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Mathematical Modeling for an Artificial Eco–System in Wild Life

Rajan Singh*[1], Nidhi Tiwari[2], B K Singh[3], Nidhi Prabhakar[4], Anshul Dubey[5], Deepak Sharma[6], R. B Tiwari[7]

[1,2,3,4,5,6,7]Department of Mathematics, IFTM University, Moradabad-244102, Uttar Pradesh, India.
Corresponding Author: rajansingh@iftmuniversity.ac.in

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ABSTRACT

In this paper an attempt has to be made to describes in investigation. This paper describes an investigation in which a genetic algorithm is used to simulate an artificial environment in which various species compete with one another. Each species that exists on this planet is the product of millennia of natural selection. Competition for finite resources has produced varied species, many of which exhibit specialized behavior that allows them to survive. Genetic algorithms acting upon a randomly chosen population, and competing for finite resources should produce a near–maximal biomass, with several distinct species exploiting different levels of the bio system. Utilizing reproduction, crossover, mutation and inching operators, the coding scheme could preserve diversity in predator/prey populations and mass while maximizing biomass and sensory performance within the population, particularly in a static environment.

Keywords: Mathematical Modeling, Differential Equations, Genetics Algorithms, Artificial Ecosystems, Population Dynamics.

1. INTRODUCTION

Darwin’s theory of evolution concludes that natural selection is the key factor in the origin of species. Within species, an individual, that reproduces passes on its genetic characteristics. Individuals that possess ‘favorable’ traits are more likely to survive, hence future generations increasingly exhibit ‘favorable’ traits. Given time, a population’s characteristics can diverge significantly from their original makeup. Examining the machinery of natural selection can lead to keener appreciation of complex interactions that shape life. Because genetic algorithms are based from the mechanisms of reproduction, they provide a clean analogy to how real populations can evolve over successive generations. Field observations yield glimpses of natural selection’s capacity to produce populations that fully exploit their environment. In the real world, this proceed takes millennia. A simulated ecosystem, with a diverse initial population, offers a means to view the effects of evolution over hundreds or thousands of generations. The recombination of individuals via a genetic algorithm provide an elegant means of rewarding variations that maximize their environment. This chapter will examine a simulated ecosystem of herbivores and carnivores. Each individual will have several characteristics that shall determine the relative success or failure of each organism within the environment. The GA operators of reproduction, crossover, mutation, and niching will operate on a multi parameter coding. Organisms that can successfully adapt to their environment will be favored within the reproductive pool. ‘Winning’ populations will have the greatest increase in mass, with the population existing near the ideal carrying capacity of the environment.

About the Work

There have been numerous works published on simulated organisms and ecosystems. Mechanisms of cell chemistry were examined by Rosenberg [18], which simulated enzyme reactions using genetic algorithm like operators. The Avida simulated ecosystem shows support for the punctuated equilibrium view of evolution, as opposed to a more Darwinian gradual model of evolution given by Adami, C.T., Brown M & Haggerty, J. 2].An artificial life program called Tierra is used to model both small and large scale ecosystems. Tierra utilizes genetic algorithms to simulate evolutionary change by Ray. T. [19] the tierra system creates a diverge population of organisms, but does not optimize resources by the population as a whole. To examine this problem, it is useful to look at models of population interaction. Two primary engines of ecological change are predation and competition. Ten components of functional response to prey and predation given by Kitching, R. L. [14] are:

1. The role of successful search
2. Time of exposure
3. Handling time (time taken to eat)
4. Hunger
5. Learning by predator
6. Inhibitions of prey
7. Exploitation
8. Interference between predators
9. Social facilitation
10. Avoidance learning by prey

Each factor has sub–factors. For instance successful search involves sensory facility, reaction distance, speed to predator speed of them and capture success. Relationships are drawn between density of predators density of resources, probability of attack, time spent in attack, expected gain and number of attacks to derive a success ratio of predation. Smith [21] draws the conclusion that species that spend most of their time searching for food that takes little effect to capture, will be generalists (e.g. hyenas), while species that have abundandent prey that takes much effort to capture will be specialists (e.g. cheetahs). Specialization leads to speciation. Sub–populations which converge at multiple along the spectrum of the initial population will eventually stop sharing genetic information with other sub–populations.

