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Genetic Algorithms for Optimum Machine Elements Design

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Abstract: The purpose of this paper is to optimize the calculation by means of a Genetic Algorithm (GA) universal for designing elements of machines. In this paper, its results are taken and compared with the standard calculations for spurs gears and for some of their parameters as axial distance, weight, etc., or even the realization of some other objectives set as an objective function and the selected variables as wheel width and the tooth number of the pinion, and placed in restrictive settings termed- flexural strain and strain in contact. Since the multi-objective function with constraints is very difficult to be optimized using the conventional optimization techniques it is recommended to use the non-traditional optimization technique called Genetic Algorithm. The non-traditional algorithms are very difficult to be solved manually. The solution for a non-traditional method can be obtained by programming the above algorithm by means of programming language "C", Visual Basic or mathematical software MATLAB, Mathematics, etc. MathCAD. In this article for the algorithm workout and the sample presentation is used MATHCAD program.

Keywords: **Optimum, Machine Elements, Genetic Algorithm, Mathcad.**

I. Introduction

Genetic Algorithm is an optimizing and researching technique based on the genetic principle and natural selection [1]. This algorithm was inspired by the theory of evolution of Darwin where among others it is stated that the best survives through selection, through crossover and natural mutation and in this concept this theory was developed later in mathematical research around the years 1960-1970 from Holland. These are the basis for the development of the research method of genetic algorithm in the engineering field and more specifically in that of mechanical engineering.

II. Genetic Algorithm Principle

Before we present the application of the genetic algorithm in machine element design in the literature [2] are provided the basic concepts of algorithm as well and its stages. The genetic algorithm is part of stochastic research methods with an objective (single-objective) or more targets (multi-objective). Its major data are variables that are taken from their definition field (which constitutes the advantage of this research method as the obtained results are taken from their field of research). If given in a mathematical manner by the above variables it will be expressed:

$$x_1 \approx X_1$$
$$x_2 \approx X_2$$
$$\ldots\ldots\ldots$$
$$x_m \approx X_m$$

So the designing vector (face) will be of the form:

$$X = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

These variables are generated randomly by their own areas of defining and incorporated in vectors create the so-called designing vector. On figure 1, there is presented the creation process of these variables in the programming language. The input of the variables in the form of vector from the set of definition (space) are given:

```
DATA(0) = for  i0 ∈ 0..5
            RNDDATA_i0,0 ← | for  i2 ∈ 0..3
                           |     Y_i2 ← rnd(space)
                           |     i2 ← i2 + 1
                           | trunc(Y)
            i0 ← i0 + 1
            RNDDATA
```

As seen on a vector with 4 variables from definition area are selected the random variables creating so a designing vector and all together grouped in the set of designing vectors called "set" which coincides in this case with 6 such vectors. Once these variables are defined, they are included in the objective function for which we are concerned where we may have one or more such and their presentation can be:

$$f_1(X^T) = f_1(x_1, x_2, x_3, \ldots\ldots\ldots\ldots, x_n) = first - objective$$

$$f_2(X^T) = f_2(x_1, x_2, x_3, \ldots\ldots\ldots\ldots, x_n) = \mathrm{sec}ond - objective$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$f_m(X^T) = f_m(x_1, x_2, x_3, \ldots\ldots\ldots\ldots, x_n) = m - objective$$

The optimized design *of projection* for some engineering applications [3] is in the nature with a target (single-objective) or more targets (multi-objective). The case when there is only one objective is simple to be solved so the attention to the problem turns to other cases. The multi-objective functions have difficulty in finding the lowest common denominator because their nature is often different, and their size is not expected to be the same. So there are processed ways for their computation. One of them is the introduction of a bigger objective function through their computation coefficients. Such action is expressed in mathematical language as follows:

$$F_{obj}(X^T) = c_1 f_1(X^T) + c_2 f_2(X^t) + ... + c_m f_m(X^T)$$

Where: c1, c2... cm are computation coefficients of objective functions and their solution and location have a great importance in the creation of a *total objective* function. A second way which comes out as a special case of the former is the holding of more primitive functions that is of more importance. In this case the other coefficients artificially put 0-zero by accepting a deviation from the correct values. The third method is by using the objective with a greater weight in the optimized solution and the other objectives set in the conditional functions but with the only difference that the research space is being artificially enlarged to facilitate the finding of solutions and convergence towards it. After finding that the objective function with one of the top ways it is passed to a standard procedure of the genetic algorithm where its second step is the assessment of the objective function through fitness function (or function of the performance). Depending on the optimization demands this function can be:

$$Fitness(X^T) = \min\left[F_{obj}(X^T)\right] \text{ or}$$
$$Fitness(X^T) = \max\left[F_{obj}(X^T)\right]$$

