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TURBO GENERATOR SYSTEM IDENTIFICATION USING GENETIC ALGORITHM

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Abstract: the turbogenerator is one of the mean important parts of the thermal power station, which is the most famous used as a generation power plants since the serving of electricity till now. The turbogenerator unit behavior is non- linear and complicated system, for this causation the identification models are use for best and close optimization to have the highest and accurate controller. In this paper we will used the conjunction of data by intelligence techniques which called "Genetic algorithm" to have the optimum behavior without using complex mathematical equations. The result we have from genetic algorithm is showing the capably to reach highest accuracy in system work identity, which are depend on a real data registered from no-load in the second unit of Mussiab thermal power station.

Keywords: *Turbogenerator, Genetic Algorithm, Optimization identification, Chromosome, Crossover point.*

تعريف منظومة توليد توربينية بأستخدام الخوارزميه الجينيه

الخلاصة: يعتبر المولد التوربيني من أهم أجزاء محطات التوليد الحرارية. التي تعتبر من أهم محطات التوليد المستخدمة لتوليد الطاقه وهي من أهم مشاريع التوليد منذ اكتشاف الكهرباء و لحد هذا الوقت. عمل وحدة التوليد التوربينية هو عمل لاخطي و معقد، ولهذا السبب فأن طرق حسابية معقدة يحتاج لتعريفها و للحصول على اعلى وأدق سيطره عليها وذلك باستخدام طريقة تعريف النظام للحصول على توصيف (تمثيل) قريب من العمل الحقيقي للمولد التوربيني . في هذا البحث تم استخدام الذكاء الصناعي لربط المعطيات باستخدام "الخوارزمية الجينية" للحصول على افضل اداء دون الحاجة الى للحسابات الرياضية المعقدة. النتيجة التي تم الحصول عليها بأستخدام الخوارزمية الجينية أظهرت قابلية عالية للوصول الى أفضل النتائج دقتا لتعريف المنظومة والذي أعتمد على قراءات حقيقية من حالة اللاحمل للوحدة الثانية لمحطة المسيب الحرارية.

1. Introduction

The design of prediction control to have a model for dynamic system that will suitable to define the system behavior.

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In general, because of the complexity externals and to have an optimum description the dynamics of plant need to be controlled.

The laws of physics are not satisfaction. The designer turns to field data in this condition.

The experiment could be conducted between the plant and measure directly. This process is known as "system identification". The system identification could be performed "on-line" which depend on plant operation.

The system identification is the important part of adaptive scheme. Appropriate techniques in control have been studied wildly in many successful applications which have been done [1]. The fact appreciated by those contains with the applications is that factual design problems are usually complex. The applications of the adaptive control for plants and the processes don't warranty successful results which predicted by the analysis and simulation [1].

2. Generator model

The motion of synchronous rotor is governing with equation that depended on the dynamics principle which states that acceleration torque is predicting from the moment of inertia with angular acceleration of the rotor [3].

By using synchronous machine to swing equation with perturbation we will have [2, 3, 4].

$$\frac{2H}{w_s}\frac{d^2\Delta\delta}{dt^2} = \Delta P_M - \Delta P_e \tag{1}$$

Or in terms of small deviation in speed:

$$\frac{d\Delta\frac{w}{w_s}}{dt} = \frac{1}{2H}(\Delta P_M - \Delta P_e) \tag{2}$$

Using speed expressed in per unit we have:

$$\frac{d\Delta w}{dt} = \frac{1}{2H}(\Delta P_M - \Delta P_e) \tag{3}$$

Transforming (2-3) to Laplace transform we have:

$$\Delta\Omega(s) = \frac{1}{2HS}[\Delta P_M(s) - \Delta P_e(s)] \tag{4}$$

Where:

H : inertia constant (M joul / MvA)

W : Rotor speed (radian/second)

δ : torque angle (degree)

Δ : deviation from steady state

P_M : mechanical power (per unit)

P_e : electrical power (per unit)

W_s : synchronous speed in electrical units.

Figure (1) is the block diagram summarized equation (4).

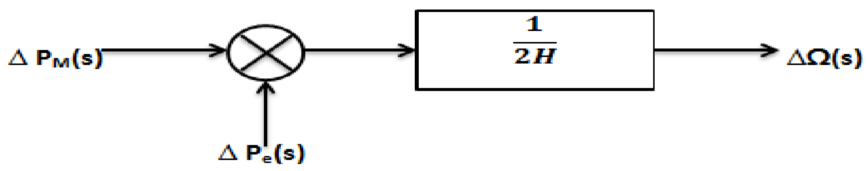

Figure (1) Generator block diagram

3. System identification

System identification is how to developing models of dynamic system from the data of experimental input and output [5].

The methodology to determination the mathematical model for a system is identifying by finding the relationship between input, output and developing of optimal than adaptive control system to obtain highly accurate system model.

The mathematical equation needs to have the system model that relates the input to output, to have such model, it's possible to survey the different input and have its responses. The next step in this process is to linking the input-output data to yield the model with priori consideration knowledge about the system. In this case classify the problems of system identification in to two categories:

- Complete identification problem: in this category it assumed that there isn't any think about the system basic properties. Such as its linearity or not, have a memory or without, and so on.
- Partial identification problems: in this category some of basic characteristic such as bandwidth, linearity of the system are known [4].

