Aerial Spray Deposition Management Using The Genetic Algorithm

(Long Paper)

W. D. Potter, W. Bi,
A. I. Center
University of Georgia,
Athens, Georgia USA
potter@cs.uga.edu

D. Twardus, H. Thistle, M. J. Twery, J. Ghent,
USDA Forest Service

M. Teske
Continuum Dynamics
Princeton, NJ

Abstract

The AGDISP Aerial Spray Simulation Model is used to predict the deposition of spray material released from an aircraft. The prediction is based on a well-defined set of input parameter values (e.g., release height, and droplet size) as well as constant data (e.g., aircraft and nozzle type). But, for a given deposition, what are the optimal parameter values? This problem is considered to be a parametric design problem or more generally a configuration problem. Attempting to optimize a configuration based on some set of constraints is known to be extremely difficult (NP-Hard). We use the popular Genetic Algorithm to heuristically search for an optimal or near-optimal set of input parameters needed to achieve a certain aerial spray deposition. Having this knowledge can benefit forest managers substantially, especially regarding such issues as cost, environmental safety, and forest treatment accuracy.

Keywords: Genetic Algorithms, Aerial Spray Deposition, Parameter Optimization.

Introduction

Determining the parameter value settings to use as input to the AGDISP Aerial Spray Simulation Model [Bila89] in order to produce a desired spray material deposition is considered an instance of a parametric design problem [Davi91]. Parametric design is a specialization or subtype of the more generic design problem. Typically, when working on a design problem, the solution representation is a set of instructions or components for achieving the design goals. This representation can also be called a configuration, especially if the elements comprising the configuration are predefined. For the parametric design problem we are dealing with, these elements correspond to the AGDISP simulation input parameters. Each parameter has its own domain and range of values. If we arrange the parameters in a one-dimensional array or vector, and select some value for each parameter from that parameter's range then we would have an input parameter configuration. Using this configuration (set of values) as input to the AGDISP simulation model would yield a prediction of the spray deposition.

For this type of problem, the total number of possible configurations can be extremely large. For example, we can calculate this value simply by multiplying together the number of possible values for all of the parameters. That is, if there were twelve parameters, and each parameter had a range of twelve values then the total number of configurations would be 12^{12}. This is indeed a very large number. Now, if we wanted to find the best configuration to achieve a desired spray deposition, then we could enumerate all the possible configurations and run the simulation on each one to see which configuration gave the best deposition. Clearly, this sort of computational task is outside the scope of current computing technology. The configuration problem suffers from what is called combinatorial explosion, that is, as the number of elements increases (e.g., add more parameters), the number of possible

configurations also increases but at an exponential rate. See the discussion by Mittal and Frayman in [Mitt89] for more on generic configuration tasks and their complexity.

One method we can use to reduce the computational burden of finding a particular configuration is a heuristic search technique. Heuristic search techniques have been shown to be effective techniques for finding acceptable solutions to problems with very large solution spaces (total number of possible solutions or configurations). The major advantage of a heuristic approach is its speed. The major disadvantage is that there is no guarantee that the heuristic search will find the best solution or configuration. However, typically the solution found is of high enough quality that the trade-off is well worth it. In other words, we may not find the best solution but the solution we do find is typically good enough for our purpose and we found it very quickly. The heuristic search technique we use is the Genetic Algorithm. In the following sections we discuss in more detail the configuration problem, the genetic algorithm, the aerial spray deposition problem, and our approach to the problem along with some recent results.

Previous Work

In the development of a good heuristic approach, two methods or knowledge-based system approaches are available to us. These are the rule-based (experiential) approach using typical if-then rules, and the functional (deep or associative) approach based on knowledge about the structure and behavior of a system and its components (see [Chan83, Chan91] for more on the two general approaches). The functional approach follows the "reasoning from first principles" paradigm. This is quite different from the rule-based approach driven by "rules of thumb". Regardless of the approach, the major point of emphasis is the heuristic synthesis of a satisfactory solution or, in our case, a satisfactory configuration. Our Spray Advisor Genetic Algorithm (SAGA) approach, however, could be considered a combination of the rule-based and functional paradigms (although we do not have a typical collection of if-then rules, expert knowledge is incorporated into SAGA in the form of the sophisticated AGDISP simulation model). For a configuration application, synthesis means incorporating a given set of parameter settings and a set of constraints associated with the parameters into a configuration that satisfies the deposition goals and constraints. Synthesis can be thought of as the design of a solution.

Probably the most famous expert system to be developed for design applications is R1 (XCON) which is used to configure computer systems from customer specifications [Bach84, McDe81]. An early example of an engineering design system for configuring networks using heuristics is DESIGNET, developed by Bolt, Beranek, and Newman in the early 1980's [Mant86]. DESIGNET is a rule based design aid that focuses on an iterative user interface approach to configuration based on the process a decision maker goes through during the design process.

Our own experience with configuration deals with designing battlefield communication networks to support specific missions. Our system, called IDA-NET, configures a “shopping list” of communication equipment indicating type of equipment and number of components [Pott92]. The “shopping list” represents the required amount of equipment to support a particular mission. The goal is to minimize the number and types of components yet still satisfy a set of constraints associated with the mission, the equipment connectivity, and the available components in inventory.

