

Generalized net model of intuitionistic fuzzy logic control of genetic algorithm parameters

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Abstract: In this paper a Generalized Net (GN) model of Intuitionistic fuzzy logic (IFL) control of two Genetic Algorithm (GA) parameters, is proposed. IFL controller is used to tune dynamically GA parameters – crossover and mutation probability. The GN-model describes the process of GA parameters control, trying to improve the algorithm performance.

Keywords: Generalized Net, Intuitionistic fuzzy logic, Parameters control, Genetic algorithm.

AMS Classification: 03E72, 65Q85, 68T20.

1 Introduction

Evolutionary algorithms, such as genetic algorithms (GA), are widely used to solve various optimization problems. The GA are highly relevant for industrial applications, because they are capable of handling problems with non-linear constraints, multiple objectives, and dynamic components – properties that frequently appear in the real-world problems [10]. Since their introduction and subsequent popularization [12], the GA have been frequently used as an alternative optimization tool to the conventional methods and have been successfully applied in a variety of areas, and still find increasing acceptance.

One of the main challenges of the field of evolutionary computation is appropriately varying parameter values during an evolutionary algorithm run (parameter control) [9]. In order to increase the performance of the regarded algorithms it is necessary to provide the adjustments of their parameters depending on the considered problem.

Finding robust control parameters setting is not a trivial task, since their interaction with GA performance is a complex relationship and the optimal one are problem-dependent [11]. An optimal or near-optimal set of control parameters for one GA does not generalize to all cases. This stresses the need for efficient techniques that help finding good parameter settings for a given problem, i.e. the need for good parameter tuning methods.

In [9] authors present that any static set of parameters, having the fixed values during the algorithm run, seems to be inappropriate. It is intuitively obvious that different values of parameters might be optimal at different stages of the evolutionary process [15]. For instance, large mutation probability can be good in the early generations helping the exploration of the search space and small mutation probability might be needed in the late generations to help fine tuning the individuals.

The problem of finding optimal control parameters for GAs has been studied by [8, 9, 15] and Fuzzy Control of Evolutionary Algorithm parameters is discussed in [11, 17]. In this paper, we investigate the use of Intuitionistic Fuzzy Logic (IFL) [4–6] for control of GA parameters. We propose a Generalized Net model describing the IFL control of GA parameters, namely crossover probability and mutation probability.

IFL and Intuitionistic fuzzy sets (IFS) have gained recognition as a useful tool for control uncertain phenomena. In [1] authors described the development of an IFL controller for heater fans, developed on the basis of intuitionistic fuzzy systems. Intuitionistic fuzzy inference systems and defuzzification techniques are used to obtain speed of the heater fan from an intuitionistic fuzzy input – ambient temperature. The speed of the heater fan is calculated using intuitionistic fuzzy rules applied in an inference engine using defuzzification methods.

Up to now, using the apparatus of Generalized Net (GN) [7] few GN-models, regarding GA performance, were developed. The first GN-model describes the GA search procedure [2, 3]. The apparatus of GN is also applied to a description of different GA operators – crossover operator [14] and mutation operator [16].

2 IFL controller

The GA performance is correlated with its careful selection of parameters. As discussed in [13] it is possible to destroy a high fitness individual when a large crossover probability is set. Whereas, for a low crossover probability, sometimes it is hard to obtain better individuals and does not guarantee faster convergence. High mutation introduces too much diversity and takes longer time to get the optimal solution. Low mutation tends to miss some near-optimal points.

The main idea is to use two IFL controllers. The controllers inputs are current GA performance measures and which outputs are GA control parameters – crossover probability (p_c) and mutation probability (p_m). Current performance measures of the GA are sent to the IFLCs, which computers new control parameters values that will be used by the GA.

The proposed strategy for updating of p_c and p_m is to consider the changes of the average fitness value in the GA population compared to the defined maximum and minimum fitness.

According to Atanassov [4–6], an IFS on the universum $X \neq \emptyset$ is an expression A given by:

$$A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle \mid x \in X \}, \quad (1)$$

where the functions

$$\mu_A, \nu_A : X \rightarrow [0, 1] \quad (2)$$

satisfy the condition

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1 \quad (3)$$

and describe, respectively, the degree of the membership $\mu_A(x)$ and the nonmembership $\nu_A(x)$ of an element x to A .

Let

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x), \quad (4)$$

therefore, function π_A determines the degree of uncertainty.

Considering fitness function of the chromosome in the GA it can be assigned intuitionistic maximum and minimum values (f_{\max} and f_{\min}). So, if the average fitness function (f_{ave}) of the current population falls between these values, then it cannot be determined unambiguously whether it is a “good algorithm performance” or “poor algorithm performance”. Conversely, values outside the intuitionistic limits can be unambiguously assigned to one of the two categories. The following membership functions are defined:

$$\mu_A : f_{\text{ave}} \leq f_{\min}, \quad (5)$$

$$\nu_A : f_{\text{ave}} \geq f_{\max}, \quad (6)$$

$$\pi_A : f_{\min} < f_{\text{ave}} < f_{\max}. \quad (7)$$

In a minimization problem, when average fitness value at the generation t ($f_{\text{ave}}(t)$) is less than f_{\min} we have “well-performing” operators, so the p_c and p_m will keep their values. If $f_{\text{ave}}(t)$ is greater than f_{\max} we have “poorly performing” operators, so the p_c and p_m have to be changed based on the scheme: p_c should be increased and p_m – decreased. If $f_{\text{ave}}(t)$ fall between f_{\min} and f_{\max} than the GA parameters have to be changed based on the scheme: p_c should be decreased and p_m – increased.