The aim is to concentrate agreeably identification model as shown in figure (2). Which is dragooned to the same input $U_m(k)$ it produced $Y_m(k)$ as an output, $Y_p(k)$.

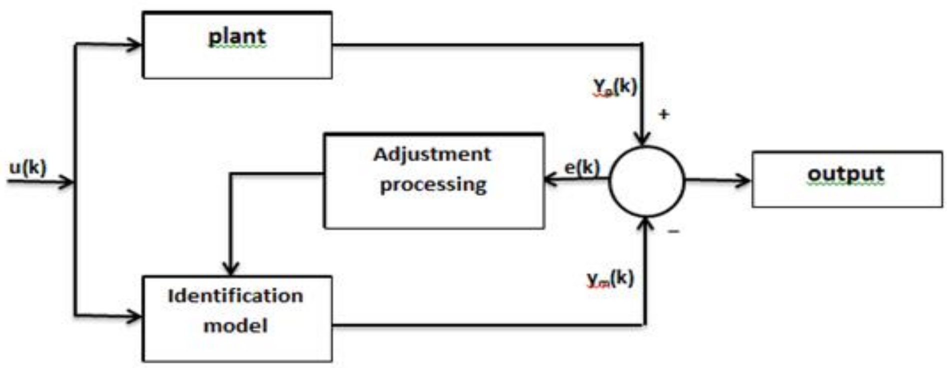

Figure (2) identification layout

4. Materials and experimental work

The process of making something better is called "optimization". For the new idea the engineer or scientist can created an optimization improves on it. Optimization is trying variations on an initial comprehend and the gained information used to improve the idea. Using the computer to have optimization for idea or variable is a suitable tool as long as it can be input them as electronic format.

Using the characteristics of device or experiment to find the maximum or minimum output or results to adjusting the input is optimization process.

The function or process is diereses as a: cost function, objective function or fitness function. These are the input variables and the output will be cost or fitness. If the process is experiment then the physical inputs are the variables to experiment. If the output is define as a function or process of cost, then the cost need to be minimized, and sometime maximized is more effect, then by putting minus sign to the output form and maximizing this will be means minimize it [6].

4.1. Genetic algorithm (G.A) fundamentals

Genetic algorithm (G.A) operators to find the suitable solution are fitting with ((survival of the fittest)), to have best approximations to a solution. The process created a new set of approximations at each generation to selecting individuals according to its fitness for a problem boundary and then breeding them together with operators from natural genetics. This population of individuals is more suited to environment from that previously created as a natural adaptation figure (3) represents the genetic algorithm

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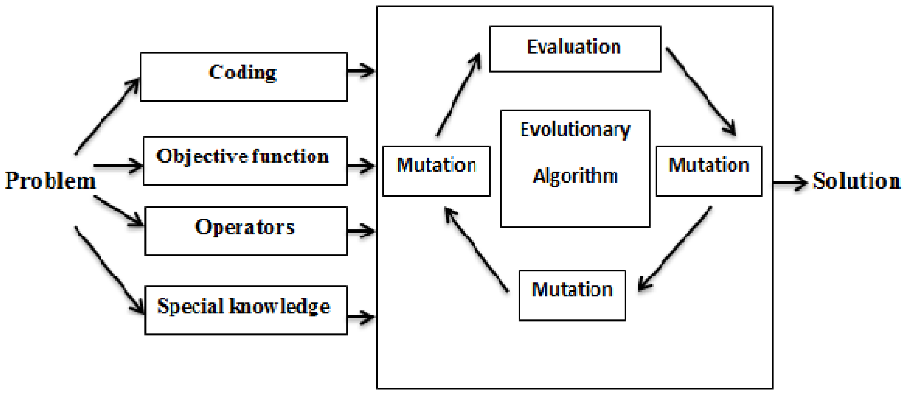

Figure (3) Genetic algorithms cycle

The current approximation or the individuals are coded as string and superimposed over alphabet(s), so that chromosome value are exclusively used to representing in genetic algorithm as a binary code (0,1), or represented as a permutation or integrator or ternary or as real values.

A chromosome is actually divided into gene which is either single bit or short block of chin bits which coded a particular element of the chosen solution.

For each gene, it has its particular ((locus)) ((position)) on the chromosome. For particular element with a different possible string of the selecting solution are ((alleles)), the allele in binary code string is (0,1), at each locus there are larger alphabets and more alleles are possible in each locus [7].

To test the chromosome string in insulate yields, if there is no data about the problem trying to find the suitable solution to it. For decoding the chromosome into a "phenotypic value" any significance can be used for the presentation.

4.2. Elements of the genetic algorithm (G.A)

The ideal G.A. is constructed of many steps to find optimum solution. There are different numbers of steps and this depends on the authors. All these authors include the properties procedure of selection, recombination, mutation and evaluation that the G.A runs in it. In figure (4) it shows the steps of ideal (G.A) [7]. The steps which presented in figure are more detailing in figure (4).