Aerial Spray Models

For many years, computer simulation models for predicting what happens to spray material released from aircraft have been a major research interest of the USDA Forest Service [Teske98b]. The

Forest Service Cramer-Barry-Grim (FSCBG) aerial spray model [Teske89, Teske93a] and the Agricultural Dispersal (AGDISP) model [Bila89, Teske98a] are examples of this research. AGDISP simulates the effects of aircraft movement and wake on material released from the aircraft. The model predicts the behavior of spray material droplet movement when sprayed from an airplane or helicopter. FSCBG predicts the dispersion of the spray material and the deposition of the material (that is, how much material settles on the ground and where). Both models analyze the movement of the spray material above the forest canopy, the movement among the trees, and the amount of material that actually reaches the ground. Getting the spray material to reach the proper location depends on many factors. These factors include: (1) the altitude of the aircraft when the material is released, (2) the speed of the aircraft, (3) whether the aircraft is an airplane or a helicopter, (4) the type of boom and nozzle system used to discharge the spray material, (5) the swath width of each pass of the aircraft, (6) the type and density of the forest, (7) wind speed and direction, (8) relative humidity, and (9) spray material characteristics. Determining the optimal set of factors in order to provide accurate (getting the spray material exactly where it should be), and inexpensive (using the exact amount of material; not too much and not too little) spraying is the goal of our research. We are currently investigating the use of a genetic algorithm to determine the parameters.

The output of the various computer simulation models typically includes three important values: the deposition composed of volume median diameter (VMD) and drift fraction, and the coefficient of variance (COV). VMD is a measure of spray material droplet size. It is important to know the expected droplet size of the spray material as it leaves the aircraft nozzle, and also to know the droplet size that hits the ground. Variations in these two values are due to a number of factors including evaporation. Ideally, the spray material is evenly distributed over the entire spray block. The coefficient of variance gives an indication of the uniformity of the deposited spray material. The simulation models track the droplets leaving the aircraft and estimate the events encountered by the droplets as the make their way through the aircraft wake and descending onto the spray block (forest or crop area). Some of the spray material is likely to drift away from the target area onto adjacent lands. The amount of spray material deposited outside the spray block is identified via the drift fraction (smaller drift is better since that means the spray material stayed within the spray block or evaporated).

The Genetic Algorithm

Genetic Algorithms [Davi91, Gold89, Holl75] are heuristic search routines that are guided by a model of Darwin's theory of natural selection or the survival of the fittest. Here the fittest means the most highly ranked solution in a large solution space. The basic idea behind the genetic search strategy is to generate solutions that converge on the global maximum (i.e., the best solution in the search space) regardless of the "terrain" of the search space. A typical terrain might resemble the Great Smoky Mountains with many peaks and valleys, an area that is relatively flat, and a highest peak (Clingman's Dome). One characteristic of genetic algorithms is that they are relatively unaffected by hill-climbing or being misled by some local maximum such as ascending Mt. LeConte and assuming that you are on the highest peak in the Smokies since other nearby peaks appear lower, depending on visibility. Likewise, with genetic algorithms the key to finding the global maximum lies in the ability to evaluate and compare possible optimal solutions.

The basic operations involved in a genetic algorithm (GA) are: 1) mate selection, 2) crossover, and 3) mutation. Typically, the major data structure is a binary string representing the possible solutions. In GA terms, a bit string corresponds to an individual, and a set of individuals is called a population. The fitness or strength of an individual is computed using some objective or fitness function, and is used to

compare an individual with other individuals in the same population. During mate selection, parent strings are stochastically selected, according to their fitness, from the current population. Then, parent strings are "mated" via crossover to produce offspring for the next generation. Fitter parents contribute more offspring to the next generation than weaker parents because they have a higher probability of being selected for mating. This is the step that models the process of natural selection in nature.

Crossover, the second operation, determines the characteristics of a child or next generation individual. In nature, children inherit good as well as bad features of their parents in varying degrees of dominance. Crossover performs this same function in a GA. One of the simplest crossover approaches is to split each parent string at the same randomly chosen location and swap their tail sections. This ensures a certain amount of inheritance and ideally, the good/strong features will dominate the children. The inheritance of features that produce stronger children throughout the generations is the source of the GA's ability to converge on the global maximum in a relatively short time.

The last basic operation is called mutation. Mutation is that extremely rare "glitch" in the inheritance mechanism that introduces or modifies some feature with unpredictable consequences. Mutation occurs in a GA immediately after the creation of a next generation individual yet before the next generation has become static. Once the new generation becomes static, we move forward in order for it to become the new current generation. Ideally, mutants would contain some useful features that may have been inadvertently lost in earlier generations.

The simple genetic algorithm described in Goldberg follows these three basic steps [Gold89]. Additional operations and modifications are described as well. One major modification to the simple crossover approach, called two-point crossover, has been shown to be an easily implemented and effective alternate to simple crossover. With two-point crossover, an individual bit string is viewed as a ring and sections of parents are interchanged. This is like cutting equal sized sections from two donuts and swapping the sections to form a new (more appetizing) pair of snacks. Another effective crossover approach is the "greedy" approach described in [Liep90]. They report encouraging results using the "greedy" approach for general set covering problems. Other variations and improvements of the GA operators can be found in [Davi91, Jog89, Pott90, Pott91].

