Control of an Exoskeleton for Lower Limb Rehabilitation Using ANFIS

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Abstract—Exoskeletons are powered robotic devices designed to be worn by humans to provide physical assistance or power augmentation. In this work, a control system for a powered exoskeleton is designed. This exoskeleton is aimed at aiding in the rehabilitation of Spinal Bifidas. Spinal Bifida is the most common disability in childhood after Cerebral Palsy, it is a defective development of the spinal cord during conception. Two phases for this work are presented: system identification and control using ANFIS. While it is difficult to attain an accurate dynamical model of complex system, this work employed ANFIS to help control and stabilize the system. Gait trajectories were obtained by modeling the system as a linear inverted pendulum, a simulation was performed with a traditional controller. Afterwards, trajectory data was obtained and used to train and test ANFIS to create the model and controller. One, two and three inputs were investigated to train the ANFIS. Results showed that the one-input model visibly failed to follow the trajectory. The average RMSE for the two-input model was 0.096, and for the three-inputs, the RMSE on average was higher; 0.19, making it worse, however the knee model contrastingly showed improvement, as the RMSE was lower by 2% for the knee specifically.

Keywords—exoskeleton, ANFIS, LIPM, PyBullet, rehabilitation

1 Introduction

The ability to walk is impaired in many individuals due to numerous motion disorders, among them are cerebral palsy, muscular atrophy, strokes and spinal bifidas, as well as spinal cord injuries (SCI) caused by traumatic injuries or complications from illnesses [1]. Patients suffering from these issues often lose mobility and functionality in their daily lives. The most common mobility aid on the market currently is the wheelchair. The wheelchair allows for a level of mobility, however, it cannot cross difficult and uneven terrains and it forces the user to be sat all the time. Sitting for long periods of time can cause physiological complications such as the degeneration of muscle and bone tissue, decrease in joint mobility, pressure related issues and urinary tract complications. As well as negatively impact the mental health and quality of life of patients [2].

Improving the symptoms of their condition will improve chronic pain and the mobility of the patient. Consequently, the user can feel more assured and get back hope in a functional life. Exoskeletons can offer an ingenious solution to this challenge. Exoskeletons are powered robotic devices designed to be worn by humans to provide physical assistance or power augmentation. They work in harmony and parallel with their users providing torque or force at the necessary limb joints.

One of the first successful powered exoskeletons is the Berkeley Lower Extremity Exoskeleton (BLEEX), BLEEX is a 7 DOF lower body exoskeleton for power augmentation. It was developed by the Berkeley Robotics and Human Engineering Laboratory. BLEEX established a standard for subsequently developed robots. Its design is anthropomorphic and allows heavy loads to be carried over rough, unstructured, and uncertain terrains [3]. The configuration of the current lower limb exoskeletons, such as ALEX, Lokomat, LOPES, and HAL, is mainly based on BLEEX [4]. Nevertheless there is vast variation in the methodology used to control the exoskeleton. In HAL, the human joint torque is estimated based on EMG signals and used to generate virtual torque for the motors [5]. In the H2 exoskeleton, a position controller guides the patient's limb to a fixed reference path, while receiving the joint angles as feedback. For lower limbs, the reference trajectory is a normal gait pattern previously recorded from a healthy subject [6]. While in the ALEX exoskeleton, tangential and normal forces are applied at the ankle of the subject based on the deviation of the actual path from the desired path [7]. In Lokomat impedance control is used. Torque is supplied by the robot based on the deviation between the actual and desired angular trajectories using a PD controller [8]. Thresholds of maximum allowed deviations are determined around the reference angular trajectory. eLEGS applies position control via Finite state machine control [9].

More recently, the use of intelligent control in exoskeletons have seen a surge of popularity as mobile robotics in general begun to implement intelligent control methods in their design. A robust neural adaptive integral sliding mode control approach was proposed to solve the issue of control for nonlinear upper exoskeleton systems. The control laws were developed to estimate unknown parameters and ensure asymptotic stability of the closed-loop system [10]. In another study, a core control system was developed based on a simplified dynamic model of a double pendulum and classical control methods. Then, its outputs were used to train an artificial neural network controller using a reinforcement learning algorithm. This strategy can be implemented on an exoskeleton to restore stable walking in individuals with paralysis caused by SCI [11]. Moreover, a convolutional neural network was used to aid a mobile robotic arm in the process of object detection and classification [12]. Other researchers in the field designed an adaptive fuzzy controller to control a robotic arm based on oscillator and differentiator. It realized trajectory tracking control for the robotic arm with high accuracy [13]. Lastly, Fuzzy control has also been applied to the control of swarm robotics. Two types of fuzzy controllers were tested and compared against each other based on the accuracy of path navigation [14].

Another approach to control of exoskeletons is the use of ANFIS as a system identifier [15]. ANFIS is a kind of artificial neural network that is based on the Takagi–Sugeno fuzzy inference system [16]. It integrates both neural networks and fuzzy logic principles. Table 1 summarizes the different ANFIS layers. Researchers used ANFIS to identify a nonlinear pneumatic artificial muscle (PAM) system [17]. Others utilized

ANFIS to determine the dynamic model of a robotic system between the inputs and outputs off-line. Then they employed another ANFIS to provide an online control for steady locomotion. This paper found the ANFIS models and controller satisfactory, they were able to reduce the error recorded to 0.0683 in 100 training epochs [18].

Table 1. Summary of ANFIS layers [16]

Layer	Description	Output Representation
1	Fuzzification Layer, it takes the input values and determines the membership functions belonging to them.	$o_i^1 = \mu_{trap}(x,a,b,c,d) = \max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right)$
2	Rule Layer, every node's output is the product of all the incoming signals from layer 1. The output of each layer 2 node is referred to as firing strength.	$o_i^2 = \bar{w} = \frac{w_i}{w_1 + w_2 + w_3}$
3	Normalization Layer, it normalizes the firing strengths.	$o_i^3 = \bar{w} = \frac{w_i}{w_1 + w_2 + w_3}$
4	Defuzzification Layer, it takes the fuzzy logic and returns it into crisp (Boolean) logic.	$o_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i)$
5	Output Layer, A single node calculates the overall outputs as the summation of all the incoming signals from the previous layer nodes.	$o_i^5 = \sum_i \bar{w}_i f_i = \frac{\sum_i \bar{w}_i f_i}{\sum_i w_i}$

In this work, ANFIS was used to identify the system of the exoskeleton. Exoskeletons generally have complex and nonlinear systems that are challenging to control. Using ANFIS as a system identifier can help in the process of controlling it. Although the exoskeleton has 12 DOF, only 10 joints were actuated. Each actuated joint was individually controlled via feedback position control. Position control ensures the joints follow the desired angle trajectory. To study the performance of the predictive ANFIS model, both PID and ANFIS controllers were tested and compared. Finally, a hybrid optimization method was used to train ANFIS. It identifies the training parameters and minimizes the error between the actual and the desired output. The hybrid optimization method uses a hybrid gradient descent algorithm and least squares algorithm [19].