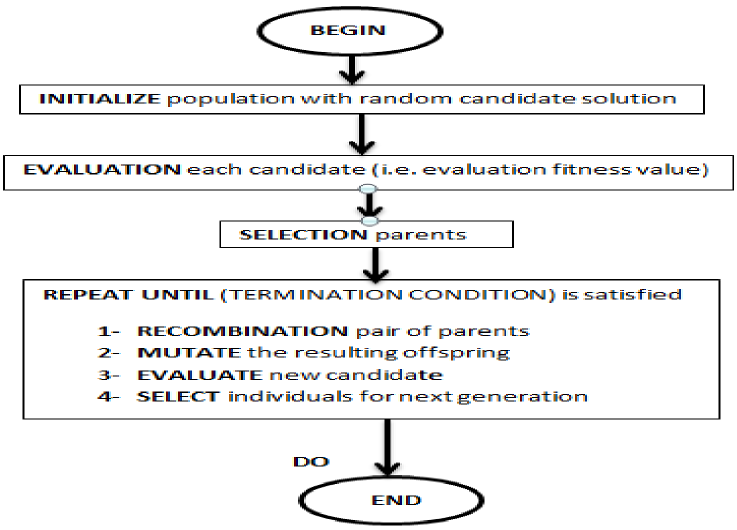

Figure (4) The flow chart of a typical genetic algorithm

4.3. Chromosome Representations

The using of G.A. is to represent the solution of problems. Since they work with decoded parameters to optimize the problem, the select of representation frame has a large effect on the performance. There are many ways of coding solution, and there is no probably one for all problems [8]. The performance of G.A. accredited on selection of the best representation technique such as:

- Real numbers (54.3 5 12.6---------- 61)
- Bits strings (000 100 111--------011)
- List of rules (R_1 R_2 R_3 ------- R_{13} R_{14})
- Program elements (Genetic programming)
- Permutation of elements (E11 E3 E7 ………….E1 E15)

4.4. Recombination

Recombination is a recruiter (crossover), which is the main role in G.A. behavior. The meeting pool individuals are recombined to have a new construction of individuals (offspring) which is combine between two parameters of G.A. as known to practitioner, that recombination aimed two purposes: first it recombines traits, be achieve the residing traits on separate partners and combine with single parent, second influence which is more subtle. The recombination generate a new traits by putting alleles in new contains. There are a large ways to execute the recombination. This depend on the problems, some are suitable for certain case than others [9].

The most using of recombination type is one point crossover. Where two of randomly individuals chose and are split from mating pool at randomly selected crossover. The parts are changed to generate two new individuals [9].

There are two common types which are ((two points crossover)) and ((uniform crossover)) [10].

Figure (5) to figure (7) show the most common types genetic crossover.

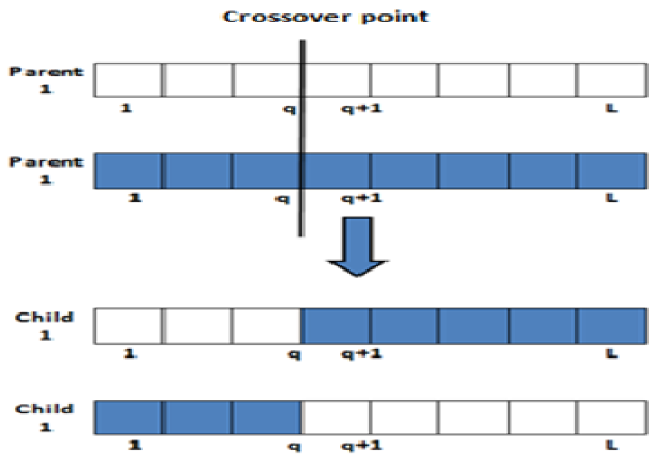

Figure (5) one- point Crossover operation

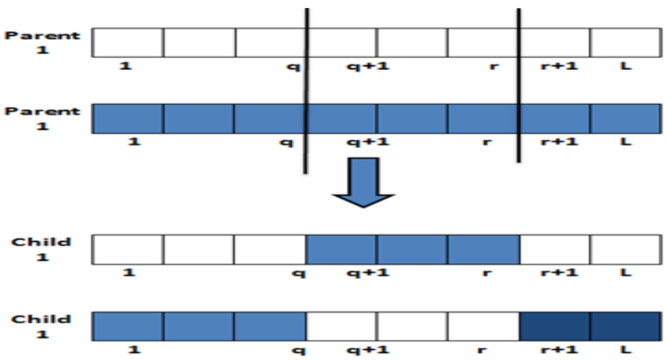

Fig (6) two – point crossover operation

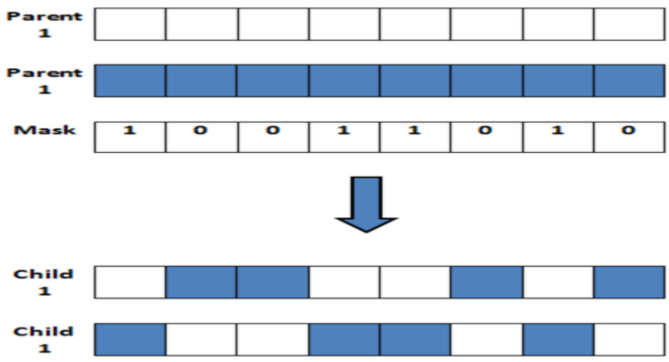

Fig (7) two – uniform crossover operation

4.5. Mutation

There are two problems with choosing "selection" and "crossover" because it will be yield a large number of different strings which are:

- They may not enough diversity due to the initial population chosen to ensure the G.A. to find the totally problem area.
- The G.A. may not determine sub-Optimum string because of bad elect of initial population.

Mutation probability in normal case is low because high mutation rate will smashed the fit string and put the G.A. in random search [9].

