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USING GENETIC FUZZY EXPERT SYSTEMS FOR DECISION SUPPORT IN THE AUTOMATED PROCESS OF SOLID WOOD CUTTING

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Abstract:

Sawing solid wood (lumber, wooden boards) into blanks is an important technological operation, which has significant influence on the efficiency of the woodworking industry as a whole. Selecting a rational variant of lumber cutting is a complex multicriteria problem with many stochastic factors, characterized by incomplete information and fuzzy attributes. About this property by currently used automatic optimizing cross-cut saw is not always rational use of wood raw material. And since the optimization algorithms of these saw functions as a “black box”, their improvement is not possible. Therefore topical the task of developing a new approach to the optimal cross-cutting that takes into account stochastic properties of wood as a material from biological origin.

Here we propose a new approach to the problem of lumber optimal cutting in the conditions of uncertainty of lumber quantity and fuzziness lengths of defect-free areas. To account for these conditions, we applied the methods of fuzzy sets theory and used a genetic algorithm to simulate the process of human learning in the implementation the technological operation. Thus, the rules of behavior with yet another defect-free area is defined in fuzzy expert system that can be configured to perform specific production tasks using genetic algorithm. The author's implementation of the genetic algorithm is used to set up the parameters of fuzzy expert system.

Working capacity of the developed system verified on simulated and real-world data. Implementation of this approach will make it suitable for the control of automated or fully automatic optimizing cross cutting of solid wood.

Key words*: cutting; wooden boards; blanks; fuzzy expert system; membership functions; the rule weight; genetic algorithm.*

INTRODUCTION

The main difference between the task of cutting timber (defect-free areas) on the specification blanks and the traditional tasks of cutting-packaging (Yemets & Yemets 2008, Kantorovich & Zalgaller 1971, Koch *et al*. 2008) lies in incomplete and unclear information on the number and placement of defects at each timber (Fig. 1). In Fig. 1 used the following notation: 1) Lumber; 2) Sawing on defect-free areas (cutting of defects); 3) Optimization without considering the quality of blanks; 4) Optimization taking into account the quality of blanks; d – defect; y – defect-free area (for finger jointing); x1, x2, x3 – blanks; z – defect-free waste (too short for finger jointing).

Lumber cross-cutting is carried out (manually or automatically) depending on the production needs (Fig. 1):

1. If blanks obtained after cutting will be jointing, we have a case of cross-cutting of lumber on defect-free area (2 on Fig. 1). This process requires the identification (preferably automatically by a scanner) unacceptable defects and their cutting.

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2. When need to cut out lumber on several groups of blanks specified size and quantity, but blanks quality requirements are not put (3 on Fig. 1). In this case we obtain a cutting stock problem that can be solved as a linear programming problem.

3. The most difficult case is similar to the previous one, but with blanks quality requirements. In this case (4 on Fig. 1), you must first identify the defect-free areas on lumber and of these areas need to saw out blanks specified length. In this case the use of classical linear programming is impossible, because the length of the defect-free areas and their sequence have an unknown probabilistic nature. Therefore, description of the values of defect-free parts, their quantities and the procedure of taking ongoing decisions about the length sawn blanks with the help of methods of the theory of fuzzy sets.

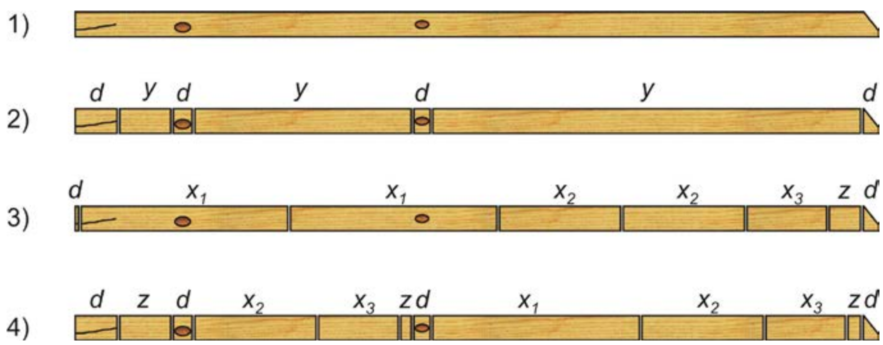

Fig. 1.
Variants of lumber cross-cutting.

Here we propose a new approach to the problem of lumber optimal cutting in the conditions of uncertainty of lumber quantity and fuzziness lengths of defect-free areas. To take into account natural uncertainty of defect-free areas lengths and fuzziness of human decisions, we applied the methods of fuzzy logic, and used a genetic algorithm to simulate the process of human learning in the implementation the technological operation. Thus, the rules of behavior with yet another defect-free area is defined in fuzzy expert system (FES) that can be configured to perform specific production tasks using genetic algorithm.

To describe the basic concepts of these ideas, we will need the following definitions (mainly from Pankevych & Shtovba 2005).

Expert system: a system that encodes knowledge through a set of rules in the form, “IFpfemise, THEN consequent.” Expert systems are nonprocedural and able to deal with a wide range of problems in the same way as a human expert.