SAGA

Figure 1 shows the architecture for our spray advisor GA. The GA sends a set of AGDISP parameters to the AGDISP simulation model. The AGDISP model calculates and sends back the deposition (drift fraction and deposit VMD) and variation for each parameter set. Based on the fitness function values (the values range from zero to 10,000) mapped from deposition and the coefficient of variation, the GA evolves an improved set of parameters and sends it to AGDISP. This process is repeated from generation to generation for each individual in the population until a satisfactory deposition is found. The corresponding parameter set is returned as the proposed set-up to achieve the desired deposition. Currently, we focus on eleven specific parameters. The eleven parameters used in this study are listed in Table 1. Other less important or more static parameters are kept constant during our experiments. However, they can become part of the variable parameter set (i.e., we can easily include additional parameters to the parameter set we are searching for) by specifying them at the beginning of each SAGA run.

Table 1. SAGA Parameters and Their Ranges

PARAMETER	LOWER	UPPER
VMD Input (mm)	100	400
Nonvolatile Fraction	0.001	1.0
Wind Speed (m/s)	0.23	4.47
Temperature (degC)	1	30
Boom Height (m)	3	30
Swath Width (fraction of wingspan)	0.3	3.0
Humidity(%)	0.0	1.0
Aircraft ID Number	1	124
Boom Length (fraction of wingspan)	0.3	1.0
Number of Nozzles	1	60
Block Size (m)	50	1000

We use a variant component of AGDISP DOS Version 7.0 for the AGDISP computation engine in SAGA. AGDISP DOS Version 7.0 has several advantages including reading its input parameters from ASCII data files, displaying output information to the screen as the run proceeds, and writing deposition output to a text file. The variant we use is a special dynamic link library (DLL) version that allows SAGA to interface with the DLL through a system of procedure calls and message passing. This gives us with the ability to make full use of the AGDISP simulation model without having to deal with the standard AGDISP user interface. The DLL version also has direct access to the aircraft characteristics database (a file containing specific physical and flight characteristics of 124 recognized aerial spray aircraft), and to the spray materials database (a file containing the specifications for a variety of aerial spray materials such as fire retardants, pesticides, and herbicides). The DLL was developed using the FORTRAN programming language while SAGA (both the genetic algorithm search engine and the user interface) was developed using Microsoft Visual Basic 5.0.

The SAGA interfaces are shown in Figures 2, 3, 4, and 5. These interface windows are designed to provide users with flexibility and convenience to group user-defined GA parameters, preset necessary spray parameters, and dynamically view the output information. Detailed discussions of these user-friendly features are in the following sections.

Depending on the user's knowledge of genetic algorithms and the application purpose, the user can select either [Gypsy Moth GA Parameters] which is a parameter set especially for Gypsy Moth spray applications, [Cool GA Parameters] which is a set of recommended GA parameters for testing purposes, or the advanced [Customized Parameters]. If the user selects the [Customized Parameters], groups of GA parameters will be displayed (shown in Figure 3) and the user can modify the default settings according to their specific application needs.

In practical spray applications, it is quite common that some spray parameters can and should be fixed based on the spray requirements. We thus provide the option to preset certain spray parameters by selecting [Preset Parameters]. A new interface window will appear with the eleven spray parameters listed (shown in Figure 4). The user can select the ones to preset and fill in appropriate values. The rest of the parameters are left open to evolution by SAGA.

The bottom half of the main interface is designed to display intermediate results with two options provided. The first option allows the user to dynamically view the values of the eleven spray parameters

and the three spray results (shown in Figures 2 and 3). These values are associated with the best individual so far as the program evolves from generation to generation. This option is set as the default output mode. The user can also click on the [View Chart] button to switch the bottom half to a fitness growth chart with the maximum and average fitness values displayed dynamically (shown in Figure 5). The user can click on the [View Parameters] to return to the parameters option.

After the user finishes setting the GA and spray parameters, clicking on the [Run SAGA] button starts the run, or clicking [Reset Window] resets the parameters to their default values. Besides the spray parameters and results displayed dynamically in the main interface, the user can also click on [View Convergence Log] to look at a detailed report.

The Genetic Algorithm Used in SAGA

The Genetic Algorithm driver in this study originated from the Simple Genetic Algorithm (SGA) described by Goldberg [Gold89]. The GA initializes the first population with individuals generated at random. An individual corresponds to a set of AGDISP parameters. We made use of one of the convenient features of visual basic, the "Type" statement, to define a new data structure that consists of the eleven spray parameters (defined as a Single array), the three return values from the DLL, and the fitness value. This new data type is named "individual". We use a real number representation for the individuals.

