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Welding Robot Controlled Using PSO-Fuzzy Technique

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Abstract

This work addressed the use of a robot arm with flexible joints as a welding robot for oil pipeline networks. One of the trickiest processes with strict quality criteria is welding oil pipelines. A highly skilled welder with considerable expertise is typically required. At the moment, robotics technology is sophisticated and is used in many technical applications. Robotics are highly precise workers; They operate with high precision and minimal error during their job implementations. In this paper, a classic PID controller is employed to control the welding robot arm movements since the Proportional-Integral-Derivative (PID) controller requires parameter tuning in the presence of any disturbance. Intelligent controllers are required, and for this purpose, a fuzzy logic controller is presented to improve the welding robot's performance during changing circumstances of operation. To optimize the fuzzy parameters, a particle swarm optimization method (PSO) is proposed to determine the selection of the optimal values of the fuzzy membership's parameters. The simulation results show that the suggested controller has high performance during welding, even in the presence of disturbances.

Keywords: Welding robot, Flexible joint robot, PID controller, Fuzzy logic control, Particle Swarm Optimization (PSO), Oil pipeline networks.

استخدام تقنية PSO-Fuzzy للتحكم بروبوت اللحَام

الخلاصة

يتناول هذا العمل استخدام ذراع روبوتي بمفاصل مرنة كروبوت اللحام لشبكات أنابيب النفط. يُعد لحام أنابيب النفط من أكثر العمليات تعقيدًا ويتطلب معايير جودة صارمة، وغالبًا ما يحتاج إلى لحّام ماهر يمتلك خبرة كبيرة. في الوقت الحاضر، أصبحت تكنولوجيا الروبوتات متقدمة وتُستخدم في العديد من التطبيقات التقنية. وتُعتبر الروبوتات عمالاً عالي الدقة، حيث تعمل بدقة عالية وأخطاء ضئيلة أثناء تنفيذ المهام.

في هذا البحث، تم استخدام متحكم PID التقليدي للتحكم بحركات ذراع روبوت اللحام، نظرًا لأن هذا النوع من المتحكمات يتطلب ضبطًا دقيقًا للمعاملات في حال وجود اي اضطراب. وللتغلب على هذا التحدي، تم تقديم متحكم ذكي يعتمد على المنطق الضبابي لتحسين أداء روبوت اللحام في ظل تغيّر ظروف التشغيل. ومن أجل تحسين معاملات المنطق الضبابي، تم اقتراح استخدام طريقة تحسين سرب الجسيمات (PSO) لتحديد القيم المثلى لمعاملات دوال العضوية الضبابية.

أظهرت نتائج المحاكاة أن المتحكم المقترح يقدم أداءً عاليًا أثناء عملية اللحام، حتى في وجود اضطرابات.

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1. Introduction

The research adopted the motion control of the welding robot arm with flexible joints. A robot is a reprogramming machine used to do human work. There are many types of robots, like robot arms, mobile robots, drive robots, welding robots, etc. A robot arm contains links, joints, and actuators. Link divide to rigid and flexible, and the same for joints; our study here is about rigid link flexible joint robot arm [1]. All robot manipulators include joints, and this calls for modeling and control design to take joint elasticity into account in order to achieve excellent control performance. Joint flexibility is primarily brought on by bearing deformation, shaft windup, and gear elasticity. Lack of joint flexibility prevents controllers from performing dynamically (vibrations, poor tracking, chattering when in touch with the environment) [2]. Figure (1) the flexible joint introduces additional dynamics.

Mechanized programmable tools (robots) are used in welding to completely automate the welding process by handling the part and welding it. For example, gas metal circular segment welding, while frequently computerized, is not truly comparable to robot welding since a human administrator at times readies the materials to be welded. Robot welding is usually utilized for opposition spot welding and bend welding in high-creation applications, like the auto industry [3].

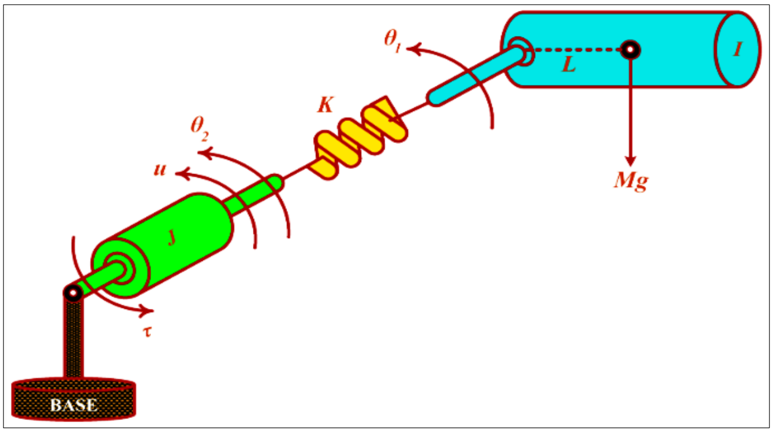

Fig. (1): Flexible joint robot arm

Where;
θ_1: Link position
$\theta 2$: Motor position
L: link length
M: Mass
g: gravity
K: Joint stiffness

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I and J are the inertias of link and actuator respectively
u: displacement of the joint

The welding torch is programmed to move in a certain orientation along the weld path by a robot. Most of the time, the robot is made up of a lot of links and linkages that are linked together with gears, chains, belts, or screws. Linear, pneumatic, or hydraulic actuators, as well as electric motors, are the primary means of control for the industrial robots. AC servo motors are currently used in the majority of high-end robots. These motors have taken the place of hydraulic actuators and, more lately, DC servo motors.