The change of the p_c and p_m values is updated using the following equations:

$$p_c(t) = p_c(t-1) \pm \Delta p_c(t), \quad (8)$$

$$p_m(t) = p_m(t-1) \mp \Delta p_m(t), \quad (9)$$

where $\Delta p_c(t)$ and $\Delta p_m(t)$ are calculated by the IFL controllers.

3 Generalized net model

The generalized net model of IFL control of GA parameters is presented in Figure 1.

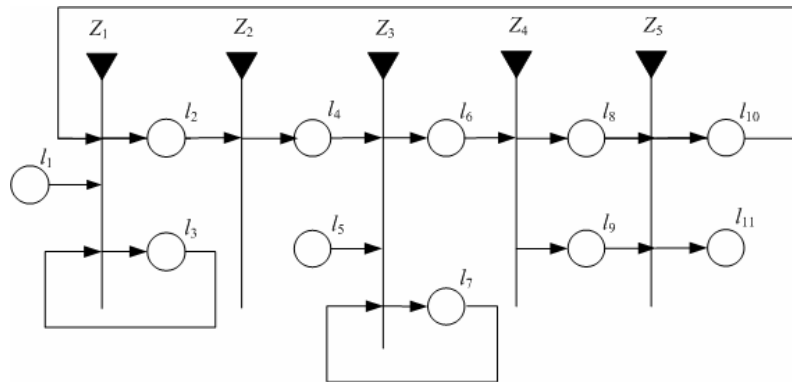


Figure 1. GN-model of IFL control of GA parameters

The token α enters GN through place l_1 with an initial characteristic “GA parameters”. The form of the first transition of the GN-model is

$$Z_1 = \langle \{l_1, l_3, l_{10}\}, \{l_2, l_3\}, r_1, \vee(l_1) \rangle,$$

$$r_1 = \begin{array}{c|cc} & l_2 & l_3 \\ \hline l_1 & true & false \\ l_3 & true & true \\ l_{10} & false & true \end{array}$$

The token α obtains the characteristics “Genetic algorithm” in place l_2 and characteristics “ $\Delta p_c(t)$, $\Delta p_m(t)$ ” in places l_3 and l_{10} . In the place l_2 could be replaced any GN-model of GA – for example, that presented in [2].

The form of the second transition of the GN-model is

$$Z_2 = \langle \{l_2\}, \{l_4\}, r_2, \vee(l_2) \rangle$$

$$r_2 = \begin{array}{c|c} & l_4 \\ \hline l_2 & true \end{array}$$

In place l_4 , the token α obtains the characteristic “ $f_{ave}(t)$ ”. The token β enters GN through place l_5 with an initial characteristic “ f_{min}, f_{max} ”.

The form of the third transition of the GN-model is

$$Z_3 = \langle \{l_4, l_5, l_7\}, \{l_6, l_7\}, r_3, \wedge(l_4, l_5, l_7) \rangle,$$

$$r_3 = \begin{array}{c|cc} & l_6 & l_7 \\ \hline l_4 & false & true \\ l_5 & true & false \\ l_7 & true & true \end{array}$$

The tokens α and β are combined in a new token γ in place l_6 . The new token γ obtains the characteristics “GA performance”. In place l_7 , the token α keeps the characteristics “ $f_{ave}(t)$ ” in place l_3 .

The form of the fourth transition of the GN-model is

$$Z_4 = \langle \{l_6\}, \{l_8, l_9\}, r_4, \vee(l_6) \rangle,$$

$$r_4 = \begin{array}{c|cc} & l_8 & l_9 \\ \hline l_6 & true & true \end{array}$$

The token γ obtains the characteristics “ $\Delta p_c(t)$ ” in place l_8 and “ $\Delta p_m(t)$ ” in place l_9 .

The form of the fifth transition of the GN-model is:

$$Z_5 = \langle \{l_8, l_9\}, \{l_{10}, l_{11}\}, r_5, \vee(l_8, l_9) \rangle,$$

$$r_5 = \frac{\quad}{\begin{array}{c|cc} & l_{10} & l_{11} \\ \hline l_8 & W_1 & \neg W_1 \\ l_9 & W_1 & \neg W_1 \end{array}}$$

where W_1 = “end of the process is not reached”.

The token γ obtains the characteristics “ $\Delta p_c(t_{\text{end}}), \Delta p_m(t_{\text{end}})$ ” in place l_{11} .

4 Conclusions

One of the main challenges of the field of evolutionary computation is the parameter control. In order to increase the performance of the algorithms it is necessary to tune the algorithm parameters during the computation. Such procedure is not a trivial. In this paper, the Intuitionistic Fuzzy Logic for control of GA parameters is used. A Generalized Net model describing the GA parameters IFL controllers is considered. Proposed GN-model performs fine-tuning of crossover probability and mutation probability, during the algorithm run, using IFL controllers.

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