As shown in Figure 3, we have various GA options that users can select from in order to set GA parameters for SAGA. The user can enter population size, generations, crossover probability, and mutation probability into the text areas. Each of these parameters has a default value, e.g., 100 for Popsize, 80 for Generations, 0.65 for Crossover Probability, 0.007 for Mutation Probability. For the GA operators, we provide several options. For the selection scheme, users can choose among Naïve Roulette Wheel selection, Tournament selection and Binary selection. For the crossover operation, users have the options of 1-point, 2-point, uniform, and average crossover. Detailed discussions of the working principles of these selection and crossover schemes are available in [Gold89]. We have Jump Mutation and Creep Mutation for mutation options. The former randomly selects a new value for a parameter within its valid range. The latter changes the old parameter by a small increment (error checking is added to make sure the new value is valid). Besides these basic GA parameters, we also add some other features such as Elitism, which will enable the GA to inherit the best individual from the previous generation when turned on. Another useful option is Fitness Scaling which is an advanced GA feature used to overcome "local maximum" convergence problems. With Elitism and Fitness Scaling turned on, SAGA normally converges in less than 30 generations. The GA population becomes basically homogenous after that and there is no necessity to run the program much longer. We thus provide a Stable Generations option so the user can specify how many stable generations (no changes in maximum fitness) are allowed before stopping SAGA. The current default value is ten. The user can also specify the tournament size used in the tournament selection scheme. The recommended value is two for selection in pairs.

Results and Discussion

For comparison and to test the feasibility of SAGA, we designed, with help from aerial spray experts, a pseudo exhaustive test. We fixed eight spray parameters and used the exhaustive combinations of the other three parameters. These eleven parameters were imported into AGDISP to produce batch results

and we used the same fitness function in SAGA to obtain their fitness value. The experiment took several days and the fitness results are listed in Table 2. It should be noted that this pseudo exhaustive experiment is dependent on the increment step adopted. Based on the precision requirements as well as the time limitation consideration, our pre-experiment conditions were as follows.

These spray parameters were fixed to these values.

DSD-VMD	100.0 micron
Temp	10.0 degC
Humidity	75.0
AircraftNum	7
BoomWidth	0.75
NumNoz	42
BlockWidth	400.0 m
SwathWidth	1.2 m

These parameters were allowed to evolve using these increment steps.

	Lower Bound	Upper Bound	Increment Step
NvFrac	0.001	1.0	0.05
Wind Speed	0.23	4.47	0.1
BoomHeight	3.0	30.0	1.0

We then ran SAGA with the same eight spray parameters set to the same values, and let SAGA evolve Non-Volatile Fraction, Wind Speed, and Boom Height to obtain their best values as well best spray results. Various crossover and mutation probability combinations were used. The fitness results are displayed in Table 3. Each experiment took about 1.5 hours to finish and the best result from SAGA was found among the top 0.1% of the exhaustive results. Table 4 shows a side-by-side comparison of best exhaustive with best SAGA results. These values are a good indication that SAGA is capable of finding near-optimal solutions for our spray application in a relatively short time.

Table 2. Top Ten Fitness Results from Exhaustive Experiment (8 fixed parameters)

No.	Best Fitness
1	9428.176
2	9427.911
3	9427.6
4	9427.257
5	9426.55
6	9426.434
7	9425.577
8	9425.041
9	9423.479
10	9422.863

Table 3. Fitness Results from GA Experiment (8 fixed parameters)

Xover/mut	0.001	0.003	0.007	0.01	0.02	0.03	Row Avg
0.60	9384.353	9329.302	9354.186	9345.647	9407.326	9416.380	9372.866
0.65	9322.343	9392.962	9399.037	9416.356	9406.362	9324.382	9376.907
0.70	9402.429	9400.000	9406.360	9387.536	9395.794	9351.680	9390.633
0.75	9403.283	9358.872	9401.998	9364.615	9404.165	9398.096	9388.505
0.80	9423.766	9411.717	9393.582	9413.530	9417.993	9397.563	9409.692
0.85	9321.064	9335.679	**9427.255**	9414.876	9396.127	9358.782	9375.631
Col. Avg.	9376.206	9371.422	9397.07	9390.427	9404.628	9374.481	

Table 4. Best Exhaustive and Best SAGA Comparison

	Exhaustive Test	GA Test
Maximum Fitness	9428.176	9427.255
Non-Volatile Fraction	0.78	0.789324
Wind Speed (m/s)	0.28	0.2823317
Boom Height (m)	6.100002	5.776807
Drift Fraction	3.087256E-02	2.968099E-02
COV	0.1648742	0.1667711
VMD (micron)	101.625	104.2233

With no spray parameters fixed, SAGA is expected to generate better results compared to those with certain parameter restrictions and, in fact, this is the case. The best fitness and the corresponding parameters we obtained are listed in Table 5.

Table 5. The Maximum Fitness from SAGA without Restrictions
(GA crossover probability=0.65 and mutation probability=0.007)

	Best Results
Maximum Fitness	9924.08
DSD-VMD (micron)	100
Non-Volatile Fraction	0.788
Wind Speed (m)	0.264
Temperature (degC)	4.941
Humidity (%)	62.71488
Aircraft	110
Boom Length (fraction of wingspan)	0.529
Nozzles	9
Boom Height (m)	7.086
Block Size (m)	964.9
Swath Width (fraction of wingspan)	0.543
Drift Fraction	0.00301
COV	0.0242
VMD (micron)	99.58

As shown in Figure 5, the expected spray droplet size is 100 microns (Drop Size Distribution). Small droplet sizes and higher non-volatile fractions are desired to avoid unnecessary evaporation and attrition loss. The non-volatile fraction of 0.788 corresponds to a high resistance to evaporation of the spray material. The weather conditions during spraying should approximate those shown: wind speed at 0.264m/s, temperature of 4.941 degrees, and relative humidity of 62.71488%. These parameters contribute to less spray evaporation and drift. The recommended aircraft number is 110, which refers to the Hiller FH 1100 airplane. The ratio of boom length to aircraft wingspan is recommended to be 0.529, and the ratio of swath width to wingspan should be 0.543 (actually, not a very practical setting since narrower means more swaths). The aircraft boom should have nine nozzles to spray the material. The recommended boom height, which refers to the height of the aircraft above the forest canopy, should be 7.086m. The ideal spray area should be a square with 964.9m edges.