Problem Statement

The simulated ecosystem will have three components – an environment, a randomly chosen initial population of herbivores and carnivores with varied characteristics, and a set of rules governing the success or failure of organisms within the ecosystem. The environment has two component values carrying capacity and flora color. Carrying capacity refers to the kilograms of vegetative matter available for consumption by herbivores and for purposes of the simulation is the product of random fluctuations of rainfall and temperature. Flora color refers to the predominant shade of the vegetation, and is expressed in terms of red, green and blue primaries that allow for colors from black to white. Carrying capacity or flora color may be varied during the course of the simulation.

The population will consist of randomly chosen individuals with the following coding scheme:

Food Source – 0 (Herbivore), 1(Carnivore)	1 byte
Ideal Body Weight of adult–5 to 500 kilograms	5 bytes
Color–Red, Green and Blue values from 0 to 256	6 bytes
Number of Legs–2 or 4 legs	1 byte
Vision–Ranging from 0(poor) to 7(great)	3 bytes
Hearing–Ranging from 0(poor) to 7(great)	3 bytes
Brain size–Ranging from 0(minimal) to 3(Human like)	5 bytes
Total:	24 bytes

Individuals are allowed to mate freely among all members of their respective herbivore or carnivore population, subject to the constraints of the fitness evaluation algorithm.

The fitness algorithm measures the competitiveness of an individual measured against his peers. In predator / prey systems prey animals in the absence of predators will show a proportional growth rate. Predators introduced into a prey–rich environment will show a high growth rate and will slow the prey growth rate. An overabundance of predators will lead to declining numbers of prey, which will, in turn, reduce the number of predators. Lotka–Volterra's equations is the basic growth relationship between number of herbivores (H) and carnivores(C).

$$\frac{dH}{dt} = aH - bHC$$
$$\frac{dC}{dT} = -cC + dHC$$

Where *HC* is the success rate of predation, and *a*, *b*, *c*, *d* are proportionality constants. *HC*, as defined by Kitching, is a function of several parameters such as detection success, learning by prey and predator and hunger. Therefore. Our fitness algorithm must take into account the factors that lead to the success of predation. Four different functions are used to determine individual success.

(1) Herbivore feeding requirements – Herbivores require an amount of food proportional to their mass, $m^{0.75}$ Food–rich environments favor larger animals, while food–poor environments will favor smaller animals. Accordingly, the success rate of foraging is:

$$f = \left(\frac{K}{Eh}\right) * \left(b * m^{0.75}\right)$$

K = the carrying capacity of the environment
Eh = energy requirement of all herbivores
b = proportional constant
m = the mass of the individual

This function determines the ability of the individual herbivore to successfully forage for food. Animals that are well fed are less likely to be caught by predators.

(2) Carnivore feeding requirements – Carnivores also require food proportional to their mass, $m^{0.75}$. Because they can convert 10% of herbivore mass into energy, their success rate for foraging is :

$$f = \left(\frac{Mh}{10}\right) / \mathrm{Ec}^{*}\left(d * m^{0.75}\right)$$

Mh = Mass of herbivores
Ec = Energy requirements of all carnivores
d is a proportional constant

Similar to herbivores, this function also shows the success that a well fed predator is likely to have, vis–a–vis, his starving brethren.

(3) Detection success ratio – The ability of an animal to make or escape detection depends upon their sight (s), hearing (h) and camouflage (c) compared to their opponents.

Herbivore = $x(s = S) + y\left(\frac{h}{H}\right) + zc$

Carnivore = $i\left(\frac{s}{S}\right) + j\left(\frac{h}{h}\right) + kc$

S,*H* are mean population values for sight and hearing
i, j, k, x. y. z are proportional constants
These factors play into the role of successful search and time of exposure. Again, both equations show how an individual must do better not only in absolute terms, but in terms of the competition.

