

Maximising the Efficiency of Bio-Control Application Utilising Genetic Algorithms

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Abstract

In the domain of mushroom farming, sciarid flies can adversely affect the quality of crop produced. One solution to this problem is the use of a bio-control agent to reduce, and ideally eliminate the presence of this pest. The nematode worm *Steinernema feltiae* provides an effective control agent against the sciarid flies. In order to maximise the effect of this agent, while also minimising the quantity of the agent required, an optimal application schedule is necessary. Our work addresses the use of Genetic Algorithms (GAs) to produce optimal bio-control application schedules.

Key words: Bio-Control, Genetic Algorithms, Scheduling.

1 Introduction

Sciarid fly larvae feeds on the mycelium layer of mushrooms causing gross deterioration of the crop. Although many approaches could be implemented to resist this pest, the nematode worm *Steinernema feltiae* has proven to be an effective bio-control agent. There is however a cost associated with using this agent, and thus its usage becomes an optimisation problem. The mushroom farmer requires the minimal use of the agent (due to its cost in both application time and money), while also maximising its application efficiency and the quality of crop produced.

Genetic Algorithms (GAs) have been used to optimise an array of problems, and as such appear to offer much to the mushroom farmer for optimising the schedule of nematode applications. GAs are a stochastic search heuristic, which have proved effective in optimising scheduling problems such as the administration of drug treatments for cancer chemotherapy (Petrovski et al, 1998, McCall et al, 1999). Although bio-control is a distinctly different application area, the underlying principles of optimising the effect of an agent while reducing the dosage level required have many similarities.

2 Mathematical model for sciarid fly levels

Recent work (Fenton et al, 2002) has produced a generalised model for the lifecycle of sciarid flies, which includes potential infection from *Steinernema feltiae*. This model is represented by a set of differential equations which calculates the lifecycle of the sciarid flies as they change from eggs to larvae, from larvae into pupae, and finally from pupae into adults, which subsequently lay more eggs. This lifecycle is shown in Figure 1. Although Fenton et al's model defines the number of sciarid flies present, we have extended this further to include a penalty cost associated with each application of the bio-control agents. This penalty represents the time and cost for the farmer in purchasing and applying the nematodes.

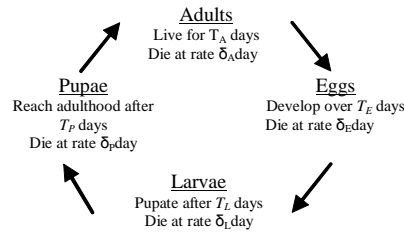


Fig. 1. The sciarid fly lifecycle. The full life cycle of the sciarid fly takes place over $T_E + T_L + T_P + T_A$ days.

3 Genetic Algorithms

GAs are a stochastic search heuristic based on Darwin’s theory of evolution. Although simple in premise, they have been used to solve a wide array of problems, throughout a plethora of application areas. They follow a simple process of creation, selection, crossover, mutation and recombination. In order to ascertain the quality of solutions, each candidate solution is passed through a fitness function to provide it with an associated fitness score, showing how good the encoded solution is. The fitness function for this work is shown in (1) where T is the number of days in the schedule, $L(t)$ is the larvae in existence at time t , N is the number of interventions used and P is the penalty per intervention.

$$F = \sum_{t=0}^T L(t) + NP \quad (1)$$

During the GA creation phase, a population of solutions is constructed, where each solution is a potential bio-control application schedule. These are evaluated using the fitness function to provide a score of their effectiveness. Solutions are then selected for breeding, based on their fitness and new solutions are produced via a crossover process, which splices the genes from solutions chosen to breed to produce another generation of solutions. Mutation can then modify these new solutions further by introducing new material into them. Finally, the new solutions are inserted into the population, replacing less fit solutions from the previous generation. This process continues until a target solution is found or for a specified number of generations.

We have conducted experiments using a traditional form of GA and also our own variations, and measured the potential of the approaches for optimising scheduling of crop spraying.

4 Results

This research is still in its early stages; however, preliminary results appear very promising. GAs provide an efficient approach to searching the vast spread of potential solutions (e.g. over a 50 day schedule, allowing for 1 application per day, there exists 50^{50} solutions, equating to 8.881×10^{84}) and early results from our novel crossover techniques seem to improve this process further. Through utilising GAs in this domain, we hope to provide mushroom farmers with a tool to calculate optimal bio-control schedules, thus facilitating a higher return on each crop produced with regard to profit, and also ensuring that the farmer is required to apply the bio-control agent as rarely as possible, thus maximising their time.

5 References

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