Vietnam Journal of Mechanics, Vol. 46, No. 2 (2024), pp. 163 – 180
DOI: https://doi.org/10.15625/0866-7136/21000

INTEGRATION OF GENETIC ALGORITHM AND HEDGE ALGEBRAS IN CONTROLLING MECHANICAL MACHINING ROBOTS

Phan Bui Khoi[1,*]
[1]*Hanoi University of Science and Technology, Hanoi, Vietnam*
[*]E-mail: khoi.phanbui@hust.edu.vn

Received: 15 March 2024 / Revised: 21 May 2024 / Accepted: 10 June 2024
Published online: xx June 2024

Abstract. Robot applications in mechanical processing have become popular. The critical issue when applying robots in mechanical processing is ensuring accuracy. Usually, robot control is based on dynamic models. This method has difficulty accurately determining the system's dynamic model because the robot has a complex structure. Besides, dynamic factors such as cutting force, friction force and machining conditions constantly change. Robot control based on Hedge Algebras gives excellent and reliable results. The critical factors that determine the quality and reliability of the Hedge Algebra controller are the Control Law, the method of Denormalization, and the determination of the Physical Value Domain. The construction of the Control Law and Denormalization is based on expert knowledge. Determining the physical value domain is problematic because it requires many experiments. This article introduces the method of applying genetic algorithms to find the appropriate physical value domain for the controller based on Hedge Algebras. The article presents a robot controller based on Hedge Algebras to do this. Numerical experiments with a mechanical machining robot verify the results.

Keywords: Genetic Algorithms, Hedge Algebras, control, mechanical machining robot, physical value domain.

1. INTRODUCTION

The application of robots in mechanical processing is already a common practice [1–5]. Compared to CNC machines, applying robots has several advantages, such as a robot structure with a multi-degree of freedom and flexible programming capabilities that allow for complex technological operations. One of the problems when using robots is controlling the robot to ensure technological manipulation as required. Conventional control methods based on dynamic models have difficulty fully and accurately determining the dynamic model. This is explained by the complex structure of multi-joint, multi-degree-of-freedom robots and constantly changing dynamic factors such as cutting force, machining conditions, etc.

The application of fuzzy logic in robot control allows us to overcome this problem because fuzzy controllers can overcome the incompleteness and accuracy of the dynamic model or even not based on the dynamic model [6–13].

Fuzzy controllers are implemented by inference and representation through natural language and based on linguistic semantic values. However, fuzzy logic does not have a mechanism to model the language semantics and ordinal structure of the language domain.

As is known, the advent of Hedge Algebras (HA) and the application of HA in engineering control problems has provided a way to model the semantics and order structure of language domains. In which linguistic values constrain the semantics of linguistic terms and preserve semantics during data processing. Here, fuzzy term sets are designed to be linked to their semantics with an inherent order-based structure. In this way, HA terms directly and quantitatively reflect natural language properties, which makes the inference mechanism of the fuzzy rule base easy to quantify.

Furthermore, the fuzzy rule base is a mathematical model that uses HA transformations and semantic quantitative mappings (SQMs). Here, SQMs of HA are functions used to calculate the semantic values of HA terms based on the fuzziness measure. Therefore, the fuzzy rule base can be constructed and represented as a real hypersurface in the Cartesian coordinate system, where a fuzzy proposition can be defined as a point in the Cartesian product of the appropriate HA. In engineering problems, this hypersurface represents the relationship between the semantic values of input and output signals. The semantic value of the output can be obtained by the interpolation method on this real mesh hypersurface. The difference in HA compared to the inference mechanism of fuzzy logic is that SQMs directly map the physical values of the input to the semantic value domain [0, 1]. Then, the semantic values of the output results are obtained by interpolation method on the real mesh hypersurface. Therefore, to get the physical values of the output, their semantic values are simply mapped from [0, 1] to their physical domain. These characteristics create favorable conditions for applying HA to solve technical control problems in general, robot control in particular, and mechanical processing robot control with high requirements for accuracy [14–20].

The structure of an HA-based controller has parts, including the Normalization of HA terms of linguistic variables (Identification Normalization of HA terms), Quantification of the rule base using Semantically Quantifying Mappings (SQMs) with control algorithms, and Denormalization.

Structure of an HA-based controller with parts including (1) Normalization of HA terms of linguistic variables (Identification Normalization of HA-terms); (2) Quantifying the rule base using SQMs with control algorithms; (3) Denormalization.

(1) Standardizing the HA terms of linguistic variables means identifying the input and output linguistic variables with the corresponding physical value domain, labeling the linguistic variables, and determining the components in the HA of the linguistic variables.

(2) Quantitative semantic mapping is a function that determines the quantitative semantic value of HA terms based on the fuzziness measure. Control algorithms based on the HA rule system are similar to the basic fuzzy rule system, built based on expert knowledge of the controlled object. Based on the control algorithm, the linguistic semantic values of the output variables are determined from the linguistic semantic values of the input variables.

(3) The standard solution is the linguistic value of the output variable on the interval [0, 1] that is mapped to the physical value domain to determine the physical value of the output variable.

The main factors determining the HA controller's accuracy are the physical value domain of the input and output language variables and the HA control rule system. Based on expert knowledge and dynamic characteristics of the controlled object, the built rule system is stable. Meanwhile, determining the physical value domain, besides relying on specialist knowledge, also requires a lot of experimentation. Manual methods take a lot of time, and it isn't easy to achieve good results. Methods that combine manual testing to get preliminary values and then train the network when combining neural networks can give better and faster results. The genetic algorithm method appears convenient for determining the physical value domain of input and output variables.

This article presents a controller based on HA for mechanical processing robots. In this controller, genetic algorithms are applied to find the physical value domain of input and output linguistic variables.