Once the identification of performance variables in objective function becomes selection (selection) of those variables that have better performance. This is accomplished through the operator "Selection". This process appears more difficult and i presented the programming language is given:

$$
\begin{aligned}
&FitnessFunction(X,n) = \text{for } nn \in 1..rows(X^{(n)})-1 \\
&\quad \text{for } i \in 0..rows(X^{(n)})-1 \\
&\quad\quad Fitness_i \leftarrow \frac{1}{1+F_{ob}\left[\left(X^n\right)_i\right]} \\
&\quad\quad i \leftarrow i+1 \\
&\quad Total \leftarrow \sum_{i=0}^{rows(X^{(n)})-1} Fitness_i \\
&\quad \text{for } m \in 0..rows(X^{(n)})-1 \\
&\quad\quad PROBA_m \leftarrow \frac{Fitness_m}{Total} \\
&\quad\quad RND_{m,n} \leftarrow rnd(1) \\
&\quad Cum_0 \leftarrow PROBA_m \\
&\quad Cum_{nn} \leftarrow PROBA_m + Cum_{nn}-1 \\
&\quad (RND \;\; Cum)
\end{aligned}
$$

In the calculating procedure presented in Table 3, between the first lines we clearly see the fitness function construction where it is shown up the optimization for the minimum of the objective function defined as appropriate to the case and for each of designing vectors defined above. Here it is made their assessment through this function that might otherwise be called a function of performance. Then in the roulette wheel process there are selected those variables that have better performance with their increased probability. This appears in the second half of the fitness function and as their results we have the randomly generated numbers from 0 to 1 and the probability of each designing vectors. In the below set it is provided the selection process of these vectors in the performance function of each of them through the selection operator:

$$
\begin{aligned}
&Index(R, Cum) = \text{for } i \in 0..5 \\
&\quad Index_i \leftarrow \text{for } j \in 0..4 \\
&\quad\quad j+1 \text{ if } Cum_j \le R_i \le Cum_{j+1} \\
&\quad\quad 0 \text{ if } 0 \le R_i \le Cum_1 \\
&\quad i \leftarrow i+1 \\
&\quad Index
\end{aligned}
$$

$$
\begin{aligned}
&Selection(X, R, Cum) = \text{for } i \in 0..5 \\
&\quad\quad A_i \leftarrow X_{Index(R, Cum)_i} \\
&\quad\quad i \leftarrow i+1 \\
&\quad A
\end{aligned}
$$

After being selected, at this stage it should be said that we have not still produced new better solutions, but made only a selection of them. Therefore it is necessary to enter new solutions in this research. This is achieved by using two other operators for the introduction and creation of new solutions hopefully to be better. The first is the operator of the crossing to which two or more solutions depending on the ratio of the crossing participate at the crossing of their variables. The second, the mutation operator where one or more randomly selected variables are changed with variables which even those are selected also randomly by their definition fields causing that the choice good or bad to be back in the field of possible solutions. The above mentioned functions and operators will be listed out step by step as follows:

$$
\begin{aligned}
&CO(X,n) = \text{for } k \in 1..rows(DATA)-1 \\
&\quad\quad R_k \leftarrow rnd(1) \\
&\quad\quad Parent_k \leftarrow (X)_k \text{ if } R_k \le pc \\
&\quad\quad k \leftarrow k+1 \\
&\quad Parent_k \text{ if } rows(Parent) \ne 0 \\
&\quad A \leftarrow Parent_{trunc(rows(DATA)-1)} \\
&\quad A \leftarrow X_{trunc(rows(DATA)-1)} \text{ if } rows(Parent) = 0
\end{aligned}
$$

