J11.4 USING A GENETIC ALGORITHM TO ESTIMATE SOURCE TERM PARAMETERS OF VOLCANIC ASH CLOUDS

Kerrie J. Long, Dustin Truesdell, and Sue Ellen Haupt Applied Research Laboratory, The Pennsylvania State University, University Park, Pennsylvania

1. INTRODUCTION

Ash clouds generated by volcanic eruptions pose a major hazard to aircraft. Consequently, they must be closely monitored on a regular basis. Agencies responsible for modeling volcanic ash clouds need to reroute aircraft effectively and efficiently. Atmospheric transport and dispersion models used for prediction of cloud movement rely on accurate knowledge of the source parameters in order to make a prediction about the future state of the cloud. In this study we focus specifically on back-calculating the emission rate that represents the amount of aerosols being pumped into the atmosphere. A method is presented that applies a genetic algorithm (GA) to observational data in order to back-calculate the source parameters governing the eruption.

The general procedure for source term estimation and prediction is outlined in Fig. 1. Following a volcanic eruption a satellite detects the ash cloud. We obtain the satellite data and process it for use in our model. We then apply our model to obtain the pertinent information regarding the emission rate of the volcano and use that to refine the forecast movement of the ash cloud. With the refined forecast we would then be able to provide a more accurate forecast to warn and reroute aircraft in the region.



Figure 1. Outline of general solution methodology.

The transmission and calculation step of the solution process is described in more detail by Fig. 2. The source term parameters, including potential solutions for the unknown emission rate,

along with the available meteorological information (section 2) are input to the dispersion model (section 3) to create a forecast. The forecasts generated are compared to the satellite data (section 4) and the potential solutions are evolved and re-evaluated using a genetic algorithm (section 5). The dispersion model is rerun iteratively and the solutions are refined until convergence where we have our best solution (section 6). A case study is made of the March 2009 eruption of Mt. Redoubt in Alaska.



Figure 2. Source Term Estimation Solution Process.

2. CASE STUDY

To test the method we selected the March 23, 2009 eruption of Mount Redoubt. Located in southern Alaska along the Cook Inlet (Fig. 3), Redoubt is a stratovolcano that rises to 3108 m above sea level (Siebert and Simkin 2002). Prior to the eruptions in 2009, the most recent activity from Redoubt took place in 1989-1990 (AVO/USGS 2009).

The eruption chosen for our case study began at approximately 10:38 PM AKDT on Sunday, March 22 as diagramed in Fig. 4. There were a series of five explosive eruptions that each lasted from four to thirty minutes. The last eruption ended at 5 AM AKDT on Monday, March 23 (AVO/USGS). For simplicity we model the release type as a single continuous, uniform eruption lasting 6.5 hours.

The ash cloud reached an estimated 60,000 ft in maximum height with the bulk of the material between 25,000 and 30,000 ft (7600 and 9100 m) above sea level (AVO/USGS). For simplicity we used a uniform wind speed and direction over the

^{*}*Corresponding author address:* Kerrie J. Long, Applied Research Laboratory, P.O. Box 30, The Pennsylvania State University, State College, PA, 16804-0030; e-mail: <u>kjl203@psu.edu</u>

entire domain and over all vertical levels. The wind speed is fixed at 20 m/s at 220°. These values are selected based on the position of the ash cloud at the time the satellite data is captured. We believe these to be the most representative values but wish to do further study in this area. The only unknown variable in the source term description is the emission rate of the eruption.



Figure 3. Location of Mount Redoubt http://www.avo.alaska.edu/image.php?id=15524



Figure 4. Timeline of March 22, 2009 eruption of Mt. Redoubt.

3. **DISPERSION MODEL**

The atmospheric transport and dispersion of the ash cloud is predicted using the Second-Order Closure Integrated PUFF (SCIPUFF) model. SCIPUFF is a sophisticated puff-based transport and dispersion model that accounts for turbulence, terrain, and weather effects in its calculations (Sykes 2004). SCIPUFF tracks individual puffs, evolves the dispersion coefficients, splits the puffs, and incorporates advanced methods to assess turbulence levels.

SCIPUFF allows the user to specify whether the material released is a particle, liquid or gas and then define certain characteristics such as density and particle size. We model the transport and dispersion of the ash particles ranging in size from 0.10 to 100 microns and having a density of 700 kg/m³ (Shipley and Sarna-Wojcicki 1982). Note that for this study we do not include effects resulting from chemical reactions.

4. SATELLITE DATA

The satellite data is derived from the Advanced Very High Resolution Radiometer (AVHRR) and was provided by the National Environmental Satellite, Data, and Information Service (NESDIS) of NOAA. Figure 5 illustrates the estimated mass loading (5a), height of the cloud ash (5b), and effective particle radius (5c). The location of Mt. Redoubt is indicated by the white circle in the bottom left of figure 5. The reader is referred to Pavolonis (2010) for details regarding the AVHRR and the satellite data processing technique.