2 Physical simulation of the exoskeleton

As ANFIS requires a lot of data for training, a physical simulation was performed using a traditional controller. The simulation was performed using PyBullet, a Python module for physics simulation designed for robotics, visual effects, and machine learning [20]. It is based on the Bullet physics engine and has built-in sensors that the controller and model signals were gathered from. First, a CAD model was designed and a URDF file [21] was created for the exoskeleton. A URDF file contains a kinematic and dynamic description of a robot, a visual representation of it, and a collision model so the simulation environment can understand it.

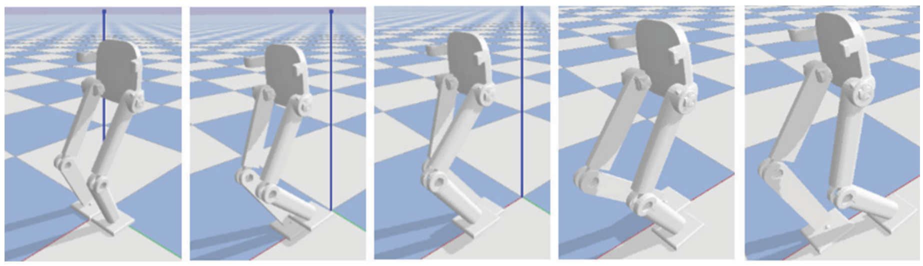
Next, a walking trajectory was created by a method novelized by Kajitia to generate a path for the exoskeleton [22]. This method simplifies the process of walking by modelling the human body as a 3D inverted pendulum whose motion is constrained to move along an arbitrarily defined plane. The equations of motion for a 3D inverted pendulum are given by [22]:

$$m(-z\ddot{y}+y\ddot{z}) = \tau_x - mgy \tag{1}$$

$$m(-x\ddot{z}+z\ddot{x}) = \tau_y - mgx \tag{2}$$

Where m is the mass of the pendulum, g is gravity acceleration, and τ_x, τ_y are the actuation torques. In the single support phase in gait, one leg is on the ground while the other is swinging in the air. The supporting leg is considered as an inverted pendulum where the base is the foot, and the concentrated mass is the torso. When one step is done, the pendulum switches to the other leg. As a result, the path of walking is symmetric around the sagittal plane. After obtaining the foot trajectory, an inverse kinematics analysis was carried out by treating the 12 DOF exoskeleton as a bipedal robot and thus obtaining the joint angles trajectories using a method presented by Ali [23].

Lastly, a simulation of the angle trajectory was performed three times using a PD controller. It was sufficient for trajectory following, but it had a lot of vibrations, and in some instances it would become unstable. During the simulation, sensors were used to collect data. The three sets of data collected were used for training, testing, and checking the ANFIS. In each simulation, the data of six steps were collected. The input and output signals of the controller and their derivatives, the input and output signals of the exoskeleton, and their derivatives were collected as well. Screenshots of the running simulation are shown in Figure 1.



a) **b)** **c)** **d)** **e)**

Fig. 1. Simulation screenshots of the exoskeleton showing different stances, a) starting position (double support), b) left foot midstance (single support), c) end of one step (double support), d) right foot midstance (single support), e) end of two steps (double support)

3 System identification and control of the exoskeleton

Using the data generated and filtered from the previous section, an ANFIS model and ANFIS controller were trained using the Fuzzy logic designer app in MATLAB. After trial and error, it was found that the trapezoidal membership function shown in Figure 2 was the best fit for the system. As for the number of membership functions, three MFs were found to be optimal for most of the joints. Finally, the training was found optimal with an epoch number of two after which the error was not found to change significantly.

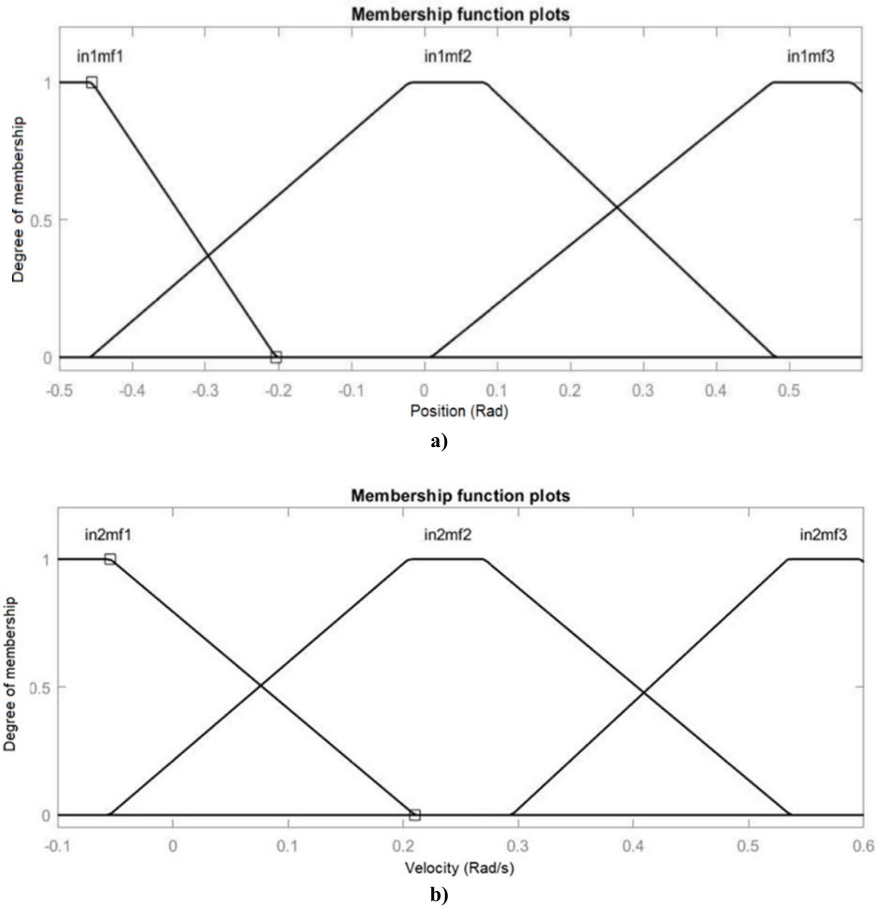


Fig. 2. Membership function plots showing trapezoidal function used in training the ANFIS models. a) First input function. b) Second input function