The first function is the Cross Over function CO. After a randomly generated number conditioned by the crossover ratio p_c becomes possible the selection of those designs vectors which will participate in the crucifying process. As seen the crossover ratio occupies a special part and are given different recommendations depending on the problem under investigation. Once the vectors are selected the process will run with:

$$
\begin{aligned}
&P(X,n) = i \leftarrow 0 \\
&\quad \text{while } i \le rows(CO(X,n))-1 \\
&\quad\quad P_i \leftarrow 1 \text{ if } CO(X,n)_i \ne 0 \\
&\quad\quad i \leftarrow i+1 \\
&\quad P
\end{aligned}
$$

Where the design vector position turns on the numbers 0 and 1 to locate and keep the location for the following processes. In short, the above function is a location function.

$$Parents(X,n)= \left| \begin{array}{l} Par \leftarrow match(1,P(X,n)) \\ for\ \ i \in 0..rows(Par)-1 \\ \quad \left| \begin{array}{l} Parents_i \leftarrow CO(X,n)_{(match(1,P(X,n))_i)} \neq 0 \\ i \leftarrow i+1 \end{array} \right. \\ Parents \end{array} \right.$$

In the above function after determining the number of designer vectors and localization it is create a subset of design vectors which will take part in the crucifixion. These vectors have a protective nature. (Parental).Then the calculating process goes on with the research, temporary functions and those of the of division line for the crucifixion of the design vectors necessary for the process continuity. These constitute the sub-routine of the algorithm.

$$Find(X,Parents,Pare)= \left| \begin{array}{l} j \leftarrow 0 \\ \left| \begin{array}{l} for\ j \in 0..rows(Pare)-1 \\ \quad while\ Pare \neq X_i \\ \quad\ i \leftarrow i+1 \\ S_i \leftarrow 1\ if\ \ Parents_j = X_i \\ S_i \leftarrow 0\ otherwise \end{array} \right. \\ T \leftarrow match(1,S) \end{array} \right.$$

$$CP(X,n)= \left| \begin{array}{l} for\ i \in 0..rows(Parents(X,n))-1 \\ \quad \left| \begin{array}{l} CP_{i,n} \leftarrow rnd(3) \\ i \leftarrow i+1 \end{array} \right. \\ ceil(CP^{(n)}) \end{array} \right.$$

$$Temp2(X,Parents,Pare)= \left| \begin{array}{l} A \leftarrow X \\ \quad for\ j \in 0..rows(Find(X,Parents,Pare))-1 \\ \quad A_{Find(X,Parents,Pare)} \leftarrow Pare_j \\ A \end{array} \right.$$

The process of crucifixion is given by the following function:(the second genetic operator, Crossover):

$$CrossOver(X,n)= \left| \begin{array}{l} Pare \leftarrow \left| \begin{array}{l} for\ \ j \in 0..rows(Parents(X,n))-1 \\ \quad \left| \begin{array}{l} A \leftarrow submatrix(Parents(X,n)_i,0,CP(x,n)_i-1,0,0)^T \\ B \leftarrow submatrix(Parents(X,n)_{i+1},CP(x,n)_i,3,0,0)^T \\ C \leftarrow submatrix(Parents(X,n)_i,0,CP(x,n)_i-1,0,0)^T \\ D \leftarrow submatrix(Parents(X,n)_0,CP(x,n)_i,3,0,0)^T \\ Pare_i \leftarrow augment(A,B)^T\ \ if\ \ i < rows(Parents(X,n))-1 \\ Pare_i \leftarrow augment(C,D)^T\ \ otherwise \\ i \leftarrow i+1 \end{array} \right. \\ Pare \end{array} \right. \\ Temp2(X,Parents(X,n),Pare) \end{array} \right.$$

