Modelling of a Roulette Wheel Selection Operator in Genetic Algorithms Using Generalized Nets

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Summary: The apparatus of Generalized Nets (GN) is applied here to a description of a selection operator, which is one of the basic genetic algorithm operators. The GN model presented here describes *roulette wheel selection*. The resulting GN model could be considered as a separate module, but it can also be accumulated into a GN model to describe a whole genetic algorithm.

Keywords: Generalized net, Genetic algorithms, Selection, Roulette wheel selection.

1. INTRODUCTION

Genetic algorithms (GA) is an adaptive heuristic search algorithm based on the evolutionary ideas of natural selection and genetics. As such they represent an intelligent exploitation of a random search used to solve optimization problems. The basic techniques of GA are designed to simulate processes in natural systems necessary for evolution, especially those following the principles first laid down by Charles Darwin of "survival of the fittest". GA is based on an analogy with the genetic structure and behaviour of chromosomes within a population of individuals.

The GA maintains a population of chromosomes (solutions) associated with fitness values. Parents are selected to mate on the basis of their fitness, producing offspring via a reproductive plan. Consequently, highly fit solutions are given more opportunities to reproduce, so that offspring inherit characteristics from each parent. Once an initial population is randomly generated, the algorithm evolves through operators:

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- *selection* which equates to survival of the fittest;
- *crossover* which represents mating between individuals;
- *mutation* which introduces random modifications.

Using a selection operator alone will tend to fill the population with copies of the best individual from the population. Using selection and crossover operators will tend to cause the algorithms to converge to a good, but sub-optimal, solution. Using mutation alone induces a random walk through the search space, while using selection and mutation creates a parallel, noise-tolerant, hill-climbing algorithm.

GAs are quite popular and applicable to many domains like industrial design, scheduling, network design, routing, time series prediction, database mining, control systems, artificial life systems, as well as in many fields of science [4, 6, 7]. On the other hand, so far the apparatus of Generalized Nets (GN) has been used as a tool for the description of parallel processes in several areas – economics, transport, medicine, computer technologies, and so on [1, 2, 3, 12-15]. That is why the idea of using GNs for the description of GA has intuitively appeared. Up to now, only a few GN models regarding genetic algorithm performance have been developed [1, 3, 12-15]. In [1, 3] a GN model for genetic algorithms learning was proposed. The GN model in [14] describes the selection of genetic algorithm operators. The model has the possibility to test different groups of the defined genetic algorithm operators and choose the most appropriate combination between them. The developed GNs execute an genetic algorithm and realize tuning of the genetic operators, as well as of the fitness function, for the problem under consideration. The GN model in [15] describes the genetic algorithm search procedure. The model simultaneously evaluates several fitness functions, ranks the individuals according to their fitness and has the opportunity to choose the best fitness function with respect to a specific problem domain. In [12, 13] the basic genetic algorithm operators – mutation and crossover are described using GN. Different types of crossover, namely one-, two-point crossover, as well as "cut and splice" techniques, are described in details in [12]. The GN model, presented in [13], describes the mutation operator of the Breeder genetic algorithm. Another basic GA operator pending for modelling is the selection operator. The selection of individuals to produce successive generations plays an extremely important role in a genetic algorithm. A probabilistic selection is performed based

upon the individual's fitness, so that the better individuals have an increased chance of being selected. An individual in the population can be selected more than once, with all individuals in the population having a chance of being selected to reproduce into the next generation. There are several schemes for the selection process: *roulette wheel selection* and its extensions, *scaling techniques*, *tournament*, *elitist models*, and *ranking methods* [8, 10]. Since the widely used Matlab Toolbox for Genetic algorithms [5, 11] contains two schemes for the selection function, namely the *roulette wheel selection method* and the *stochastic universal sampling*, the goal of this investigation is to develop a GN model for the *roulette wheel selection method*.

2. ROULETTE WHEEL SELECTION

A common selection approach assigns a probability of selection P_j to each individual j based on its fitness value. A series of N random numbers is generated and compared against the cumulative probability $C_i = \sum_{j=1}^{i} P_i$ of the population. The appropriate individual i is selected and copied into the new population if $C_{i-1} < U(0, 1) \le C_i$. Various methods exist to assign probabilities to individuals: *roulette wheel*, *linear ranking* and *geometric ranking*.

Roulette wheel, developed by Holland [9], is the first selection method. The probability P_i for each individual is defined by:

$$P \text{ [Individual } i \text{ is chosen]} = \frac{F_i}{\sum_{j=1}^{PopSize} F_j}$$

where F_i equals the fitness of individual i. The use of *roulette wheel selection* limits the genetic algorithm to maximization, because the evaluation function must map the solutions to a fully ordered set of values on $\Re^+$. Extensions, such as windowing and scaling, have been proposed to allow for minimization and negativity.