Despite the fact that robots were first introduced into the U.S. industry in the 1960s, robot welding is a comparatively new application of robotics. The use of robots in welding didn't truly take off until the car industry started using them extensively for spot welding in the 1980s. Both the number of industrial robots and their applications have significantly increased since then. Over 120,000 robots were in use in North American industry in 2005, with welding accounting for approximately half of those robots [7]. Figure (2) illustrate the industrial Robot welder.

Fig. (2): Pipeline welding robot

Pipeline welding robots require high precision and adaptability, especially when dealing with flexible joints that introduce vibrations and nonlinearities. Traditional control methods such as PID may struggle under these conditions due to fixed gains and limited adaptability.

To overcome this, several studies have explored intelligent control strategies. For instance, [4] demonstrated effective speed control of multiple PMSM motors using PID-based systems, while [5, 6] applied machine learning and deep reinforcement learning to optimize HVAC&R systems, highlighting the potential of adaptive control in complex environments. The novelty of this work lies not only in combining PSO with fuzzy logic but also in its application to robotic welding

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systems subjected to structural flexibility, which has been rarely addressed in prior literature [8], [12], [15], [16]. Unlike previous applications focused on rigid manipulators, our system explicitly accounts for joint elasticity and vibration damping during trajectory tracking.

2. Method

2.1. Modelling

The dynamic model of the following n-link flexible-joint robot manipulator system is described in [13]:

$$D(q_1)\ddot{q}_1 + C(q_1,\dot{q}_1)\ \dot{q}_1 + G(q_1) + K(q_1 - q_2) = 0 \dots\dots\dots (1)$$

$$J\ddot{q}_2 + B\dot{q}_2 + K(q_2 - q_1) = T \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

eq. (1) is called Link equation, eq. (2) is called Motor (Actuator) equation.

where ***q*1** and ***q*2** respectively represent the vectors of link positions and actuator positions.

***D*(*q*1)** *is* the link inertia matrix(nxn).

$\boldsymbol{C(q_1,\dot{q}_1)\ \dot{q}_1}$ represents the Corioles and centrifugal term(nx1).

***G*(*q*1)** represents the gravitational terms (nx1).

K *is* the diagonal positive-definite matrix (nxn) representing joint stiffness.

J *is* the diagonal positive-definite matrix(nxn) representing actuator inertia.

B (nxn) is the diagonal matrix representing actuator damping.

T *(nx1) is* the vector of actuator input torques.

The single link with flexible joint robot arm will be:

$$I(\ddot{q}_1 + Mgl\,sin(q_1) + K(q_1 - q_2) = 0 \dots\dots\dots\dots\dots\dots\dots\dots\dots (3)$$

$$J\ddot{q}_2 + B\dot{q}_2 + K(q_2 - q_1) = T \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4)$$

Now to build a model it should transform the (3) and (4) equations to state space model, Assuming:

$$q_1 = x_1, \dot{q}_1 = \dot{x}_1 = x_2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (5)$$

$$q_2 = x_3, \dot{q}_2 = \dot{x}_3 = x_4 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (6)$$

The state model will be:

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = \frac{mgl}{I} * sin(x_1) - K/I * (x_1 - x_3) \dots\dots\dots\dots\dots\dots\dots\dots\dots (7)$$

$$\dot{x}_3 = x_4$$

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$$\dot{x}_4 = \frac{1}{J} * (T) - (B * x_4) - K * (x_3 - x_1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

The upper is the state space model of the single link with flexible joint of the welding robot arm for the oil and gas pipeline.

2.2. PID Controller

The tracking predicted time-varying trajectories for rigid robot arms is more difficult for robots with elastic joints than it is for robots that can achieve constant regulation, especially when it comes to tracking fuel pipe gaps for welding. With a control strategy that merely achieves local stability regarding the reference trajectory, linear control design has the key benefit of applying linear and decoupled performance to the trajectory error dynamics. [12]:

$$T1 = K_p * e(t) + K_d * \frac{de(t)}{dt} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Where T1 is the output of the PD controller

While the *Kp* and *Kd* are the proportional and derivative controller gain which should be adjusted to make the robot welding arm for the desired path along the pipeline.

To control a robot arm for welding with flexible joint the control equation will be: -

$$T = \tau_d + K_p(q_d - q) + K_d(\dot{q}_d - \dot{q}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

Where;

$(q_d - q)$ is the error

$(\dot{q}_d - \dot{q})$ is the Diffrentination of error

Figure (3) shows the PD controller scheme for the welding robot arm.

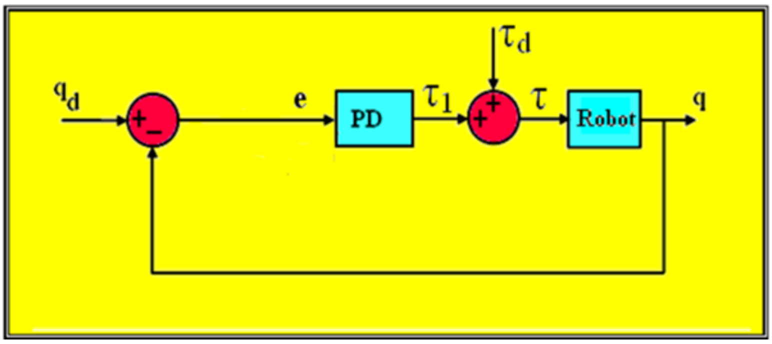

Fig. (3): Block diagram for the PD controller

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2.3. Fuzzy Control System

The theory of fuzzy logic was proposed by Lotifi Zadeh in 1965. The idea was to introduce a degree of membership to a set instead of the usual concept. It is possible to use the theory of fuzzy sets to create expert systems. This type of expert system is called a fuzzy logic system (FLS). [13]. The basic parts of the FLS showed in Figure (4).