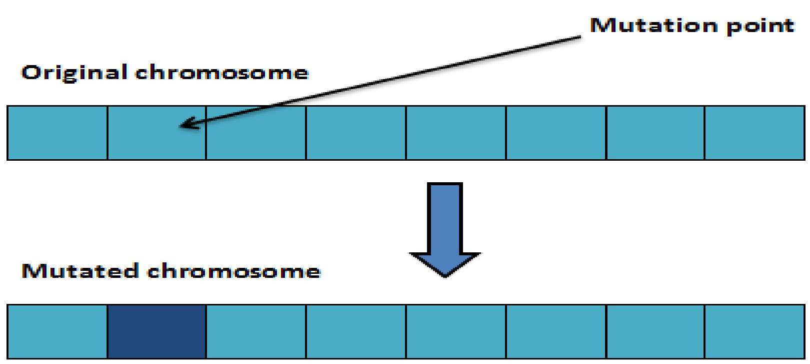

Figure (8) Mutation operation

4.6. Termination of the GA

The termination criteria ((convergence)) for genetic action may be concerted by reaching a perceptible approximation solution and find the search stop. Termination criteria are one or more of that [10]:

- Generation: this process illustrates the highest number of generation.
- Time limit: illustrate the highest time in second.
- Fitness limit: the algorithm will stop if the best fitness value is equal or less than the fitness limit.

5. Plant description

The unit considered in this work it's second unit for Al-mussib power plant, a two pole turbo generator driven at (3000 r.p.m. , 300 MvA , 20 Kv , 50 Hz and excitation voltage 625 volt). The steam is produced by a conventional fuel fired boiler at pressure (180 bar) and steam flow is controlled by both main and interceptor valves. Figure (9) shows a possible physical and computations logic layout for a turbo generator (TG) identification scheme of Al-mussib power plant.

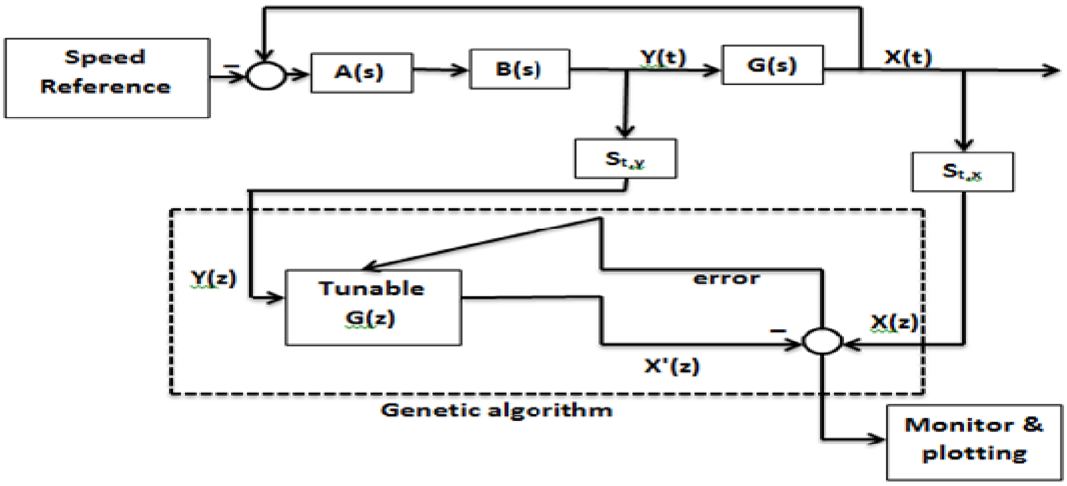

Figure (9) Turbo generator block diagram

The samplers, S_t, are connected to the input and output of G(s), sampling the gate position, y(z) and x(z), as shown in figure (9). The sample rate was taken to be (100 samples /sec). The GA used the sampled filed data for input to develop a discrete time transfer function, G (z), of the same dynamics as G(s). This is done by inputting the gate position filed data, y(z), into the G(z) of the GA, calculating the G(z) output, x'(z), and comparing that output to the frequency filed data , x(z).this process is repeated for all G(z) in the GA's population at every generation.

From the prior knowledge of the plant, turbogenerator dynamics for off line is known. This knowledge indicates a 5^{th} order transfer function model for the TG to be appropriate. The turbogenerator was therefore modeled by following structure:

$$G(z) = \frac{K}{(z+p_1)(z+p_2)(z+p_3)(z+p_4)(z+p_5)} \quad (5)$$

Where (p1, P2, P3, P4, P5, K) are chromosome variables.

A 5th order turbogenerator transfer function was estimated using the data from the AL- Mussiab power plant given in figure (10).