The following sections include: Section 2 presents the general structure of the HA controller; Section 3 presents the application of a genetic algorithm and an integrated program to determine the physical value domain of input and output linguistic variables;

Section 4 presents the application of HA controller for mechanical processing robots; Section 5 concludes on the feasibility and effectiveness of the genetic algorithm and HA controller and research and development directions.

2. ROBOT CONTROLLER BASED ON HEDGE ALGEBRAS

The general structure of a robot controller is shown in Fig. 1. In which the "Input" block carries the input signal; the "Control" block calculates the output quantity, which is the control quantity based on the input signal and control algorithm; The "robot" block is the control object; the "Graph" displays the results. The characteristics of HA-based controllers (from now on referred to as HA controllers or Hedge Algebras Control - HAC) compared to other controllers are in the "input" block and "Control" block.

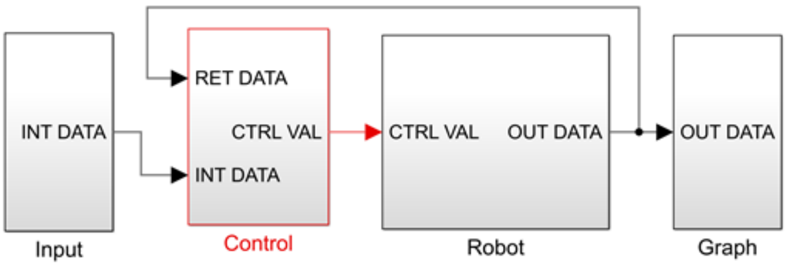


Fig. 1. The general structure of a robot controller

Fig. 2 shows the "Input" block, in which nodes 1 and 2 represent the feedback and desired signal of position and velocity, respectively. Node 3 is the physical value domain of the input and output variables.

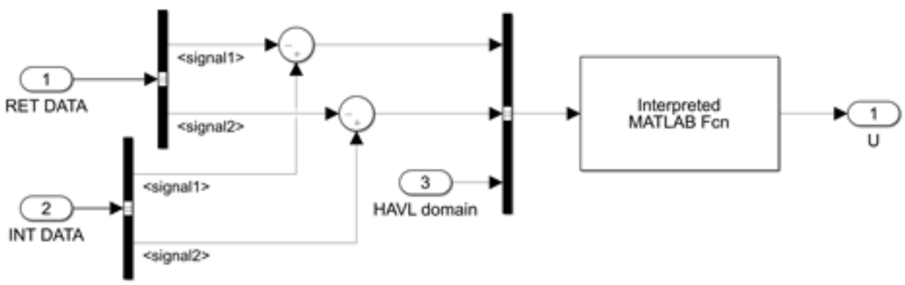


Fig. 2. The "Input" block of fuzzy logic controller

Fig. 3 shows the "Control" block. Its sub-blocks include normalizing HA terms of linguistic variables (HA Normalization), Semantic Quantitative Mapping and Control Algorithms (SQMs & HA Rule Base), and Mapping the output semantics to the physical value of the control quantity (HA Denormalization).

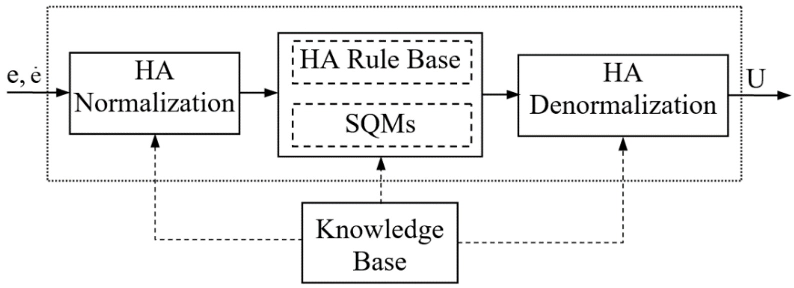


Fig. 3. The "Control" block of fuzzy logic controller

2.1. HA Normalization

Variable language of input signals: position error $e(t)$, velocity error $\dot{e}\,(t)$, and control force $U(t)$. Hereafter referred to as position, velocity, and control force variables.

The HAC controller calculates the control quantity, the output signal $U(t)$, based on the HA control law and the physical value domain of the language variables of the input and output signals $e(t)$, $\dot{e}\,(t)$, respectively. The physical value domain of the language variable is the MAX-MIN value limits, expressed as follows

$$\begin{cases} e_i = [e_{i\,\min}, e_{i\,\max}], & i = 1, \ldots, n \\ \dot{e}_i = [\dot{e}_{i\,\min}, \dot{e}_{i\,\max}], & i = 1, \ldots, n \\ U_i = [U_{i\,\min}, U_{i\,\max}], & i = 1, \ldots, n \end{cases} \tag{1}$$

In general, the HA of linguistic variables can be arbitrary. However, for ease of presentation and programming, the HAs of language variables are formally standardized to be the same to realize their interrelationship in a unified whole, while their physical values are different.

Thus, the HA of the linguistic variables of $e(t)$, $\dot{e}\,(t)$ and $U(t)$ are expressed: AX = (X, G, C, HI, $\leq$).

X consists of all HA terms of a linguistic variable, $\leq$ is an order relation on X.

G = $\{c^-, c^+\}$ is a set of generators, $c^- \leq c^+$, where c^- = S, c^+ = B. S and B are Small and Big, respectively.

C = {0, W, 1}, where 0, W, and 1 are fixed points, respectively, called the smallest, neutral, and biggest terms of the specified HA.

HI = H ∪ {I}, where H = $\{H^-, H^+\}$ is a set of unary operations representing linguistic hedges of X, HI = {L, V} ∪ {I}=$\{h^-, h^+\}$, where h^- = L; h^+ = V, that L and V stand for Little and Very, respectively.

The sets G, C, and HI are similar for all HAs of the selected linguistic variables as follows:

With definite sets, the atomic generators S and B of G combine with the hedges L and V of H to produce the entire set X consisting of all HA of linguistic variables in an ordered relation linear, $X = H(G) \cup C$.