Fuzzy proposltion: a statement of fuzzy relationships in the form, “xis Y,” where x is a scalar variable (such as Length) and Y is a fuzzy set associated with x, such as Long. A proposition is evaluated in terms of its truth, which can be a value in the interval (0,l).

Fuzzy set: a special type of set that admits to partial membership. A fuzzy set measures the compatibility between a value in the set’s domain and the concept supported by the set. This compatibility is also interpreted as a degree of membership in the interval (0,l).

Thus, unlike known approaches to solving the cutting task (Ferreira *et al*. 1990, Carnieri *et al*. 1994, Wagner 1999, Dikili & Barlas 2011, Suliman Saad 2001), the simulation of decision-taking process done by human operator is the basis of the fuzzy expert system. This idea really works (Matsyshyn *et al*. 2011, Matsyshyn 2012, Matsyshyn *et al*. 2012), but as the man should constantly learn and improve their skills so the fuzzy system should have the ability to learn in order to make effective decisions in accordance with pre-specified criteria. For training fuzzy system it is appropriate to apply a particular embodiment of genetic algorithms, which are successfully applied for solving complex optimization tasks.

The article is a continuation of a series of papers (Matsyshyn 2012, Matsyshyn *et al*. 2012), in which the fuzzy expert system for decision support on choosing a scheme for cross-cutting timber on blanks are proposed (hereinafter FES) (Matsyshyn 2012) on the basis of which the software "SAWing_lumber" is developed, enabling the simulation of cross-cutting process of timber into blanks and ensure the specification of blanks with minimal pieces of wooden boards (Matsyshyn *et al*. 2012).

The efficiency of fuzzy systems significantly depends on the type and parameters of the membership functions of linguistic variables and values of rules of weight coefficients (Pankevych & Shtovba 2005, Mytyushkyn *et al*. 2002, Syavavko 2007). For expert-human it sometimes impossible to choose the correct values of indicated parameters, so for the efficiency of the FES it is reasonable to make their automatic settings on the problem which is being solved.

Recently, genetic and evolutionary algorithms are successfully used as means for solving this type of optimization problems (Pankevych & Shtovba 2005, Mytyushkyn *et al*. 2002, Syavavko 2007, Rothstein 1996).

Genetic and evolutionary algorithms are the methods of random search in which the search for the optimal solution is performed simultaneously in several set points of possible solutions. It allows us to decrease significantly the search time for the solution, and decreases the probability of finding local extremum as well (Rothstein 1996).

OBJECTIVES

The rational cutting yields is a condition of lean manufacturing in the process of solid wood cutting.

The aims of this paper is the development and verification of a fuzzy expert system for modeling and automated control of solid wood cross-cut process, capable to take into account the natural uncertainty of lumber quantity and fuzziness lengths of its defect-free areas. Moreover, the developed system must be able to adjust to a given specification of blanks.

From a practical point of view, we need to develop the FES for making rational decisions about the necessary length of the blanks, which should be cut when the information comes about the length of a defect-free area of each board, and provided that the number of already sawn blanks of each size is known.

METHOD, MATERIALS AND EQUIPMENT

To take into account the natural uncertainty of the characteristics of lumber and elements of experience and intuition of human operator, we applied the methods of fuzzy sets theory, and used a genetic algorithm to simulate the process of human learning in the implementation the technological operation.

The structure of fuzzy expert system is shown in Fig. 2. Notations, used on these figure described below in fuzzy knowledge base about the process of lumber cross cutting into blanks (Table 1) and in Table 2.