In *roulette wheel selection*, the individuals are mapped to contiguous segments of a line, such that each individual's segment is equally sized to its fitness. A random number is generated and the individual whose segment spans the random number is selected. The process

repeats until the desired number of individuals is obtained (called *mating population*). This technique is analogous to a *roulette wheel* with each slice proportionally sized to the fitness.

3. GN MODELS OF ROULETTE WHEEL SELECTION

Figure 1 presents the Matlab code from genetic algorithms Toolbox of the function *roulette wheel selection* (*rws.m*), also known as *stochastic sampling with replacement* (SSR):

```
% RWS.m - Roulette Wheel Selection
%
%       Syntax:
%               NewChrIx = rws(FitnV, Nsel)
%
%       This function selects a given number of
%       individuals Nsel from a population. FitnV is
%       a column vector containing the fitness values
%       of the individuals in the population.
%
%       The function returns another column vector
%       containing the indexes of the new generation
%       of chromosomes relative to the original
%       population matrix, shuffled. The new
%       population, readyfor mating, can be obtained by
%       calculating OldChrom(NewChrIx, :).

% Author: Carlos Fonseca, Updated: Andrew Chipperfield
% Date: 04/10/93,         Date: 27-Jan-94

function NewChrIx = rws(FitnV,Nsel);

% Identify the population size (Nind)
  [Nind,ans] = size(FitnV);

% Perform Stochastic Sampling with Replacement
  cumfit  = cumsum(FitnV);
  trials = cumfit(Nind) .* rand(Nsel, 1);
  Mf = cumfit(:, ones(1, Nsel));
  Mt = trials(:, ones(1, Nind))';
  [NewChrIx, ans] = find(Mt < Mf & ...
          [ zeros(1, Nsel); Mf(1:Nind-1, :) ] <= Mt);
```

Fig. . Matlab function *rws.m*

The GN model standing for the *roulette wheel selection method*, as described by function *rws.m* in Matlab, is presented in Fig. 2.
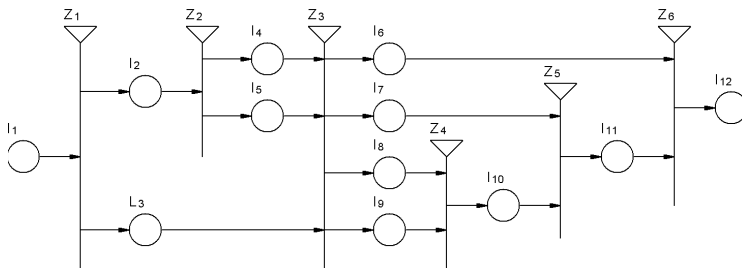
Fig. 2 GN model of *roulette wheel selection method*

Token α enters GN in place l_1 with an initial characteristic "Pool of possible parents". The token α splits into new tokens β and γ, which obtain respective characteristics "Fitness values of the individuals in the population (*FitnV*)" in place l_2 and "Number of individuals to be selected (*Nsel*)" in place l_3. The form of the first transition of the GN model is as follows:

$$Z_1 = <\{l_1\}, \{l_2, l_3\}, r_1, \wedge(l_1) >, \ r_1 = \begin{array}{c|cc} & l_2 & l_3 \\ \hline l_1 & true & true \end{array}$$

Token β splits into new tokens δ and ε, which obtain respective characteristics "Calculation of the function *comfit = cumsum(FitnV)*" in place l_4 and "Identification of the population size (*Nind*)" in place l_5, according to Fig. 2. The form of the second transition of the GN model is as follows:

$$Z_2 = <\{l_2 \}, \{l_4, l_5\}, r_2, \wedge(l_2) >, \ r_2 = \begin{array}{c|cc} & l_4 & l_5 \\ \hline l_2 & true & true \end{array}$$

Further, tokens δ and γ are combined in a new token φ in place l_6 with the characteristic "Calculation of the function $M_f = cumfit(:, ones(1, Nsel))$". Token ε keeps its characteristic "Identification of the population size (*Nind*)" in place l_7. In place l_8 tokens δ and ε are combined in a new token η with a characteristic "Calculation of the function *cumfit(Nind)*". In place l_9 token γ obtains a new characteristic "*rand(Nsel)*". The form of the third transition of the GN model is as follows:

$$Z_3 = <\{l_3, l_4, l_5\}, \{l_6, l_7, l_8, l_9\}, r_3, \wedge(l_3, l_4, l_5) >,$$

$$r_3 = \begin{array}{c|cccc} & l_6 & l_7 & l_8 & l_9 \\ \hline l_3 & true & false & false & true \\ l_4 & true & false & true & false \\ l_5 & false & true & true & false \end{array}$$

