Identifying Induction Machine Parameters Using A Genetic Optimization Algorithm

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abstract - Genetic algorithms can be used to find the global minimum of functions that are multimodal or that contain noisy data that render them intractable to gradient descent methods. Furthermore, the genetic approach is robust, requiring little preprocessing of data. The algorithm employs a random starting point, and is compatable with parallel processing. In this paper, the method is applied to identifying the parameters of an induction motor from load test data.

INTRODUCTION

Conventional gradient descent techniques for finding the minima of functions are fast and efficient from a computational point of view, but they are of limited value when several local minima exist. Such multimodal behavior is often associated with functions that involve noisy experimental data which define a "rough" search surface, such as is found in the case of test measurements on induction motors. When test measurements are used to find the internal circuit representation, the data may provide a close fit to several different sets of parameters.

It may therefore be necessory, in using motor test data to find equivalent circuits, to use an alternate approach. Genetic algorithms (GA's) have been gaining popularity as an optimization technique because of their inherent robustness. They may locate a global minimum, and hence be used for curve fitting with experimental data, even when many local minima exist. Reference [1] documents their use in biology, computer science, operations research, image precessing, and the social sciences. However, GA's have not been widely applied in electrical engineering, probably because the parallel search route and the probabilistic transition rules involved require what may be regarded as excessive computer time in many instances.

GENETIC ALGORITHMS

The genetic minimization process can be described as follows: It is desired to find a set of parameters which will minimize a "fitness" function (in this case, a parameter error function). Several possible parameter sets (the "population") are chosen at random. Each parameter set takes the form of a string of binary bits representing parameter values. Each bit string (member of the population) is tested to find its fitness by substitution into the parameter error equation. The population is then reproduced, with the same total number of bit strings. However, the new generation contains the same members as the old, but now in numbers proportional to their fitness. Thus the parameter sets tending to minimize error occur in greater numbers. This is the reproduction step in the algoritrhm.

Next, to produce variety, the members are randomly paired. Each paired string exchanges a randomly chosen portion of its bits with its mate. This produces a new set of members which maintain many of the characteristics of their predecessors. This is the crossover step, shown in Fig. 1.

After crossover, the population undergoes mutation, the third operation in the genetic algorithm. In this step, some portion of the bits in the total population is randomly altered. Typically, an average of one in one thousand bits is changed. This function prevents the algorithm from losing some potentially useful information. For example, if the entire population of bit strings has zero for its second bit, this condition cannot be altered by the reproduction and crossover steps. Eventually mutation will change this bit, which might have prevented an optimal bit string from forming. The whole process is then reiterated until convergence is obtained.

INDUCTION MOTOR PARAMETER ESTIMATION

Figure 2. is a steady state motor equivalent circuit adapted from [2]. The objective of motor load tests is to determine the value of parameters x_1, r_2, x_3, and r_3. The other

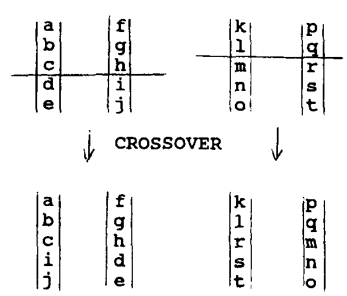

Figure 1.
Diagram of the crossover process. Two pairs of mated strings exchange a randomly chosen number of bits.

parameters, r_1 and x_2, are found from other tests or handbook data, and may be considered known.

In [2], motor parameters are found from an iterative solution of three algebraic equations using test data given in the reference's Form F 1. The test may be repeated at several speeds. This results in sets of parameter values corresponding to each speed which are then smoothed graphically. The problem of finding a single set of parameters arises because the values may actually change under load, and because of measurement noise.

Measurement noise and parameter variation present a challenge in using conventional parameter estimation, or data fitting, techniques. In these techniques, motor test data are compared with calculated test data from an image motor. The parameters of the image motor equivalent circuit are adjusted to

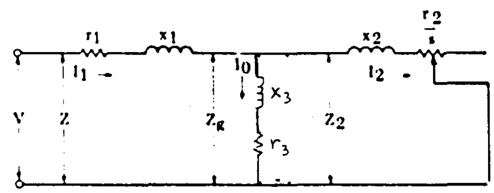

Figure 2.
Induction motor equivalent circuit.

minimize the difference between real and calculated test data. The problem arises when parameters of the real machine vary under load while the image parameters remain constant. Since directed search algorithms, which search the parameter space for a minimum difference between real and image machine test response, are typically stopped by local minima, the algorithm may go to one or the other of the changing parameter values, without finding the globally best value. For this reason, it was decided to use the genetic algorithm to minimize difference function.