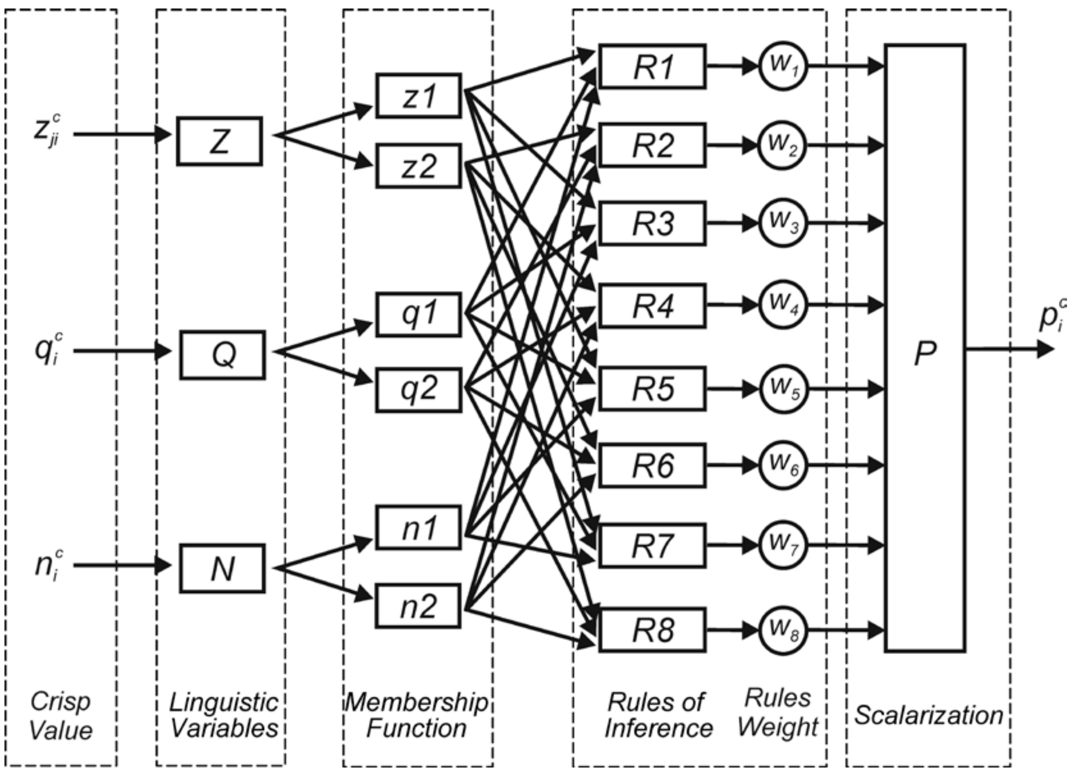

Fig. 2.
Structure of FES for decision support in the process of automated optimizing cross cutting of lumber.

In order to reduce the number of adaptive parameters for the description of the term-sets of linguistic variables, the Gaussian (bell-shaped) function is used, which depends only on two parameters (coordinates of maximum *b* and concentration coefficient *c*).

Table1

Fuzzy knowledge base about the process of lumber cross cutting into blanks

Input linguistic variables					Outcome linguistic variable
IF					THEN
Value of received defect-free waste (Z)		***The number of actually sawed out blanks (Q)***		***Expected number of defect-free areas, from which the blanks can be sawed out (N)***	***The priority blanks for sawing out (P)***
small	**AND**	small	**AND**	small	very high
large		small		small	high
small		many		small	high
large		many		small	low
small		small		many	high
large		small		many	medium
small		many		many	medium
large		many		many	very low

As a measure of a cutting process efficiency the coefficient of the specified blanks yield is accepted – the ration of volume of the blanks to volume of the sawn wooden boards.

In order to improve the efficiency of process of wooden boards cutting on the basis of taken decisions by FES it is necessary to develop genetic algorithm that would give the possibility to set up FES parameters automatically. The FES settings consist in its parameters that allow achieving rational (quasioptimal) value of specified blanks outcome *k*, which is a measure of specifications performance.

The structure of fuzzy-genetic system is shown in Fig. 3. All communication with the unit of the genetic algorithm (GA on Fig. 3) are used only in a learning mode, in operating mode they are disabled. Notations, used on these figure described below.

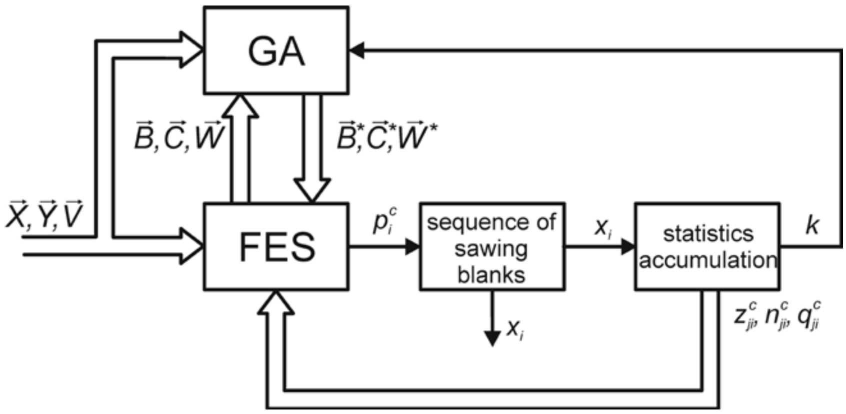

Fig. 3.
The structure of genetic fuzzy expert system.

For the mathematical formulation of the problem of FES learning the following notations are introduced:

$\vec{Y} = \{y_1,\ldots y_d,\ldots y_U\}$ – vector of wooden board lengths (defect-free areas),

$\vec{X} = \{x_1,\ldots x_f,\ldots x_T\}$ – vector of blanks lengths,

$\vec{V} = \{v_1,\ldots v_f,\ldots v_T\}$ – vector of blanks dimensions (quantity),

$\vec{B} = \{b_{11},\ldots b_{ij},\ldots b_{NM}\}$ – vector of maximum coordinates of membership functions of term-sets of linguistic variables,

$\vec{C} = \{c_{11},\ldots c_{ij},\ldots c_{NM}\}$ – vector of concentration coefficient of membership functions of term-sets of linguistic variables,

$\vec{W} = \{w_1,\ldots w_l,\ldots w_R\}$ – vector of rules weight coefficients.

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where: y_d - d-length of wooden board (defect-free areas) that enters to the cutting $(d=\overline{1,U})$; x_f – f-th blank length size-quality group ($f=\overline{1,T}$); v_f – volume (quantity) of f-th blanks size-quality group ($f=\overline{1,T}$); b_{ij} and c_{ij} – membership function parameters (maximum coordinate and concentration coefficient of j-th term of i-th linguistic variable ($i=\overline{1,N}$; $j=\overline{1,M}$)); w_l – l-th rule weight coefficient ($l=\overline{1,R}$).

Note that, on practice, the coordinates of vector Y are random variables with distribution law which is beforehand unknown.