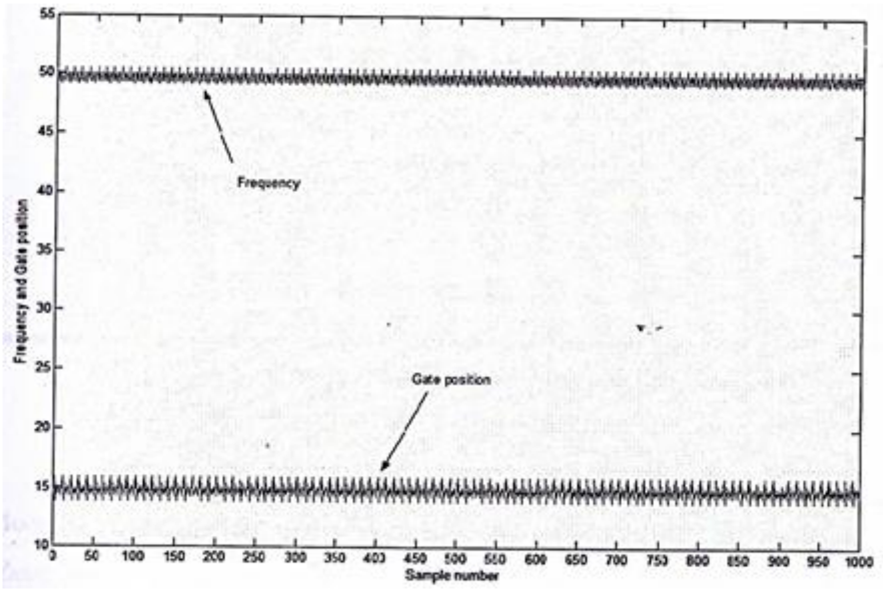

Figure (10) AL- Mussiab off line Data

6. GA solution

The important and first step in G.A. is the representation of chromosome. Turbogenerator plant prior knowledge is the 5th order transfer function, for this the chromosome variable are (P_1, P_2, P_3, P_4, P_5, K) which means five poles and gain.

Three dimension array and six pages these variables are shown. Each variable has one page, and there are (n) rows in each page, which means population size and (m) columns which means the number of bit in each variable as figure (11) shown.

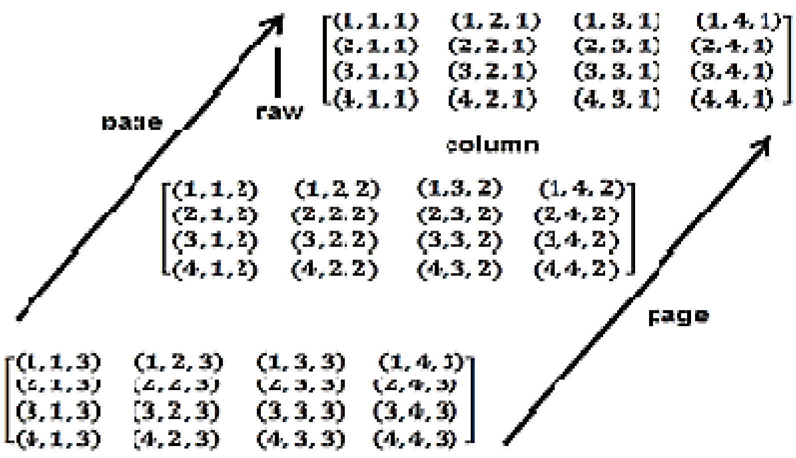

Figure (11) illustrates the pages representation

(1bits) is the number of bits, the right bit show the integer part with dynamic rang (-2, +1). The left bit is the Most Significant Bit (MSB), this bit is the sign of number (if its zero means +ve pole and if it's one means –ve pole), because of using 2's complement [12].

In table (1) it can be seen that in the 2's complement there is only one characterization for each number and dynamic range, which signed magnitudes greater than 1's complement as shown in table (1).

The 8-bits remains are characterizing the 3- decimal digit fraction quietly, having a decimal fraction (x) with (d) digit quietly as in equation (6) [13].

$$X = \pm 0.5 \times 10^{-\mathrm{d}} \qquad (6)$$

If the same number is characterizing in binary (B) bit will be equ. (7):

$$X = \pm 0.5 \times 2^{-\mathrm{B}} \qquad (7)$$

To go back the same quietly characterizing required:

$$\pm 0.5 \times 10^{-d} = \pm 0.5 \times 2^{-B} \quad \rightarrow \quad B = d\, log10 \quad B = 3.3d\ bits$$

By using Math lab function (rand) initial population is generated randomly using the function (rand) to have a binary number (0, 1). After that taking the 2's complement for this population it must be use the defined function of population matrix. The G.A. will minimize the selection of objective function in the next step. The objective function will have the Exponential of Median Error, because it's ability to have significant different in population.

The fitness value shows the opposite of error magnitude. To have better solution it must be chose a good objective function, a good chromosome solution select according to objective function. To find the transfer function, which is the final step, the numbers are decoded to a decimal. The fitness value shows the opposite of error magnitude. To get a better solution it must be chose a good objective function, because a good chromosome solution select depend on objective function. To find the transfer function, which is the final step, the numbers are decoded to a decimal.

Table (1) sign representation [14]

Decimal	2's complemer	1's complement	Signed magnitud
-8	1000	___	___
-7	1001	1000	1111
-6	1011	1001	1110
-5	1011	1010	1101
-4	1100	1011	1100
-3	1101	1100	1011
-2	1110	1101	1010
-1	1111	1110	1001
0	0000	1111 or 0000	1000 or 0000
1	0001	0001	0001
2	0010	0010	0010
3	0011	0011	0011
4	0100	0100	0100
5	0101	0101	0101
6	0110	0110	0110
7	0111	0111	0111

In this research it have been used the process of selection and methodology of crossover point.

The first point (q_1) generated aimlessly with using Math lab function (rand) (from 1 to 4) and then by using equation (8) will have (q_2):

$$q1 = ceil\ ((rand) \times 4)$$

$$q2 = q1 + 6 \tag{8}$$

This process will change 50% of data. The termination of genetic algorithm in this paper are used either fitness limits or maximum generation. The program will stop if it reaches specified fitness, otherwise the program will continue till it reaches the maximum generation. After many course of generation the genetic algorithm created G (z)'s which is the minimum error between x'(z) s and x (z) s.