Then, the HA terms of the linguistic variables are presented as shown in Table 1.

Table 1. The HA terms of the linguistic variables

HA terms	0	VS	LS	W	LB	VB	1

X in every HA of $e(t)$ and $U(t)$ are defined similarly. Accordingly, the semantic relationships and values of HA terms of linguistic variables are also similar. However, the semantic values of the HA terms of $e(t)$ and $U(t)$ only realize their semantic relationship separately because their physical domains are different.

2.2. HA rule base and Semantic quantitative mapping SQMs

Building the base rule system for the HA controller is similar to the control rule for the fuzzy controller. Table 2 shows the basic HA rule system.

Table 2. HA rule base system, input $e(t)$, $\dot{e}\,(t)$, output $U(t)$

	$\dot{e}\,(t)$							
	U	**0**	**VS**	**LS**	**W**	**LB**	**VB**	**1**
$e(t)$	**0**	1	1	1	VB	VB	LB	W
	VS	1	VB	VB	VB	LB	W	LS
	LS	1	VB	LB	LB	W	LS	VS
	W	VB	VB	LB	W	LS	VS	VS
	LB	VB	LB	W	LS	LS	VS	0
	VB	LB	W	LS	VS	VS	VS	0
	1	W	LS	VS	VS	0	0	0

The semantic value of HA terms belongs to the domain [0, 1], and therefore, points 0 and 1 are used in the HA rule base as semantic limits for interpolation methods and to preserve data during processing.

The following calculation functions are shown to determine the measure of fuzziness of linguistic terms of linguistic variables and quantify the semantics of linguistic terms for the HA rule base.

2.2.1. *Fuzziness measure*

The fuzziness measurement function f_m: X → [0, 1] of linguistic terms is determined based on the following formulas

$$(c^-) + f_m(c^+) = 1, \tag{2}$$

$$\sum_{h \in H} f_m(hx) = f_m(x), \qquad \sum_{-q \le i \le p, i \ne 0} f_m(h_i x) = f_m(x) \quad \forall x \in \mathrm{X}, \tag{3}$$

$$\sum_{-q \le i \le p, i \ne 0} f_m(h_i c) = f_m(c), \quad c \in \{c^-, c^+\}, \tag{4}$$

$$f_m(x) = 0, \quad \forall x, \quad H(x) = \{x\}, \quad f_m(0) = f_m(\mathrm{W}) = f_m(1) = 0, \tag{5}$$

$$\frac{f_m(hx)}{f_m(x)} = \frac{f_m(hy)}{f_m(y)}, \quad \forall x, y \in \mathrm{X}, h \in H_I, \tag{6}$$

$$f_m(hx) = \mu(h) f_m(x), \quad \forall x \in \mathrm{X}, \tag{7}$$

where $\mu(h)$ is often called the fuzziness parameter, which measures the fuzziness of the hedge h.

$$\sum_{h \in H} \mu(h) = 1. \tag{8}$$

By recursion, with $x = h_m, \ldots, h_1 c \in \mathrm{X}$, where $c \in \mathrm{G}$,

$$f_m(x) = \mu(h_m) f_m(x|_m) = \mu(h_m) \ldots \mu(h_1) f_m(c), \tag{9}$$

where $x|_m = h_{m-1}, \ldots, h_1 c$ is the m^{th} suffix of x.

$$\begin{cases} \sum_{i=-q}^{-1} \mu(h_i) = \alpha, \\ \sum_{i=1}^{p} \mu(h_i) = \beta, \\ \alpha > 0, \beta >, \alpha + \beta = 1 \end{cases} \tag{10}$$

Based on expert knowledge and given the systems in which the language terms represent, fuzziness measurement functions can be determined according to the formulas given. For example, the opacity measurement functions $f_m(c^-)$ and $f_m(c^+)$ are chosen arbitrarily but must satisfy (2). The measure of hedges $\mu(h)$ can be chosen arbitrarily but must satisfy (8).

2.2.2. *Semantic Quantitative Mapping SQMs*

SQMs calculate the semantics of HA terms. Based on Table 2 and the formulas below, the HA law base of $U(t)$ in Table 2 is converted into semantic value relationships and determined.

Combined with the fuzziness measure function f_m on X, the semantic quantification function v on X is determined as follows

$$v\left(W\right)=\theta=f_m\left(c^-\right),\quad 0<\theta<1, \tag{11}$$

$$v\left(c^-\right)=\theta-\alpha f_m\left(c^-\right)=\beta f_m\left(c^-\right), \tag{12}$$

$$v\left(c^+\right)=\theta+\alpha f_m\left(c^+\right), \tag{13}$$

$$v\left(h_jx\right)=v\left(x\right)+\operatorname{sign}\left(h_jx\right)\left\{\sum_{i=\operatorname{sign}(j)}^{j} f_m\left(h_ix\right)-\omega\left(h_jx\right)f_m\left(h_jx\right)\right\}, \tag{14}$$

$$\begin{cases}\omega\left(h_jx\right)=\dfrac{1}{2}\left[1+\operatorname{sign}\left(h_jx\right)\operatorname{sign}\left(h_ph_{j-1}x\right)\left(\beta-\alpha\right)\right],\\ j\in\{-q\le j\le p, j\ne 0\}=[-q,\ldots,p].\end{cases} \tag{15}$$