One, two, and three input models were examined, namely the joint angles, angular velocity, and angular acceleration of the exoskeleton model. As for training the controller, the error, first derivative and second derivative were used. Multiple inputs were used to study the effect of increasing the number of inputs on the training performance. The surface function for the two input model provides a relation between the two inputs and the output of the system and is shown in Figure 3. Finally, the model file was imported to Simulink to check its performance against various input signal.

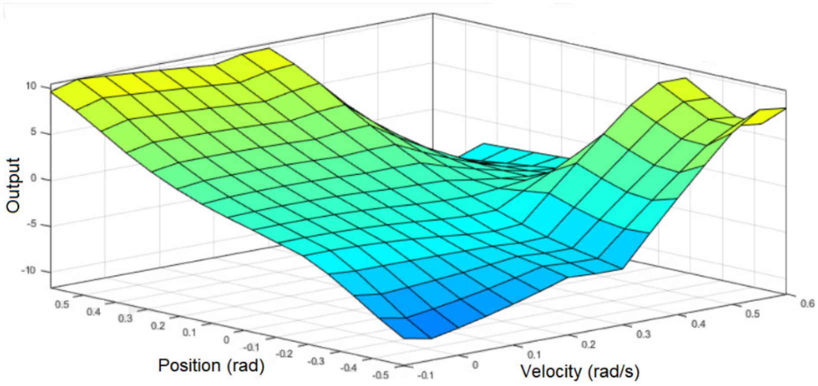


Fig. 3. Surface function of two inputs ANFIS model

Simulink was used to simulate ANFIS models and controllers. A PID controller was tuned with the MATLAB tuning app for comparison. Each angle had an ANFIS model as ANFIS permits only one output. Figure 4(a) and (b) show the feedback control loop for a PID and ANFIS controllers, respectively, with an ANFIS model.

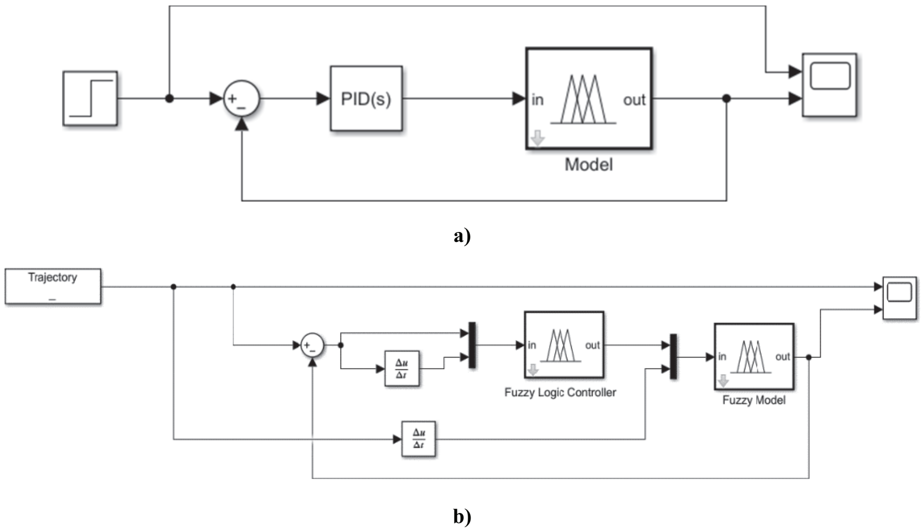


Fig. 4. Control loops in Simulink for the ANFIS model on different controllers and inputs. a) One input ANFIS model implemented on a PID controller for a step input reference. b) Two input ANFIS model implemented on a two input ANFIS controller using the walking trajectory input reference

4 Results and discussion

This section showcases the results obtained from simulating the ANFIS models and controllers against the trajectory of each joint and compared with a PID controller. A step input was also tested versus the ANFIS controller for verification of the model.

4.1 One input model

The model was trained using a single input, namely, the control law. The actual position was the output. Table 2 shows the properties for the hip, knee, and ankle left pitch joints. Since the pitch joints are the main joints responsible for motion, showing results only for them was suitable to highlight the performance of a single input model. The model was tested on a step input using both PID and ANIFS controllers, and the joint trajectory input using an ANFIS controller.

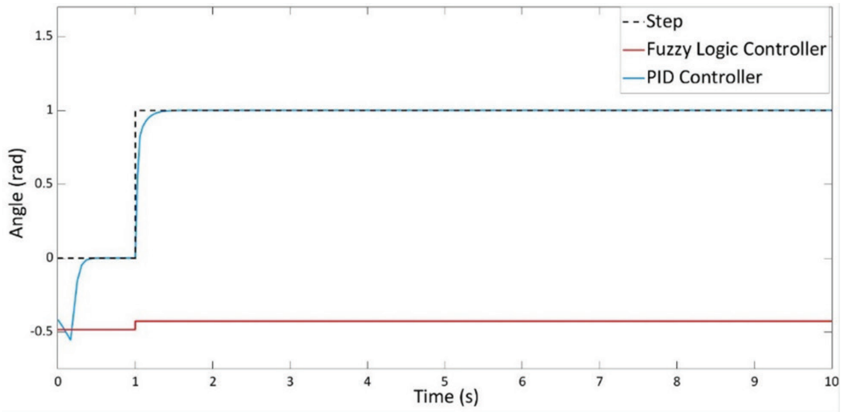
Table 2. Model parameters and RMSE for a single input

Model	MFs	Training Error	Checking Error	Type	Epochs
LHP	3	0.081	0.083	Trap	2
LKP	3	0.104	0.102	Trap	2
LAP	3	0.181	0.174	Trap	2