(4) Intelligence success ratio – The intelligence of an individual relative to their opponents. Highly intelligent bipedal organisms are given additional credit for tool–use capability.

$$i = \left(\frac{b}{B}\right)(g\, c)$$

b is brain size of individual
B is average brain size of population
g is a proportionality constant
c is 1 for two legged animals, 0 for four legged animals.

Intelligence is a grab–bag of all of the individual's various abilities to out–wit the opponent. The sum of the criteria produces the fitness value for the organism. The fitness value reflects the innate ability of an individual to survive the effects of environment and predation. For herbivores, this means the ability to avoid predators while successfully competing for limited forage resources. Carnivore fitness is measured by the ability to catch the prey and fend off fellow carnivores. Once determined, a stochastic remainder selection utilizes the fitness values to reproduce and crossover the fittest individuals. A mutation operator randomly modifies alleles during crossover. The population size will be determined each generation. First, the carrying capacity of the environment is determined for each round simulating the random effects of sunshine and rainfall. This value, taken in conjunction with the total mass of herbivores from the prior round, will determine the current round's population size. Reproduction and crossover will fill all of the available slots in the population according to the dictates of the fitness function for herbivores and carnivores. Because the amount of food available to sustain the population is variable particularly for carnivores wild swings in food supply could wipe out a particular food source. A photo types speciation operator smoothes fitness functions based upon food source mass Animals with different food sources are considered dissimilar. Mass is apportioned with a linear smoothing. This accords well with common sense, since mating individuals that range in size from 5 to 500 kilograms which might be inclined to eat the mate are unlikely at best. The expectation is that species should form based upon food source and mass. Within each species, there should be improvement in the quality of its individuals, with optimizations of prey and predator near the carrying capacity of the environment.

2. RESULTS

The following parameters were used in all tests:

Initial Population size	25
Generations	100
Prob. of Crossover	0.6
Prob. of Mutation	0.001

Two series of tests were conducted. In the first test, the carrying capacity remained constant, which led to a static population size. In the second test, the carrying capacity could vary as much as 66% from one generation to another, with the population size varying as well. For the first test, the carrying capacity remained constant at 1500 kg, and the population size was 25. For all individuals, the allele values were randomly selected. Figure 5.1 tracks the absolute variance between ideal total mass and actual total mass of herbivore and carnivores over 100 generations. Over succeeding generations, the population converged to approximately 1% variance, while allowing for crossbreeding of herbivores and carnivores. The average fitness value of all generations can be seen in Fig. 5.2. A 100% improvement in total fitness occurred over 100 generations due to maximizations of values for sight, hearing, color and brain size. The speciation algorithm helped to maintain a relatively static number of carnivores and herbivores, with the quantity of either food type fluctuating between 8 and 17 for most of the simulation. At 100 generations, the range of individual's mass still ran from 160 to 420 kg. The average mass had gone from 260 kg initially to 320 kg at the end, reflecting the higher mass requirements of the herbivore population. Carnivores, which depended on herbivores for their food, tended to remain at a lower weight. The average value for vision went from 3.7 to 7. The average value for hearing went from 2.7 to 6.7. Brain size went from 13.4 to 29.2. Color went from an even distribution to varying shades of green. The number of legs per individual went from an even distribution to 90% 2–legged, reflecting greater tool use. The second series of tests examined various carrying capacities and population sizes. The carrying capacity was allowed to range over 1000 – 1500 kg for each generation. The population size was incremented or decremented in proportion to the carrying capacity. Again allele values were selected randomly. Figure 5.3 tracks the absolute variance between ideal total mass and actual total mass of herbivore and carnivores over 100 generations. Over succeeding generations the variation did evidence some smoothing but remained overall at approximately the 10% level. The average fitness value of all generations can be seen in fig. 5.4. A 350% improvement in total fitness occurred over 100 generations due to near maximizations of values for sight, hearing, color and brain size. The speciation algorithm helped to maintain the relative proportion of carnivores and herbivores, although variances were higher than in the static algorithm. Because the food requirements had a much greater range, the mass of individuals also evidenced a greater range, from 20 to 420 kg. The average mass, which started at 260 kg. Finished at 275 kg. The distribution contained substantial accumulation at either extreme. The values for sight, hearing, brain size and color mimicked the results of the static run, showing good optimization performance.

