J1.4 SOURCE TERM CHARACTERIZATION OF FFT07 DATA USING A GENETIC ALGORITHM

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1. INTRODUCTION

The Defense Threat Reduction Agency (DTRA) established that it is important to be able to predict the atmospheric transport and dispersion (AT&D) of chemical, biological, nuclear, or radioactive (CBNR) materials. However, sometimes there is inadequate source information to predict how these materials transport and disperse; therefore it becomes necessary to characterize the source of a CBNR airborne contaminant from remote measurements of the resulting concentration field. To generate a comprehensive meteorological and tracer AT&D dataset suitable for testing current and future CBNR algorithms the FUsing Sensor Information from Observing Networks (FUSION) Field Trial 2007 (FFT07) was executed. Part of the FFT07 data release plan was to make the data available in phases. In the first of these phases, the actual release location and quantity of the agent was withheld and the different research groups with CBNR algorithms submitted predictions of locations of the source releases. The first part of this paper consists of discussing our Phase 1 results using our Genetic Algorithm (GA) approach to source characterization while the second part discusses some lessons learned using Trial data.

2. DATA

The initial FFT07 data released, known as Trial data, contained readings from 100 sensors with the source information (location and amount) and abundant meteorological information. These data were made available to test and train the current CBNR algorithms with the intention that sparser datasets could be constructed by data denial. After 6 months, Phase 1 data, known as Case data, was made available. These Case data contained 104 different release events with limited meteorological data and concentration data for only four or 16 sensors.

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3. EXPERIMENTAL METHODS

Figure 1 depicts the GA procedure for source characterization that has also been proven to work with identical twin data in Allen et al. 2006, 2007, Haupt 2005, Haupt et. al. 2006, 2007a, 2007b, 2007c, and Long et. al. 2010. We begin with a set of trial solutions that are then fed into an AT&D model. The AT&D models used in this study were a Gaussian Puff Model, a Gaussian Plume Model, and the Second-Order Closure Puff Model (SCIPUFF). The resulting concentration fields of these models are then compared via a cost function and the best solutions mate and mutate. This process iterates until it converges to a best solution.

4. PHASE 1

For Phase I of FFT07 we submitted predictions of the cases containing concentration information from 16 sensors. For all of our predictions we manually calculated the atmospheric stability, used 10 s averages of the concentration data as the time interval, determined the stop and start time of each release by visual inspection, and did not filter noise. Some meteorological data was provided for each case; however, we used the GA to determine the prevailing wind direction and speed. When using SCIPUFF as our AT&D model we visually inspected the concentration data to see whether it was a puff or a plume. When using the Gaussian models, every case was run for both puff and plume, and we took the lowest cost function and submitted that result as our prediction for the case.

Figure 2 shows an example of our predictions for a puff and a plume case. As you can see in Figure 2, the case data has concentration values from a selection of sensors downwind of the source release. Our predictions vary some depending on the AT&D model used. We were able to achieve lower cost function values and better source location predictions when using SCIPUFF as our AT&D.

5. SENSIVITY

After submitting predictions for Phase 1 we did a more thorough analysis of the timestep average, use of the meteorological data, and how to threshold the data for noise. Figure 3 shows an example of using different averaging periods for the concentration data. The 10 s average was not as computationally intensive as the 1 s average yet still captures most maximum concentration peaks.

We temporally and spatially averaged the meteorological observations and compared results obtained using the provided data with using wind speed and direction computed directly by the GA. Figure 4 indicated the problems that arise with the measured wind. In that case, the wind turns through 180 ° with height. That implies that a key issue is determining what is the appropriate steering level for the wind advecting the plume. We compared using a vertically average wind, a wind from the mean level of the layer, and a wind speed and direction determined as part of the genetic algorithm optimization. The GA-determined advecting wind produced better concentration predictions, which resulted in better estimates of the source location. In the future we would like the GA to determine the advecting wind speed and direction as a function of time.

To avoid fitting sensor noise we applied thresholds equally to all sensors. We found that applying this threshold equally may not be the best approach given that our cost function values did not vary much between out high thresholds and low thresholds. However, we expect that applying thresholds individually to sensors will greatly improve our predictions.

6. DISCUSSION

We have shown some success at estimating source term variables with a genetic algorithm and several different dispersion models. The trial cases from FFT07 allowed analysis of our routines with real field data.