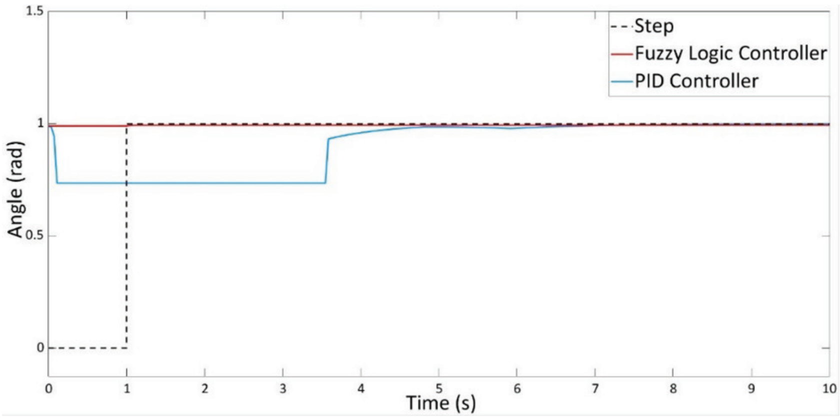
Figure 5 shows the ANFIS and PID outputs against the reference signal. As can be seen in Figure 5(a), a very high steady state error was noticed for the hip pitch joint. As for the knee joint, a high settling time was noticed as seen in Figure 5(b). Finally, the ankle joint demonstrated strange behavior as well as large steady state error, see Figure 5(c). Figure 6 illustrates the performance using an ANFIS controller. Thus, a single input model is clearly unsatisfactory to identify a nonlinear system as the exoskeleton. A second input was added for further investigation.

4.2 Two inputs model

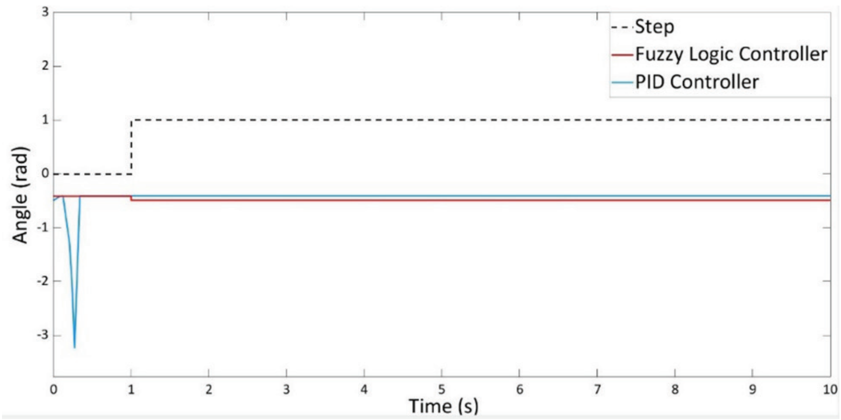
This section studies the two-input trained model using the position and the velocity as inputs. Table 3 shows the training specification for the hip, knee, and ankle pitch joints models. The models were adequately trained with two epochs. Figure 7 shows the ANFIS and PID outputs against the reference value, using a step input. Moreover, Figures 8 and 9 show the PID and ANIFS performances against the trajectory obtained in the previous chapters, respectively.



A) Hip pitch

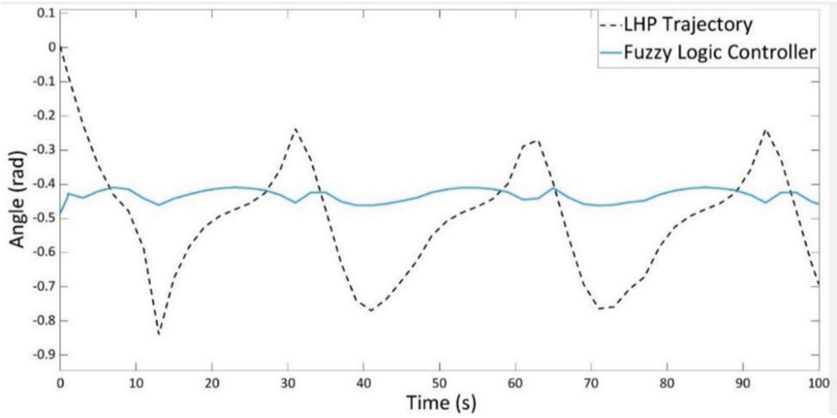


B) Knee pitch

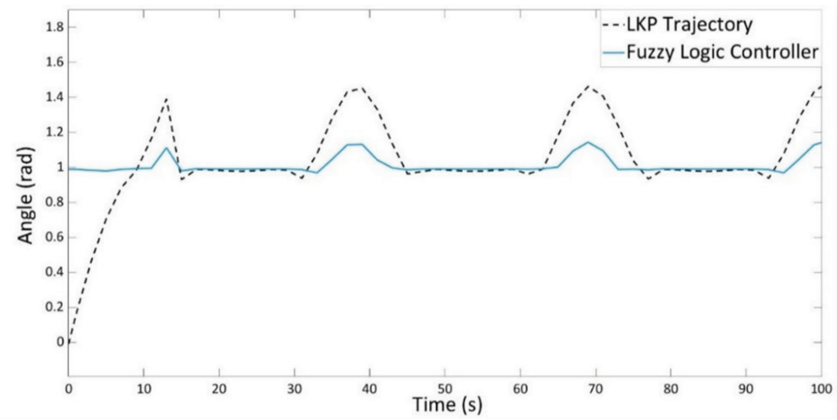


C) Ankle pitch

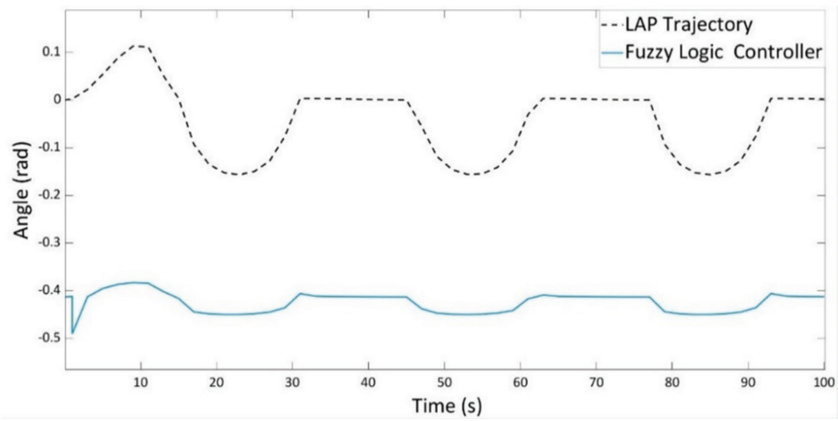
Fig. 5. Single input system response using PID and ANFIS controllers for a step input on Simulink. Step input (dotted line), ANFIS controller (red line), PID controller (blue line). A) Left leg hip pitch joint. B) Left leg knee pitch joint. C) Left leg ankle pitch joint



