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# A GENETIC ALGORITHM TOOLBOX FOR MATLAB[1]

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The genetic algorithm appears to be a useful tool in a wide spectrum of activities in control engineering. This paper reports on a Genetic Algorithm Toolbox for the widely accepted computer aided control system design package MATLAB that enables control engineers to use genetic search methods readily, within the framework of an existing software tool. With the aid of an example, it is demonstrated how the Toolbox may be used to apply genetic methods to problems in control system design.

## 1. INTRODUCTION

There has been widespread interest from the control community in applying the Genetic Algorithm (GA) to problems in control systems engineering. Compared to traditional search and optimization procedures, such as calculus-based and enumerative strategies, the GA is robust, global and generally more straightforward to apply in situations where there is little or no *a priori* knowledge about the process to be controlled. As the GA does not require derivative information or a formal initial estimate of the solution region and because of the stochastic nature of the search mechanism, the GA is capable of searching the entire solution space with more likelihood of finding the global optimum.

GAs have been shown to be an effective strategy in the off-line design of control systems by a number of practitioners. For example, Krishnakumar and Goldberg [1] and Bramlette and Cusin [2] have demonstrated how genetic optimization methods can be used to derive superior controller structures in aerospace applications in less time (in terms of function evaluations) than that of traditional methods such as LQR and Powell's gain set design. Porter and Mohamed [3] have presented schemes for the genetic design of multivariable flight control systems using eigenstructure assignment, whilst others have shown how GAs can be used in the selection of controller structures [4]. In the field of robotics, GAs have been used successfully for path planning problems in both stationary and non-stationary environments (see, for example, [5]). Possible on-line applications of GAs have been presented for the genetic tuning of non-adaptive and adaptive multivariable digital PID controllers by Porter and Jones [6], Karr's adaptive fuzzy logic controller [7], Nordvik and Render's Hybrid GA [8] and the adaptive genetic based controllers of McGregor *et-al* [9].

MATLAB has become a *de-facto* standard in Computer Aided Control System Design (CACSD) for the control engineer. The complete design cycle from modelling and simulation

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through controller design is addressed with a wide range of toolboxes, notably the Control System [10] and Optimization [11] Toolboxes, and the SIMULINK non-linear simulation package [12] along with extensive visualisation and analysis tools. In addition, MATLAB has an open and extensible architecture allowing individual users to develop further routines for their own applications. These qualities provide a uniform and familiar environment on which to build genetic algorithm tools for the control engineer. This paper describes and discusses the development and implementation of a Genetic Algorithm Toolbox for the MATLAB package.

## 2. THE MATLAB GA TOOLBOX

Whilst there exist many good public-domain genetic algorithm packages, such as GENESYS [13] and GENITOR [14], none of these provide an environment that is immediately compatible with existing tools in the control domain. The MATLAB Genetic Algorithm Toolbox aims to make GAs accessible to the control engineer within the framework of an existing CACSD package. This allows the retention of existing modelling and simulation tools for building objective functions and allows the user to make direct comparisons between genetic methods and traditional procedures.

### 2.1 Data structures

MATLAB essentially supports only one data type, a rectangular matrix of real or complex numeric elements. The main data structures in the GA Toolbox are chromosomes, phenotypes, objective function values and fitness values. The chromosome structure stores an entire population in a single matrix of size $N_{ind} \times L_{ind}$, where $N_{ind}$ is the number of individuals and $L_{ind}$ is the length of the chromosome structure. Phenotypes are stored in a matrix of dimensions $N_{ind} \times N_{var}$ where $N_{var}$ is the number of decision variables. An $N_{ind} \times N_{obj}$ matrix stores the objective function values, where $N_{obj}$ is the number of objectives. Finally, the fitness values are stored in a vector of length $N_{ind}$. In all of these data structures, each row corresponds to a particular individual.

### 2.2 Toolbox structure

The GA Toolbox uses MATLAB matrix functions to build a set of versatile routines for implementing a wide range of genetic algorithm methods. In this section we outline the major procedures of the GA Toolbox.

