learn from experts, experience, and experiments. Add routines to deal with documented local effects and with special situations such as radiation fog and blowing snow.

**More predictors:** allow data-mining to be better conditioned, e.g., map types (based on synoptic situation), duration of precipitation, recent trends (C&V, pcpn, dp/dt), sun factors (length of day, strength of sun), wind (back trajectory, wind run, source region, cyclonic / anticyclonic flow), etc.

**Faster retrieval algorithms:** use reliable tree-based indexing algorithms for data retrieval to make data retrieval 1000 times faster. A faster algorithm would help WIND to scale up and would help us to test a wider range of data retrieval strategies, e.g., for testing what-if scenarios, forecasters could adjust conditions with a sliding widget and see a virtually instantaneous response.

---

Decision Support Systems Design

**Generic:** no-name, conceptual design that could link and integrate the most useful elements of WIND, AVISA, MultiAlert, SCRIBE, FPA, URP, and so on in evolving WSP application, NinJo.

**Modular:** shows where distinct sub-tools / agents can be developed. Working in this way, individual developers could work on isolated sub-problems and anticipate how to plug their results into a larger shared system. As technology inevitably improves, improved modules can be easily installed and quickly implemented.

**User-centered:** forecast decision support systems from forecaster's point of view, designed to increase situational awareness.

**Hybrid:** combines complementary sources of knowledge, forecasters and AI, to increase the quality of input data and output information. Intelligent integration of data, information, and model output, and use of adaptive forecasting strategies are intrinsic in this design.
Hybrid Forecast Decision Support Systems

Hybrid forecast system development is a current direction of the Aviation Weather Research Program (AWRP) \(^1\) and the Research Applications Program (RAP), \(^2\) NCAR (the main organizers of AWRP R&D).

“If a statistical / analog forecast disagrees with a model forecast, or if different sensors disagree about how C&V are measured, what should we do about it? Fuzzy logic could simulate how humans might apply confidence factors to different pieces of information in different scenarios.” \(^3\)

AWRP Terminal Ceiling and Visibility Product Development Team (PDT) project, Consensus Forecast System, a combination of:

• COBEL, a physical column model \(^4\)
• Statistical forecast models, local and regional
• Satellite statistical forecast model

---

Hybrid Forecast Decision Support Systems

AWRP National Ceiling and Visibility PDT research initiatives:  

- Data fusion: intelligent integration of output of various models, observational data, and forecaster input using fuzzy logic  
- Data mining, C5.0 pattern recognition software for generating decision trees based on data mining, freeware by Ross Quinlan (http://www.rulequest.com), like CART  
- Analog forecasting using Euclidean distance development of daily climatology for 1500+ continental US (CONUS) sites  
- Incorporate AutoNowcast of weather radar in 2004-2005  
- Incorporate satellite image cloud-type classification algorithms

Hybrid Forecast Decision Support Systems

Current

- **RUC20**
  - C & V values derived from forecast hydrometeor and humidity fields.

- **Persistence**
  - Statically carries forward current C & V conditions.

- **Eta Model**
  - Augments RUC in CONUS and will support subsequent Alaska product.

- **Improved C&V Translation**
  - Experimental use of data mining for improved translation.

- **Obs-Based Techniques**
  - First trials of forecasts from historical data using obs inputs.

**EXPERT SYSTEM-BASED FORECAST MERGE PROCESS**
*(Weighted Simple Additive Model)*

- **Rule-Based Methods**
  - Practical forecast methods from operations for targeted locale.

- **COBEL Column Model**
  - Column model with initial focus on fog and low cloud in NE.

- **Others TBD. Hybrids**
  - Future methods focused on C & V.

- **FORECAST COMPONENT WEIGHTS BASED ON PERFORMANCE DATABASE.**

Future

- **Forecast of Ceiling, Visibility & Flight Category on RUC Grid**

- **Display: NCV web, ADDS, Cockpit, Other.**

- **DataBase of Forecast Component Performance vs Weather Condition.**

Feedback Loop
*Using FY03-04 Mods*

---

Future Role of Operational Meteorology

Scientific and systematic forecast process

Partnership with technology

How?
Intelligent Weather Systems (RAP/NCAR)

IWS Design

- Expert system development framework
- Achieves intelligent integration of all relevant, real-time data
- Applies existing knowledge, techniques and/or algorithms
- Supports rapid development of useful, maintainable operational applications

Intelligent Weather Systems (RAP/NCAR)

Fuzzy logic integration algorithm

For example, a fuzzy rule for forecasting radiation fog:

If sky clear and wind light and humidity high and humidity increasing
Then chance of radiation fog is high

Matrix of fuzzy rules covers space of all predictors

System can run continuously to give real-time, smart forecast quality control.

For details, see examples.

Operational Meteorology
A Scientific and Systematic Forecast Process: a partnership with technology!