A) Hip pitch



B) Knee pitch



C) Ankle pitch

Fig. 6. Single input system response using ANFIS controller for a joint trajectory input on the ANFIS model on Simulink. Reference trajectory (dotted line), ANFIS controller (Blue line). A) Left leg hip pitch joint. B) Left leg knee pitch joint. C) Left leg ankle pitch joint

Table 3. Model parameters and RMSE for two inputs

Model	MFs	Training Error	Checking Error	Type	Epochs
LHP	3	0.073	0.075	Trap	2
LKP	3	0.110	0.126	Trap	2
LAP	3	0.079	0.087	Trap	2

The two inputs models performed exceptionally better than the single input models as expected. Figure 7 shows the performance of the PID and ANFIS controllers against a step input for the hip, knee, and ankle left pitch joints. It was noticed that the settling time and the steady state error were reduced greatly with respect to the single input models, except for the ANFIS controller for the ankle joints which showed a weak response due to the complexity of the ankle. Analyzing Figures 8 and 9, it can be seen that the PID controller performs better in following the reference signal. However, dealing with a human-machine interaction, the spikes seen in the PID response can cause great harm to the human body. As a result, the ANFIS controller shows a more promising results for its intended purpose as it is quite smoother.

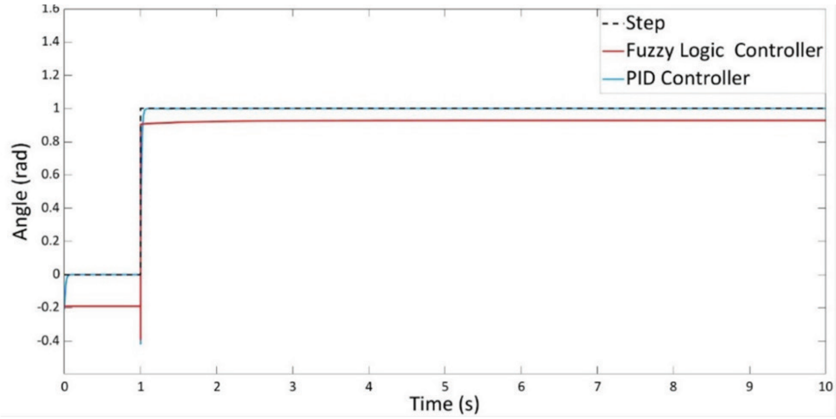
4.3 Three inputs models

This section presents the result of three-inputs trained models. The inputs consist of the position, velocity, and acceleration. Table 4 shows the properties of the trained models for the left leg joints. However, the best number of MFs was not fixed for all the joints as per the table. Figure 10 below shows the PID controller against the ANFIS controller tested for a step input. The performance of an ANFIS controller tested on the hip, knee and ankle pitch joints trajectories is shown in Figure 11.

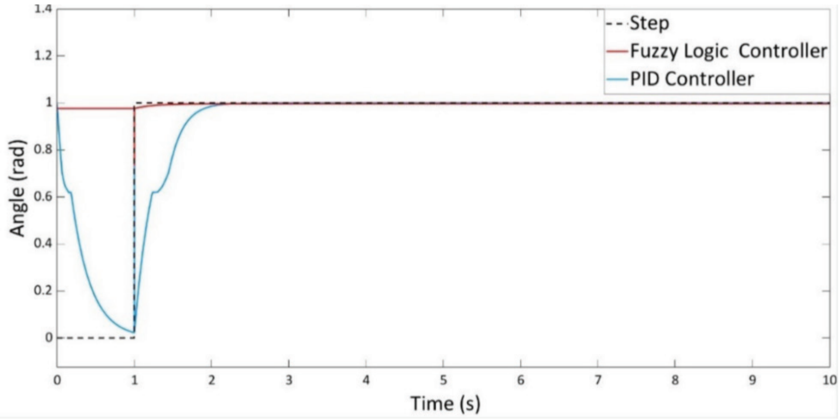
Table 4. Model parameters and RMSE for three inputs

Model	MFs	Training Error	Checking Error	Type	Epochs
LHP	2	0.066	0.370	Trap	2
LKP	3	0.107	0.124	Trap	2
LAP	4	0.068	0.077	Trap	2

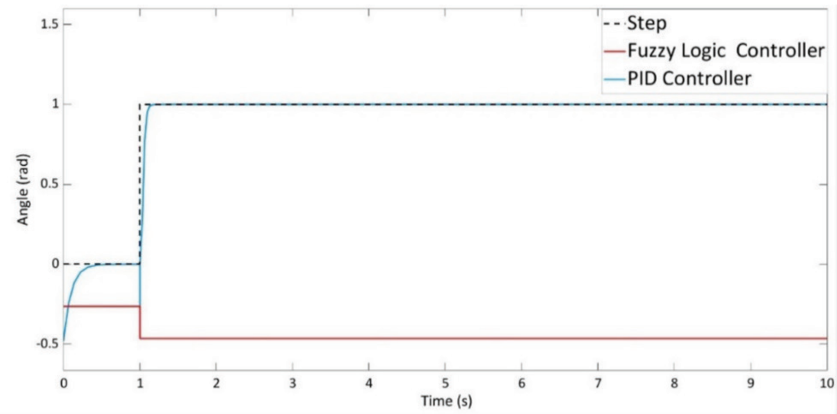
The PID controller with a step input was noticed to perform relatively similar to its performance with two inputs models except for the ankle joint. While for ANFIS controllers, the response for the hip and ankle joints were found to perform worse than their respective joints for two inputs models. As for the knee joint, it achieved moderately better results than the two inputs model. However, a reasonable steady state error was still noticed.



