

**New Trends in Fuzzy Sets,
Intuitionistic Fuzzy Sets,
Generalized Nets and Related Topics
Volume II: Applications**

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Generalized Nets Model of Rank-Based Fitness Assignment in Genetic Algorithms

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Abstract

The theory of Generalized Nets is applied here to describe one of the basic functions in genetic algorithms, namely *rank-based fitness assignment*. This function ranks individuals represented by their associated costs, to be “minimized”, and results in a set of corresponding individual fitnesses. The generalized net model developed here could be considered as a separate module, but it can also be assembled into a larger generalized net model to describe a whole genetic algorithm.

Keywords: Generalized net, Genetic algorithm

1 Introduction

Genetic Algorithms (GA) are an adaptive heuristic search algorithm [5], that simulate processes in natural systems necessary for evolution following the principles of “survival of the fittest”, first formulated by Charles Darwin. GAs are implemented in a computer simulation in which a population of abstract representations (chromosomes) of candidate solutions to an optimization problem (individuals) evolves towards better solutions.

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After the definition of genetic representation and the fitness function, GAs proceed to initialize a population of solutions randomly. Once the offspring have been produced by *selection*, *recombination* and *mutation* of individuals from the old population, the offspring *fitness* is determined. To maintain the size of the original population a reinsertion scheme is going to be used to determine which individuals are to appear in the new population whether less offspring are produced than the size of the original population, or not all offspring are to be used at each generation, or if more offspring are generated than the size of the old population. The newly obtained population is then used in the next algorithm iteration. Commonly, GAs terminate when either a maximum number of generations has been fulfilled, or a satisfactory fitness level has been reached for the population.

The idea of using Generalized Nets (GN) theory for the description of GA has intuitively appeared based to a variety of successive implementations of GNs for description of parallel processes in different areas [1-3]. The first GN model of a GA was a description of search procedures [1, 3]. The GN model simultaneously evaluates several fitness functions, ranks the individuals according to their fitness and chooses the best fitness function in relation to the specific problem domain. Another GN model relating to GA was developed to evaluate the algorithm fitness function [12]. By performing a series of experiments, a GN model can define the “best” fitness function for each considered problem domain. An extension of the GN model in [12] was presented in [13]. It allows different groups of the defined GA operators to be tested and the most appropriate combination among them to be chosen.

Another GN model was developed in [7] to describe one of the basic GA functions, namely *reinsertion*. A few GN models have also been developed for describing basic genetic operators [6, 8-11], namely *selection*, *crossover* and *mutation*. The GN model of a *roulette wheel selection* method, which is one of the most widely used selection functions, was developed in [8], while a GN model of a *stochastic universal sampling* was presented in [9]. A GN model which allows the user to choose between different selection functions has been elaborated in [6]. Different types of *crossover*, namely *one-*, *two-point crossover*, as well as “*cut and splice*” techniques, were described in detail in [10]. The GN model, presented in [11], describes the *mutation* operator of the Breeder GA.

The purpose of the present investigation is to develop a GN model to describe the function for *ranking* the individuals represented by their associated costs, as it is realized in a *Genetic Algorithm Toolbox* [4]. The function *ranking* results in a set of corresponding individual fitnesses.

2 Algorithm for Ranking

The *Genetic Algorithm Toolbox* [4] supports both linear and non-linear ranking methods, *ranking*, and includes a simple linear scaling function, *scaling*, for completeness. The algorithms for both linear and non-linear ranking first sorts the objective function values into descending order. The least fit individual is placed in position 1 in the sorted list of objective values and the most fit individual – position $Nind$, where $Nind$ is the number of individuals in the population. A fitness value is then assigned to each individual depending on its position, Pos , with selection pressure SP , in the sorted population.

For linear ranking individuals are assigned fitness values according to:

$$FitnV(Pos) = 2 - SP + 2 \times (SP - 1) \times (POS - 1) / (Nind - 1),$$

and for non-linear ranking according to:

$$FitnV(Pos) = \frac{Nind \times X^{Pos-1}}{\sum_{i=1}^{Nind} X(i)},$$

where X is computed as the root of the polynomial:

$$0 = (SP - 1) \times X^{Nind-1} + SP \times X^{Nind-2} + \dots + SP \times X + SP.$$

The vector $FitnV$ is then unsorted to reflect the order of the original input vector, $ObjV$.

3 GN model for ranking functions

The GN model standing for *ranking* function, as described by function *ranking.m* [4] in Matlab, is presented in Fig. 1.