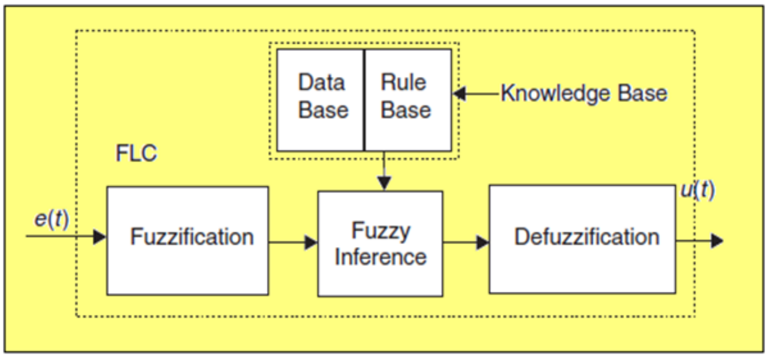

Fig. (4): Fuzzy Logic System

The three basic components of the fuzzy system are:

2.3.1 The Fuzzification process

The process of converting inputs to the FLC's many input universes of discourse into fuzzy set membership values is known as fuzzification. Decisions must be made with reference to:

- Number of inputs.
- Size of universe of discourse.
- Number and shape of fuzzy membership functions.

2.3.2 The Inference

The inference system is then used to perform the actual calculation after the fuzzy sets have been propagated. The input is integrated with the rules base, which contains the expert knowledge, and the inference engine generates an output for each rule in the rules base.

2.3.3 The Defuzzification process

The process of mapping from a collection of inferred fuzzy control signals constrained inside a fuzzy output window to a non-fuzzy (crisp) control signal is known as defuzzification.

The most popular defuzzification method is the center of area method.

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2.3.4 Membership function

There are different types of membership like Gaussian, bell and triangular. Here we will use the triangular shape Figure (5) of membership function for all inputs and output [13] [14].

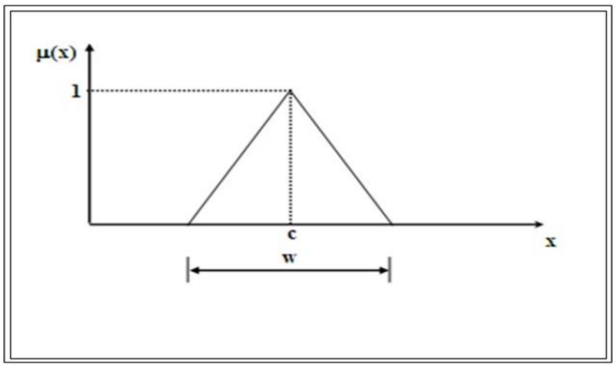

Fig. (5): Triangular membership function

Where;

c: the center of the membership function

w: the width of the membership function

μ: Membership of the function

x: universe of discourse

2.4. Fuzzy Logic Controller

A PID controller is a classical controller. If something in the work environment occurs, the gain or the controller parameters should be adjusted manually; otherwise, the robot will not follow the desired track and the error will be increased. Fuzzy control is suggested to give the system robustness against changing circumstances. A fuzzy controller transfers expert data to rule bases that define the action of the controller [13]. Figure (6) shows the structure of the fuzzy controller for the welding robot.

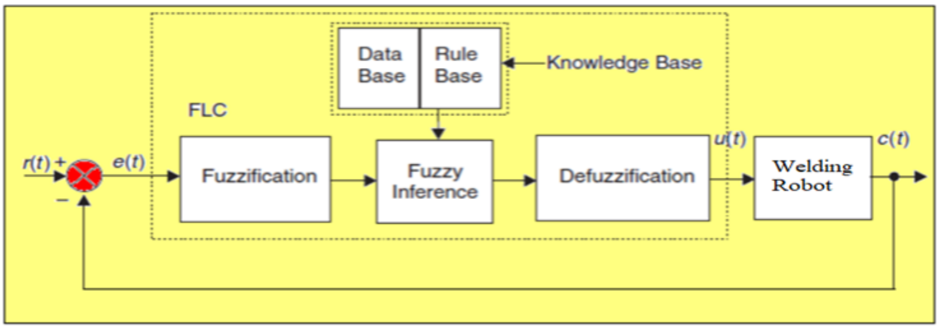

Fig. (6): Fuzzy Logic Controller

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To design a fuzzy controller for a process such as a welding robot with flexible joint it will need to define the following:

1- Number for inputs and outputs.
2- Number of membership function for each input and outputs.
3- The type or the shape of membership function.
4- The choice of universe of discourse.
5- Method of defuzzification.
6- Number of rules.

Figure (7) clearly the fuzzy controller with error and differentiate of error.