The FES setting consists in finding such vectors as $\vec{B}$, $\vec{C}$, $\vec{W}$, which would provide the maximum value of the coefficient of specified blanks yield:

$$k(\vec{Y},\vec{X},\vec{V},\vec{B},\vec{C},\vec{W}) \to \max, \qquad (1)$$

under the following constraints:

1) the coordinates of vector $\vec{W}$ should be in the unit interval $w_l \in [0,1]$;

2) the coordinates of vector $\vec{B}$, should be within the range of possible values of the proper term-set and the terms of their linear order should not be violated;

3) the coordinates of vector $\vec{C}$, should be positive: $c_{ij} > 0$.

In order to decrease the dimension of the optimization problem (1), the maximum coordinates of membership functions should be set up only for utmost linguistic terms. For example, for the outcome linguistic variable "*Priority blanks"* the terms will be *"low "*, *"medium "*, *"high"* (b_{p2}, b_{p3}, b_{p4}). Maximum coordinates of membership functions of utmost terms *"very low"* and *"very high"* are set as the utmost points of variation range of linguistic variable ($b_{p1} = 0$; $b_{p5} = 1$) [1].

FES parameters that are subjected to setting provided in Table 2.

Table 2

FES parameters that are subjected to learning

FES parameters	Notation
1. Input linguistic variables:	
Value of received defect-free waste (Z)	c_{z1}, c_{z2}
The number of actually sawed out blanks (Q)	c_{q1}, c_{q2}
Expected number of defect-free areas, from which the blanks can be sawed out (N)	c_{n1}, c_{n2}
2. Outcome linguistic variable:	
➢ *The priority blanks for sawing out (P)*	b_{p2}, b_{p3}, b_{p4}, c_{p1}, c_{p2}, c_{p3}, c_{p4}, c_{p5}
3. The rules weights	w_1, w_2, w_3, w_4, w_5, w_6, w_7, w_8

First of all, FES guided parameters are summarized in one vector:

$$\vec{S} = \{\vec{B},\vec{C},\vec{W}\} = \{b_{p2}, b_{p3}, b_{p4}, c_{z1}, c_{z2}, c_{q1}, c_{q2}, c_{n1}, c_{n2}, c_{p1}, c_{p2}, c_{p3}, c_{p4}, c_{p5}, w_1, w_2, w_3, w_4, w_5, w_6, w_7, w_8\} \qquad (2)$$

Vector S can be represented by chromosome A_t, ($t=\overline{1,U}$).

$$A_t = (a_1^{(t)},...a_2^{(t)},...a_F^{(t)}) \qquad (3)$$

where: - $a_s^{(t)}$ s-like gene of t-like chromosome ($s=\overline{1,F}$).

Chromosome A_t - is a set of genes, which is the only variant of problem solution (1). A set of chromosomes forms a population. At each stage of the algorithm over the population crossing, mutation and breeding operations are executed.

On the next stage of genetic algorithm construction the approaches towards implementation of basic genetic operations: genetic coding, the selection of parents-chromosomes, crossing, mutation and breeding (Table 3).

Table 3

Approaches towards implementation of basic genetic operations

Operation	Method of implementation
Genetic coding	*Encoding by real numbers*
The selection of parents-chromosomes	*Roulette-wheel selection method*
Crossing	*Homogeneous crossing method*
Mutation	*Probability mutation method*
Breeding	*Roulette-wheel selection method with elitism*

The genetic algorithm is used for the FES setting, the block diagram of which is provided in Fig. 4.

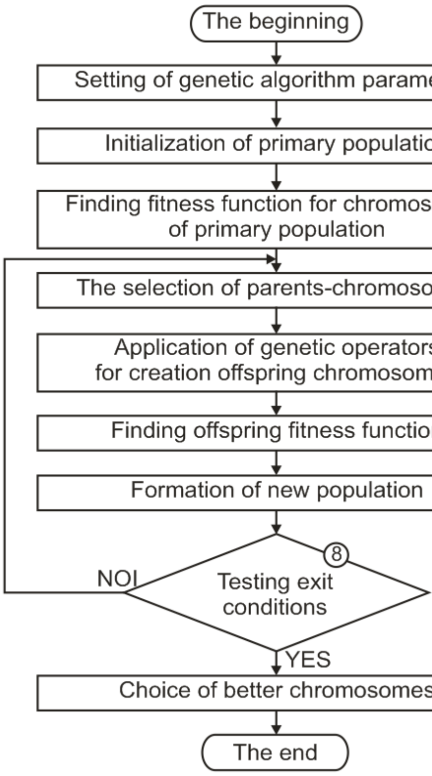

Fig. 4.
Block diagram of genetic algorithm.

RESULTS AND DISCUSSION

For verification of the developed systems used the following technique:

1. Was considered the simplest case (3 on Fig. 1), allowing the formulation and solution of the classical linear programming problem, and the results were compared with the results of the fuzzy system (genetic learning is not used);

2. The ability fuzzy system to training tested on nonlinear analytic functions which the known ekstrema;

3. The suitability of the developed system for solving real cutting problems was checked on real-world data example.

The simplest case (3 on Fig. 1). Because this case is well known, restrict ourselves to indication of the results and their comparison with the results obtained by fuzzy system (Table 4).