7. Results

In the GA optimization algorithm, therefore, need many generations to reach the optimal solution. The GA was stopped at reach the fitness limit.

The result program when using sample rate (30 sampler/sec) and:

Population size = 50

Tournament size = 5

Crossover probability = 0.88

Mutation probability = 0.01

Maximum generation = 20

Time elapsed = 20 sec

Table (2) show number of generation program reached to optimal values in this case and minimum error when using objective function Exponential of Median Error. We obtain minimum error was not satisfy because the sampling rate was not adequate to translate most component of system behaviors.

Table (2) Result of GA at sampling rate (30 sampler/sec)

No. of generation	Exponential of Median error
1	1.5597
2	1.2082
3	1.2019
4	1.1944
5	1.1897
6	1.1851
7	1.1841
8	1.1833
9	1.1827
10	1.1764
11	1.1662

After end the program at number of generation (11) and minimum error (1.1662) can be obtain the transfer function G(z) in the following structure equ. (9):

$$G(z) = \frac{0.4726}{(z-0.1055)(z+0.1426)(z+0.332)(z-0.375)(z-0.4785)} \tag{9}$$

And also the result of program when put real input (the gate position) of the plant as an input to G(z) to produce estimated output x'(z)as shown in figure (12).

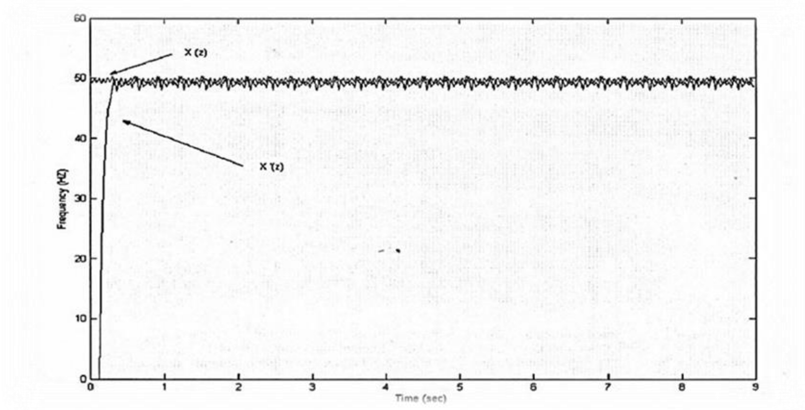

Figure (12) Result of GA at sampler rate (30 sampler/sec.)

The result program when using sample rate (50 sampler/sec) and:

Population size = 50

Tournament size = 5

Crossover probability = 0.88

Mutation probability = 0.01

Maximum generation = 20

Time elapsed = 31 sec

Table (3) show number of generation program reached to optimal values in this case and minimum error when using objective function Exponential of Median Error. We obtain minimum error was not satisfy but better from the sampling rate (30 sampler/sec.) because the sampling rate was not adequate to translate most component of system behaviors.

Table (3) Result of GA at sampling rate (50 sampler/sec.)

No. of generation	Exponential of Median Error
1	1.1587
2	1.1587
3	1.1488
4	1.0933
5	1.0933
6	1.0786
7	1.0640
8	1.0626
9	1.0531

After end the program at number of generation (9) and minimum error (1.0531) can obtain the transfer function G(z) in the following structure equ. (10)

$$G(z) = \frac{0.78516}{(z-0.082)(z-0.1504)(z-0.1816)(z+0.1036)(z+0.04102)} \tag{10}$$

And also the result of program when real input (the gate position) of plant as an input to G(z) to produce estimated output x'(z)as shown in figure (13):

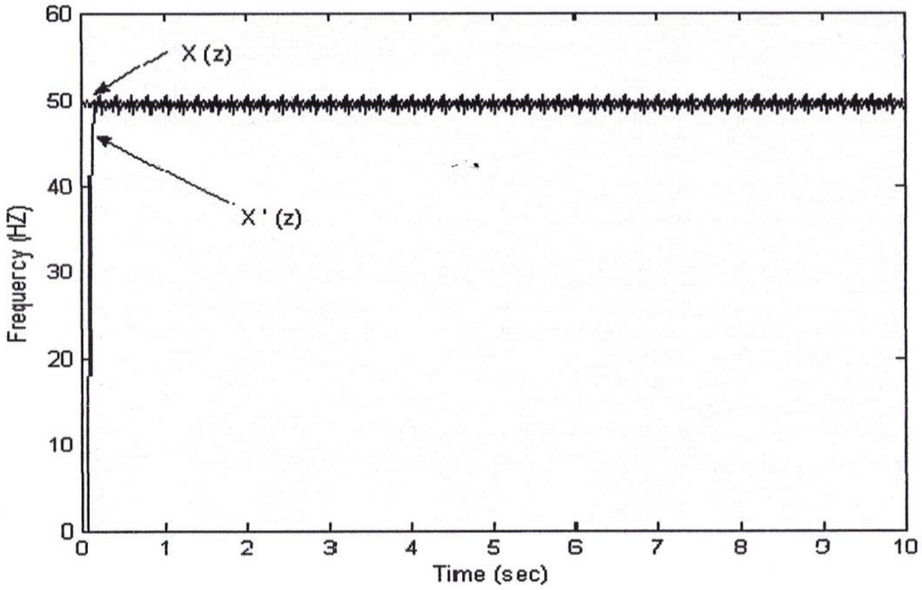

Figure (13) Result of GA at sampler rate (50 sampler/sec.)