**Population representation and initialisation:** `crtbase`, `crtbp`, `crtrp`

The GA Toolbox supports binary, integer and floating-point chromosome representations. Binary and integer populations may be initialised using the Toolbox function to create binary populations, `crtbp`. An additional function, `crtbase`, is provided that builds a vector describing the integer representation used. Real-valued populations may be initialised using `crtrp`. Conversion between binary and real-values is provided by the routine `bs2rv` that also supports the use of Gray codes and logarithmic scaling.

**Fitness assignment:** `ranking`, `scaling`

The fitness function transforms the raw objective function values into non-negative figures of merit for each individual. The Toolbox supports the offsetting and scaling method of Goldberg [15] and the linear-ranking algorithm of Baker [16]. In addition, non-linear ranking is also supported in the routine `ranking`.

**Selection functions:** `reins`, `rws`, `select`, `sus`

These functions select a given number of individuals from the current population, according to their fitness, and return a column vector to their indices. Currently available routines are roulette wheel selection [15], `rws`, and stochastic universal sampling [17], `sus`. A high-level entry function, `select`, is also provided as a convenient interface to the selection routines, particularly where multiple populations are used. In cases where a generation gap is required, i.e. where the entire population is not reproduced in each generation, `reins` can be used to effect uniform random or fitness-based reinsertion [15].

**Crossover operators:** `recdis`, `recint`, `reclin`, `recmut`, `recombin`, `xovdp`, `xovdprs`, `xovmp`, `xovsh`, `xovshrs`, `xovsp`, `xovsprs`

The crossover routines recombine pairs of individuals with given probability to produce offspring. Single-point, double-point [18] and shuffle crossover [19] are implemented in the routines `xovsp`, `xovdp` and `xovsh` respectively. Reduced surrogate [14] crossover is supported with both single-, `xovsprs`, and double-point, `xovdprs`, crossover and with shuffle, `xovshrs`. A general multi-point crossover routine, `xovmp`, that supports uniform crossover [20] is also provided. To support real-valued chromosome representations, discrete, intermediate and line recombination are supplied in the routines, `recdis`, `recint` and `reclin` respectively [21]. The routine `recmut` performs line recombination with mutation features [21]. A high-level entry function to all the crossover operators supporting multiple subpopulations is provided by the function `recombin`.

**Mutation operators:** `mut`, `mutate`, `mutbga`

Binary and integer mutation are performed by the routine `mut`. Real-value mutation is available using the breeder GA mutation function [21], `mutbga`. Again, a high-level entry function, `mutate`, to the mutation operators is provided.

**Multiple subpopulation support:** `migrate`

The GA Toolbox provides support for multiple subpopulations through the use of high-level genetic operator functions and a function for exchanging individuals amongst subpopulations, `migrate`. A single population is divided into a number of subpopulations by modifying the data structures used by the Toolbox routines such that subpopulations are stored in contiguous blocks within each data element. The high-level routines, such as `select` and `reins`, operate independently on each subpopulation contained in a data structure allowing each subpopulation to evolve in isolation from the others. Based on the *Island* or *Migration* model [22], `migrate` allows individuals to be transferred between subpopulations. Uni- and bi-directional ring topologies as well as a fully interconnected network are selectable via option settings as well as fitness-based and uniform selection and reinsertion strategies.

## 3. EXAMPLE APPLICATION

In this section we consider a simple example demonstrating how the GA Toolbox can be applied to problems in control system design. Consider the SIMULINK model of the control system of Fig. 1. Assuming that the DC gain meets system specification, the task is to select the compensator parameters Wc(1) and Wc(2) to yield the minimum rise time to a step input, subject to the constraint that the overshoot does not exceed 15%.