It is obviously seen that each two design vectors (parental) through the crucifixion factor CP (X, n) is made possible a combination of design variables. At the end of this operation it is expected to have created designing vectors with variables that have better performance but however this process is also subject to the mutation operator which is completed with the following mutation steps:

$$Muta(X)= \left| \begin{array}{l} B \leftarrow \left| \begin{array}{l} k\ \ \leftarrow 0 \\ \quad Field \leftarrow rows(X_0)*rows(X) \\ \quad while\ k < ceil(pm*Field)-1 \\ \quad\quad \left| \begin{array}{l} R_k \leftarrow rnd(Field) \\ k \leftarrow k+1 \end{array} \right. \\ ceil(R) \end{array} \right. \\ A \leftarrow X \\ for\ \ j \in 0..rows(Pare)-1 \\ \quad \left| \begin{array}{l} \left(A_{floor(\frac{B_j-1}{4})} \right)_{mod(B_j-1,4)} \leftarrow floor(rnd(Field)) \\ for\ \ m\ \in\ 0..5 \\ \quad (A_m)_0 \leftarrow trunc(rnd(Condition)) \end{array} \right. \\ A \end{array} \right.$$

At the above figure it given the mutation operator divided in two sectors. At the first sector there is a selection of the variables that will participate in the process and in the second sector their replacement with variables selected form their field of definition. Even here it is expected to be created design vectors with better performance.

In this way to enable finding the optimum algorithm there are needed its 4 operators:

1) *The generating operator of the variables of the initial generation "DATA₀"*
2) *(Selection*
3) *Crossover*
4) *Mutation*

III. Block Scheme of Genetic Algorithm

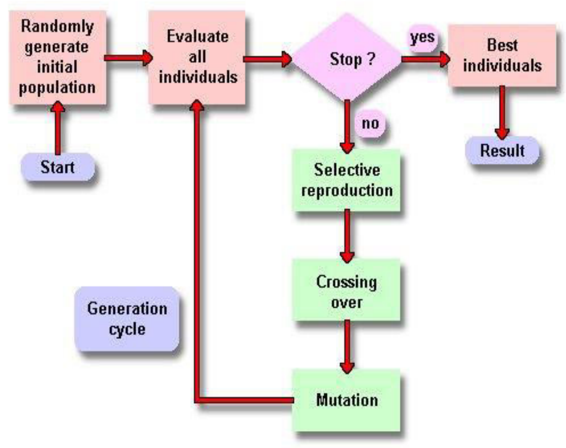

Fig 1. Block scheme of genetic algorithm

All the above procedure is given in a more detailed way in the above block scheme and its programming in MATHCAD where all operators and functions are placed into a single and generated depending on the number of generations or on the convergence condition. In genetic algorithm:

$$GA = \begin{array}{|l} for\ \ i \in 0..100 \\ \quad \begin{array}{|l} DATA^{(0)} = for\ \ i0 \in 0..5 \\ \quad \begin{array}{|l} RNDDATA_{i0,0} \leftarrow \begin{array}{|l} for\ \ i2 \in 0..3 \\ \quad \begin{array}{|l} Y_{i2} \leftarrow rnd(\text{space}) \\ i2 \leftarrow i2+1 \end{array} \\ \text{trunc}(Y) \end{array} \\ i0 \leftarrow i0+1 \\ \text{RNDDATA} \end{array} \\ Temp1 \leftarrow FitnessFunction(\text{DATA}, n) \\ Temp2 \leftarrow Selection(DATA^{(n)}, Temp1_{0,0}{}^{(n)}, Temp1_{0,1}) \\ Temp3 \leftarrow CrossOver(Temp2, n) \\ DATA^{(n+1)} \leftarrow Muta(Temp3) \\ n \leftarrow n+1 \\ break\ \text{if}\ F_{ob}(\text{DATA}_{0,n}) = 0 \end{array} \\ DATA \end{array}$$

So in algorithm ordering we have the variable generation, fitness function, selection operators, crossover operators, mutation ones as well and the criteria of detention.

IV. Application of Genetic Algorithm

A. The general

The field of mechanical engineering is broad and the genetic algorithm method finds its place for its application. Therefore, we will list at table 1 the sectors where this algorithm find place for its application.