Sign is a sign function, sign: X$\rightarrow\{-1,0,1\}$, defined recursively as follows

$$\begin{array}{l}
1)\ \operatorname{sign}\left(c^-\right)=-1, \operatorname{sign}\left(hc^-\right)=+\operatorname{sign}\left(c^-\right), hc^-<c^-, \operatorname{sign}\left(hc^+\right)=-\operatorname{sign}\left(c^-\right), hc^->c^-\\
2)\ \operatorname{sign}\left(c^+\right)=+1, \operatorname{sign}\left(hc^+\right)=+\operatorname{sign}\left(c^+\right), hc^+>c^+, \operatorname{sign}\left(hc^+\right)=-\operatorname{sign}\left(c^+\right), hc^+<c^+\\
3)\ \operatorname{sign}\left(h\right)=+1, h\in H^+, \operatorname{sign}\left(h\right)=-1, h\in H^-\\
4)\ \operatorname{sign}\left(h'hx\right)=-\operatorname{sign}\left(hx\right), h' \text{ negative w.r.t. } h, h'hx\ne hx\\
5)\ \operatorname{sign}\left(h'hx\right)=\operatorname{sign}\left(hx\right), h' \text{ positive w.r.t. } h, h'hx\ne hx\\
6)\ \operatorname{sign}\left(h'hx\right)=0, h'hx=hx
\end{array} \tag{16}$$

The impact of a hedge h' on a hedge h depends on whether h' strengthens or weakens h's tendency to influence. Sign$(h'h)=+1$ or sign$(h'h)=-1$.

The sign function of a point is not fixed

$$\operatorname{sign}\left(x\right)=\operatorname{sign}\left(h_mh_{m-1}\right),\ldots,\operatorname{sign}\left(h_2h_1\right)\operatorname{sign}\left(h_1\right)\operatorname{sign}\left(c\right),\quad \forall x=h_m,\ldots,h_1c. \tag{17}$$

Based on expert knowledge about technical systems in general and robots in particular, the fuzziness measurement functions of linguistic terms are selected and determined according to (2)–(10). Thus, based on understanding the robot system and realizing the impact of the hedges in H on the generators in G can be considered similar, the fuzziness measures of the hedges and the generators chosen as follows

$$\begin{cases}f_m\left(S\right)=\theta=0.5\\ \mu\left(L\right)=\mu\left(V\right)=0.5\end{cases}\rightarrow\begin{cases}\alpha=\beta=0.5\\ f_m\left(B\right)=1-f_m\left(S\right)=0.5\end{cases} \tag{18}$$

Table 3. The semantic value relationship of $e(t)$ and $\dot{e}\,(t)$with $U(t)$

		$\dot{e}\,(t)$						
	U	**0**	**VS**	**LS**	**W**	**LB**	**VB**	**1**
	0	1	1	1	0.875	0.875	0.625	0.5
	VS	1	0.875	0.875	0.875	0.625	0.5	0.375
	LS	1	0.875	0.625	0.625	0.5	0.375	0.125
$e(t)$	**W**	0.875	0.875	0.625	0.5	0.375	0.125	0.125
	LB	0.875	0.625	0.5	0.375	0.375	0.125	0
	VB	0.625	0.5	0.375	0.125	0.125	0.125	0
	1	0.5	0.375	0.125	0.125	0	0	0

With the defined fuzziness measurement functions, applying the formulas from (11)–(17), the semantic quantitative functions of HA terms are calculated, and Table 2 is converted into Table 3, representing the semantic value relationship of $e(t)$, $\dot{e}\,(t)$ and with $U(t)$.

The semantic relationship between position error $e(t)$, velocity error $\dot{e}\,(t)$, and control force $U(t)$ at the robot joints in Table 3 is represented by super surfaces in Euclidean space, as shown in Fig. 4.

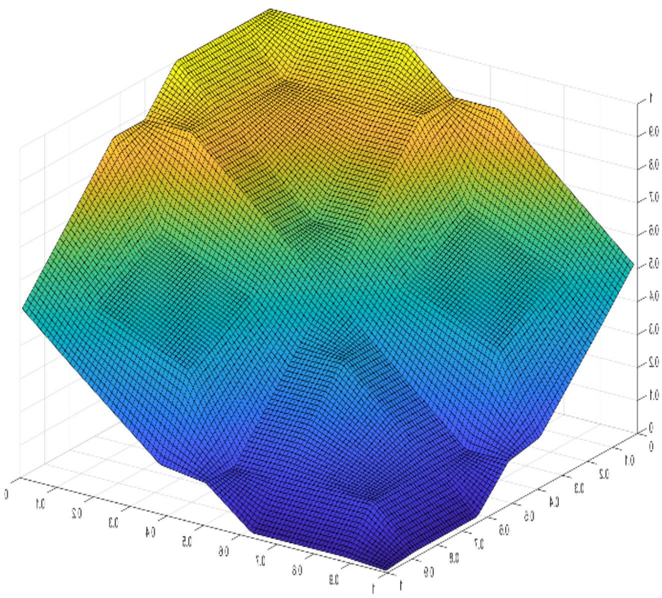


Fig. 4. The grid hypersurfaces represent the relationship between input state variables and output control variables (Control Surfaces)

2.3. HA Denormalization

Interpolation is used to approximate the semantic values of the output quantity, the control force $U(t)$, through the semantic relationships between the inputs and outputs in Table 3. Below is the four-point bilinear interpolation method.

Fig. 5 shows a part of the real mesh super surface, bounded by four points $Q_{11}(x_1, y_1), Q_{12}(x_1, y_2), Q_{21}(x_2, y_1)$, $Q_{22}(x_2, y_2)$, corresponding to the pairs value $(x_i, y_j, i, j = 1, 2)$ on the x, y axes. Call the coordinates of the corresponding points on the z-axis are $z_{11}, z_{12}, z_{21}, z_{22}$. A point $Q(x, y)$ on the surface will have coordinates along the z-axis calculated according to the formulas below