A) Hip pitch

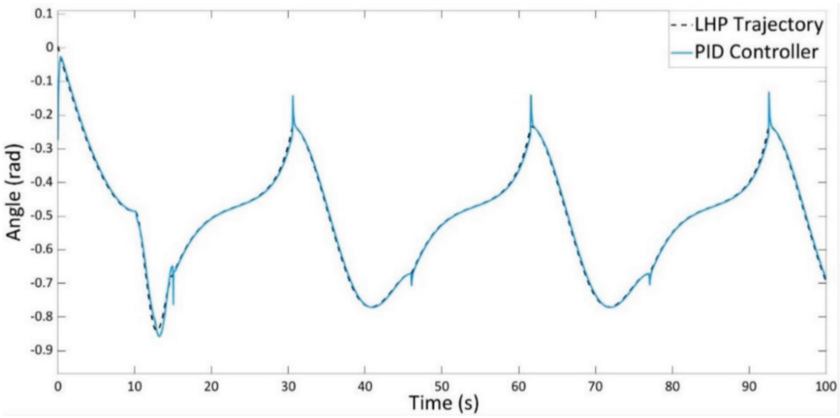


B) Knee pitch

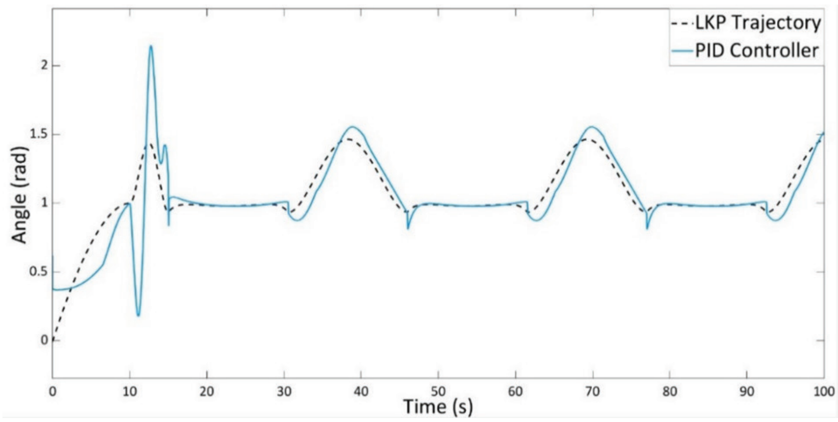


C) Ankle pitch

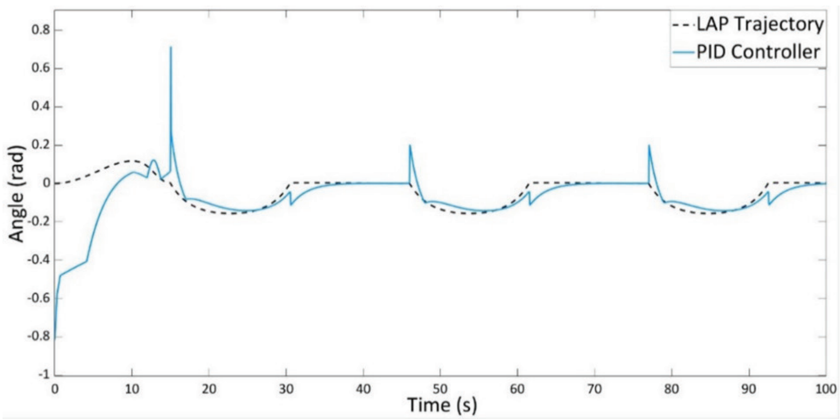
Fig. 7. Two input system response using PID and ANFIS controllers for a step input on Simulink. Step input (dotted line), ANFIS controller (red line), PID controller (blue line). A) Left leg hip pitch joint. B) Left leg knee pitch joint. C) Left leg ankle pitch joint