Based on these spray parameters, the best spray result we obtain has a very low drift fraction 0.00301. An important goal is to minimize drift loss in order to reduce waste and achieve better spray coverage. COV is found to be 0.0242. The low value of COV is desired in order to achieve even distribution of the spray material. The simulated VMD is 99.58 micron, which is very close to the desired size. This indicates there is little evaporation or attrition loss of the spray droplets. Taken as a whole, these values indicate that the GA is capable of finding highly fit sets of parameters. However, in practice, there are typically several constraints to deal with in the spray scenario. In any case, the GA is highly robust and finds highly fit settings as shown below.

We also ran two groups of experiments based on the practical spray parameter specification scenarios provided by USDA Forest Service experts. The maximum fitness obtained based on the first group of specifications was 9710.885 and the spray parameters corresponding to this maximum fitness are listed in Table 6. Detailed results are listed in Table 7. DSD-VMD, Aircraft, Block Size and Swath Width were fixed in this case, which is very typical.

Table 6. Experiment 1: Practical Settings with Maximum Fitness = 9710.885

Evolving Param:	NvFrac	WindSpd	Temp	Humidity	BoomLen	Nozzles	BoomHeight
	0.853028	0.251727	24.65103	66.68903	0.60416	29	3.218699
Fixed Param:	DSD-VMD	Aircraft	Block Size	Swath Width			
	100	6	400	1.2			

Table 7. Experiment 1: Practical Settings Details

Crossover	Mutation	Max Fit	DriftFrac	COV	VMD
0.65	0.007	9681.238	0.024264	0.075137	102.1929
0.65	0.02	9521.977	0.043287	0.104543	100.3391
0.7	0.007	9669.712	0.028459	0.082142	100.5931
0.7	0.02	**9710.885**	0.022601	0.064461	102.2375
0.75	0.007	9651.816	0.028348	0.080639	101.5573
0.75	0.02	9574.656	0.026514	0.117077	100.2037
0.8	0.007	9609.734	0.033884	0.086671	101.4445
0.8	0.02	9691.885	0.021839	0.07862	100.6032
0.85	0.007	9694.788	0.025709	0.070153	100.8018
0.85	0.02	9639.846	0.033055	0.077817	99.59053

The second group of experiments had the highest fitness of 9750.743; its corresponding spray parameters are listed in Table 8. Detailed results are listed in Table 9. DSD-VMD, Aircraft, Block Size and Swath Width were fixed in this case.

Table 8. Experiment 2: Practical Settings with Maximum Fitness = 9750.743

Fixed Param:	DSD-VMD	NvFrac	WindSpd	Humidity	Temp	Nozzles	Block Size
	200 micron	0.45	0.5m/s	75%	10degC	6	400m
Evolving Param:	Boom Height	Boom Length	Aircraft	Swath Width			
	4.232688	0.321571	7	0.697707			

Table 9. Experiment 2: Practical Settings Details

Crossover	Mutation	Max_Fit	DriftFrac	COV	VMD
0.65	0.007	9643.027	0.010314	0.065517	217.0752
0.65	0.02	9021.266	0.040434	0.096909	234.6726
0.7	0.007	9623.292	0.014304	0.063063	217.4393
0.7	0.02	9250.907	0.028835	0.098085	227.8699
0.75	0.007	**9750.743**	0.074591	0.030589	216.6913
0.75	0.02	9642.524	0.011115	0.06124	217.5165
0.8	0.007	9642.524	0.011115	0.06124	217.5165
0.8	0.02	9263.371	0.029171	0.099688	227.102
0.85	0.007	9263.371	0.029171	0.099688	227.102
0.85	0.02	9551.506	0.011498	0.071744	221.0305

These results were evaluated by forest experts and regarded as excellent predictions with high practical importance. More experiments are to be run to test other scenarios and the results are expected to assist practical spray applications, including selecting optimal spray conditions, estimating spray results, reducing spray cost, and minimizing spray drift.

We ran numerous experiments to determine which GA parameters appeared to produce the best results. The selection of GA parameters such as population size, number of generations, crossover type and probability, and mutation probability is a key facet of the speed and success of the evolutionary process. These parameters are typically domain dependent. Similar experiments were run to help determine values for other GA parameters. Our current GA parameter setup includes a population size of 100, between 50 and 100 generations, a crossover probability between 0.65 and 0.85, and a mutation probability between 0.005 and 0.02.