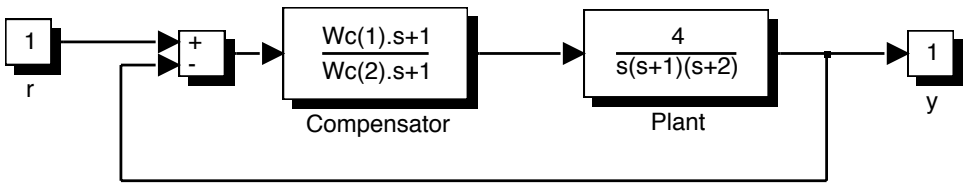


***Figure 1: SIMULINK Model of Control System Example***

The first step in solving this problem is to construct a suitable objective function. A typical technique to incorporate constraints into an optimization is to factor penalties for constraint violation into the objective function. This is the approach adopted for this example with the maximum value of the objective function bounded at 1000, although methods more applicable for genetic optimization have been described in the literature (see, for example, [23]). Fig. 2 shows an outline of the MATLAB code for the objective function used in this example.

```
function ObjV = objfun(Phen)                % Objective function

Wc = Phen                                   % This estimate
x0 = zeros(4,1);                            % Initial conditions
ut = [(0:.1:20)',ones(201,1)];              % Step input
[t,x,y] = linsim('example',20,x0,[],ut);    % Simulate system
ObjV = riset(y,t);                          % Calculate rise time

const = overshoot(y,t);                     % Constraint evaluation
if const > 15                               % Test constraint
      ObjV = ObjV+const/3;                  % Penalty function
end
```

***Figure 2: MATLAB Code for Example Objective Function, gaobjfun***

The objective function of Fig. 2 results in the search space shown in Fig. 3. From the figure, it can be seen that the objective function space is multimodal and, using conventional optimization algorithms, sensitive to the selection of the initial starting point for the search. The global minimum of this function is located at the point $Wc = [161.78, 662.46]$.

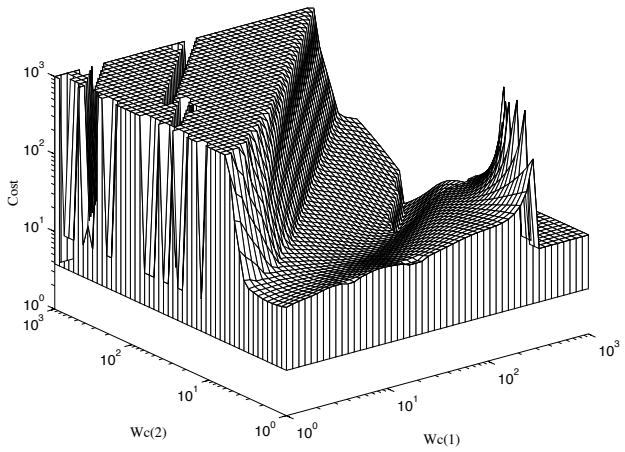


***Figure 3: Objective Function Space***

Fig. 4 shows the MATLAB code for a Simple GA to solve this problem. The first few lines of the code set the parameters that the GA uses, such as the number and length of the chromosomes, the crossover and mutation rates, the number of generations and the binary representation scheme. Next, an initial uniformly distributed random binary population, `Chrom`, is created using the GA Toolbox function `crtbp`. The objective function, `objfun`, is then evaluated to produce the vector of objective values, `ObjV`. Note that as we do not need the phenotypic representation inside the GA, the binary strings are converted to real values within the objective function call.

The initialisation complete, the GA now enters the generational loop. First, a fitness vector, `FitnV`, is determined using the ranking scheme of Baker [17]. Visualisation and preference articulation can be incorporated into the generational loop by the addition of extra functions. In this example, the routine `plotgraphics` displays the performance of the current best controller allowing the user to asses the state of the search. Individuals are then selected from the population using the stochastic universal sampling algorithm, `sus`, with a generation gap, `GGAP = 0.9`. The 36 (`GGAP` $\times$ `NIND`) selected individuals are then recombined using single-point crossover, `xovsp`, applied with probability `XOV = 0.7`. Binary mutation, `mut`, is then applied to the offspring with probability `MUTR = 0.0175`, and the objective function values for the new individuals, `ObjVSel`, calculated. Finally, the new individuals are reinserted in the population, using the Toolbox function `reins`, and the generation counter, `gen`, incremented.