The result program when using sample rate (100 sampler/sec) and, objective function (Root Mean Square Error) and:

Population size = 50

Tournament size = 5

Crossover probability = 0.88

Mutation probability = 0.01

Maximum generation = 20

Time elapsed = 78 sec

Table (4) show number of generation program reached to optimal values in this case and minimum error when using objective function (Root Mean Square Error). Although we observe figure (14) has small minimum error but not adequate for find optimal poles and gain of the system and not able to reduce minimum error more than from this

After end the program at number of generation (15) and minimum error (3.6671) can obtain the transfer function G(z) in the following structure equ. (11):

$$G(z) = \frac{0.8633}{(z+0.8828)(z-0.2676)(z-0.02617)(z-0.2187)(z+0.00976)} \qquad (11)$$

And also the result of program when real input (the gate position) of plant as an input to G(z) to produce estimated output ẋ(z)as shown in figure (14):

Table (4) Result of GA at sampling rate (100 sampler/sec.) objective function (Root Mean Square Error).

No. of generation	Root Mean Square Error
1	4.0527
2	3.7260
3	4.0527
4	3.7260
5	3.7260
6	3.7197
7	3.7191
8	3.7173
9	3.7191
10	3.7127
11	3.7126
12	3.7120
13	3.7120
14	3.7120
15	3.6671

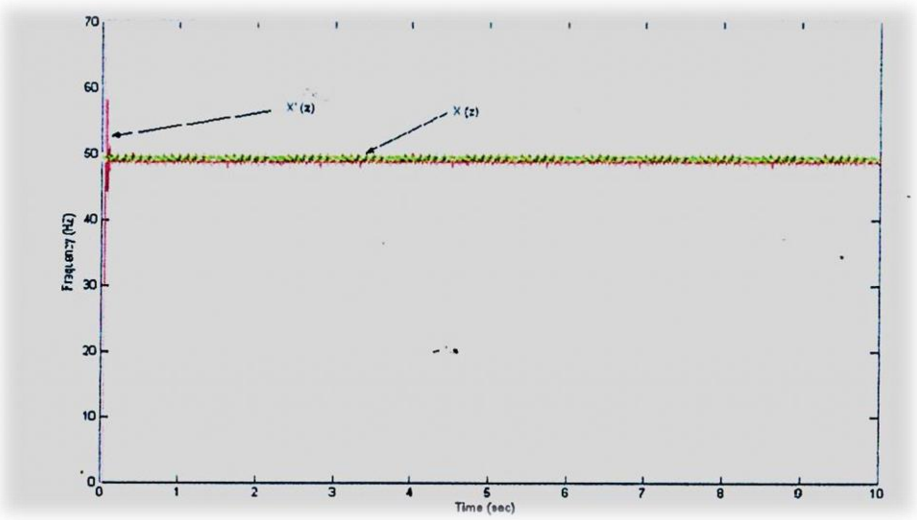

Figure (14) Result of GA at sampling rate (100 sampler/sec.) objective function (Root Mean Square Error).

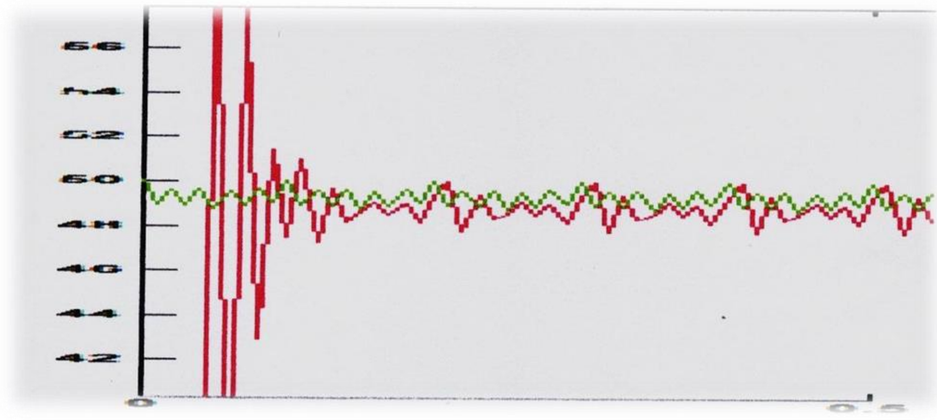

Figure (15) Clipboard of Figure (14)

The result program when using sample rate (100 sampler/sec) and, objective function (Root Mean Square Error) are:

Population size = 50

Tournament size = 5

Crossover probability = 0.88

Mutation probability = 0.01

Maximum generation = 20

Time elapsed = 51 sec

Table (5) show number of generation program reached to optimal values in this case and minimum error when using objective function Exponential of Median Error. We observe minimum error was satisfy because the function Exponential of Median Error able to reduce minimum error more than other objective function using for that application

After end the program at number of generation (8) and minimum error (1.0179) can obtain the transfer function G(z) in the following structure equ. (13) :

$$G(z) = \frac{1.3047}{(z-0.1641)(z-0.5527)(z+0.5156)(z+0.8125)(z+0.2695)} \quad (13)$$

Table (5) Result of GA at sampling rate (100 sampler/sec.), objective function (Exponential of Median Error)

No. of generation	Exponential of Median Error
1	1.0364
2	1.0202
3	1.0271
4	1.0344
5	1.0210
6	1.0210
7	1.0195
8	1.0179

Few points can be observed in figure (16):

- Matching region is relatively large
- Refereeing to table (5) we can see that the error has become minimum.
- After 30 sample the oscillation has been minimized so that the real system and the estimated system are approximately identified.