Tokens η and γ are combined in a new token λ in place l_{10}, and this new token obtains the characteristic "Calculation of the function *trials = cumfit(Nind).*rand(Nsel, 1)*". The form of the fourth transition of the GN model is as follows:

$$Z_4 = <\{l_8, l_9\}, \{l_{10}\}, r_4, \wedge(l_8, l_9)>, \quad r_4 = \begin{array}{c|c} & l_{10} \\ \hline l_8 & true \\ l_9 & true \end{array}$$

Tokens ε and λ are combined in a new token θ in place l_{11} with a characteristic "Calculation of the function $M_t = trials(:, ones(1, Nind))$". The form of the fifth transition of the GN model is as follows:

$$Z_5 = <\{l_7, l_{10}\}, \{l_{11}\}, r_5, \wedge(l_7, l_{10})>, \quad r_5 = \begin{array}{c|c} & l_{11} \\ \hline l_7 & true \\ l_{10} & true \end{array}$$

Finally, tokens φ and θ are combined in a new token ω in place l_{12} with a characteristic "Calculation of the function *[NewChrIx, ans] = find (M_t < M_f & … [zeros(1, Nsel); M_f(1:Nind-1, :)] $\leq M_t$)*". The form of the sixth transition of the GN model is as follows:

$$Z_6 = <\{l_6, l_{11}\}, \{l_{12}\}, r_6, \wedge(l_6, l_{11})>, \quad r_6 = \begin{array}{c|c} & l_{12} \\ \hline l_6 & true \\ l_{11} & true \end{array}$$

In the place l_{12} the new chromosome is created and the selection function, performing *Roulette Wheel Selection method*, is completely fulfilled.

The GN model of the *selection* operator presented here could be considered as a separate module, but it can also be collected into a GN model to describe a whole genetic algorithm.

4. ANALYSIS AND CONCLUSIONS

The theory of Generalized Nets has been applied here to a description of one of the basic operators of genetic algorithms, namely the *selection* operator. A GN model of one of the mostly used selection functions, the *roulette wheel selection method*, has been developed. Such a GN model could be considered as a separate module, but it can also be accumulated into one GN model, describing a whole genetic algorithm.

In future, we plan to construct some GNs to represent the functioning of results of the work of whole genetic algorithms. The final aim is to produce GNs, which are universal for all genetic algorithms.

REFERENCES

1. Aladjov H., K. Atanassov, A Generalized Net for Genetic Algorithms Learning, *Proc. of the XXX Spring Conference of the Union of Bulgarian Mathematicians*, Borovets, Bulgaria, April 8-11, 2001, 242–248.
2. Atanassov K., *Generalized Nets*, World Scientific, Singapore, New Jersey, London, 1991.
3. Atanassov K., H. Aladjov, *Generalized Nets in Artificial Intelligence, Vol. 2: Generalized Nets and Machine Learning*, Prof. M. Drinov Academic Publishing House, Sofia, 2000.
4. Bies R., M. Muldoon, B. Pollock, S. Manuck, G. Smith, M. Sale, A Genetic Algorithm-based, Hybrid Machine Learning Approach to Model Selection, *Journal of Pharmacokinetics and Pharmacodynamics*, 2006, 196–221.
5. Chipperfield A., P. J. Fleming, H. Pohlheim, C. M. Fonseca, *Genetic Algorithm Toolbox for Use with MATLAB*, 1993.
6. Davis L., *Handbook of Genetic Algorithms*, Van Nostrand Reinhold, 1991.
7. Fogel D., *Evolutionary Computation: Toward a New Philosophy of Machine Intelligence*, IEEE Press, NJ, Third Edition, 2006.
8. Goldberg D. E., *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison Wesley, 1989.
9. Holland J., *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor, 1975.

10. Houck C., J. Joines, M. Kay, A Genetic Algorithm for Function Optimization: AMatlab Implementation, NCSU-IE TR 95–05, 1995
11. MathWorks, Genetic Algorithm Toolbox User's Guide for MATLAB.
12. Pencheva T., O. Roeva, A. Shannon, Generalized Net Models of Crossover Operator of Genetic Algorithm, *Proceedings of Ninth International Workshop on Generalized Nets*, Sofia, Bulgaria, July 4, 2008, 2, 64–70.
13. Roeva O., A. Shannon, A Generalized Net Model of Mutation Operator of the Breeder Genetic Algorithm, *Proceedings of Ninth International Workshop on Generalized Nets*, Sofia, Bulgaria, July 4, 2008, Vol. 2, 59–63.
14. Roeva O., K. Atanassov, A. Shannon, Generalized Net for Selection of Genetic Algorithm Operators, *Annual of "Informatics" Section, Union of Scientists in Bulgaria*, Vol. 1, 2008, 117–126.
15. Roeva, O., K. Atanassov, A. Shannon, Generalized Net for Evaluation of the Genetic Algorithm Fitness Function, *Proc. of the Eighth International Workshop on Generalized Nets*, Sofia, Bulgaria, June 26, 2007, 48–55.