Another key issue in the development of SAGA is the mapping of the drift fraction, COV and VMD onto the fitness function. Our goal is to minimize the drift fraction, minimize the COV, and minimize the difference between the output VMD and the desired VMD. That is, get the exact amount of spray material evenly distributed over the spray block with the least loss due to evaporation and attrition. Our current fitness formulation is given below. Drift fraction has a higher weight because our main goal is to reduce drift and maximize deposition.

$$Fitness = 100 \times \left\{ [50 \times (1.0 - DriftFrac)] \times [25 \times (1 - COV)] \times \left[25 \times \exp\left(-8.0 \times \left(\frac{VMD}{VMDCenter} - 1 \right)^2 \right) \right] \right\}$$

We are currently working to incorporate AGDISP parameter dependencies and practical application considerations (spray knowledge) into a revised fitness measure. We are also working to improve the GA computing engine to produce better results faster. Our proposed new features include Engineered Conditioning [Pott91] and other Fitness Scaling methods besides the linear scaling we are using now. Due to historical and technological reasons [Park82], COV is recommended to be close to 0.3. Once we have sufficient reliability with SAGA, we plan to investigate the appropriateness of this rule-of-thumb constant. Our progress so far is promising, we expect to make SAGA more comprehensive and reliable by combining feedback from forest managers and catering to the practical needs of aerial sprayer applicators. Our long-term goal is to make SAGA an instrumental tool for aerial spray applications.

References

[Bach84] Bachant, J., and J. McDermott (1984). "R1 Revisited: Four Years in the Trenches," in *AI Magazine*, Vol. 5, No. 3.

[Bila89] Bilanin, A. J., M. E. Teske, J. W. Barry and R. B. Ekblad (1989). "AGDISP: The Aircraft Spray Dispersion Model, Code Development and Experimental Validation". *Transactions of the ASAE* 32(1):327-334.

[Chan83] Chandrasekaran, B., and S. Mittal (1983). "Deep versus Compiled Knowledge Approaches to Diagnostic Problem Solving," in the *International Journal of Man-Machine Studies*, Vol. 19, No. 5, pp. 425-436, November.

[Chan91] Chandrasekaran, B. (1991). "Models Versus Rules, Deep Versus Compiled, Content Versus Form," in *IEEE Expert*, Vol. 6, No. 5, April.

[Davi91] Davis, L., (ed.) (1991). *Handbook of Genetic Algorithms*, Van Nostrand Reinhold, New York.

[Gold89] Goldberg, D.E. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley Publishing Co.

[Holl75] Holland, J.H. (1975). *Adaptation in Natural and Artificial Systems*, Ann Arbor: The University of Michigan Press.

[Jog89] Jog, P., J.Y. Suh, and D.V. Gucht (1989). "The Effects of Population Size, Heuristic Crossover and Local Improvement on a Genetic Algorithm for the Traveling Salesman Problem," in the *Proceedings of the 3rd International Conference on Genetic Algorithms*, Morgan Kaufmann Publishing, San Mateo, CA.

[Liep90] Liepins, G.E., M.R. Hilliard, J. Richardson, and M. Palmer (1990). "Genetic Algorithm Applications to Set Covering and Traveling Salesman Problems," in *OR/AI: The Integration of Problem Solving Strategies*, (Brown, ed.).

[Mant86] Mantelman, L. (1986). "AI Carves Inroads: Network Design, Tes
Data Communications, pp. 106-123.

[McDe81] McDermott, J. (1981). "R1: The Formative Years," in *AI Magazine*, Vol. 2, No. 2.

[Mitt89] Mittal, S., and F. Frayman (1989). "Towards a generic model of configuration tasks," in the *Proceedings of the Eleventh International Joint Conference on Artificial Intelligence*, Vol. 2, pp. 1395-1401.

[Park82] Parkin, C.S., and J.C. Wyatt (1982). "The Determination of Flight-Lane Separations for the Aerial Application of Herbicides," in *Crop Protection*, 1 (3), pp. 309-321.

[Pott90] Potter, W.D., J.A. Miller, and O.R. Weyrich (1990). "A Comparison of Methods for Diagnostic *Expert Systems with Applications: An International Journal*, vol. 1, pp. 425-436.

[Pott91] Potter, W.D., J.A. Miller, B.E. Tonn, R.V. Gandham, and C.N. Lapena (1991). "Improving the Reliability of Heuristic Multiple Fault Diagnosis Via The Environmental Conditioning Operator," in the *International Journal of Applied Intelligence*, vol. 2, pp. 5-23.

[Pott92] Potter, W.D., R. Pitts, P. Gillis, J. Young, and J. Caramadre (1992) "IDA-NET: An Intelligent Decision Aid for Battlefield Communication Network Configuration," in the *Proceedings of the Eighth IEEE Conference on Artificial Intelligence for Applications* (CAIA'92), pp. 247-253.

[Teske89] Teske, M.E., Curbishley, T.B. (1989), "Forest Service Aerial Spray Computer Model FSCBG -06.

[Teske93a] Teske, M.E., Bowers, J.F., Rafferty, J.E., and Barry, J.W., (1993). "FSCBG: An Aerial Spray Dispersion Model for Predicting the Fate of Released Material Behind Aircraft" in *Environmental Toxicology and Chemistry*, Vol. 12, pp. 453-464.