Table 4

Comparison results for the simplest test case

№	Length of lumber, m	Blanks specifications, m	Coefficient of the specified blanks yield *k*	
			Linear programming	FES using "SAWing Lamber" software
1	3.5	0.5/0.8/1.2	0.9524	0.9400
2	4	0.5/0.8/1.2	0.9984	0.9557
3	4.6	0.5/0.8/1.2	0.9811	0.9674

As the tab. 4 shows, the results of the fuzzy system is always worse than the results of solving the linear programming problems and depend on the length of lumber and blanks specifications. Therefore fuzzy system need to be configured.

Because try all variants of cutting problem setting are impossible, and can not be possible to direct application of linear programming method in most practical cases, to test the ability of fuzzy systems to configure using nonlinear analytical functions with known extrema.

Verification of genetic algorithm and ability fuzzy system to training. Before applying genetic algorithm for setting the FES parameters it is advisable to check its efficiency on standard optimization problems (for the search of functions extremum) that make it verified. To do this, we have developed the software "GA_SAWing_lumber", which sold above genetic algorithm (Fig. 4).

In the main window of the software in the tab "Setup Model" (Fig. 5), you can specify a function to find the extrema, and range (minimum and maximum) and change stage of input variables of the function.

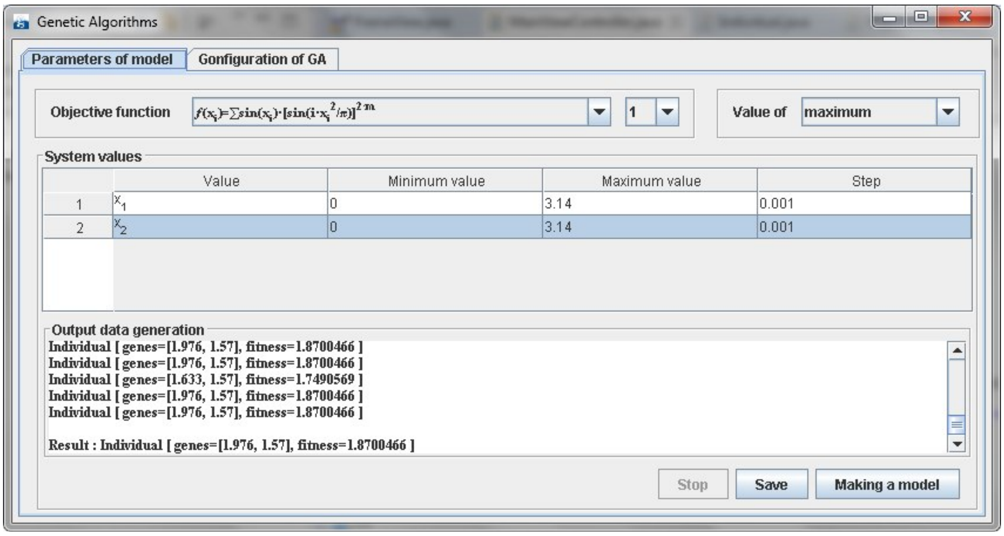

Fig. 5.
The main window of the software "GA_SAWing_lumber".

In the tab 'Settings GA "(Fig. 6) you can specify the basic parameters of the genetic algorithm:

- Probability of crossing *Ps;*
- Probability of mutation *Pm;*
- Population size *Nchr*;
- Number of genes in the chromosome *Ngen*;
- Number of populations *Npop*.

Number of pairs of parents-chromosomes *Nb*.

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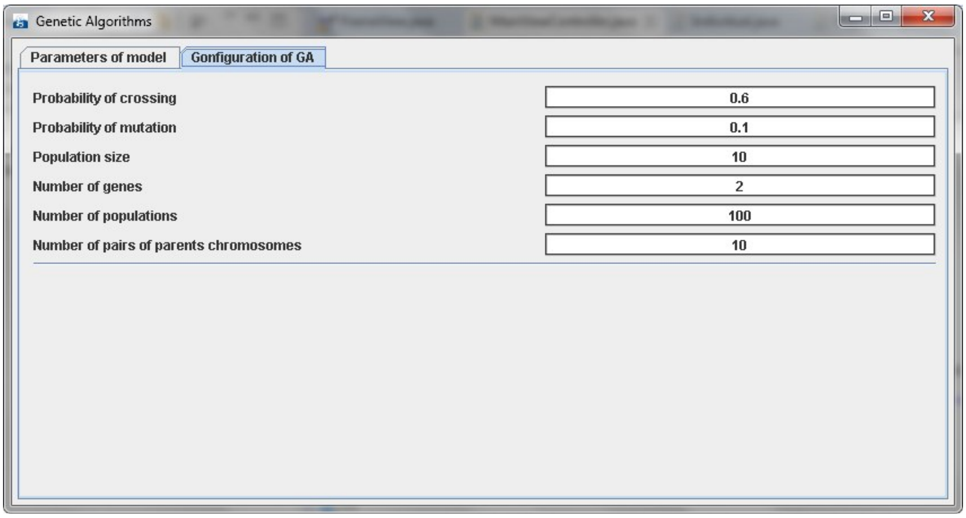

Fig. 6.
View of the dialog for genetic algorithm parameters setting

The verification of the genetic algorithm is performed by searching the maxima of analytic functions (Table 5) for different number of generations. In order to ensure the authenticity of algorithm verification, the function with one and with few extremums is selected (Fig. 7). Search for the maxima functions was performed for the following parameters of genetic algorithm: $Ps = 0.6$; $Pm = 0.1$; $Nchr = 10$; $Nb = 10$; $Npop = (10, 100, 500, 1000, 5000)$. The verification results of the genetic algorithm are shown in table 6 and shown on Fig 8.