Table 1 Application of the method GA

Machine Details	Weight, Distance, Deformations, strains, cost etc
Connections	Spesori, screw bolt number, screwbolt metric etc
Pattern	Shovel Profiles, aircraft design etc.
Transport	Linking network, Roads etc.
Production	Production processes, producion costs
CNC	Process steps

It seems clear that this algorithm includes a broad application field. The task of the designer in the case of the use of genetic algorithm is to draw clearly the objectives and to lay them in mathematical functions making thus possible the functioning of this algorithm. In the design practice for machine details in general we often encounter in the design of studded tires, different mechanical transmissions, bearings choice, calculations of different bolts joints, linchpin etc. which can be adapted according to the genetic algorithm logic and satisfactory results are obtained in the designing practice.

In particular, the utilization of genetic algorithm is successfully used as related to the optimization of the calculation of the results obtained through genetic algorithm. To illustrate the successful use of such method and algorithm in the design calculations of the machine elements is chosen to go on with the design calculations [3] by means of an algorithm for the case of the transmissions by means of studded tires.

B. Gears transmissions

Database and design practice functions for the Gears transmissions [5] are successfully exploited in the application of genetic algorithm method. Without a doubt, in this case as a basic condition of calculating serve terms of calculating the solidity and contact of the design studded tires.

C. The design variables in gears

Variables [6] that can be optimized in their design in the field of mechanical designs are diversified. In the case of the optimization of spurs gears we are presenting a list of some of these parameters that have an interest to be studied:

a) *Weight Minization*
b) *Axial distance Minimization*
c) *Width Minimization*
d) *Teeth correction*
e) *Teeth bend Minimization*
f) *Transmitted power maximization*
g) *Longevity maximization*

These are some of the parameters that can be optimized. The main object in this article is just the optimization of the studded tire weight and loading at the maximum of the material limits.

D. Weight

Weight is a very important objective in the design of a pair of cylindrical teeth tires as it is directly linked with the used material for the production of this tire. This parameter, considered important, will bring to the reduction of production costs and for non stationed machines the reduction of the fuel necessary for the movement parameters guarantee. The relation used for the weight calculation (by accepting the same calculating formula as for the standard method and for that of genetic algorithm) is given as follows:

$$Weight = Section * Width * Density$$

$$Weight = \frac{\pi}{4} D_{p1}^2 b \rho_1 g + \frac{\pi}{4} D_{p2}^2 b \rho_2 g$$

Where:
Dp – primitive diameter of tires
b – Tire width
ρ – density of tire material
g – Acceleration of free fall

Acknowledging the material with the same weight and part of the top of the tooth removed from the primitive diameter we compensate it with the "pit" that exists between the teeth of the tire and the part of moco be for the both methods we have:

$$D = m * z$$

$$Weight = \frac{\pi * g}{4} b m^2 z_1^2 (\rho_1 + i^2 \rho_2) = m^2 z_1^2 b \left[\frac{\pi * g}{4} (\rho_1 - i^2 \rho_2) \right]$$

Where:
z - Number of tire teeth's respectively pinion
m – Module

Mark with λ the characteristic of the material and construction.

$$\frac{\pi * g}{4}(\rho_1 + i^2 \rho_2) = \lambda$$

So as we see the weight is given by the product of a constant [Λ] parameter for the same request and the variable product of module square, square of the teeth number of pinion and tire width:

$$Weight = Variable * Constant$$
$$Weight = m^2 z_1^2 b$$

E. Stress

The destruction [7], [8], [9] in bending is generally undesirable. To avoid breaking of the tooth, it is needed that the bending stress should not exceed those allowed for the material:

$$\sigma_{pk} = \frac{2}{z_1 m^2 b y_1 \cos\alpha} * M_{p1} \leq [\sigma]_{pk}$$

where:
z_1– the number of teeth of the pinion
m– module
b – width of the wheel
y_1 – coefficient of tooth shape
α – angle of gearing
M_{t1}– Torsion moment (total)
$[\sigma]_{pk}$ – allowed strain in bending for material provided

The same argumentation can also be followed even for these constraints where the calculation condition in contact is presented as follows:

$$\sigma_{pk} = \frac{1.62}{z_2 m} * \sqrt{\frac{M_{t2}}{b \sin\alpha} * \frac{E_1 E_2}{(E_1 + E_2)} \frac{i_p + 1}{i_p}} \leq [\sigma]_k$$