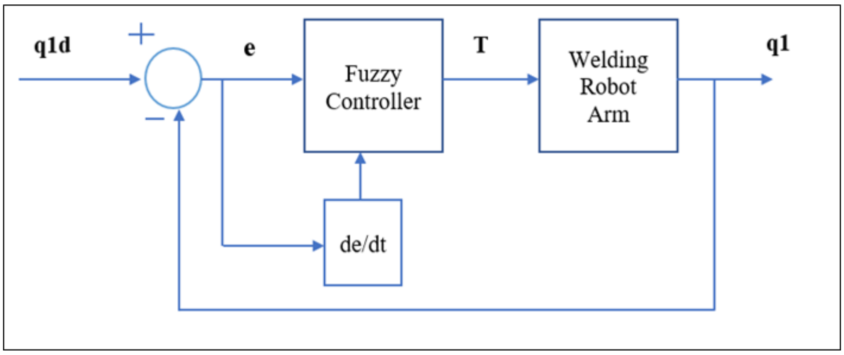

Fig. (7): Fuzzy Controller for welding robot

This design follows established principles in intelligent control systems [5], where fuzzy logic provides robustness against uncertainty and nonlinearity. The rule base is optimized through simulation and expert knowledge.

Due to its lack of adaptability due to its lack of ideal parameters, the PID controller will not be able to operate the system if there is a change in the system's operating conditions. [14]. A fuzzy controller is a robust controller, but to improve the controller's performance and minimize error as much as possible, it is necessary to modify the fuzzy membership functions' parameters. This can be done by using a suitable optimization method, such as optimizing the controller parameters, to find the best performance even in changing work environment circumstances. One intelligent technique must be employed to optimize the controller parameters by obtaining the ideal values in order to explain this problem. The following strategies can be utilized to address the mentioned issue [14]:

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- Genetic algorithm optimization (GA)
- Particle swarm optimization (PSO)
- Neural Networks (NN)
- Ant colony (ACO)

The Particle Swarm Optimization (PSO) approach is suggested in this work to optimize the membership function parameters of fuzzy controller inputs and outputs because of the ability of working perfectly at this kind of applications.

2.5. Partical Swarm Optimization (PSO)

In order to find these optimal values of the fuzzy membership function (MF) parameters across the enormous search space, it should be utilized an optimization approach. The ideal values can be obtained in a wide range of values. The PSO is one of many techniques that can be used to determine the ideal MF coefficient.

James Kennedy and Russell C. Eberhart first introduced the PSO approach in 1995, drawing motivation from the social behavior of flocks of birds and schools of fish [11,12].

Using PSO has a number of benefits, including:

- Easy to understand and achievable.
- Parallel calculation.
- Considers a faster way than any other methods.
- Reaching Convergence very fast.
- Simple to adjust the parameters.
- Effective for complex systems.

The fact that information may be distributed across particles is this procedure's main advantage and what sets it apart from other methods. By updating their position and velocity, the particles can select the best route or solution, thanks to this sharing. The PSO-based method is straightforward to calculate and only requires a few parameter adjustments. This algorithm has been proven to be more effective than others like neural networks or genetic algorithms [15][16]. Figure (8) illustrates the principle of sharing information between PSO particles like the information's sharing between a swarm of birds to find the best (optimal) direction to reach their goal .

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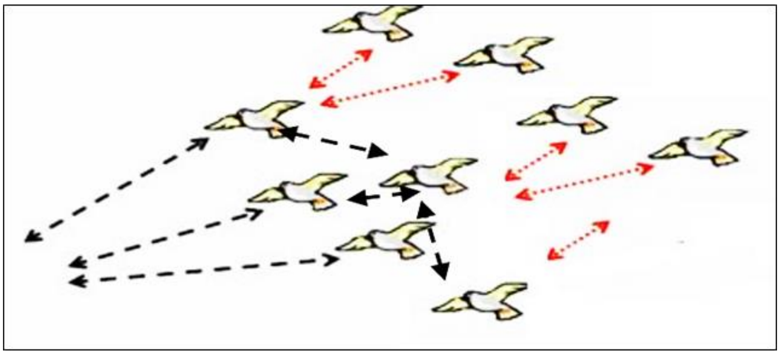

Fig. (8): Sharing information in the PSO

Additional major PSO properties provide the advantage of coping with many local minima in the search space, as shown in Figure (9). These properties can be effective for continuous, discrete, or mixed systems.

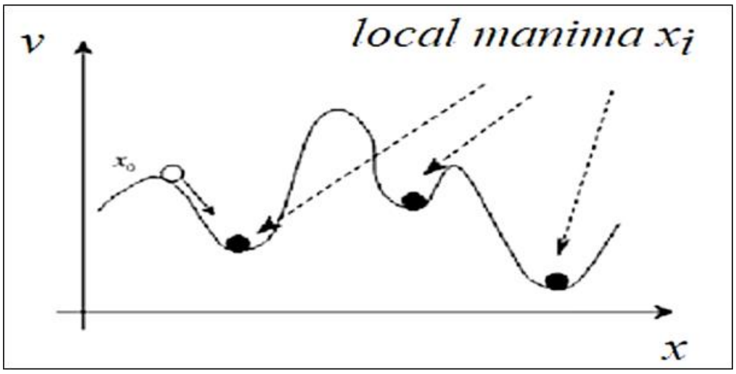

Fig. (9): Multiple local minima

The particle swarm optimization strategy is similar to other optimization strategies in that the system should be started with a population of random solutions. The key difference between this algorithm and the others, though, is that each particle (potential solution) is assigned a randomized velocity before being launched into hyperspace. According to the best possible solution that can be calculated, each prospective solution advances along its hyperspace coordinates. The fitness value is a shorter version of this number. As P_{best}[17].