St. John’s

Fit
Loose       Tight
Ceiling
Visibility
Direction
Speed
Time
...
Weather

Wind
Weather
00h 1215 00h R-L-
01h 1314 01h R-L-
02h 1412 02h L-
... 12h 1408 12h L-

AMD TAF CYYT 270010Z 270024
1315KT 2SM -RA BR OVC006
TEMPO 0002 1/2SM -DZ FG OVC003
FM0200Z 14010KT 1/2SM -DZ FG OVC002
TEMPO 0224 1/4SM -DZ FG OVC001
RMK NXT FCST BY 06Z=
Fuzzy k-nearest neighbors algorithm

Three steps to construct and use algorithm.

1. Configure similarity-measuring function.
2. Traverse case base to find $k$-nn.
3. Make prediction using weighted median of $k$-nn.
Expertly configured similarity-measuring function

Expert weather forecaster uses a fuzzy vocabulary to provide knowledge about how to perform case comparisons. Specifies attributes to compare and the order in which they are to be compared.

Expert fills in a questionnaire:

Attributes to compare – in the order that they should be compared – most discriminating attributes first:

- date of the year
- hour of the day
- cloud amount
- cloud ceiling height
- visibility
- wind direction
- wind speed
- precipitation type
- precipitation intensity
- dew point temperature
- dry bulb temperature
- pressure trend
Expertly configured similarity-measuring function

Expert specifies thresholds for various degrees of *near*

<table>
<thead>
<tr>
<th>Attribute</th>
<th><em>slightly near</em></th>
<th><em>near</em></th>
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<tbody>
<tr>
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<td>pressure trend</td>
<td>0.20 kPa · hr⁻¹</td>
<td>0.10 kPa · hr⁻¹</td>
<td>0.05 kPa · hr⁻¹</td>
</tr>
</tbody>
</table>
Prediction System – Collect Most Similar Analogs

Compose present case: recent obs + NWP
Collect most similar past cases

Present Case

<table>
<thead>
<tr>
<th>Recent past</th>
<th>Time zero</th>
<th>Future</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a(t_0-p)$</td>
<td>$a(t_0)$</td>
<td>?</td>
</tr>
</tbody>
</table>

Similarity measurement

<table>
<thead>
<tr>
<th>Past Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b(t_0-p)$</td>
</tr>
</tbody>
</table>

Traversing Case Base
**Prediction System**

Rate past cases according to their overall similarity with present case.

Threshold for admission to the $k$-nn set is $\alpha$-level, lowest level of similarity among the $k$-nn

$$0.0 \leq \alpha \leq 1.0$$

$\alpha$-level initialized to 0.0

$\alpha$-level rises during traversal

Computational cost of similarity measurement decreases steadily

$O(n^3) \rightarrow O(n)$

In essence, $(1.0 - \alpha)$ is the radius of a contracting hypersphere, centered on the many, expertly described dimensions of the present case, which contains $k$-nn after case base traversal.
Prediction System

Algorithm

\[ \alpha = 0.0 \]

for every past case in the case base

\[ \text{min\_similarity} = 1.0 \]

for every hour in each case

for every attribute in each hour

\[ x = \text{sim} \text{ (past case, present case)} \]

if \[ x < \alpha \]

stop similarity measurement

\[ \text{min\_similarity} = \min(\text{min\_similarity}, x) \]

if \[ \text{min\_similarity} > \alpha \]

\[ \alpha = \text{min\_similarity} \]

save past case in k-nn set

next case

linked list
Prediction System

Save most similar past cases in linked list ordered according to degree of similarity.

Threshold for admission = $\alpha$-level = $sim[k]$
Fuzzy logic

Since we can assign numeric values to linguistic expressions, it follows that we can also combine such expressions into rules and evaluate them mathematically.

A typical fuzzy logic rule might be:

If temperature is warm and pressure is low then set heat to high

How Rules Relate to a Control Surface

A fuzzy associative matrix (FAM) can be helpful to be sure you are not missing any important rules in your system. Figure shows a FAM for a control system with two inputs, each having three labels. Inside each box you write a label of the system output. In this system there are nine possible rules corresponding to the nine boxes in the FAM. The highlighted box corresponds to the rule:

If temperature is **warm** and pressure is **low** then set heat to **high**

![Fuzzy Associative Matrix (FAM)](image)

---

The input to output relationship is precise and constant. Many engineers were initially unwilling to embrace fuzzy logic because of a misconception that the results were not repeatable and approximate. The term fuzzy actually refers to the gradual transitions at set boundaries from false to true.

CBR needs methods for acquiring domain knowledge for retrieval and adaptation.

difficult problem

potential endless loop

1. Adapted from Riesbeck and Schank, 1989
Infrared Satellite Image
Satellite Image Segmented Using Quadtree Algorithm