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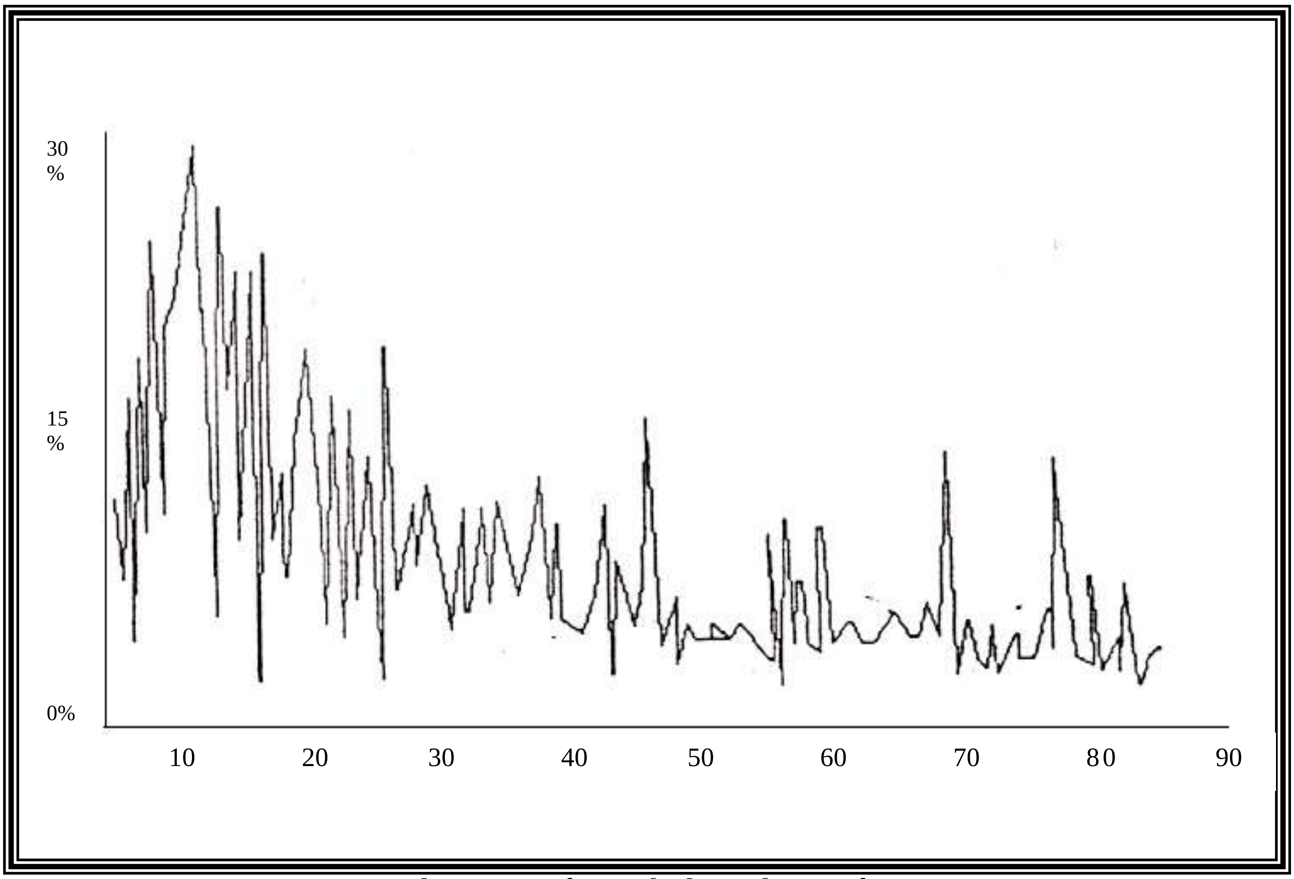