The global best value, or g_best, is another value that ought to be kept on the particle's reserved track. It represents the predicted population's overall best value. Each particle's associated velocity needs to be adjusted to its P_best and g_best at every iteration. The following updating equations should be used at each step time to update each particle's velocity and position. (11,12):

$$v_i(t+1) = w * v_i(t) + c_1 * r_1(t) * \left(P_{best}^i - p_i(t)\right) + c_2 * r_2(t) * \left(g_{best} - p_i(t)\right) \quad ..(11)$$

$$p_i(t+1) = p_i(t) + v_i(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

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Where;

v_i: velocity of particle i,

p_i: current position,

w: inertia weight (linearly decreasing from 0.4 to 0.9),

$c1$, $c2$: acceleration coefficients (set to 2.0),

$r1$, $r2$: random values in [0,1],

$p$best,i : best solution found by particle i ,

$g$best: best solution found by swarm.

2.6. PSO-Fuzzy Controller

The PSO algorithm is only used to adjust the input and output membership function values in this work; the membership function parameters, which are constrained by the range of discourse, are moved right and left until the ideal location with the smallest possible error is found, as shown in Figure (10). First, the maximum number of iterations (T), the PSO procedure's parameters—the social, cognitive, and momentum constants—as well as the output membership functions—which represent the primary swarm particles—are initiated at random. Second, the global best value, g_best, is determined by calculating the best answer for each particle, P_best. The output membership functions' designated values then indicate the best values; if not, equations (5) and (6) are used to update the values of the swarm particles (output membership function) [18][19]. The new control signal of the fuzzy controller is then calculated using the revised output membership functions. The maximum number of iterations is reached or the minimal cost function is computed (The ideal output membership function values are found). Figure (11 a, b) depicts the flow conversation for updating the fuzzy controller's parameters using the PSO algorithm and the fuzzy controller that has been optimized using PSO, PSO parameters shown in Table (1) [20].

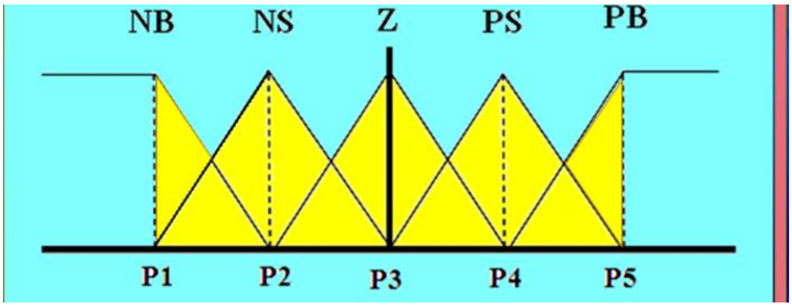

Fig. (10): Fuzzy membership parameters

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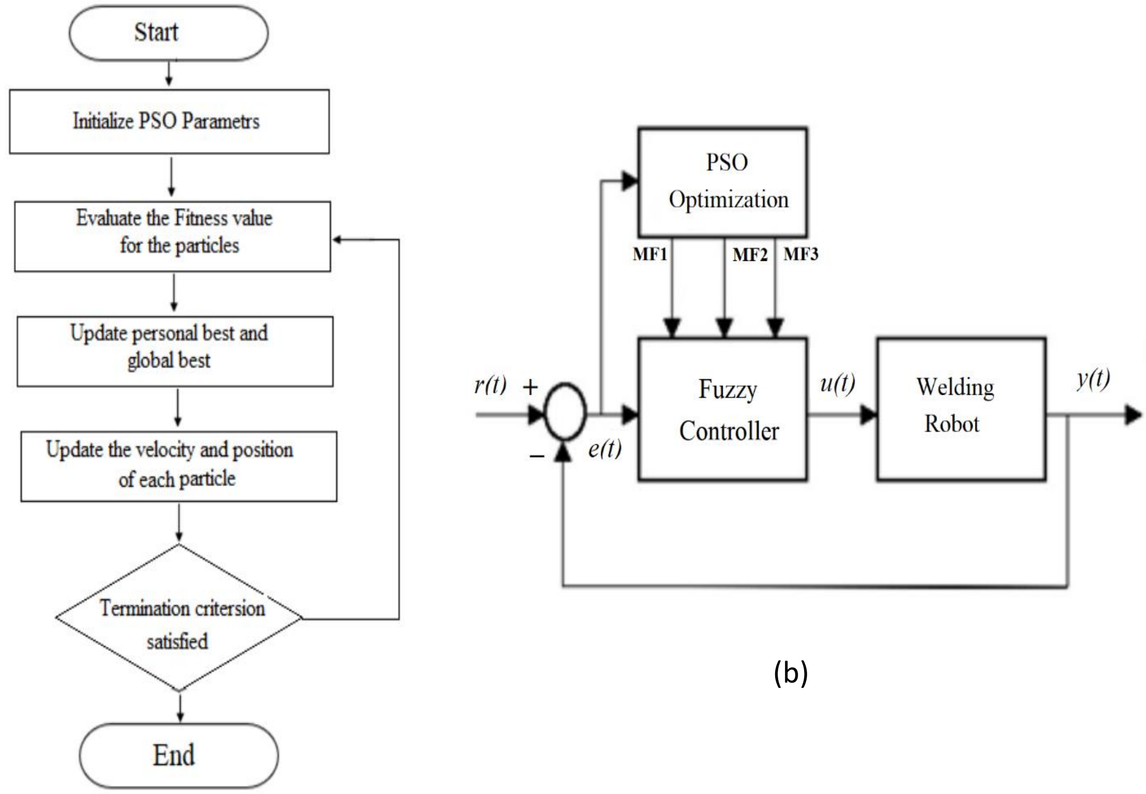

(b)

(a)

Fig. (11): PSO flow chart (a) and PSO -fuzzy controller (b)

Table (1): PSO parameters

Parameters	**value**
Population size	30
Maximum iterations	100
Inertia weight	1
C1	2
C2	1.5
Search space limit	[0.1 10]
Cost function	IAE

3. Simulation Results and Discussion

3.1. PID controller

In this scenario PID controller will be used to control the welding robot arm, the desired input will be a sinewave, the welding robot will try to track the input for pipe welding. The mean square

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error (MSE) will be defining the controller performance for all suggested controllers. Figure (12) shows the desired input and the actual output of the welding robot using PID controller.