[Teske93b] Teske, M.E. and J.W. Barry (1993). "Parameter Sensitivity in Aerial Application" in *Transactions of the ASAE*, Vol.36(1), pp. 27-33.

[Teske98a] Teske, M.E. (1998) "AGDISP DOS Version 7.0 User Manual".

[Teske98b] Teske, M. E., H. W. Thistle and B. Eav. (1998a) "New Ways to Predict Aerial Spray *Journal of Forestry* 96(6):25-31.

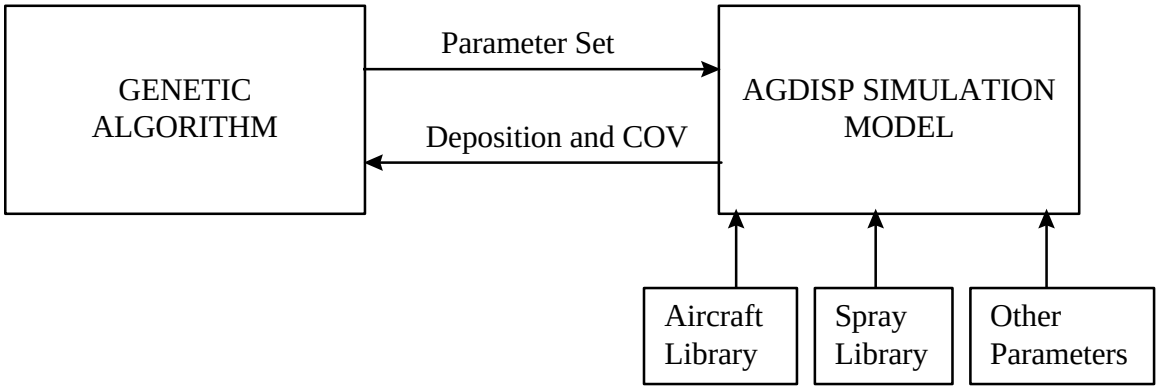

Figure 1. SAGA Architecture.