Therefore we conclude that GA has the ability for convergence to optimal value using system parameters and so the proposed system response and behavior is satisfactory and also the result of program when put real input (the gate position) of the plant as an input to G(z) to produce estimated output to x'(z) as shown in figure (16):

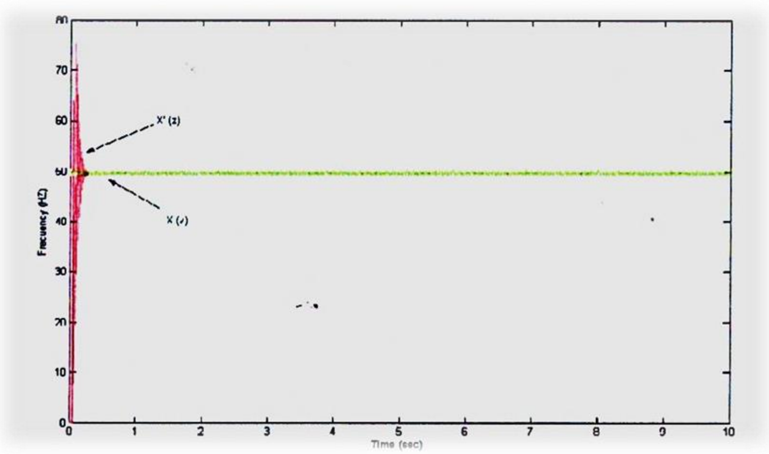

Figure (16) Result of GA at sampling rate (100 sampler/sec.), objective function (Exponential of Median Error)

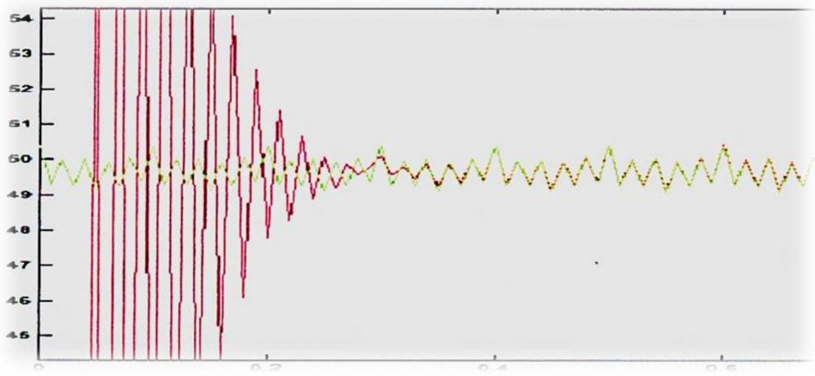

Figure (17) Clipboard of Figure (16)

8. Discussion

The important choice for suitable sampling rate to translate the system behavior, therefore, we can select many sampling rate reach for convenient vale of sampling rate. From experimental results illustrate that sampling rate of (100 sample/sec.) has a better ability to show most component of device behavior that other sampling (30, 50 sample/sec.), table (6) illustrate number of differences among (30, 50, 100 sampler/sec.).

Table (6) illustrate using difference sampling rate

	30 sampler/sec	50 sampler/sec	100 sampler/sec
No. of generation	11	9	8
Min. of Error	1.662	1.0531	1.0179
Time elapsed (sec)	20	31	51

The objective function (Exponential of Median Error) was selected over number of other objective function for:

- Its ability to provide significant differences in minimum error.
- The function also reduce the skewing of population's fitness values for population containing one very good, or one very bad transfer function. Table (7) show that capability of Exponential of Median Error for reduces minimum error from Root Mean square Error.

Table (7) show compare between Exponential of Median Error and Root Mean square Error.

	Root Mean Square	Exponential of Median Error
No. of generation	15	8
Min. of Error	3.6671	1.0179
Time elapsed (sec)	78	51

Values of probability of mutation (p_m = 0.01), probability of crossover (p_c = 0.88) and population size (50) where chosen as being the best values for obtaining a better transfer.

9. Conclusions

The following conclusions can be pointed out:

1. Modeling process of turbogenerator used in this research is based on gray- box principle. The model is established by iteration process data. More prior knowledge of process is needed.
2. The structure of model is represented by transfer function of finding the optimal poles and gain for the system.
3. The GA can effectively identify a Turbogenerator system in the off-line using sampled frequency and gate position field data.
4. It can also adaptively identify a plant recursively and change the GA model as the dynamics of the plant change. The GA's transfer functions were better, i.e. had a smaller error.
5. Facilitates for both structure and parameter identification in complex model because of flexibility.
6. GAs are family of adaptive search procedures whereby adaptation proceeds not by making incremental changes to a signal structure, but by maintaining a population of structure from which to create new structure using genetic operators.
7. GAs have the quality of robustness in that, while special case algorithms may find more optimal solutions to specific problems, GAs perform very well over a large number of problem categories.
8. Optimal parameter setting (including population size, operator probabilities) is proportional to the desired performance measure.

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