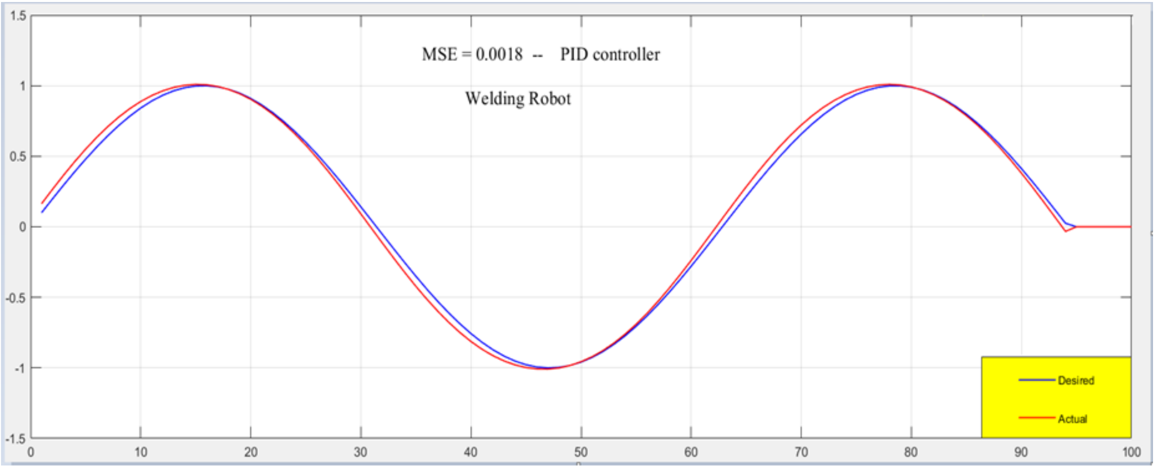

Fig. (12): Welding robot using PID controller

Now to show the PID controller performance against any disturbance it will increase the link weight of the robot arm by 30% to show the robustness of the controller Figure (13).

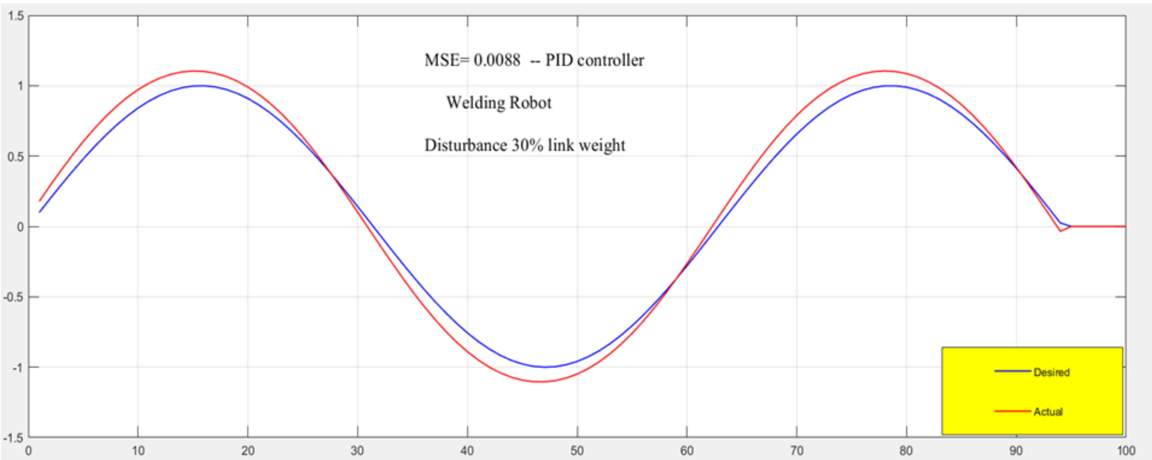

Fig. (13): Welding robot using PID controller with disturbance

3.2. Fuzzy Controller

In this scenario the suggested controller will be the fuzzy controller, the inputs of the controller will be the error and the derivative of the error while the output will be torque of the welding robot arm, the MF will be the triangular function and the number of the membership function will be five for each the inputs and the output, the defuzzification method will be centroid Figure (14).