Table 5

Functions for genetic algorithm testing

№	**Function**	**Change range of input variables**	**Analytic maximum**
F_1	$f(x)=\sum_{i=1}^{2}\sin(x_i)\cdot\sin(\frac{ix_i^2}{\pi})$	$0\le x_i \le 3.14$	$f^*=1.87$ $x_i^{*T}=(1.976;1.571)$
F_2	$f(x_1;x_2)=\cos^2(9\pi r)\cdot e^{r^2/\sigma^2}$ $r=(0.5-x_1)^2-(0.5-x_2)^2;\ \sigma^2=0.15$	$0\le x_i \le 1$	$f^*=1$ $x_i^{*T}=(0.5;0.5)$
F_3	$f(x_1;x_2)=x_1^2+\frac{1}{2}x_2^2+3$	$0\le x_i \le 10$	$f^*=153$ $x_i^{*T}=(10;10)$
F_4	$f(x_1;x_2;x_3;x_4)=x_1^2+x_2^2+x_3^2+x_4^2$	$0\le x_i \le 10$	$f^*=400$ $x_i^{*T}=(10;10;10;10)$
F_5	$f(x_1;x_2)=(x_1^2+x_2-11)+(x_1+x_2^2-7)$	$-10\le x_i \le 10$	$f^*=202$ $x_i^{*T}=(10;10)$

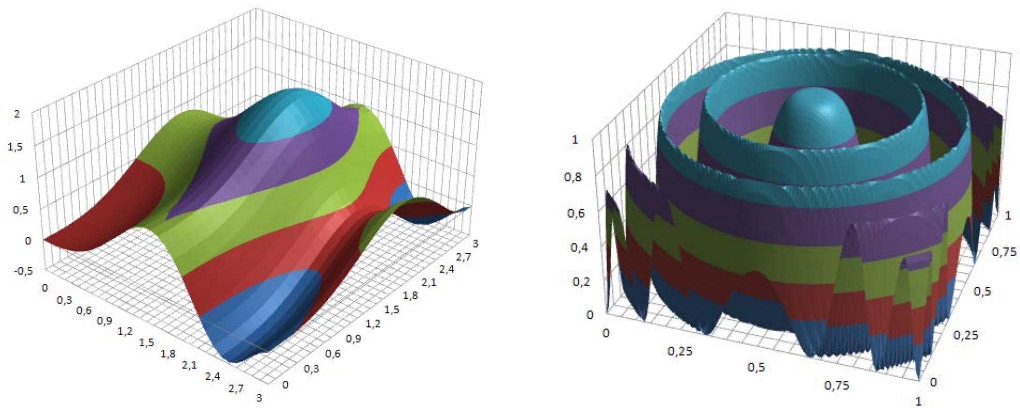

Fig. 7.
Test functions F1 and F2.

Table 6

Results of genetic algorithm verification

Function	***Relative deviation of maxima functions (δ,%), found by genetic algorithm from analytic ones for different numbers of generations (Npop)***				
	N_{pop} =10	**N_{pop} =100**	**N_{pop} =500**	**N_{pop} =1000**	**N_{pop} =5000**
F_1	δ =11.07 x_i =(1.985;1.847)	δ =0.17 x_i =(1.966;1.605)	δ =0 x_i =(1.98;1.571)	δ =0 x_i =(1.975;1.572)	δ =0 x_i =(1.976;1.571)
F_2	δ = 8.40 x_i =(0.437;0.604)	δ =7.90 x_i =(0.435;0.41)	δ =7.80 x_i =(0.439;0.592)	δ =0.20 x_i =(0.499;0.499)	δ =0 x_i =(0.5;0.5)
F_3	δ =5.92 x_i =(9.793;9.492)	δ =1.86 x_i =(9.903;9.909)	δ =0.28 x_i =(9.979;9.999)	δ =0.03 x_i =(9.998;9.999)	δ =0.01 x_i =(10;9.998)
F_4	δ =15,36 x_i=(9.889;7.973; 8.924;9.877)	δ =3.09 x_i=(9.981;9.898; 9.675;9.821)	δ =0.28 x_i=(9.988;9.987; 9.980;9.988)	δ =0.11 x_i=(9.993;9.998; 9.997;9.990)	δ =0.02 x_i=(10;10;10; 9.997)
F_5	δ =10.60 x_i =(9.027;9.908)	δ =2.33 x_i =(9.882;9.893)	δ =0.15 x_i =(9.994;9.991)	δ =0.08 x_i =(9.998;9.994)	δ =0.02 x_i =(10;9.998)