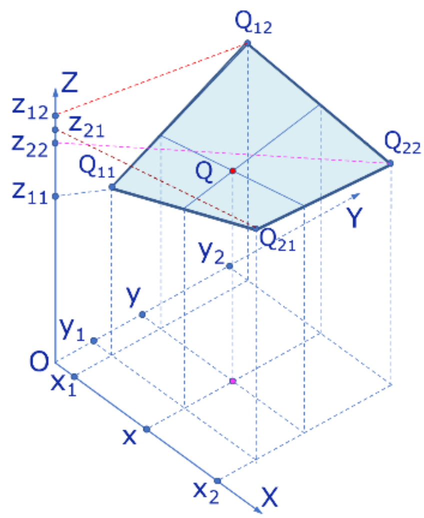


Fig. 5. The four-points bilinear interpolation

$$T_I = (x_2 - x_1)(y_2 - y_1), \tag{19}$$

$$X_I = \begin{bmatrix} x_2 - x & x - x_1 \end{bmatrix}, \tag{20}$$

$$Y_I = \begin{bmatrix} y_2 - y \\ y - y_1 \end{bmatrix}, \tag{21}$$

$$A_I = \begin{bmatrix} z(x_1, y_1) & z(x_1, y_2) \\ z(x_2, y_1) & z(x_2, y_2) \end{bmatrix} = \begin{bmatrix} z_{11} & z_{12} \\ z_{21} & z_{22} \end{bmatrix}, \tag{22}$$

$$z(x, y) = \frac{1}{T_I} X_I A_I Y_I. \tag{23}$$

3. GENETIC ALGORITHM TO CALCULATE THE PHYSICAL VALUE DOMAIN OF LINGUISTIC VARIABLES

Fig. 6 shows the genetic algorithm diagram integrated with the HA controller simulation program. Accordingly, the genetic algorithm calculates the physical value domains of the language variables. The calculation results are transmitted to the simulation program to calculate the errors of the controlled variables as position errors. The position errors provide to the genetic algorithm program for calculating the objective function. One algorithm-stopping condition is that the objective function reaches a value less than or equal to the allowed value.

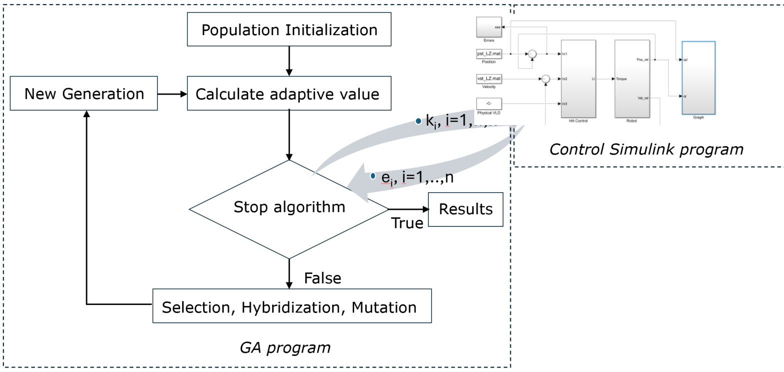


Fig. 6. The genetic algorithm diagram integrated with the HA controller simulation program

The main steps to apply the genetic algorithm to find the physical value domain of the language variables of the HA controller:

(1) Construct the objective function as the sum of squared position errors of joint variables during the control process.

$$f = \sum_{i=1}^{n} e_i^2, \tag{24}$$

where n is the number of joint variables.

(2) Select encryption parameters:

- The parameters chosen for encoding are the physical values domain of the input variable e_i, $\dot{e}_i$ and $U_i, i = 1, \ldots, n$, are denoted $k_j, j = 1, \ldots, m$. Each joint variable has three language variables: position, velocity, and control force. The physical value domain can be symmetric or asymmetric, i.e.: $|e_{\min}| = |e_{\max}|$ or $|e_{\min}| \neq |e_{\max}|$. Thus, in detail, with a robot with n-actuated joints, it will be possible to find $m = 3n$ or $m = 6n$ parameters $k_j, j = 1, \ldots, m$ that determine the physical value domain of all language variables corresponding to the symmetric or asymmetric case.

(3) Initialization parameters for the genetic algorithm are preliminarily selected based on expert knowledge, including:

- Selectivity constant, for example: $P_c = 0.9$;

- Mutation constant, for example: $P_m = 0.5$;

- Population size, for example: $N = 100$;

- Algorithm stopping error, for example: 0.00001;

- Maximum number of generations, for instance: $gen_{\max} = 100$;

- The maximum number of generations of the objective function does not change; for instance, $gens = 50$;

- Preliminary search domain can be selected: $k_j = [0.01; 1], \ldots, j = 1, \ldots, m$.

(4) Select encryption method: Select real number encryption method.

(5) Programming is based on the GA algorithm diagram, as shown in Fig. 6, linked to the HA controller simulation program.

4. APPLICATION OF HA CONTROLLER FOR MECHANICAL PROCESSING ROBOTS

4.1. Integrated controller based on GA + HA for robot in mechanical machining by laser

Apply HAC to control the machining robot to create detailed profiles using laser beams, as shown in Fig. 7.

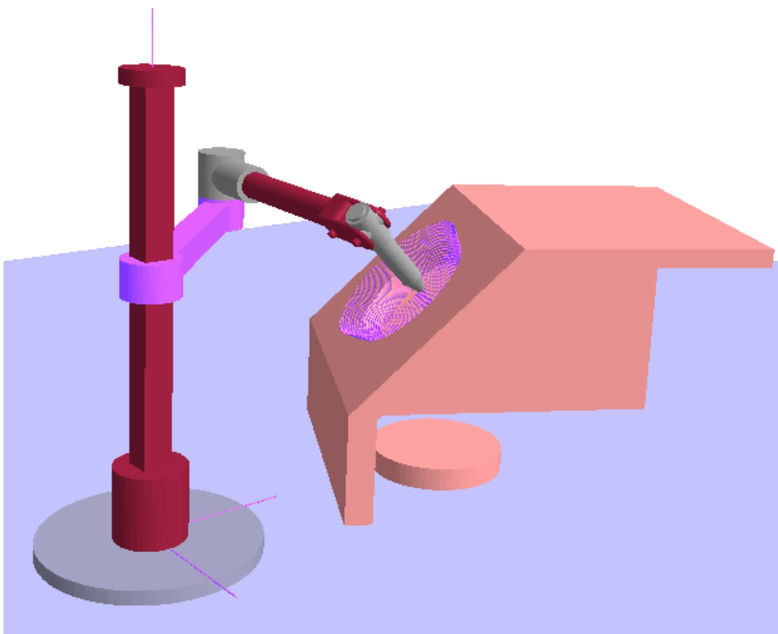


Fig. 7. The model of the machining robot to create detailed profiles using laser beams

Robot kinematic parameters are shown in Table 4. Where a_2 = 400 mm, d_3 = 80 mm, d_4 = 400 mm, a_5 = 150 mm.