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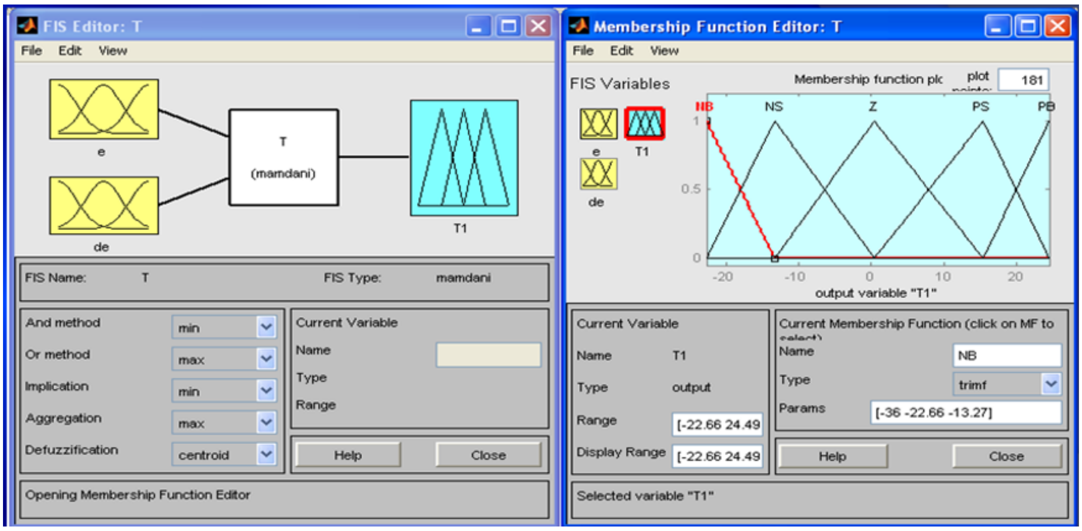

Fig. (14): Fuzzy Controller with membership function

Figure (15) shows the fuzzy controller attached to the welding robot simulation output with mean square error.

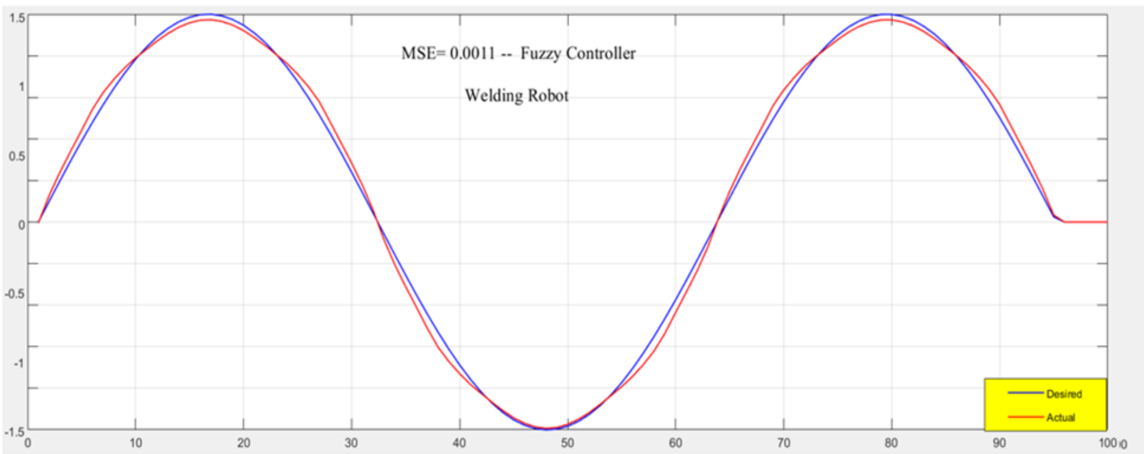

Fig. (15): Welding robot using Fuzzy controller

It is clearly shown that the error decreases by using fuzzy controller, now to show the robustness of the fuzzy controller performance against the disturbance it will increase the link weight of the robot arm by 30%, Figure (16).

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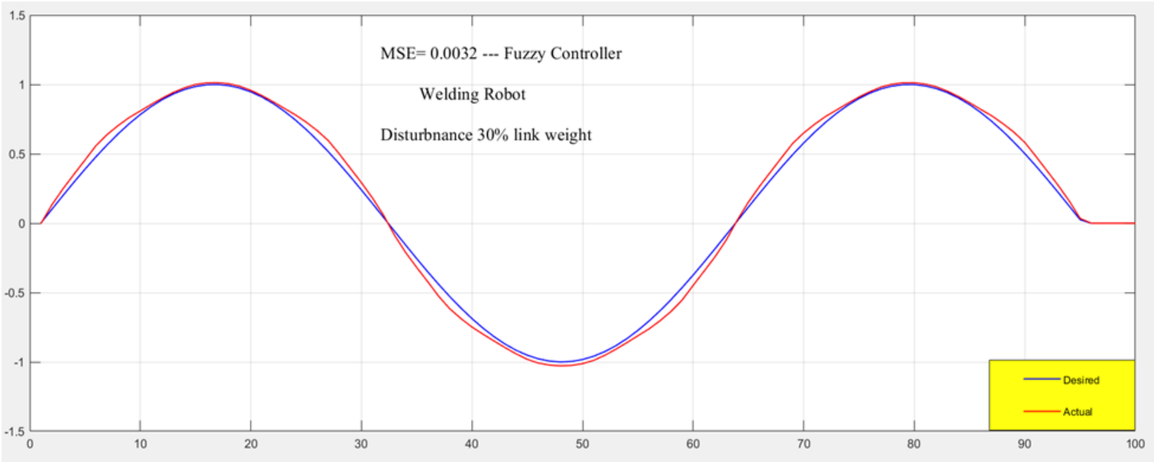

Fig. (16): Welding robot using Fuzzy controller with disturbance

3.3. PSO-Fuzzy Controller

In this scenario PSO applied on the MF parameters of the fuzzy controller's inputs and output to determine the best position for the triangular MF parameters. The PSO parameters are chosen carefully to give the best performance of the optimization process as below in Table (1):

Figure (17) shows the PSO-Fuzzy controller for the welding robot simulation with mean square error.