ACKNOWLEDGEMENTS

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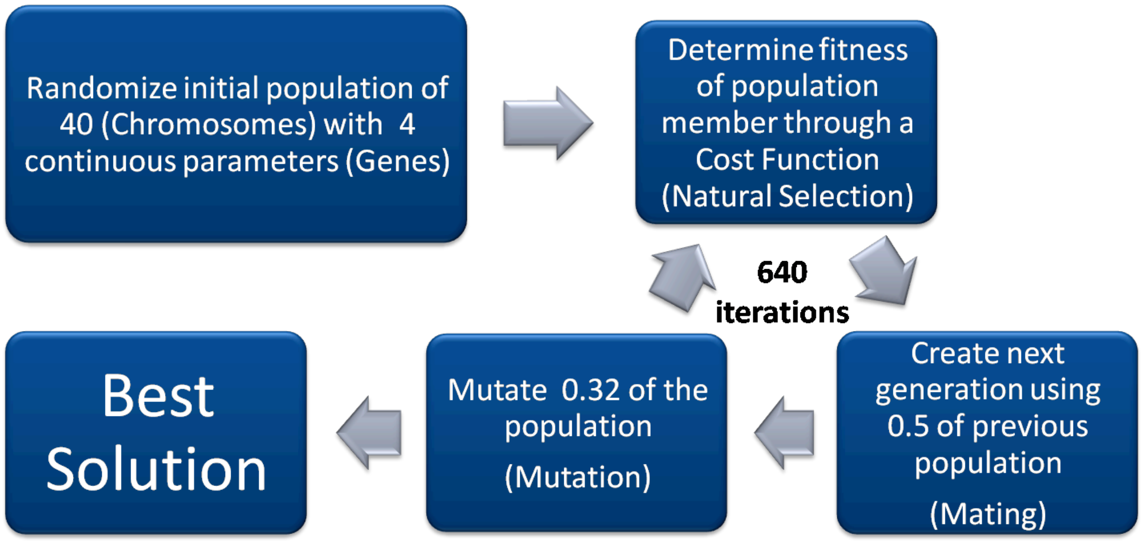

Figure 1. Schematic of Genetic Algorithm.

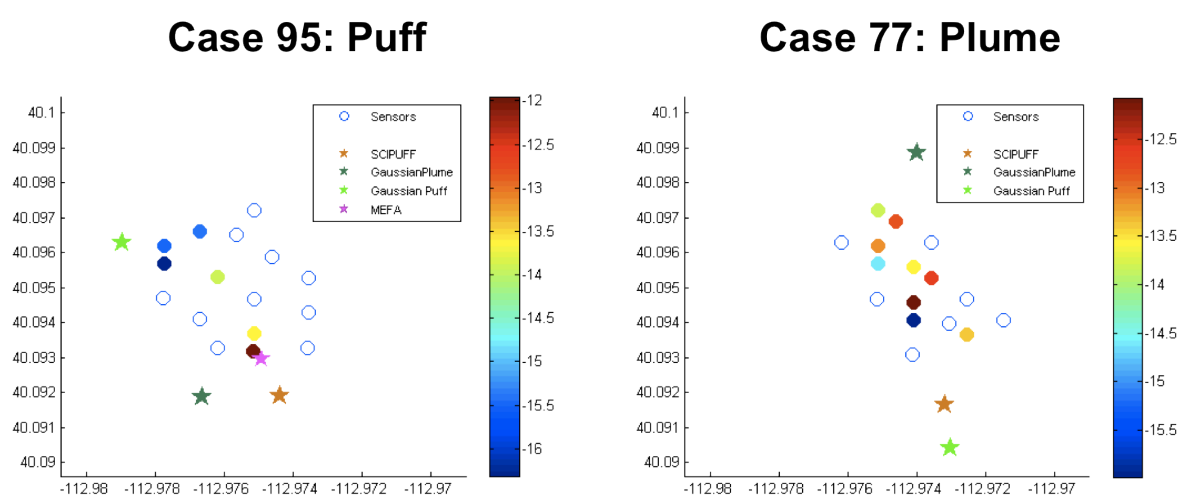

Figure 2. Source location predictions for a puff and a plume case submitted to Phase I of FFT07.