The token α enters GN in place l_1 with an initial characteristic “parameters of GA”. Some of the most common considered parameters of GA are: number of individuals ($Nind$), maximal number of generations ($Maxgen$), number of variables ($Nvar$), objective values of the individuals ($ObjV$), etc. The token β enters GN in place l_2 with an initial characteristic “pool of individuals”. Tokens α and

β are combined and appear as a token γ , which splits into two new tokens γ_1 and γ_2 respectively in places l_3 and l_4 with the following characteristics:

- γ_1 in place l_3 – “objective values of the individuals (*ObjV*)”;
- γ_2 in place l_4 – “number of individuals (*Nind*)”.

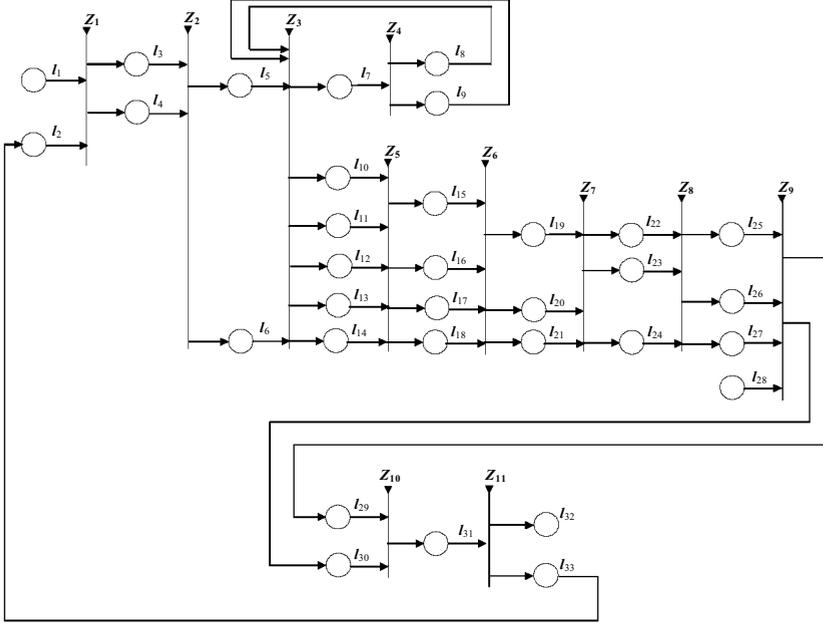


Fig. 1 GN model of *ranking* function

The form of the first transition of the GN model is as follows:

$$Z_1 = \langle \{l_1, l_2\}, \{l_3, l_4\}, \begin{array}{c|cc} & l_3 & l_4 \\ \hline l_1 & true & true \\ l_2 & true & true \end{array}, \wedge(l_1, l_2) \rangle$$

Tokens γ_1 and γ_2 are combined and appear in place l_5 as a token σ with a characteristic “*ObjVSub = ObjV((irun - 1)*Nind + 1:irun*Nind)*”, where *irun* is a loop counter. The token γ_1 keeps its characteristic, namely “number of individuals (*Nind*)”, in place l_6 .

The form of the second transition of the GN model is as follows:

$$Z_2 = \langle \{l_3, l_4\}, \{l_5, l_6\}, \begin{array}{c|cc} & l_5 & l_6 \\ \hline l_3 & true & true \\ l_4 & true & true \end{array}, \wedge(l_3, l_4) \rangle$$

In place l_7 the token σ obtain a new characteristic “ $NaNix = isnan(ObjVSub)$ ” and further splits into two new tokens σ_1 and σ_2 respectively in places l_8 and l_9 with the following characteristics:

- σ_1 in place l_8 – a new characteristic “ $Validix = find(\sim NaNix)$ ”;
- σ_2 in place l_9 – keeps the characteristic of the token σ , namely “ $NaNix$ ”.

Tokens σ and σ_1 are combined and appear in place l_{10} as a token ε with a characteristic

“ $[ans, ix] = sort(-ObjVSub(Validix))$ ”. In places l_{11} to l_{14} the tokens appear with the following characteristics:

- σ_1 in place l_{11} – keeps its characteristic “ $Validix$ ”;
- σ_2 in place l_{12} – keeps its characteristic “ $NaNix$ ”;
- σ in place l_{13} – keeps its characteristic “ $ObjVSub$ ”;
- γ_2 in place l_{14} – keeps its characteristic “ $Nind$ ”.