Table 4. Denavit-Hartenberg (DH) kinematic parameters of the robot

$i-1 \leftarrow i$	Parameters			
	θ_i	d_i	a_i	α_i
1	θ_1	0	0	0
2	0	d_2	a_2	0
3	θ_3	d_3	0	90°
4	θ_4	d_4	0	90°
5	θ_5	0	a_5	0

Joint coordinates:

$$q = [q_1, \ldots, q_5]^T = [\theta_1, d_2, \theta_3, \theta_4, \theta_5]^T. \tag{25}$$

Robot dynamic parameters are shown in Table 5. The processing object is a tapered hole. Accordingly, the robot's movement is such that the laser machining tip moves along a circle with a radius $r = 10$ cm. The laser axis is in the plane containing the conical hole axis and is inclined to the conical hole axis at an angle of α = 30 degrees.

Table 5. Dynamic parameters of the robot

Links		1	2	3	4	5
Mass (kg)		35	25	5	20	5
Origin position of the center of mass coordinate system with respect to the link's coordinate system	x_{ci} (m)	0	−0.1916			0.10796
	y_{ci} (m)	0	0	0	0.144551	0
	z_{ci} (m)	0.229	0.02	0.022924	0	0
Inertia tensor of the links ${}^{ci}\Theta_{ci}$ (kg.m^2)	I_{xx}	1.437777	0.010409	0.008052	0.166565	0.012375
	I_{yy}	1.437777	0.554153	0.007806	0.006129	0.012355
	I_{zz}	0.026774	0.556332	0.003120	0.165564	0.000718
	I_{xy}	0	0	0	0	0
	I_{xz}	0	0	0	0	0
	I_{yz}	0	0	0	0	0

The digital data files about the movement trajectory of active joints are calculated and saved in a file.mat format, in which:

pst_LZ.mat is the motion trajectory for the position of the links; **vst_LZ.mat** is the velocity. Fig. 8 shows the numerical simulation model of the HA controller's operation.

Block K receives a signal that is a physical value domain from the GA algorithm program. With a survey robot with 5 degrees of freedom, there are 3 × 5 = 15 physical value domains to find. Thus, we can see 15 or 30 parameters corresponding to the case where the physical value domain is symmetric or asymmetric. If many parameters are to be found, the calculation time will be significant. We present a calculation plan with fewer parameters to verify the algorithm while evaluating its effectiveness.

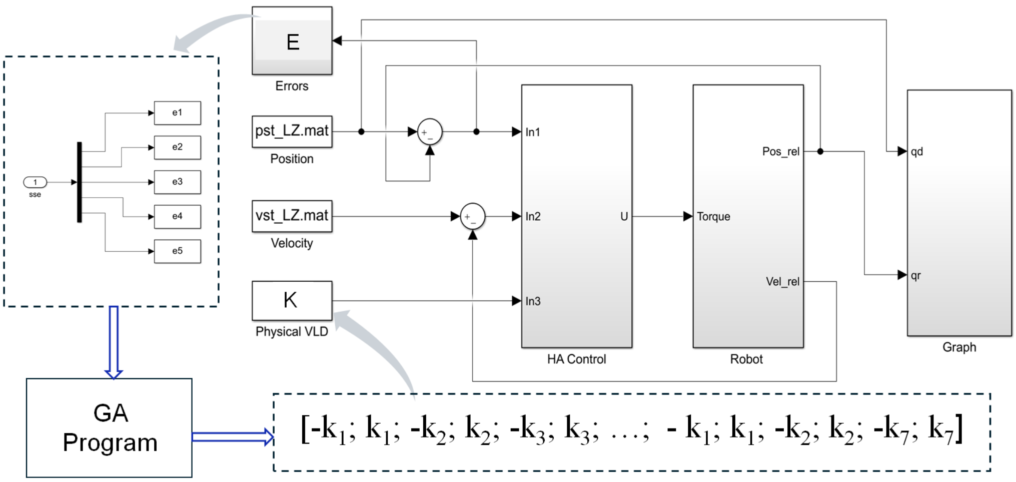


Fig. 8. The program integrates a genetic algorithm and HA controller simulation

Accordingly, the domain of physical values of the linguistic variables of position and velocity of all joint coordinates is assumed to be the same, and the symmetric form is chosen. Thus, with the linguistic variables position e_i and velocity $\dot{e}_i, i = 1, \ldots, 5$, determining two parameters, k_1, and k_2, will be necessary.

Because the loads at the joints are quite different, each joint must find a physical value range of the control force. Therefore, with the language variables $U_i, i = 1, \ldots, 5$ it will be necessary to determine five parameters, $k_j, j = 3, \ldots, 7$. Thus, the number of parameters determining the physical value domains will be $k_j, j = 1, \ldots, 7$.

Seven values are preliminarily selected according to Table 6 based on expert knowledge of the controlled object, the parameters $k_j, j = 1, \ldots, 7$.

Table 6. The HA terms of the linguistic variables

k_j	k_1	k_2	k_3	k_4	k_5	k_6	k_7
Min	0	0	0	0	0	0	0
Max	0.2	2	200	1500	200	100	60

Other parameters are selected as described in Section 3.