Where:
z_2 – the number of teeth of the guide wheel
m – Module
b – width of the wheel
α – angle gearing
M_{t2} – torsion moment(total) of the wheel guide
$[\sigma]_k$ – Strains allowed in touch material provided

V. Formulation of the Problem

For research on this method we used MATHCAD program. Hence the whole problem is posed in a matrix form where by them are given the designing variables which consist the grounds for beginning of the algorithm. We have made use of the case where one of the objective functions is set as conditional function since its defining values are limited by the above. A formulation of the respective problem is presented as follows:

Variables $DATA = \begin{Bmatrix} m \\ b \\ z \end{Bmatrix}$

Objective function $F_{ob} = P$

Conditions $\sigma_{pk} \leq [\sigma]_{pk}$ and $\sigma_k \leq [\sigma]_k$

VI. Input Data of the Problem

The data of the problem are presented in the table [2] and these are taken from a solved example in the machine details text

Table 2. Input Data

Input	Value
Power (P)	7 [kW]
Rotating number (n)	960 [min^{-1}]
Transmission ratio (i)	4
Service schedule (T)	20000 [hr]
Steel mark of pinion	Steel 45 CrNi (improved)
Steel Mark of crown	45CrNi
Production type	Tire stamped by normalized steel
Tire correction	0

VII. Results and Comparison of Methods

Acknowledging the same data of the problem and the same definitions for the design variables, the objective and problem conditions we estimate by means of genetic algorithm method:

Table 3 Results according to AG method

Objective	Classic method	AG method
Module (m)	4 [mm]	2.5
Pinion teeth number (Z1)	20	34
Width of tire (b)	40 [mm]	23
Evaluating Parameter	0.256	0.08

VIII. Graphics of Variables in Function of Genetic Algorithm (AG)

Below there are shown the graphics obtained from the genetic algorithm method for the three designing variables as well and the graphics of comparing the methods with their comparative parameter.

As seen from the graphics after a relatively small number of cycles have almost stabilization of the functions of the relevant variables and of the evaluation parameter of the weight. This is achieved as the method used converges in the solution, whose performance is evaluated in the last graphics. The abnormalities that appear in the form of dance are nothing but a large percentage of the mutation ratio depending on the initial community. This is done for the only reason to reach the desired solution quickly. The constraints imposed on the objective function also play an important role because they direct the problem towards the best solution which is clearly seen even in the weight evaluation graphic where we have a weight reduction of 5 to 20% this subject to the initial values randomly generated by the algorithm.

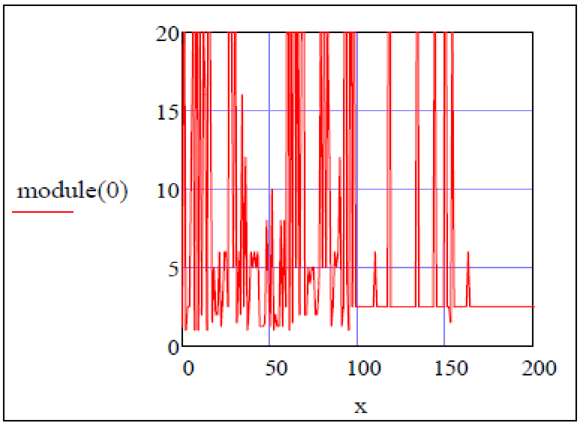

Fig. 2 Graphic of the studded tire module depending on the number of generation in algorithm

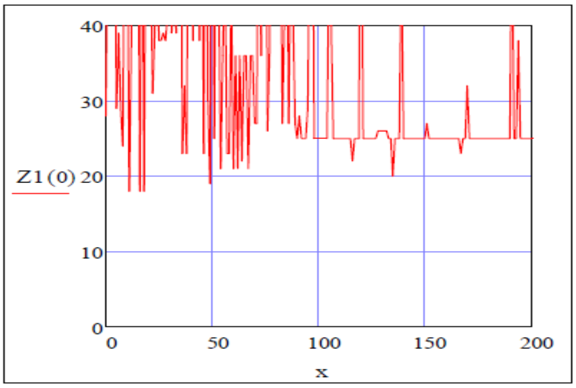

Fig. 3 Graphic of teeth number depending on the number of generation in algorithm