Fig. 5.1 Actual Variance from Ideal Total Mass for Static Environment

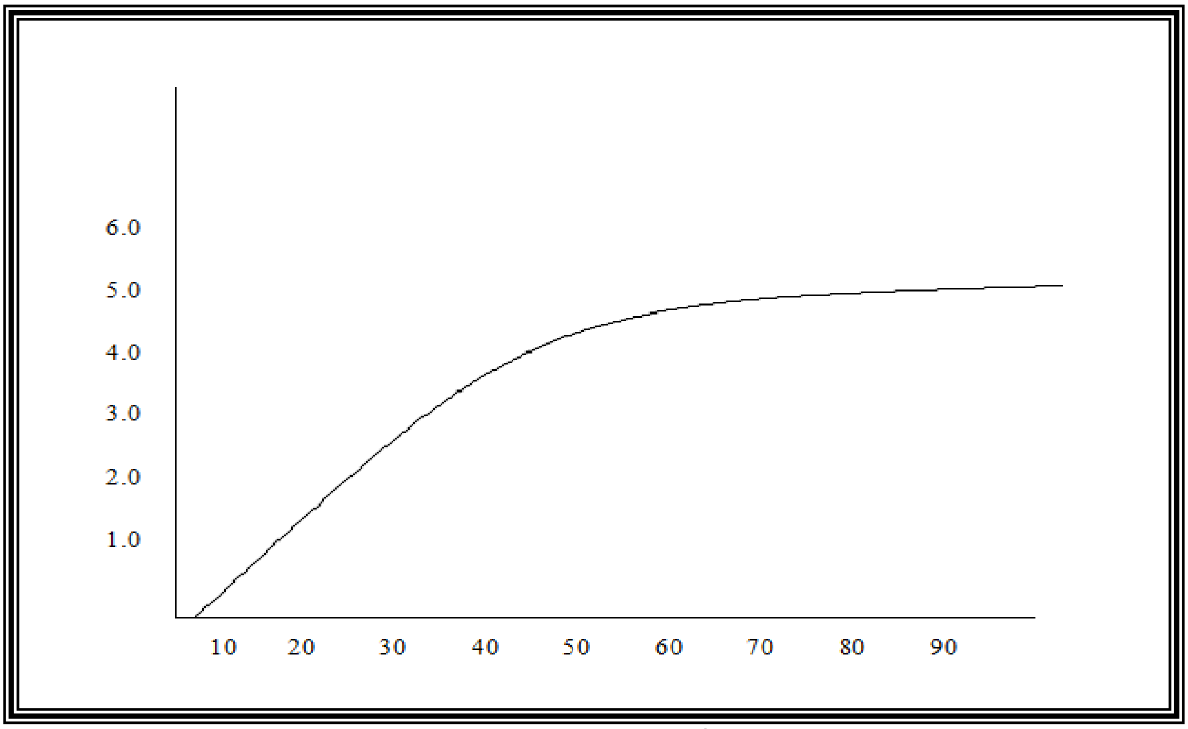

Fig. 5.2 Average Fitness Value for Static Environment

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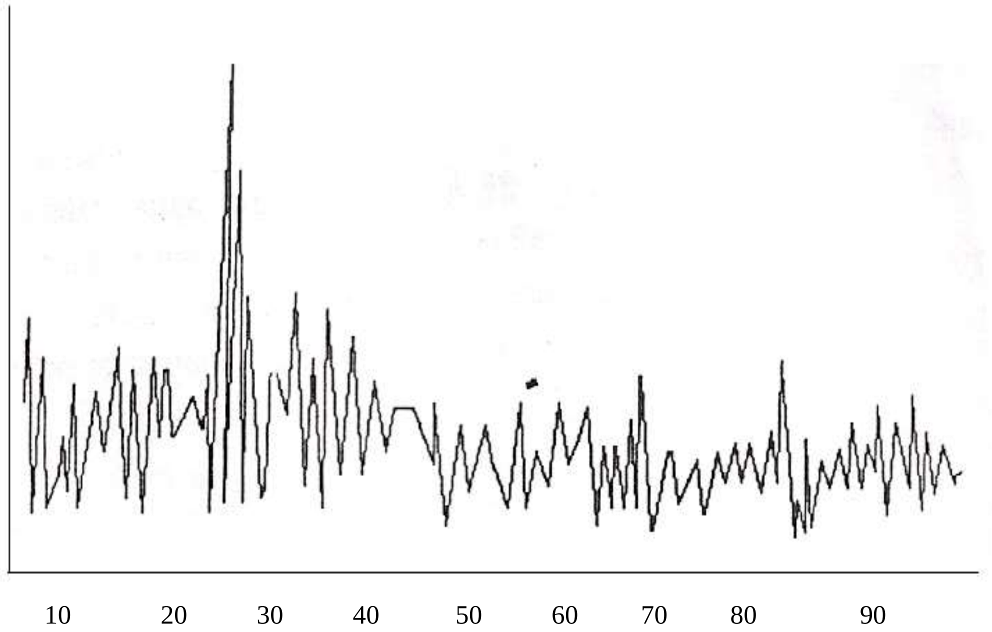