The GA terminates after `MAXGEN` iterations around the generational loop. The current population, its phenotypic representation and associated cost function values remain in the users workspace and may be analysed directly using MATLAB commands.

```
LIND = 15;                                % Length of individual vars.
NVAR = 2;                                 % No. of decision variables
NIND = 40;                                % No. of individuals
GGAP = 0.9;                               % Generation gap
XOV = 0.7;                                % Crossover rate
MUTR = 0.0175;                            % Mutation rate
MAXGEN = 30;                              % No. of generations
                                          % Binary representation scheme
FieldD = [LIND LIND; 1 1; 1000 1000; 1 1; 0 0; 0 0; 0 0];

% Initialise population
Chrom = crtbp(Nind, Lind*NVAR);           % Create binary population
ObjV = objfun(bs2rv(Chrom, FieldD));      % Evaluate objective fn.
Gen = 0;                                  % Counter

% Begin generational loop
while Gen < MAXGEN
    % Assign fitness values to entire population
    FitnV = ranking(ObjV);

    % Visualisation
    plotgraphics

    % Select individuals for breeding
    SelCh = select('sus', Chrom, FitnV, GGAP);

    % Recombine individuals (crossover)
    SelCh = recombin('xovsp', SelCh, XOV);

    % Apply mutation
    SelCh = mut(SelCh, MUTR);

    % Evaluate offspring, call objective function
    ObjVSel = objfun(bs2rv(SelCh, FieldD));

    % Reinsert offspring into population
    [Chrom ObjV]=reins(Chrom, SelCh, 1, 1, ObjV, ObjVSel);

    % Increment counter
    Gen = Gen+1;

end

% Convert Chrom to real-values
Phen = bs2rv(Chrom, FieldD);
```

***Figure 4: MATLAB Code for a Simple GA***

Although the illustrative problem presented here is trivial, we have used the GA Toolbox on a number of linear and non-linear continuous and discrete time control applications. In particular, the SIMULINK package allows models to be directly expressed as block diagrams and simulated via MATLAB function calls, thus considerably reducing the development time of code for cost functions. The versatility of the MATLAB language allows the GA parameters and functions to be changed without the need for recompilation and graphical user interfaces constructed that allow the user to monitor and guide the GA.

## 4. FUTURE DEVELOPMENTS

The GA Toolbox is currently under test at approximately 20 sites world-wide in a range of control applications. In future releases we plan to incorporate support for multiobjective

optimization. Multi Objective GAs (MOGA) evolve a population of solution estimates thereby conferring an immediate benefit over conventional MO methods. Fonseca and Fleming [23] have demonstrated how, using rank-based selection and niching techniques, it is feasible to generate populations of non-dominated solution estimates without combining objectives in some way. This is advantageous because the combination of non-commensurate objectives requires precise understanding of the interplay between those objectives if the optimization is to be meaningful. The use of rank-based fitness assignment permits different non-dominated individuals to be sampled at the same rate thereby according the same preference to all Pareto-optimal solutions. Because MOGAs are susceptible to unstable converged populations, due to the potential for very different genotypes to result in non-dominated individuals, a particular problem is the production of *lethals* when fit members of the population are mated. The search then becomes inefficient and the GA is likely to converge to some suboptimal solution. In general, a combination of mating restriction, niche formation and redundant coding may be appropriate.

## 5. CONCLUDING REMARKS

Together with MATLAB and SIMULINK, the GA Toolbox described in this paper presents a familiar and unified environment for the control engineer to experiment with and apply GAs to tasks in control systems engineering. Whilst the GA Toolbox was developed with the emphasis on control engineering applications, it should prove equally as useful in the general field of GAs, particularly given the range of domain-specific toolboxes available for the MATLAB package.

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