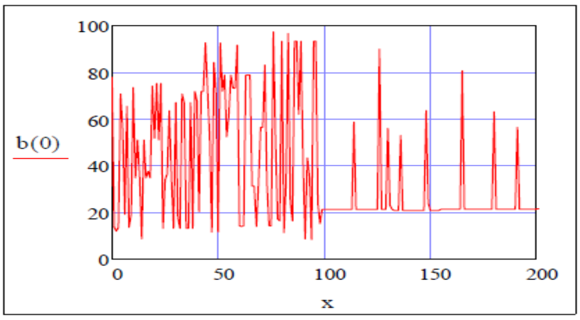

Fig. 4 Graphic of tire width depending on the number of generation in algorithm

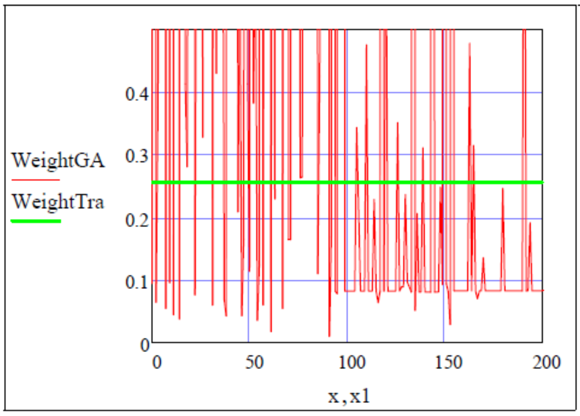

Fig. 5 Graphic of comparison of evaluating parameters depending on the number of generation in algorithm

IX. Conclusions

During introduction of the problem by the genetic algorithm method and obtaining the results from it we draw some important conclusions when using this method:

It was certified that the method works and gives results that are very close to the results of the classical method which is verified for its accuracy. This means that for designing a couple of studded tires pinion-krone we can use the method AG.

The speed of obtaining results is faster than a standard procedure.

In comparison with the classical method where we project by following the design-control procedure in the case of this method we follow only one design way which simultaneously satisfies both conditions required by the project to estimate the solidity and control in touch.

From the obtained results it is indicated that by using this method is reduced the weight of the pair of studded teeth with approximately 5% -20% (this is seen in the evaluation graph) with the classical method. This is an important conclusion that gives great advantage to this calculating optimization procedure which guarantees the weight reduction of studded toothed tire pair in case of this application, and generally in all steps of mechanic design where this algorithm can eventually be used.

The method of genetic algorithm can be used in many other areas in general engineering and mechanical engineering in particular because it is a method that can contain many design variables, modal functions, non-linear, non-differential with one or more targets, conditions of different nature so today it has found a wide use

References

[1] Optimization of gear parameters by using genetic algorithm T Raja Dawit Gebreamlak Teklemarian and GNA Senthil Kumar.

[2] Arora, Jasbir S., "Introduction to Optimum Design," McGraw-Hill, 1989 Lin CYand Hajela P, "Genetic Algorithms in Optimization Problems with Discrete and Integer Design Variables," Eng., Opt., Vol.19, pp. 309-327, 1992.

[3] American Gear Manufactures Association, AGMA2001-B88, "Fundamental Rating factors and Calculation Methods for involutes Spur and Helical Gear Teeth," 1988.

[4] Spurs gear optimization by using genetic algorithm .Yallamanti Murali Mohan, T.Seshaiah Vol2 Issue 1, Jan-Feb. 2012, pp. 311-318Introduction to optimum design. Second Edition. Jasbir S. Arora
[5] ISO 54. Second Edition 1996-12-15 .Cylindrical gears for general engineering and for heavy engineering – Modules
[6] ISO 6336-1 Calculation of load capacity of spur and helical gears —'97Part 1: Basic principles, introduction and general influence factors
[7] ISO 6336-2 Calculation of load capacity of spur and helical gears —'97Part 2: Calculation of surface durability (pitting)
[8] ISO 6336-3 Calculation of load capacity of spur and helical gears —'97Part 3: Calculation of tooth bending strength
[9] ISO 6336-5 Calculation of load capacity of spur and helical gears —'97Part 5: Strength and quality of materials

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