Searching for Risk in Large Complex Spaces

Kester Clegg, Rob Alexander

University of York, York, U.K.
{kester.clegg|rob.alexander}@york.ac.uk

Keywords: Search, Risk, Safety, Air Traffic Control, Simulation, RAMS.

Extended Abstract.

Safety analysts are starting to worry that large complex systems are becoming too difficult to analyze when part of the system is changed or placed under stress. Traditional safety analysis techniques may miss safety hazards or (more likely) some of the circumstances that can cause them. To help analysts discover hazards in complex systems, ASHiCS has created a proof-of-concept tool that uses evolutionary search and fast-time air traffic control (ATC) simulation to uncover airspace hazards.

We use a fast-time ATC simulation (using RAMS Plus[1]) of an en-route air sector containing multiple flight paths and aircraft types, and into this we inject a serious incident (cabin pressure loss) that requires one aircraft to make an emergency descent. We then use a near-neighbor random hill-climber to search for high-risk variants of that situation: we run a wide range of variants, select the subset of variants that caused the most risk, and then mutate the aircraft entry times to create a new set of situation variants that will hopefully have even greater risk. Weighted heuristics are able to focus on specific events, flight paths or aircraft so that the search can effectively target incidents of interest.

Air traffic is generated by specifying the characteristics of each aircraft entering the sector, namely aircraft type, aircraft entry time, its entry and exit flight level and the waypoints specifying its flight path and any level changes. The traffic input files are created using genetic algorithms with restrictions on the distribution of aircraft to predetermined flight paths and an enforcement of wake turbulence separation. Once the input files have been created, a non-graphic version of RAMS Plus (i.e. a version that runs without any visualization to speed up simulations) is executed and the outputs analyzed by heuristics in the ASHiCS software.

The solution space is extremely large and cannot be exhaustively searched for the worst case; this is a problem for safety analysts who need a context to the search results so that they can determine event probabilities. Our initial approach has been to conduct a sensitivity analysis to try and discover more about the average fitness of the population during the evolutionary search. This provides some insight to the nature of the solution space, in terms of the frequency of other high risk scenarios and how sensitive such solutions are to mutation of their input configuration. Our initial results suggest that for very large solutions spaces, where high scoring solutions are relatively rare, the range of the mutation operator (i.e. the degree to which the mutation operator can change the original) has a significant effect on the average fitness of the population. From our experiments, mutation operators with large ranges that permit radical changes to the genotype perform significantly worse than operators with small ranges that permit gradual changes.

[1] http://www.eurocontrol.int/eec/public/standard_page/WP_Fast_Time_Simulation_Tools.html

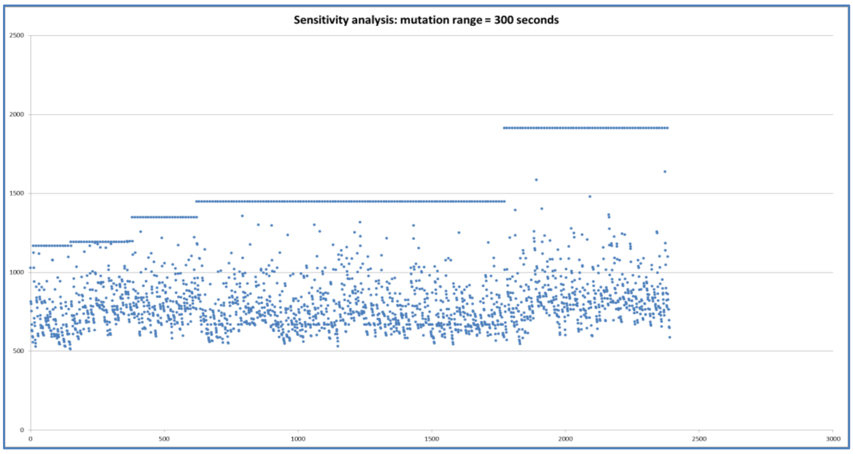

Fig. 1. Sensitivity analysis. Mutation range = 300s.

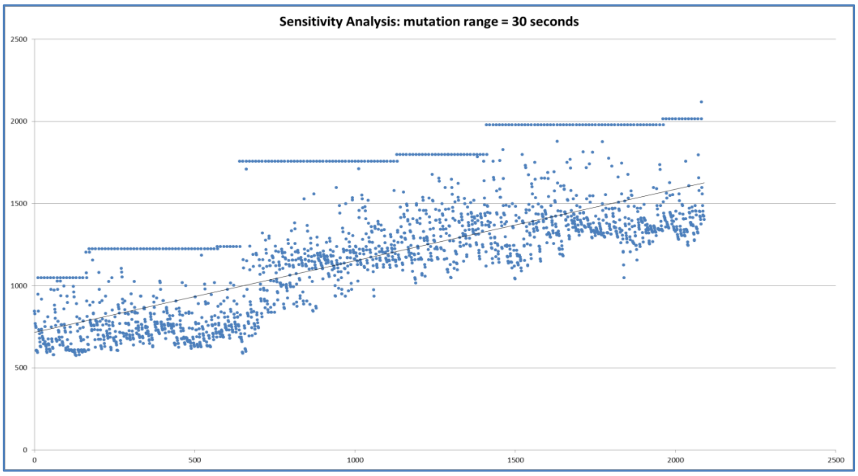

Fig. 2. Sensitivity analysis. Mutation range = 30s.