Figure 5. The mass loading in ton/km² (a), height of the ash cloud in km (b), and radius of the ash in microns (c) determined by the satellite.

5. GENETIC ALGORITHM

We choose a genetic algorithm, which mimics the natural selection process of mating and mutation to evolve a solution as our optimization tool. Fig. 6 illustrates the technique.



Figure 6. The Genetic Algorithm (GA) procedure.

A population of potential emission rates is randomly initialized and input into the SCIPUFF dispersion model. The resulting forecast is then compared to the observed concentration field pictured in Fig. 5a. The difference between the two fields is calculated via the following cost function:

$$\cos t = \frac{\sqrt{\sum_{s=1}^{TS} [O_s - C_s]^2}}{\sqrt{\sum_{s=1}^{TS} [O_s] \sum_{s=1}^{TS} [C_s]}}$$
(1)

where:

 C_s is the forecast concentration at sensor, s, O_s is the observed concentration at sensor, s, and TS is the total number of sensors.

The population of chromosomes, representing emission rates is sorted based on cost function value. The best potential solutions will produce a lower cost function value. Then a fixed percentage (50%) of the population is selected to participate in mating. Here, two parent chromosomes are blended to create two offspring chromosomes. Next, twenty percent of the population mutates where a specified number of chromosomes are replaced with a new randomly generated emission rate. This encourages a complete search of the solution space. After these operations are complete, SCIPUFF is run again and the new forecasts are computed and the cost functions recalculated. The population of chromosomes is then resorted. The GA procedure is repeated for one hundred generations until the cost function value converges. The mutation rate, population size and number of generations were selected based on previous experience. For more details regarding the proper selection of GA parameters the reader is referred to Haupt and Haupt (2005).

6. RESULTS

We allow the GA to search for an emission rate spanning four orders of magnitude: 1x10³ to 1x10⁷ kg/s. Since the GA is initialized with a random number, we run the algorithm ten times in order to gain statistics about the algorithm performance. Figure 7 plots the cost function value for the population average and the best solution as a function of generation for a single GA run. Notice that the best solution begins to asymptote in fewer than five generations but continues to improve slightly until just after 40 generations. Figure 8 plots the results of ten runs of the GA listed in Table 1. Each marker represents the best solution found by the GA after 100 generations. Notice that eight of the solutions cluster between 7.5-8x10⁴ kg/s with several overlapping. Two solutions are slightly higher and lower but the cost function values associated with them are higher and therefore less desirable than the other eight. The lowest cost function values correspond to the best solutions and are indicated by bold in Table 1. The mean emission rate of the ten runs is 7.6×10^4 kg/s. This value represents the release rate of the volcano for a period of 6.5 hours meaning that the model predicts an estimated 1.7x10⁹ kg of ash is pumped into the atmosphere throughout the entire period. The plume generated by using this value

as the emission rate is plotted in Fig. 9. Note that the general footprint and concentration magnitude matches the satellite observation data fairly well.



Figure 7. Example of convergence from sample run. The average cost function value of the 16 population members is shown in dashed red and the best solution is shown in solid blue.



Table 1. Emission rate and cost function value for ten model runs.

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Run #	Emission Rate (kg/s)
1	76572
2	76555
3	62564
4	76527
5	77916
6	77810
7	76492
8	87298
9	76244
10	76460
Mean	76444
Standard Deviation	5912
10 Mean Standard Deviation	76460 76444 5912



7. DISCUSSION

Verifying the value for emission rate is challenging given the nature of a volcanic release. The Volcanic Explosive Index (VEI) characterizes the explosivity or size of an eruption on a 0 to 8 scale. The March 2009 eruption of Redoubt was classified as a large eruption or VEI 4 (Siebert and Simkin 2010). The VEI classification for the 2009 Redoubt eruption is greater than the 1989 eruption which was classified as a VEI of 3. Previous studies have determined that the 1989 eruption of Redoubt, which lasted for approximately one hour, emitted at an estimated rate of 4-7x10⁶ kg/s (Mastin et al. 2009).

We have successfully demonstrated that a genetic algorithm can be applied to determine the emission rate of a volcanic eruption. In future work we would apply the genetic algorithm approach developed here to search for additional variables such as wind direction and wind speed. It is possible that the most representative wind speed and direction are not the surface level winds. In fact, on this particular day the surface level winds were nearly opposite the upper level winds which transported the bulk of the cloud. In this case, modelers would need a wind profile which may not be available. Thus, for the next step of this project we propose to back-calculate the wind speed and wind direction that most closely represents the transport of the ash cloud. This information would provide additional guidance for the prediction of the future state of the cloud as well. In addition, the problem would become multi-dimensional and necessitate a robust optimization technique like the GA.

We plan to further test the algorithm by examining other eruptions as satellite data becomes available.

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