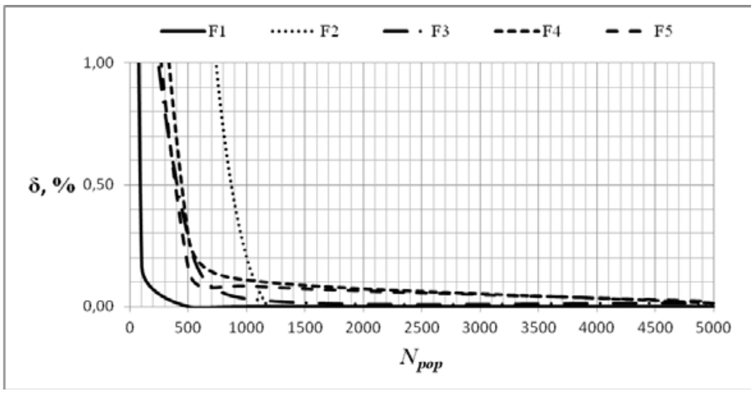

Fig. 8.
Graphical interpretation of the relative deviations of the maxima function (δ, %), found by genetic algorithm from analytic ones for different numbers of generations (Npop).

As can be seen from the graphic (Fig. 8), the value of relative deviations of the maxima of functions found by the genetic algorithm from analytic ones decreases monotonically then the number of generations are increase. In particular, after the 1000th generation, this is less than 0.2% for all functions. Received results confirm the adequacy of the functioning of genetic algorithm, and suggest the possibility of its application for FES parameters setting.

Real-world data example. The validation of work (checking the possibility of using it on practice) of developed system, imlemented in software "GA_SAWing_lumber", is performed by examining ways to increase the value of the coefficient of specified blank yield *k* by means of setting FES parameters (Table 2).

For example, FES setting conducted for this blank specification:

- the length of blanks - $x1$ = 1.2 *m;* $x2$ = 0.8 *m;* $x3$ = 0.4 *m;*
- the number of blanks that should be sawed out - $v1$ = 500 *pc;* $v2$ = 500 *pc;* $v3$ = 500 *pc.*

The parameters of genetic algorithm adopted as: *Ps* = 0.6*; Pm* = 0.1*; Nchr* = 10*; Ngen* = 22*; Npop* = 100*; Nb* = 10.

On the first stage of FES parameters setting the process of blanks cross-cutting for adopted blank specification is simulated with the help of the software "SAWing_lumber". Parameters of membership functions and weight coefficients of rules (basic version) are adopted in conformity to the vector $\vec{S} = \{\vec{B},\vec{C},\vec{W}\}$ = {0.25, 0.5, 0.75, 0.3, 0.3, 0.3, 0.3, 0.3, 0.3, 0.1, 0.1, 0.1, 0.1, 0.1, 1, 1, 1, 1, 1, 1, 1, 1}. As a result of simulation of blank cross-cutting the coefficient of specified blank yield is obtained *k* = 0.,682.

On the next stage, the FES parameters setting are conducted with the help of software "GA_SAWing_lumber". Consequently, parameters of membership function of linguistic variables and weights coefficient rules are selected (vector $\vec{S}^* = \{\vec{B}^*,\vec{C}^*,\vec{W}^*\}$= {0.26, 0.41, 0.69, 0.49 , 0.2, 0.44, 0.23, 0.38, 0.16, 0.14, 0.14, 0.07, 0.14, 0.1, 0.57, 0.3, 0.33, 0.69, 0.83, 0.63, 0.23, 0.1}), which made it possible to obtain the coefficient of specified blank yield *k** = 0.781. Thus, by virtue of FES parameters setting the growth of coefficient of specified blank yield was achieved by 14.5% (for provided blanks specification).

Graphics of membership functions of the input and output linguistic variables for the basic version *(Z, Q, N, P)*, and found through genetic parameters *(Z*, Q*, N*, P*)* are provided in Fig. 9.