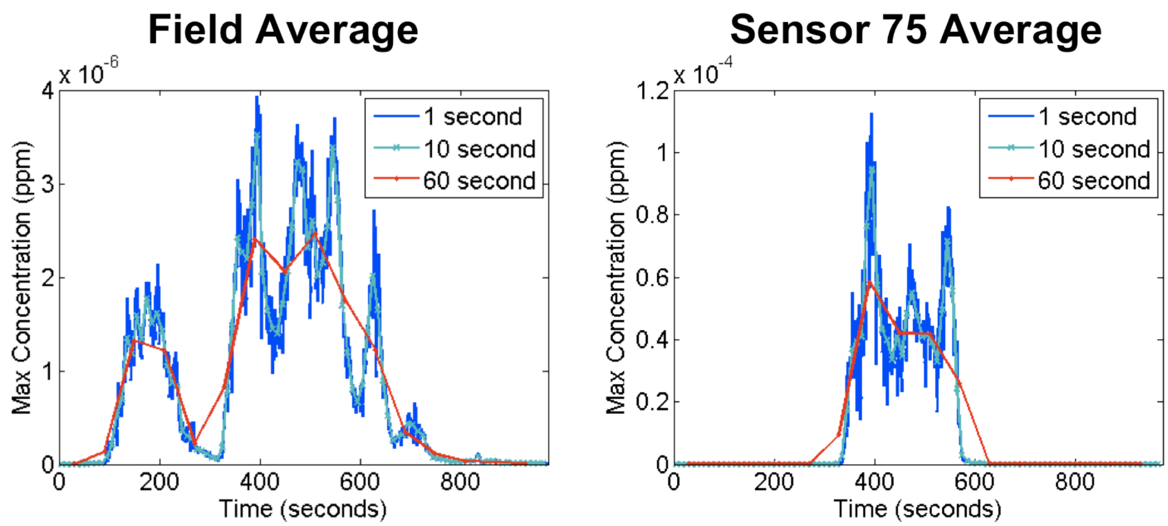

Figure 3. The Field Average is the spatial mean using different averaging periods for the concentration data for Trial 15. Sensor 75 Average is the mean using different averaging periods for the concentration data of sensor 75 for Trial 15.

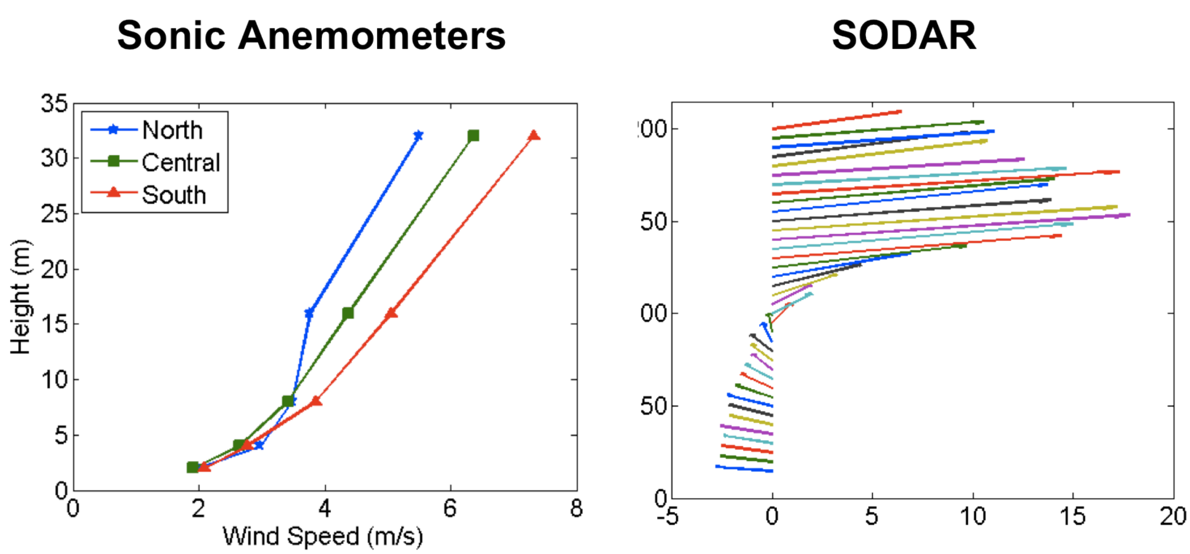

Figure 2. We temporally averaged the meteorological observations for the Sonic Anemometers and the SODAR.