The motor load tests consist of measurement of motor terminal complex impedance, Z_m, at rated voltage for at least two different values of slip, s_1 and s_2. A measurement of electrical torque, T_m, is also made at each of the test speeds. In the image machine, Fig. 2, torque is found from

$$T = (3I_2/n)(r_2/s), \qquad (1)$$

where T is image machine torque in n-m, n is the synchronous shaft speed in radians per second, and s is slip set to correspond to the test slip.

The genetic algorithm is now used to find a set of parameters for the circuit of Fig. 2 that will minimize an error function at a slip, s1:

$$E_{s1} = k_1(\mathrm{Re}(Z_m) - \mathrm{Re}(Z))^{2m} + k_2(\mathrm{Im}(Z_m) - \mathrm{Im}(Z))^{2m} + k_3(T_m - T)^{2m} \qquad (2)$$

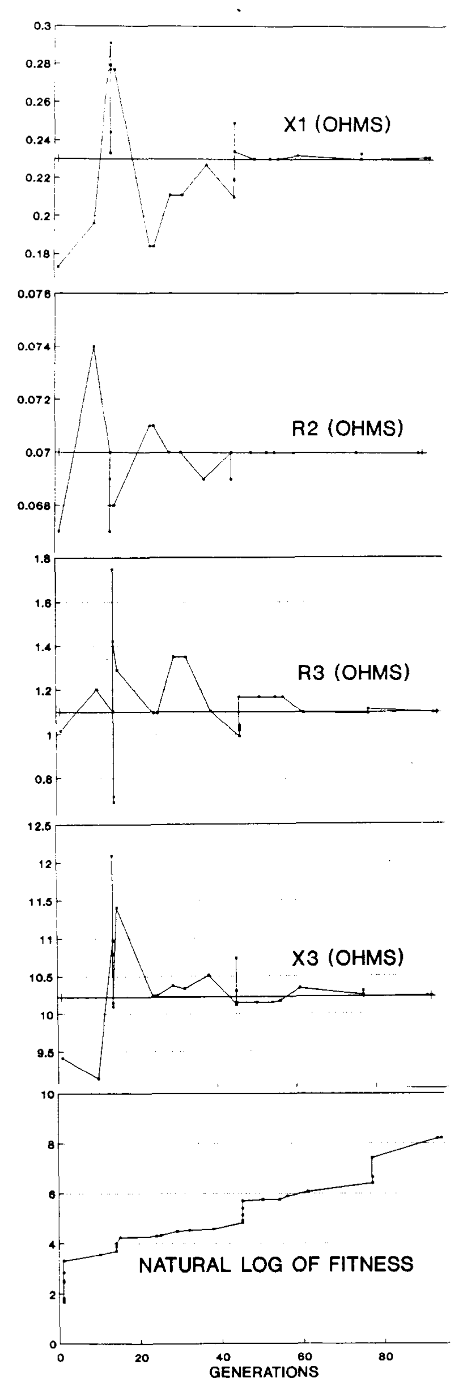

Figure 3.
Plot of updated parameter values vs. time (generation) for simulated test. Bottom plot is natural log of fitness.

where Z is the complex impedance of the image circuit in figure 2, and the weights k_1, k_2, and k_3 are found by engineering judgement. The exponent m may also be adjusted to affect the sharpness of the error function, but will normally be unity. E_{s1} is the error for a test done at slip 1. If the test is to be repeated at several slips, the sum of all errors is E:

$$E = E_{s1} + E_{s2} + \ldots \quad (3)$$

SIMULATION TEST

To try out the genetic algorithm, a motor test was simulated using the steady state model, Fig. 2. The motor parameters were taken from [3], $r_1 = .0483$, $x_1 = .230$, $r_2 = .0677$, $x_2 = .230$, $r_3 = 1.10$, $x_3 = 10.22$, all values in ohms. Following [2], the parameter r_1 was taken as known, and the ratio x_1/x_2 was known to be unity, reducing the unknowns to four. After some experimentation, the genetic algorithm was constructed with a population of 500 bit strings. Each string represented a set of four parameters with four consecutive ten bit binary numbers, for a total of 40 bits per string. The binary numbers were scaled to include up to approximately double the expected parameter values.