Thus, the form of the third transition of the GN model is as follows:

$$Z_3 = \langle \{l_5, l_6, l_8, l_9\}, \{l_7, l_{10}, l_{11}, l_{12}, l_{13}, l_{14}\}, r_3, \wedge(l_5, l_6, l_8, l_9) \rangle$$

$$r_3 = \begin{array}{c|cccccc} & l_7 & l_{10} & l_{11} & l_{12} & l_{13} & l_{14} \\ \hline l_5 & true & W_{5,10} & false & false & true & false \\ l_6 & false & false & false & false & false & true \\ l_8 & false & true & true & false & false & false \\ l_9 & false & false & false & true & false & false \end{array}$$

where $W_{5,10}$ is “there is a token in place l_8 ”.

The form of the fourth transition of the GN model is as follows:

$$Z_4 = \langle \{l_7\}, \{l_8, l_9\}, \begin{array}{c|cc} & l_8 & l_9 \\ \hline l_7 & true & true \end{array}, \wedge(l_7) \rangle$$

Tokens ε and σ_1 are then combined in a token π in place l_{15} with a characteristic “*Validix(ix)*”, while the tokens σ_2 , σ and γ_2 keep their characteristics respectively in places l_{16} , l_{17} and l_{18} , namely σ_2 in place l_{16} – “*NaNix*”, σ in place l_{17} – “*ObjVSub*” and γ_2 in place l_{18} – “*Nind*”.

Thus, the form of the fifth transition of the GN model is as follows:

$$Z_5 = \langle \{l_{10}, l_{11}, l_{12}, l_{13}, l_{14}\}, \{l_{15}, l_{16}, l_{17}, l_{18}\}, r_5, \wedge(l_{10}, l_{11}, l_{12}, l_{13}, l_{14}) \rangle$$

$r_5 =$		l_{15}	l_{16}	l_{17}	l_{18}
	l_{10}	<i>true</i>	<i>false</i>	<i>false</i>	<i>false</i>
	l_{11}	<i>true</i>	<i>false</i>	<i>false</i>	<i>false</i>
	l_{12}	<i>false</i>	<i>true</i>	<i>false</i>	<i>false</i>
	l_{13}	<i>false</i>	<i>false</i>	<i>true</i>	<i>false</i>
	l_{14}	<i>false</i>	<i>false</i>	<i>false</i>	<i>true</i>

Tokens π and σ_2 are then combined in a token η in place l_{19} with a characteristic “ $ix = [find(NaNix); Validix(ix)]$ ”, while the tokens σ and γ_2 are still keeping their characteristics respectively in places l_{20} and l_{21} , namely σ in place l_{20} – “*ObjVSub*” and γ_2 in place l_{21} – “*Nind*”.

Thus, the form of the sixth transition of the GN model is as follows:

$$Z_6 = \langle \{l_{15}, l_{16}, l_{17}, l_{18}\}, \{l_{19}, l_{20}, l_{21}\}, r_6, \wedge(l_{15}, l_{16}, l_{17}, l_{18}) \rangle$$

$r_6 =$		l_{19}	l_{20}	l_{21}
	l_{15}	<i>true</i>	<i>false</i>	<i>false</i>
	l_{16}	<i>true</i>	<i>false</i>	<i>false</i>
	l_{17}	<i>false</i>	<i>true</i>	<i>false</i>
	l_{18}	<i>false</i>	<i>false</i>	<i>true</i>

The token η keeps its characteristic “ix” in place l_{22} . Tokens η and σ are combined in a token μ in place l_{23} with a characteristic “Sorted = ObjVSub(ix)”, while the token γ_2 is still keeping its characteristic “Nind” in place l_{24} .

The form of the seventh transition of the GN model is as follows:

$$Z_7 = \langle \{l_{19}, l_{20}, l_{21}\}, \{l_{22}, l_{23}, l_{24}\}, \begin{array}{c|ccc} & l_{22} & l_{23} & l_{24} \\ \hline l_{19} & true & true & false \\ l_{20} & false & true & false \\ l_{21} & false & false & true \end{array}, \wedge(l_{19}, l_{20}, l_{21}) \rangle$$

The token η is still keeping its characteristic “ix” in place l_{25} . Tokens μ and γ_2 are combined in a token λ in place l_{26} with a characteristic “j = [find(Sorted(1:Nind - 1) ~ = Sorted(2:Nind)); Nind]”, while the token γ_2 obtains a new characteristic “FitnVSub = zeros(Nind, 1)” in place l_{27} .