Fig. 1 and 2 show the effect of altering the mutation operator by a factor of ten. Fitness score is plotted vertically, with the number of generations horizontally. The best scenario is passed on unchanged to the following generation (leading to plateaus where no mutation improves the previous best). The ten best of each generation are also plotted showing that as evolution proceeds, in the case of the large mutation operator, the distance between the best and the next ten best fitness increases, indicating that the mutations are largely destructive in nature. Conversely, when a small mutation operator is used, the average fitness of the leading scenarios increases as the best of each generation increases, and the gap between them is much narrower, indicating that a mutation operator with a small range (therefore less destructive) will perform much better for our type of solution space.

In our paper we describe the evolutionary search used by ASHiCS to discover high risk configurations of air sector traffic. We provide arguments that show the use of destructive operators are unlikely to be effective in the type of high dimensional solution space represented by an air sector. The sensitivity analysis suggests that the solution landscape is composed of steep-sided, narrow peaks of high fitness, in which only very small mutations are likely to result in a fitness improvement. We believe this is an accurate characterization of the solution landscape, given that adjusting the start times of aircraft by just a few minutes can make a difference to conflict separation of several nautical miles.

In our more recent work, we have increased the complexity of our scenarios by adding storms represented by a series of timed no-fly zones whose speed and direction are configured by the evolutionary search. We further extended our study into the nature of the solution landscape by providing detailed information of nearby variants of the final scenario discovered by the search using a two stage process (this research is still in progress). The information from the second stage should allow safety analysts to examine input parameter ranges of high risk variants, enabling them to better judge the probability of hazardous situations occurring in the sector being modeled, leading to more accurate recommendations for the implementation of safety barriers.

Bibliography.

1. Koza, J., Keane, M., Streeter, M.: Evolving inventions. Scientific American, 52–59 (2003)
2. Fonlupt, C.: Book review: Genetic programming IV: Routine human competitive machine intelligence. Genetic Programming and Evolvable Machines 6, 231–233 (2005)
3. Alam, S., Zhao, W., Tang, J..: Discovering Delay Patterns in Arrival Traffic with Dynamic Continuous Descent Approaches using Co-Evolutionary Red Teaming. In : 9th ATM Seminar, Berlin (2011)
4. Alam, S., Lokan, C., Abbass, H.: What can make an airspace unsafe? characterizing collision risk using multi-objective optimization. In : IEEE Congress on Evolutionary Computation (CEC), 2012, pp.1-8 (2012)
5. White, D. R., Poulding, S.: A rigorous evaluation of crossover and mutation in genetic programming. In Vanneschi, L., Gustafson, S., A., D., Ebner, M., eds. : 12th European Conference, EuroGP 2009, Tübingen, Germany, pp.220-231 (2009)
6. Goldberg, D.: Genetic algorithms in search, optimization, and machine learning. Addison-Wesley (1989)
7. De Jong, K., Spears, W.: An analysis of the interacting roles of population size and crossover in genetic algorithms. In : Lecture Notes in Computer Science. Springer Berlin / Heidelberg (1991) 38-47
8. Lima, C., Goldberg, D., Sastry, K., Lobo, F.: Combining competent crossover and mutation operators: A probabilistic model building approach. In Beyer, H.-G., ed. : Proceedings of the 2005 conference on Genetic and evolutionary computation (GECCO '05), New York, pp.735-742 (2005)
9. Perrin, E., Kirwan, B., Stroup, R.: A Systemic model of ATM Safety: the integrated risk picture. In : 7th ATM Seminar, Barcelona (2007)
10. ARMS Working Group, 2007-2010: The ARMS Methodology for Operational Risk Assessment in Aviation Organisations. (v 4.1, March 2010)
11. Beyer, K., Goldstein, J., Ramakrishnan, R., Shaft, U.: When Is “Nearest Neighbor” Meaningful? In : Database Theory — ICDT’99: Lecture Notes in Computer Science. Springer, Berlin (1999) 217-235
12. Merz, P., Freisleben, B.: On the effectiveness of evolutionary search in high-dimensional NK-landscapes. In : Evolutionary Computation Proceedings, IEEE World Congress on Computational Intelligence, pp.741-745 (1998)
13. Anderson, D., Lin, X.: “A collision risk model for a crossing track separation methodology. Journal of Navigation 49(3), 337-349 (1996)