The GA algorithm program determines the parameter set k_j for each calculation step and sends it to the controller simulation program.

Block E, which contains the position errors determined by the control simulation program, is fed back to the GA program to continue the loop.

4.2. Calculation and simulation results

Table 7 shows the results of calculating the physical value domain of the input and output linguistic variables.

Table 7. Physical value domains of input and output linguistic variables

Joint	e_i	$\dot{e}_i$	U_i
1	$[-0.0017, 0.0017]$ (rad)	$[-0.7445, 0.7445]$ (rad/s)	$[-98.9144, 98.9144]$ (N.m)
2	$[-0.0033, 0.0033]$ (m)	$[-0.3388, 0.3388]$ (m/s)	$[-1081.1081]$ (N)
3	$[-0.0011, 0.0011]$ (rad)	$[-0.0740, 0.0740]$ (rad/s)	$[-87.2828, 87.2828]$ (N.m)
4	$[-0.0071, 0.0071]$ (rad)	$[-0.07182, 0.07182]$ (rad/s)	$[-81.5385, 81.5385]$ (N.m)
5	$[-0.0010, 0.0010]$ (rad)	$[-0.1254, 0.1254]$ (rad/s)	$[-47.9604, 47.9604]$ (N.m)

With the physical value domain determined, the HA controller simulation program receives the results shown in Fig. 9.

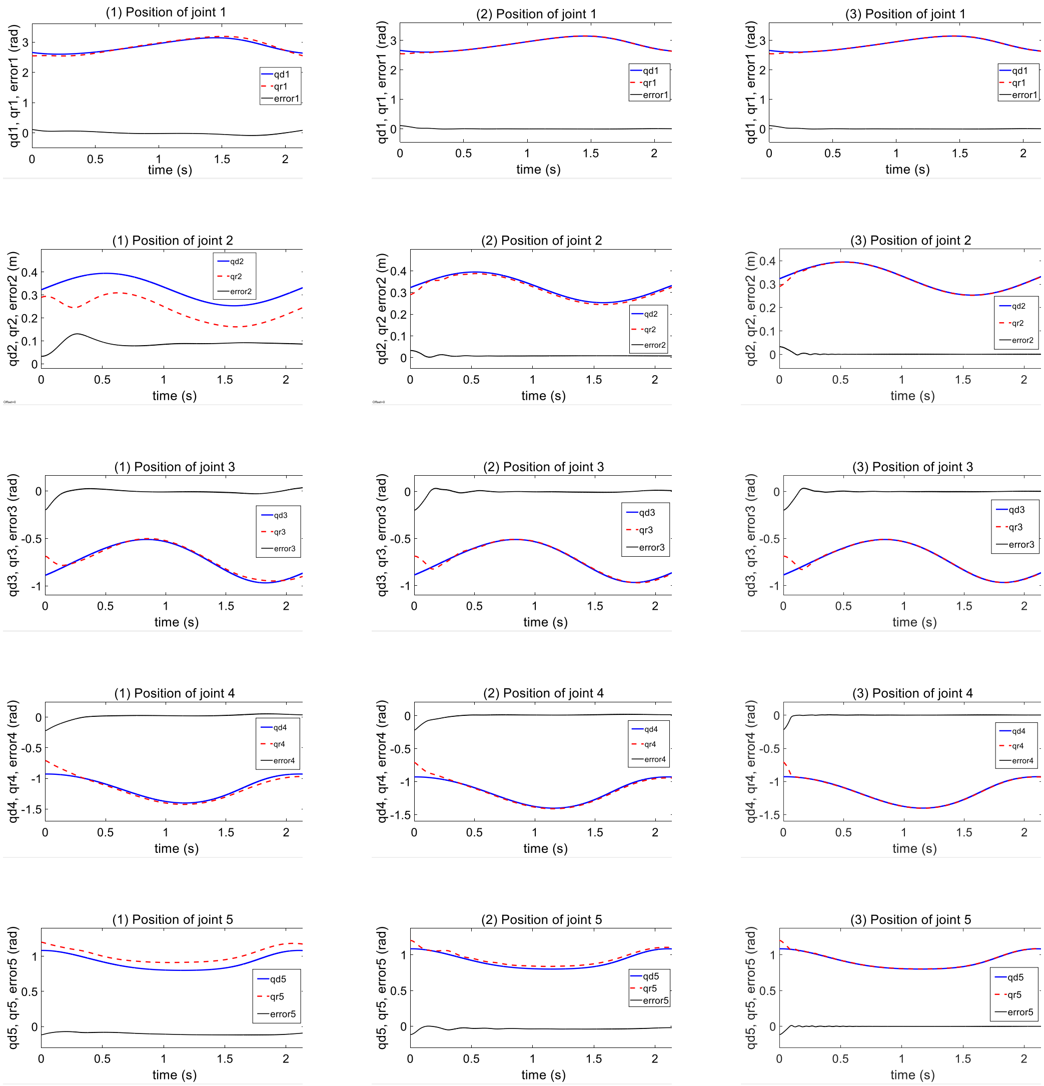
Fig. 9 shows the simulation results corresponding to several physical value domain choices to identify the evolutionary process, i.e., gradually improving the controller's simulation results.

The images in Fig. 9(a) left column (corresponding to symbol (1) in the title) represent controller simulation results corresponding to the physical value domain of language variables preliminarily selected based on expert knowledge.

The images in the middle column of Fig. 9(b) (corresponding to symbol (2) in the title) show the controller simulation results corresponding to the physical value domain of the linguistic variables found in generation 30 of the genetic GA.

The images in the right column of Fig. 9(c) (corresponding to symbol (3) in the title) show the controller simulation results corresponding to the physical value domain of the language variables found at the end of the GA.

The above results show that the GA algorithm program allows for finding the appropriate domain of physical values of language variables so that the HA controller operates to ensure accuracy and reliability.