A) Hip pitch

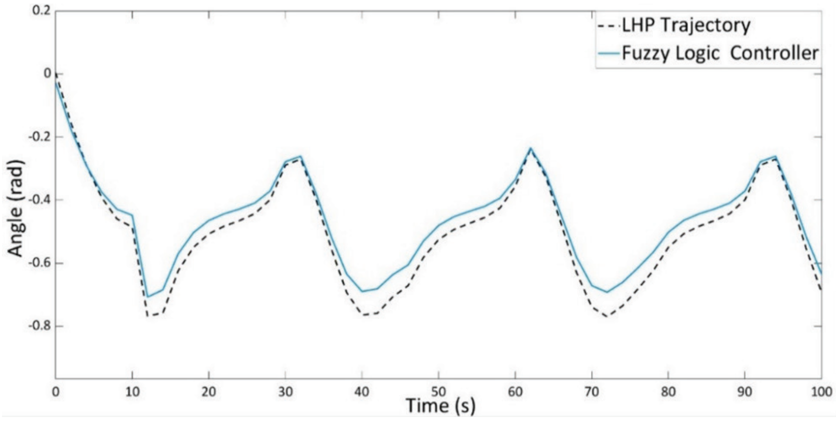


B) Knee pitch

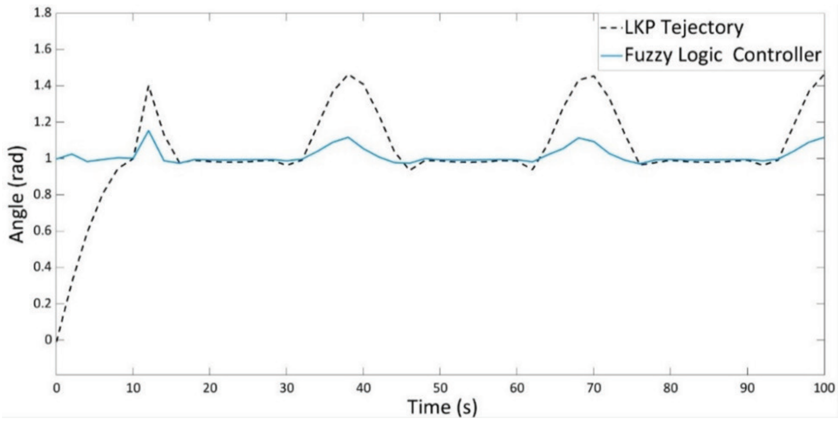


C) Ankle pitch

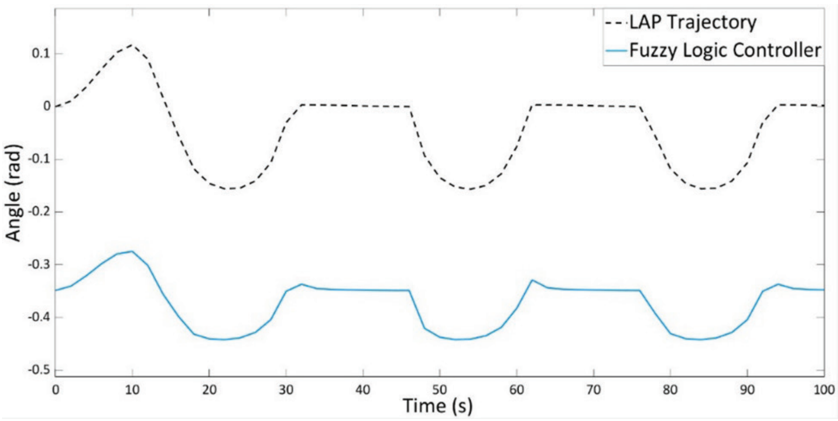
Fig. 8. Two input system response using PID controller for a joint trajectory input on the ANFIS model on Simulink. Reference trajectory (dotted line), PID controller (Blue line). A) Left leg hip pitch joint. B) Left leg knee pitch joint. C) Left leg ankle pitch joint



A) Hip pitch

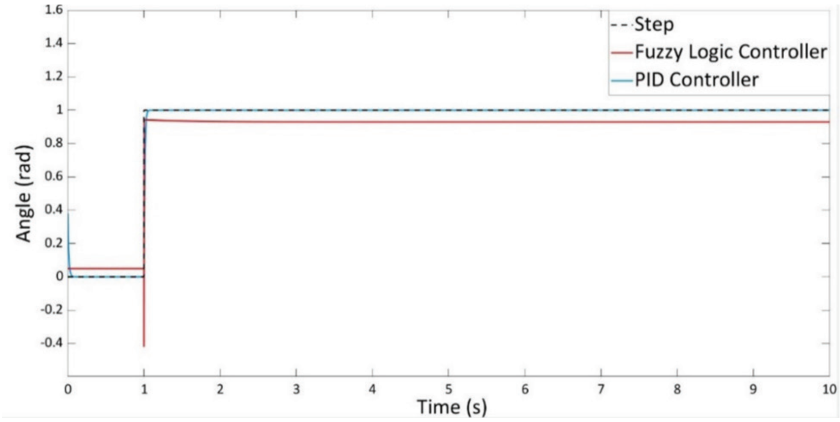


B) Knee pitch

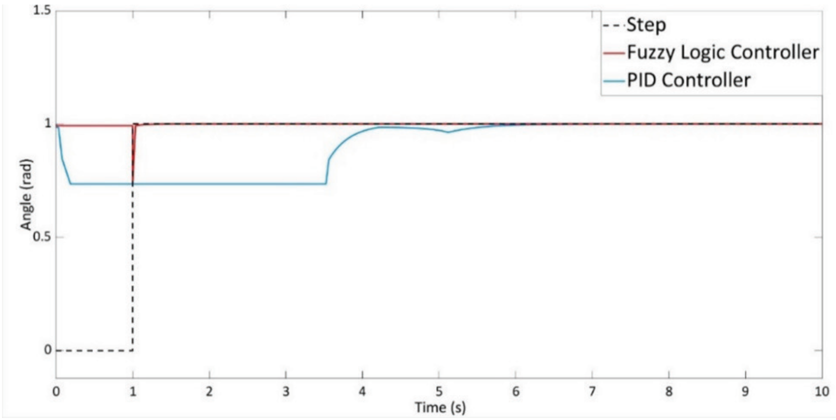


C) Ankle pitch

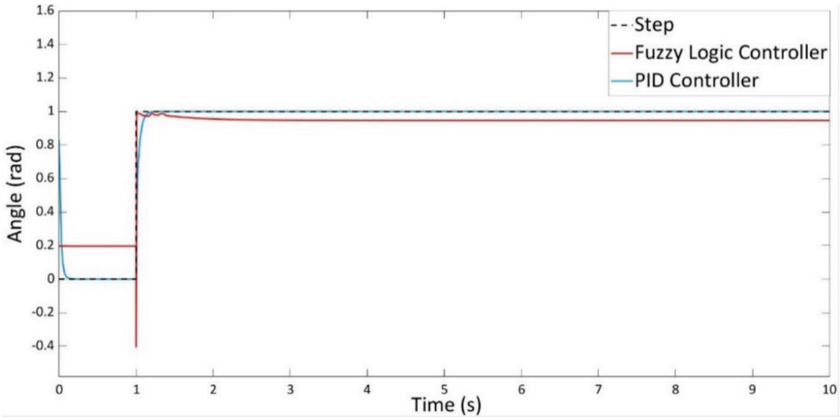
Fig. 9. Two input system response using ANFIS controller for a joint trajectory input on the ANFIS model on Simulink. Reference trajectory (dotted line), ANFIS controller (Blue line). A) Left leg hip pitch joint. B) Left leg knee pitch joint. C) Left leg ankle pitch joint