The strings were reproduced in numbers proportional to their ability to maximize a fitness function. Since the object is to minimize an error, E, in eq.(3), fitness was taken as the reciprocal:

$$\text{Fitness} = 1/E. \quad (4)$$

The test parameters, Z and torque, were taken for two slip values, s = .0001 for light load and s = .025 for full load.

After the reproduction step, the population was randomly paired. Each pair exchanged a randomly chosen portion of each member's bits for the crossover step. Then the mutation step was accomplished by randomly changing one of every one hundred bits in the whole population. The process was then reiterated for the next generation.

Fig. 3 is a plot of the parameter values plotted against the algorithm's "generations", or reproduction cycles. The parameters plotted represent the parameters contained in the string that scored the highest fitness value up to that point in time. Also included is the log of the value of the fitness corresponding to the parameter values, which is a monotonically increasing curve.

In the original program, the parameters tended to converge slowly as the fitness function became high because of the effect of mutation on the parameters that were not very sensitive to the test values. For example, a change in an insignificant bit of x_3 would have strong consequences for x_1, which is in series with it, and much smaller. To make the values settle down sooner, the range of possible parameter values was reduced after the fitness function reached a predetermined value. This prevented change in the most significant bits of the parameters and facilitated convergence.

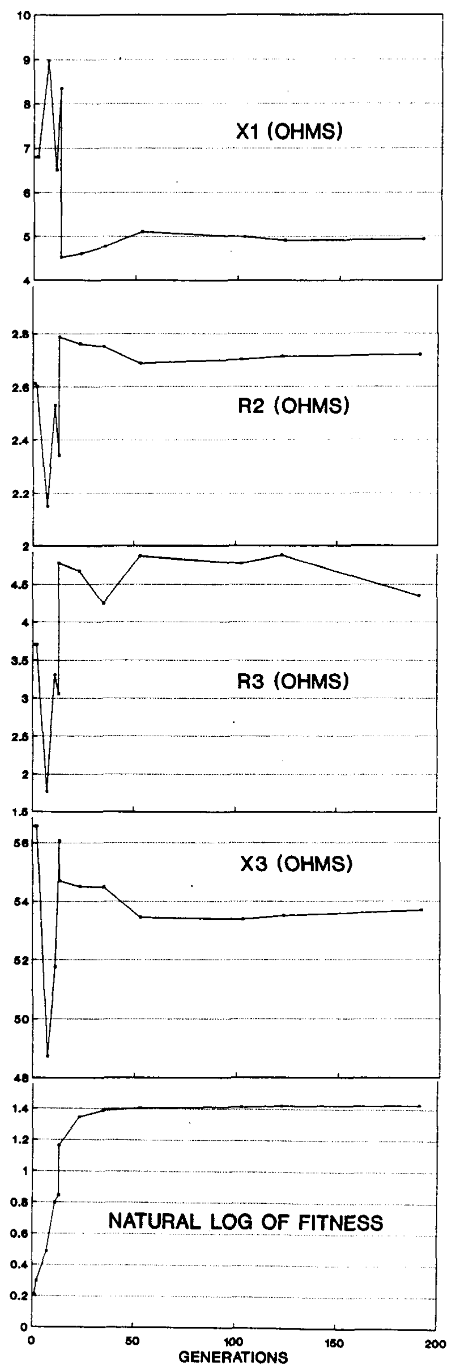

Figure 4.
Plot of parameter values vs. generation for laboratory test. Bottom plot is natural log of fitness.

In /Fig. 3, the parameter range was reduced from $\mp$ 100% of actual value to $\mp$ 30% after approximately 80 generations. Computing each generation took approximately 40 seconds on a Z-248 PC with a math co-processor.

LABORATORY TEST

The algorithm was tested using data from a laboratory 1/2 hp three phase induction motor. The result is shown in Fig. 4. The convergence obtained is similar to the simulated test above. Range reduction was done after the 100th generation.

CONCLUSION

A genetic algorithm for identifying induction motor parameters from machine test data was written and tested. The results indicate that genetic algorithms can be used for this purpose. Experience with the algorithm indicates that it is robust and may find results under conditions of noisy and inconsistent test data.

REFERENCES

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[2] "IEEE Standard Test Procedure for Polyphase Induction Motors and Generators", IEEE Std. 112-1984

[3] Matsch, Laender W.,"Electromagnetic and Electromechanical Machines", Second Edition, 1977, IEP