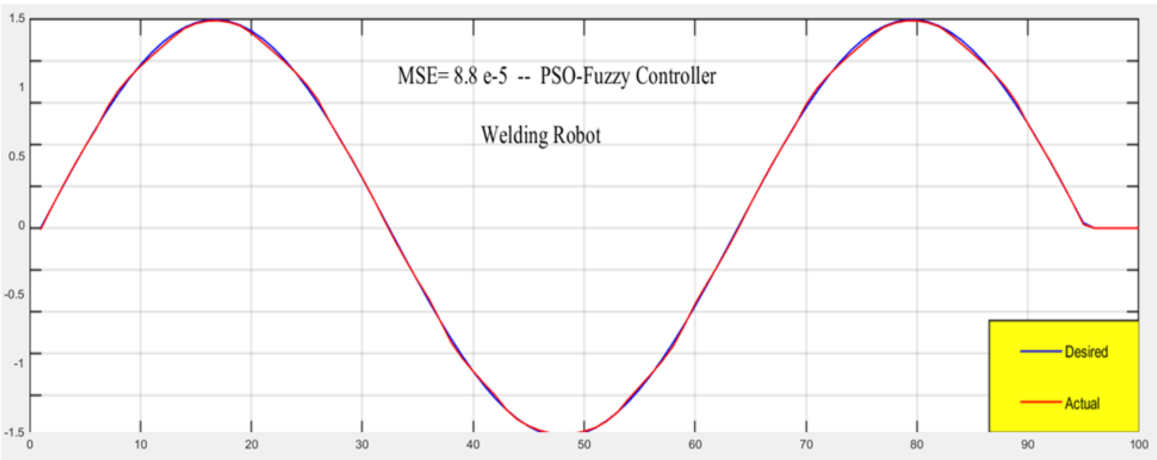

Fig. (17): Welding robot using PSO- Fuzzy controller

As shown in Figure (17) the result clearly shown that the error decreases and not easy to recognize the desired input from the actual output they The curves are nearly superimposed, now to show the PSO- Fuzzy controller performance against the disturbance it will increase the link weight of the robot arm by 30% to show the robustness of the PSO- Fuzzy Controller, Figure (18).

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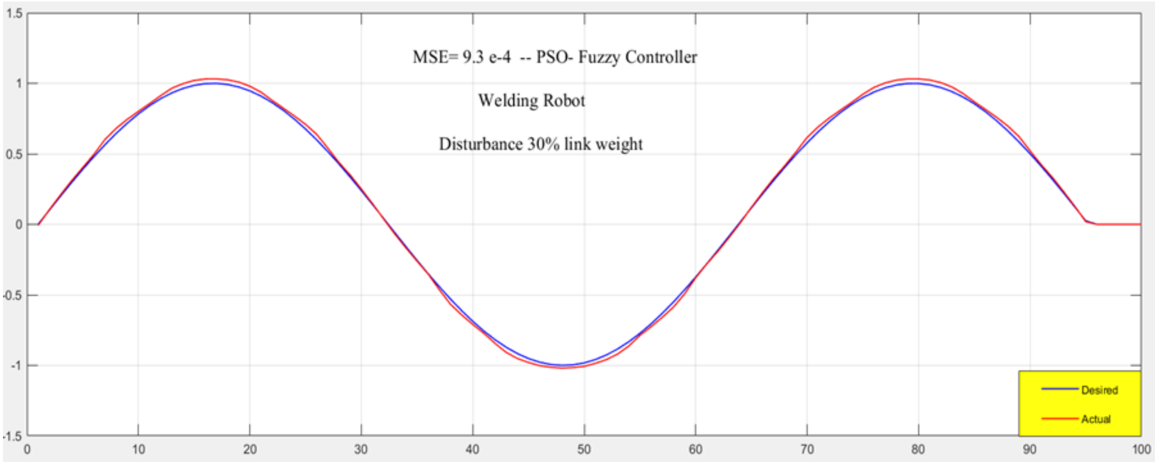

Fig. (18): Welding robot using PSO- Fuzzy controller with disturbance

Table (2) shows the Comparison of Controller Performance before and after disturbance.

Table (2): Controller's performance comparison

Controller	MSE Before Disturbance	MSE After Disturbance	IAE	Settling time(s)	Rise time (s)	Overshoot%
PID	0.0018	0.0088	2.15	2.3	0.9	18.5
Fuzzy	0.0011	0.0032	1.73	1.8	0.7	12.5
PSO-Fuzzy	8.8 e^{-5}	9.3e^{-4}	0.95	0.95	0.4	5.7

4. Conclusions

A welding robot is very important to use for pipelines, especially in the oil industry. It should be very accurate and well controlled. A PID controller was used, and it was good to track a desired welding line, but unfortunately, it has poor performance against disturbance. A fuzzy controller was used to increase the robustness of the welding robot arm, and it was better than a PID until disturbances happened by increasing the link weight of the robot by 30%. "Although the fuzzy controller outperformed PID, it still exhibited reduced performance under disturbance when used separately without an optimization process. The PSO-Fuzzy controller, on the other hand, showed perfect performance even in the presence of disturbance. The welding robot stayed on the line of welding. The simulation results, with no doubt, showed that the PSO-Fuzzy has the best performance and proved that using the intelligent controller will be useful for controlling in the oil industry with minimizing error and with the most desirable tracking of the path. It can also be used in flow, temperature, and pressure control, which are found in many other processes in the oil and gas industry.

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