A) Hip pitch

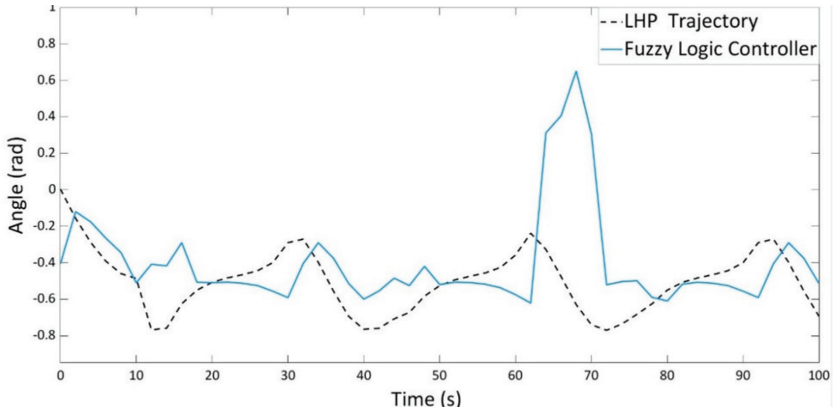


B) Knee pitch

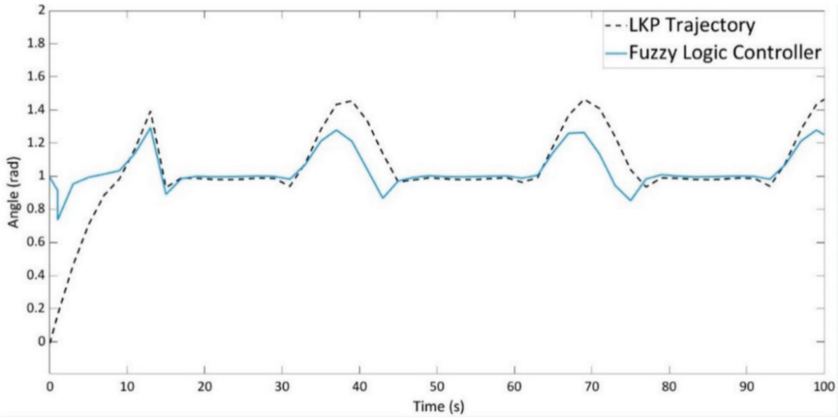


C) Ankle pitch

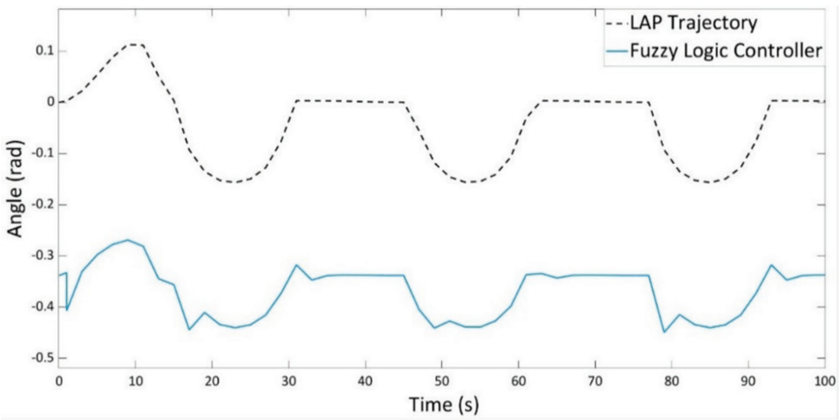
Fig. 10. Three input system response using PID and ANFIS controllers for a step input on Simulink. Step input (dotted line), ANFIS controller (red line), PID controller (blue line). A) Left leg hip pitch joint. B) Left leg knee pitch joint. C) Left leg ankle pitch joint



A) Hip pitch



B) Knee pitch



C) Ankle pitch

Fig. 11. Three input system response using ANFIS controller for a joint trajectory input on the ANFIS model on Simulink. Reference trajectory (dotted line), ANFIS controller (Blue line). A) Left leg hip pitch joint. B) Left leg knee pitch joint. C) Left leg ankle pitch joint

The main advantage of ANFIS is its capability to always identify complex and nonlinear systems accurately, especially ill-defined, and uncertain systems. This capability was investigated for an exoskeleton model. Models were trained using an optimum number of membership functions that could capture the system properly. Increasing the number of MFs will lead to overfitting. Thus, causing the model to be hard trained for a specific set of data, and the system would not capture the real behavior of the exoskeleton. The RMSEs for the two-input model for the hip, knee and ankle were 0.075, 0.126 and 0.087, respectively, for an average of 0.096. As for the three-inputs, the RMSE on average was higher, with a value of 0.19, which means it was worse. However, the knee model showed some improvement, as the RMSE was lower by 2%. Observing the system's response in Figure 7a and c, it can be seen that even though the system follows the input signal, it follows it too fast judging from the response time, a characteristic of a static system not a dynamic one, which means the ANFIS model is too simplistic in modelling the exoskeleton. Other responses showed a more dynamic behavior, as there is a delay before steady state.

First, ANFIS was trained with one input to the system, and one output. The results, in the form of trajectory following, were unsatisfactory and erratic. Thus, completely unsafe for humans. This was not too surprising as the exoskeleton system is complicated and nonlinear. The controllers used to verify the results were PID and ANFIS for step inputs, and ANFIS for following the joint trajectories, as the step input results were not promising, and so only the better performing controller was used to further verify that the ANFIS model has failed to capture the system.

Next, two inputs were assessed, and the results were promising, as both controllers succeeded in following the path relatively, the hip pitch trajectory was very close to the real trajectory and had low overshoot for both controllers and low steady state error. The overshoot for the PID was 1.3% and the ANFIS 6.17%. PID was better in following the trajectory of the hip joint with less steady state error and overshoot, but the ANFIS controller was smoother and had less irregular behavior throughout the trajectory. The overshoot for the knee was high for both controllers, at approximately 30%. Finally for the ankle, ANFIS showed significantly better results compared to the PID controller, but higher steady state error. PID had extremely high overshoot of 111% and ANFIS had an overshoot of 15%. PID showed highly irregular spikes in the signal, while ANFIS followed the trajectory more smoothly but had a large steady state error.

Lastly, joint acceleration was added as input to the ANFIS model to test if it would accomplish better results. The hip joint was noticeably inferior to the two-inputs model with an overshoot of 43%. No obvious changes were observed in the ankle joint trajectories. But a large improvement was observed in the knee over the two-inputs model with an overshoot of 5.12% compared to 33%. All joints of the exoskeleton were studied, but the pitch joints hold the most significant, as the roll joints have an extremely small ROM, and they do not need a lot of power.

5 Conclusions

This paper investigated exoskeletons for rehabilitation, particularly for Spinal Bifida patients. The presented work was focused on the design of a control system using artificial intelligence, it implemented ANFIS as a model identifier and a controller and compared its performance with a conventional PID controller.

One, two and three inputs were considered to train the ANFIS. Investigations revealed that the one-input model showed poor results in following joint trajectories. Thus, a two-inputs model was suggested to obtain a better behavior in capturing the nonlinear system. It demonstrated significant improvements, and succeeded in following the trajectories, however, some joints were not adequate. Further analysis was carried out using a three-input model; it was tested to find a better behavior. In contradiction to what was projected, the model performed worse for both the hip and ankle joints, despite providing more inputs. Nonetheless, the knee joint model was improved. As a result, the two-input model was chosen to be implemented on the system for the hip and ankle, while the three-inputs model was selected for the knee.

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