Fig. 5.3 Actual Variance from Ideal total Mass for Varying Environment

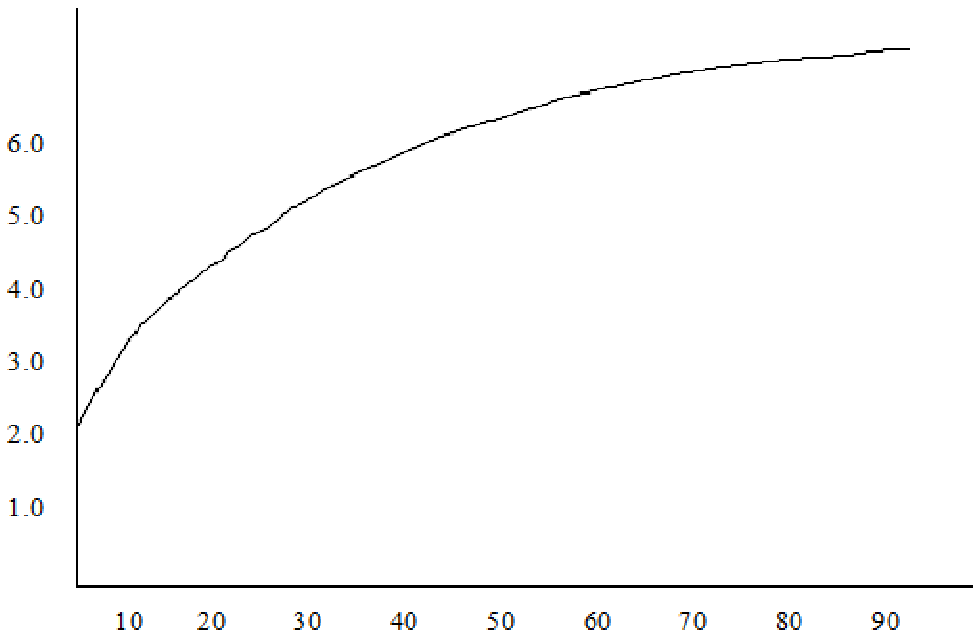

Fig. 5.4 Average Fitness Value for Static Environment

3. CONCLUSION

The genetic algorithm was able to optimize the static environment's biomass much better than in the dynamic environment. Because herbivores had a constant amount of food to draw from, the optimization routine narrowed the mass range of the population considerably. This would indicate that less speciation took place in the static environment. The relatively poor optimization of biomass in the dynamic environment could be expected, because of the additional uncertainty introduced into the herbivore food chain. The algorithm did show robustness by quickly recovering from swings in the food supply, due to the wide range of body mass preserved by the speciation algorithm. This evidence would seem to accord well with observations that changing environmental conditions aggravate the swings of the predator–prey cycle. Both environments performed well in optimizing attributes unconcerned with food requirements. The values for vision, hearing and brain size all showed advancement from average initial values to near optimal values. Genetic algorithms can be a useful method for determining optimal biomasses within a static, and to a lesser extent dynamic, environment. The use of tools such as speciation more closely mimic natural processes, and preserve the diversity necessary for successful response to dynamic environmental changes. At the same time, a GA is able to optimize attributes that relate to an individual's fitness.

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