The form of the eighth transition of the GN model is as follows:

$$Z_8 = \langle \{l_{22}, l_{23}, l_{24}\}, \{l_{25}, l_{26}, l_{27}\}, \begin{array}{c|ccc} & l_{25} & l_{26} & l_{27} \\ \hline l_{22} & true & false & false \\ l_{23} & false & true & false \\ l_{24} & false & true & true \end{array}, \wedge(l_{22}, l_{23}, l_{24}) \rangle$$

A new token χ enters GN in place l_{28} with a characteristic “RFun”. According to [4] *RFun* is an optional parameter:

- If *RFun* is a scalar in [1, 2] linear ranking is assumed and the scalar indicates the selective pressure.
- If *RFun* is a 2 element vector:
 - *RFun*(1): SP - scalar indicating the selective pressure
 - *RFun*(2): RM - ranking method
 - RM = 0: linear ranking
 - RM = 1: non-linear ranking.
- If *RFun* is a vector with length(Rfun) > 2 it contains the fitness to be assigned to each rank. It should have the same length as *ObjV*.
- If *RFun* is omitted or NaN, linear ranking and a selective pressure of 2 are assumed.

The token η obtains a new characteristic “[*ans*, *uix*] = *sort(ix)*” in place l_{29} . Tokens λ , γ_2 and χ are combined in a token θ in place l_{30} with a characteristic “*FitnVSub(i;j) = sum(RFun(i;j)) * ones(j - i + 1, 1)/(j - i + 1)*”.

The form of the ninth transition of the GN model is as follows:

$$Z_9 = \langle \{l_{25}, l_{26}, l_{27}, l_{28}\}, \{l_{29}, l_{30}\}, \begin{array}{c|cc} & l_{29} & l_{30} \\ \hline l_{25} & true & false \\ l_{26} & false & true \\ l_{27} & false & true \\ l_{28} & false & true \end{array}, \wedge(l_{25}, l_{26}, l_{27}, l_{28}) \rangle$$

Tokens η and θ are combined in a token ω in place l_{31} with a characteristic “*FitnVSub = FitnVSub(uix)*”. The form of the tenth transition of the GN model is as follows:

$$Z_{10} = \langle \{l_{29}, l_{30}\}, \{l_{31}\}, \begin{array}{c|c} & l_{31} \\ \hline l_{29} & true \\ l_{30} & true \end{array}, \wedge(l_{29}, l_{30}) \rangle$$

After the ranking in place l_{31} , the token ω could pass to place l_{32} with a characteristic “*end of ranking function*” or in place l_{33} with a characteristic “*FitnV = [FitnV; FitnVSub]*”. The form of the eleventh transition of the GN model is as follows:

$$Z_{11} = \langle \{l_{31}\}, \{l_{32}, l_{33}\}, \begin{array}{c|cc} & l_{32} & l_{33} \\ \hline l_{31} & W_{31,32} & W_{31,33} \end{array}, \wedge(l_{31}) \rangle,$$

where $W_{31,32}$ is “*end of ranking function*” and $W_{31,33} = \neg W_{31,32}$.

4 Analysis and conclusions

The theory of Generalized Nets has been here applied to describe one of the basic functions in genetic algorithms, namely *ranking function*. Such a GN model could be considered as a separate module, but can also be assembled into a single GN model for description of a whole genetic algorithm.

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The papers presented in this Volume 2 constitute a collection of contributions, both of a foundational and applied type, by both well-known experts and young researchers in various fields of broadly perceived intelligent systems.

It may be viewed as a result of fruitful discussions held during the Eleventh International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2012) organized in Warsaw on October 12, 2012 by the Systems Research Institute, Polish Academy of Sciences, in Warsaw, Poland, Institute of Biophysics and Biomedical Engineering, Bulgarian Academy of Sciences in Sofia, Bulgaria, and WIT - Warsaw School of Information Technology in Warsaw, Poland, and co-organized by: the Matej Bel University, Banska Bystrica, Slovakia, Universidad Publica de Navarra, Pamplona, Spain, Universidade de Tras-Os-Montes e Alto Douro, Vila Real, Portugal, Prof. Asen Zlatarov University, Burgas, Bulgaria, and the University of Westminster, Harrow, UK:

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The consecutive International Workshops on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGNs) have been meant to provide a forum for the presentation of new results and for scientific discussion on new developments in foundations and applications of intuitionistic fuzzy sets and generalized nets pioneered by Professor Krassimir T. Atanassov. Other topics related to broadly perceived representation and processing of uncertain and imprecise information and intelligent systems have also been included. The Eleventh International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2012) is a continuation of this undertaking, and provides many new ideas and results in the areas concerned.

We hope that a collection of main contributions presented at the Workshop, completed with many papers by leading experts who have not been able to participate, will provide a source of much needed information on recent trends in the topics considered.

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