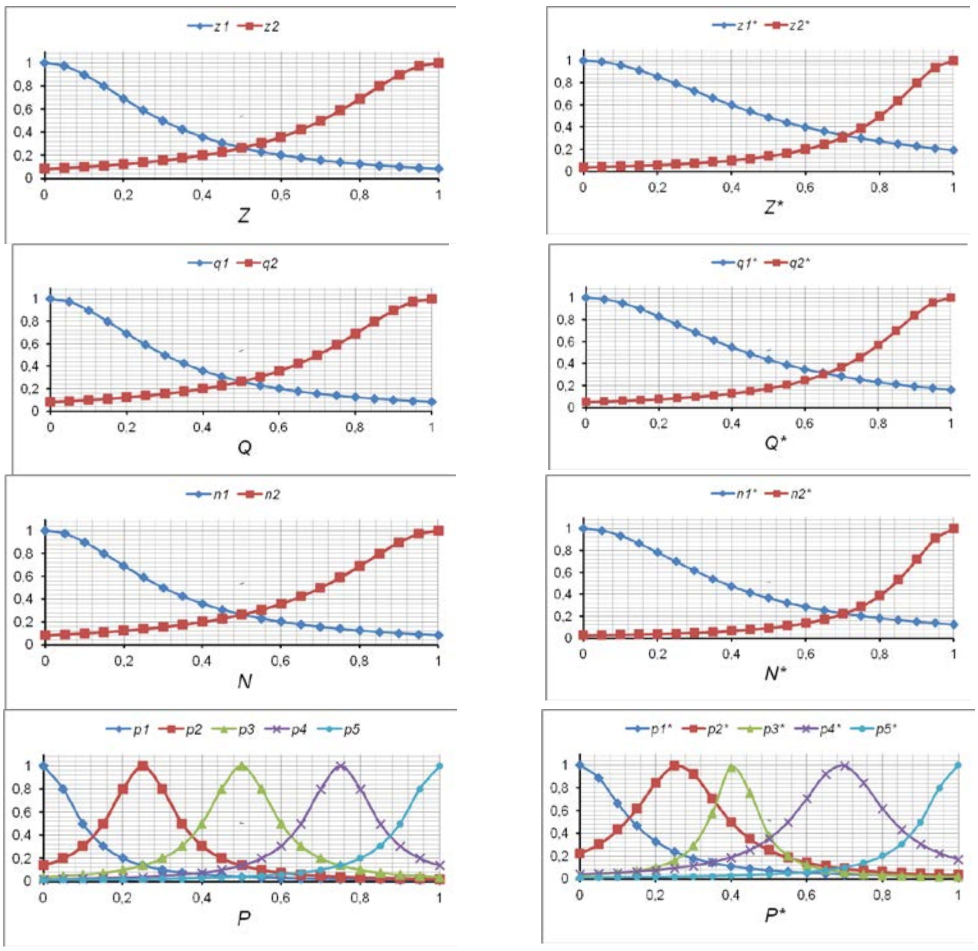

Fig. 9.
Membership functions for linguistic basic version (Z, Q, N, P) and after genetic tuning parameters (Z*, Q*, N*, P*)

Change of maximum *max*, average *aver* and minimum *min* values of the coefficient of specified blanks yield *k* in the process of FES parameters setting is in Fig. 10. From figure it is seen that depending on the FES settings, the value of coefficient of specified blanks yield can vary in quite wide range (from 0.654 to 0.781 — for concerned option).

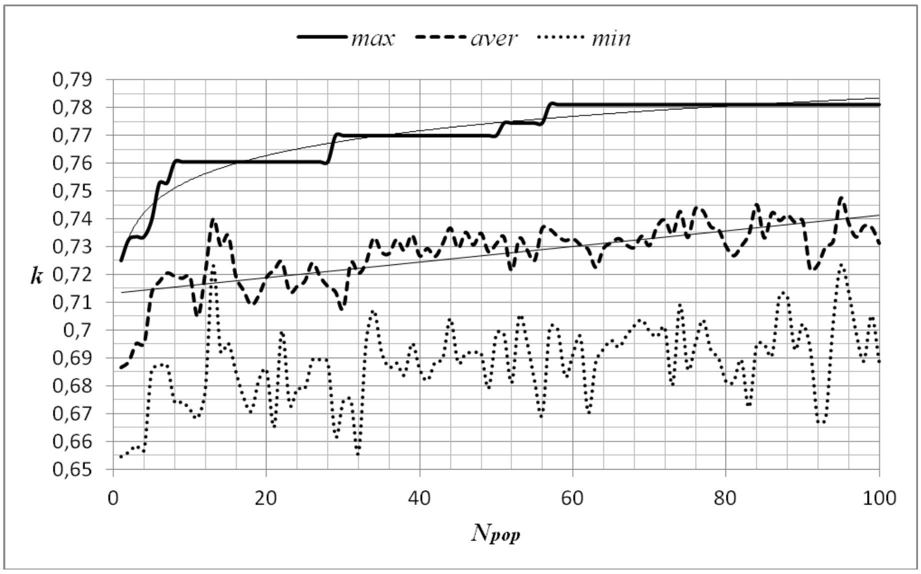

Fig. 10.
Change of the maximum (max), average (aver) and minimum (min) values of specified blanks yield in the FES setting process.

The obtained results confirm the reasonability of FES parameters setting as it will increase the efficiency of decisions taken in the process of solid wood cutting and as a result will decrease the usage of resources in the cutting process.

CONCLUSIONS

Application of the theory of fuzzy sets is an effective approach to modeling and control of solid wood cross-cutting process. Research results of the authors provide a basis for the development of hierarchical fuzzy "predictive" models that can take into account the natural uncertainty and fuzziness of the solid wood characteristics and elements of experience and intuition of human operator.

To make better decisions in real conditions the fuzzy system parameters must be configured to perform a specific production tasks. Way of this adjustment may be the use of genetic algorithm optimization.

To configure fuzzy expert system for decision support in the automated process of solid wood cutting genetic algorithm is developed and confirmed the adequacy of the work by verified on simulated and real-world data.

As a result of genetic setting of fuzzy expert system parameters the increase of coefficient of specified blank yield was achieved *(k*=* 0.781*)* by 14.5% compared with the value *(k =* 0.682*),* derived for basic settings of fuzzy expert system parameters. During this the value of coefficient of specified blanks yields was being varied from 0.654 to 0.781.

Application of the proposed genetic fuzzy expert systems in a production environment will ensure the rational cutting yields as a condition of lean manufacturing in the process of solid wood cutting.

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