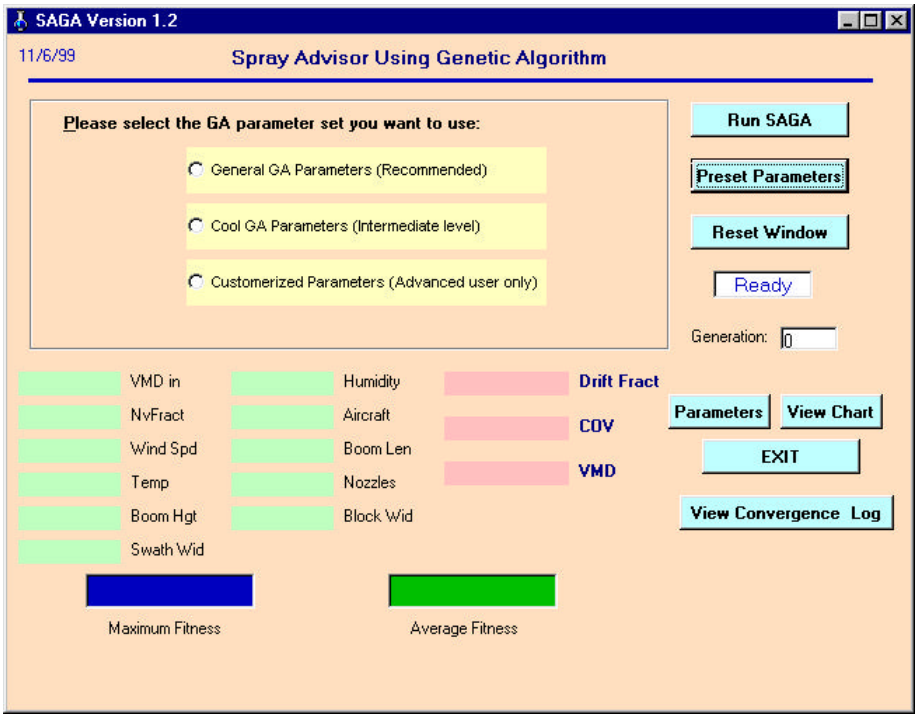

Figure 2. SAGA Main Interface

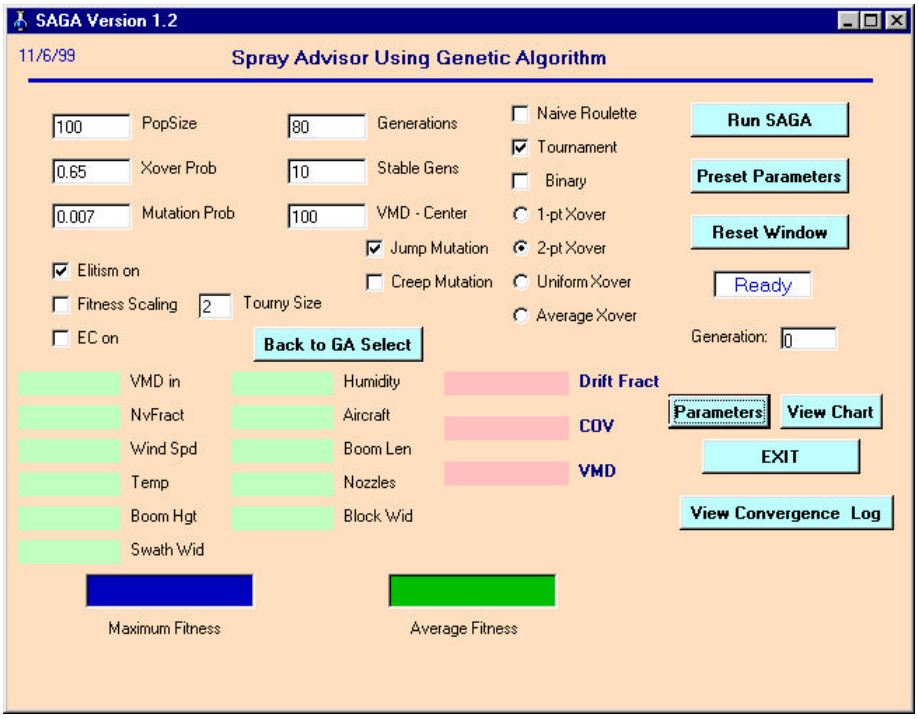

Figure 3. SAGA Main Interface with Customized GA Parameter Settings

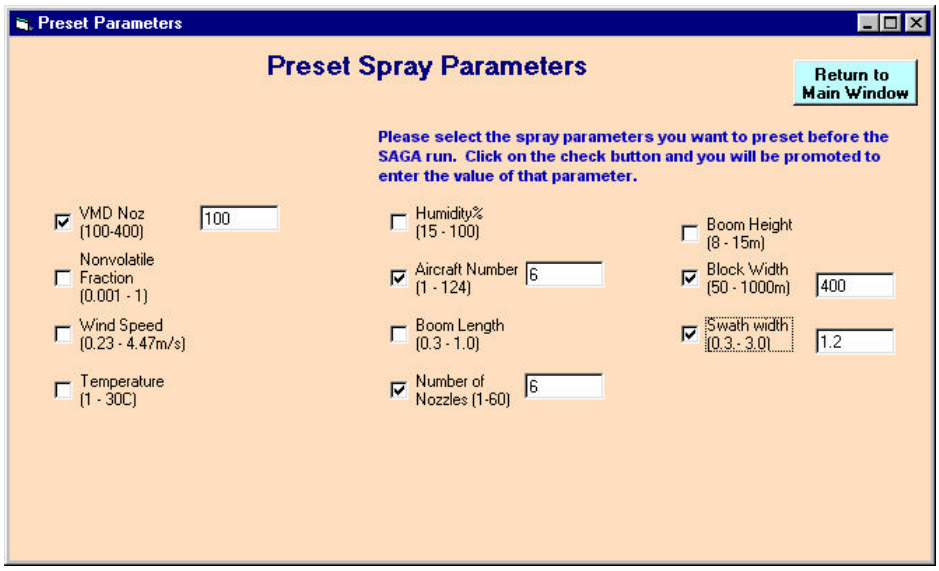

Figure 4. SAGA Secondary Interface to Preset the Spray Parameters

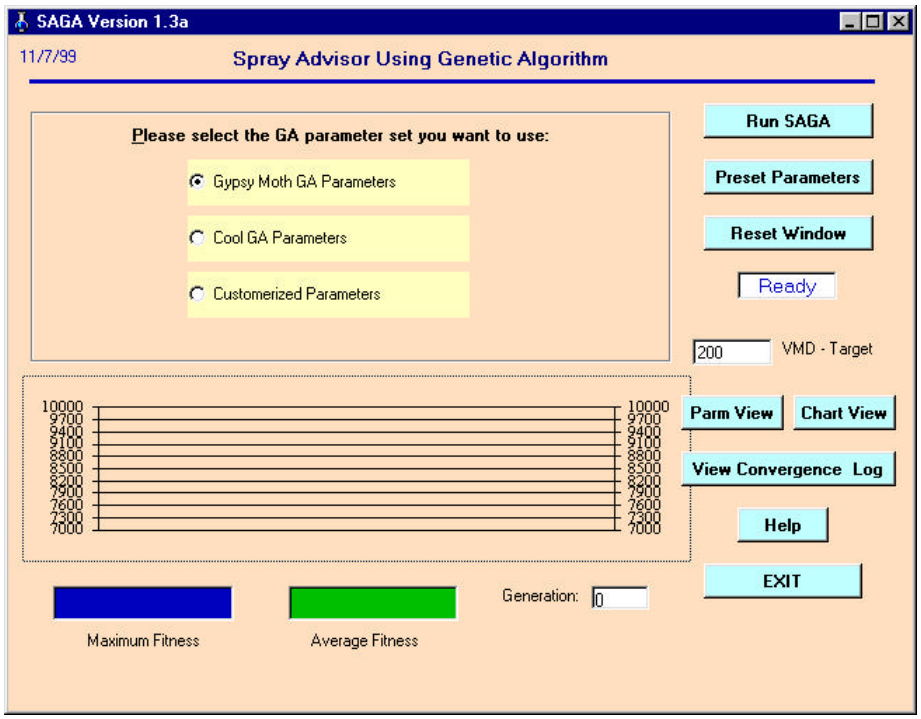

Figure 5. SAGA Main Interface with Chart View Option On