(a) (b) (c)

Fig. 9. The controller simulation results correspond to the physical value domains (a), (b), and (c)

5. CONCLUSION

Calculation and simulation results show that the physical value domain of language variables is found based on the GA algorithm, allowing the HA controller to operate with accuracy and reliability.

Control quality depends on the control law and the physical value domain of the input and output variables. The control law may be stable, but the physical value domain may change due to uncertain dynamic factors. Therefore, applying a genetic algorithm is one possible solution to finding the appropriate physical value domain.

The next focus of research and development is on researching and optimizing the GA algorithm, for example, by learning methods of selection, crossbreeding, and mutation so that new generations gradually give better results and achieve the goal optimally.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

[1] I. Iglesias, M. A. Sebastián, and J. E. Ares. Overview of the state of robotic machining: Current situation and future potential. *Procedia Engineering*, **132**, (2015), pp. 911–917. https://doi.org/10.1016/j.proeng.2015.12.577.

[2] M. Petko, G. Karpiel, K. Gac, G. Góra, K. Kobus, and J. Ochoński. Trajectory tracking controller of the hybrid robot for milling. *Mechatronics*, **37**, (2016), pp. 100–111. https://doi.org/10.1016/j.mechatronics.2016.03.012.

[3] G. Gołda and A. Kampa. Modelling of cutting force and robot load during machining. *Advanced Materials Research*, **1036**, (2014), pp. 715–720. https://doi.org/10.4028/www.scientific.net/amr.1036.715.

[4] COMET, EU. *P7-project: Plug-and-produce COmponents and METhods for adaptive control of industrial robots enabling cost effective, high precision manufacturing in factories of the future*, (2011).

[5] W. Ji and L. Wang. Industrial robotic machining: a review. *The International Journal of Advanced Manufacturing Technology*, **103**, (2019), pp. 1239–1255. https://doi.org/10.1007/s00170-019-03403-z.

[6] A. M. Abdul-Sadah, K. M. H. Raheem, and M. M. S. Altufaili. A fuzzy logic controller for a three links robotic manipulator. In *AIP Conference Proceedings*, AIP Publishing, (2022). https://doi.org/10.1063/5.0066871.

[7] N. V. Toan and P. B. Khoi. Fuzzy-based-admittance controller for safe natural human–robot interaction. *Advanced Robotics*, **33**, (2019), pp. 815–823. https://doi.org/10.1080/01691864.2019.1607551.

[8] P. B. Khoi and N. V. Toan. Application of fuzzy logic for controlling mechanism of relative manipulation robot (MRM robot). *Vietnam Journal of Science and Technology*, **54**, (2016), pp. 386–401. https://doi.org/10.15625/0866-708x/54/3/7333.

[9] P. B. Khoi and H. Nguyen Xuan. Fuzzy logic-based controller for bipedal robot. *Applied Sciences*, **11**, (2021). https://doi.org/10.3390/app112411945.

[10] K. B. Phan, H. T. Ha, and S. V. Hoang. Eliminating the effect of uncertainties of cutting forces by fuzzy controller for robots in milling process. *Applied Sciences*, **10**, (2020). https://doi.org/10.3390/app10051685.

[11] N. V. Toan and P. B. Khoi. A control solution for closed-form mechanisms of relative manipulation based on fuzzy approach. *International Journal of Advanced Robotic Systems*, **16**, (2019). https://doi.org/10.1177/1729881419839810.

[12] C. W. de Silva. Applications of fuzzy logic in the control of robotic manipulators. *Fuzzy Sets and Systems*, **70**, (1995), pp. 223–234. https://doi.org/10.1016/0165-0114(94)00219-w.

[13] P. B. Khoi. Application of fuzzy logic in the robot control for mechanical processing. *Vietnam Journal of Science and Technology*, **61**, (2023), pp. 531–569. https://doi.org/10.15625/2525-2518/18069.

[14] P. B. Khoi and N. V. Toan. Hedge-algebras-based controller for mechanisms of relative manipulation. *International Journal of Precision Engineering and Manufacturing*, **19**, (2018), pp. 377–385. https://doi.org/10.1007/s12541-018-0045-8.

[15] T. Nguyen Van, S.-Y. Yi, and P. Bui Khoi. Hedge algebras-based admittance controller for safe natural human–robot interaction. *Advanced Robotics*, **34**, (2020), pp. 1546–1558. https://doi.org/10.1080/01691864.2020.1852958.

[16] N.-V. Toan, P.-B. Khoi, and S.-Y. Yi. A MLP-Hedge-Algebras admittance controller for physical human–robot interaction. *Applied Sciences*, **11**, (2021). https://doi.org/10.3390/app11125459.

[17] N. V. Toan, M. Do Hoang, P. B. Khoi, and S.-Y. Yi. The human-following strategy for mobile robots in mixed environments. *Robotics and Autonomous Systems*, **160**, (2023). https://doi.org/10.1016/j.robot.2022.104317.

[18] N. Van Toan, P. B. Khoi, and S.-Y. Yi. A single 2-D LiDAR extrinsic calibration for autonomous mobile robots. *IEEE Transactions on Instrumentation and Measurement*, **72**, (2023), pp. 1–9. https://doi.org/10.1109/tim.2023.3325856.

[19] N. D. Anh, H.-L. Bui, N.-L. Vu, and D.-T. Tran. Application of hedge algebra-based fuzzy controller to active control of a structure against earthquake: HA-based fuzzy controller to structural active control. *Structural Control and Health Monitoring*, **20**, (2011), pp. 483–495. https://doi.org/10.1002/stc.508.

[20] D. Vukadinović, M. Bašić, C. H. Nguyen, N. L. Vu, and T. D. Nguyen. Hedge-algebra-based voltage controller for a self-excited induction generator. *Control Engineering Practice*, **30**, (2014), pp. 78–90. https://doi.org/10.1016/j.conengprac.2014.05.006.