Comparison Of Traditional Thermal And Intelligent Controllers In Fusion With Neural Networks For Regulation Of Robotic Manipulator

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Since the 1950s, scientists have faced an immense challenge in managing robotic systems. The Proportional-Integral-Derivative (PID) controller was the industry standard for controlling complex structures in the early days. Nevertheless, fuzzy logic controllers emerged as a result of the inadequacy of PID controllers for nonlinear systems. Researchers continued to pursue more effective control techniques, despite the fact that these controllers offered a viable solution for nonlinear systems. One such technique that emerged as a promising solution was the neurologic controller. This controller is capable of managing systems that are highly complex, nonlinear, and inadequately analyzed. The neurologic controller is constructed in accordance with the principles of artificial neural networks, which are intended to replicate the behavior of the human brain. These neural networks are capable of learning from experience, recognizing patterns, and making decisions based on the data they receive. The neuro PID and neuro Fuzzy PID controllers were subsequently developed by combining the neurologic controller with conventional controllers. These controllers integrate the advantages of both conventional and intelligent controllers. They are well-suited for a variety of applications due to their ability to manage systems that are extremely complex, nonlinear, and poorly analyzed. This paper conducts a thorough examination of both conventional and intelligent controllers, elucidating the critical role that neural networks play in each scenario. The investigation offers valuable information regarding the controller that is most appropriate for particular applications. The results of this investigation will assist engineers and researchers in the development and implementation of more efficient control systems for robotic applications.

Keywords: Traditional controllers, Intelligent Techniques, non-linearity, neural network controller, fuzzy logic

Introduction

The world is currently experiencing a transition toward artificial intelligence and robotics, and this transition is certainly warranted. Robots provide exceptional performance in a shorter amount of time, alleviate the scarcity of qualified workers, assist in managing the pressures of increasing yields to remain competitive in the industry, and enhance the image of the brand. Nevertheless, a robotic manipulator, which is a control system, is required to move the robot arm in order to guarantee safety and efficiency. Without it, an automaton may pose a threat to its environment. Operators employ a variety of methodologies and command systems to manage and operate robots. The management of robots has always been a difficult task for scientists, and it will only become more difficult in the future. An sophisticated control scheme that is both flexible and robust is necessary to satisfy modern demands. Multidisciplinary areas, such as the control of a robotic manipulator, are the result of the utilization of a variety of devices and management strategies. The control system can be rendered more independent, adaptable, and considerate by employing machine learning and neural networks within the context of applied mathematics. In summary, this proposed investigation is a critical amalgamation of numerous disciplines. In order to satisfy contemporary specifications, an intelligent, adaptable, and reliable controller is necessary. The development of these controllers is significantly influenced by interdisciplinary disciplines. The potential of robots is boundless when equipped with an appropriate control system. They have the potential to transform our work, enhancing its efficiency, safety, and speed. The advantages are evident, and the necessity for such solutions will only intensify in the years ahead. Let us collaborate to establish a more prosperous future through the utilization of artificial intelligence and robotics.

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Traditional Controller (PID Controller and Thermal Controller)

Traditional methods may be straightforward and rapid to execute; however, they must evolve to realize the complete potential of control systems. The techniques and algorithms used to obtain PID controllers are the true power, as they have the potential to revolutionize the way we regulate non-linear systems and undefined applications. In order to guarantee optimal efficiency and productivity, it is imperative that experienced human operators and process managers be capable of adapting and making the requisite adjustments as we transition to a world of automation and artificial intelligence. We have made significant progress in our comprehension of feedback control loop technology and the advantages it can provide for the regulation of intricate systems since James Watt developed the first controller in 1788. A controller that is appropriate can unlock boundless potential in the transportation, energy, and manufacturing sectors. Let us leverage the capabilities of sophisticated control schemes and collaborate to establish a more promising future through the application of artificial intelligence and robotics[1-3].

PID Controller

The block diagram depicted in the image is a conventional PID controller, which is a composition of all three controllers. One benefit of a derivative controller is that it can generate a transient surge in the controller output in response to a rapid shift in the setpoint. Nevertheless, the most difficult aspect of implementing this form of PID controller is determining the appropriate PID controller [Figure 1] settings, which can be difficult to ascertain.

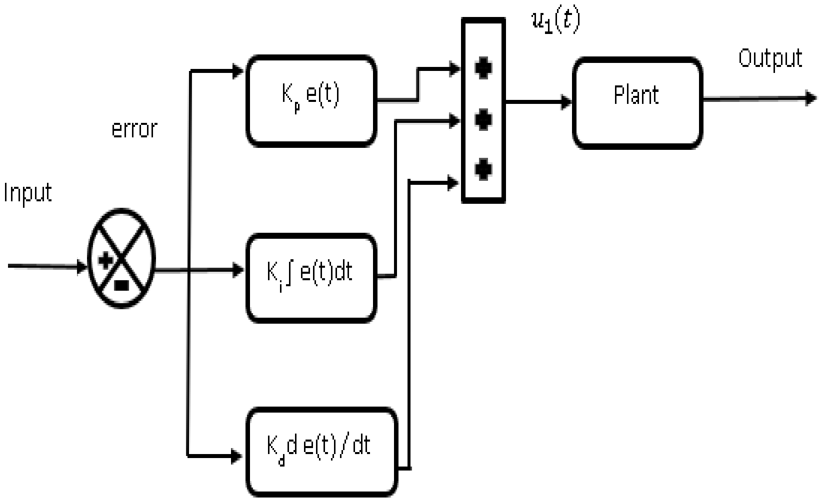

Figure. 1. Block Diagram of PID Controller

$$.u(t) = K_p e(t) + k_i \int e(t)dt + k_d \frac{de(t)}{d(t)} \qquad (1)$$

During 1942-43, the issue of tuning control loops was resolved by two Taylor engineers, Ziegler and Nichols. They developed a method of adjustment that is extensively used in the twenty-first century and is named after them[4-6] Additionally, they published two research articles regarding this refining procedure. The initial article focused on open-loop plant testing, while the subsequent article focused on closed-loop plant testing. Over the subsequent two to three years, additional research was conducted on parameter refining. Cohen and Coon introduced parameter tuning flexibility in 1950 by permitting alternative parameter choices for a specific plant.

Thermal Controller

In the 1880s, Warren S. Johnson was a professor at Whitewater Normal School, where he pioneered the concept of automatic temperature control. This innovation revolutionized the regulation of temperature in a variety of environments. Prior to this invention, the process of sustaining a comfortable temperature in a room necessitated the manual adjustment of dampers situated in the basement, which was both time-consuming and labor-intensive. Thermal control systems (TCS) are essential in the design of spacecraft to guarantee that all components remain within secure temperature ranges throughout the mission. Considering the harsh external environment of a spacecraft, such as the intense heat of unfiltered sunlight or the freezing temperatures of deep space shadows, the TCS design is complex and multifarious. The internal heat generated by the spacecraft must also be regulated by the TCS, as it has the potential to cause substantial damage if not properly managed. In order to optimize thermal management, TCS designers implement both passive and active cooling strategies. Graphite and other materials with high thermal conductivity are employed in passive cooling methods to transfer heat to frigid regions of the spacecraft. Externally mounted infrared radiation coils that emanate thermal radiation into space and cooling loops that utilize fluids to transfer heat away from the spacecraft's critical components are examples of active cooling techniques. In summary, Warren S. Johnson's invention of automatic temperature control revolutionized the management of temperature in a variety of contexts, and thermal control systems are essential for the optimal performance and success of spacecraft[7-9]. In order to guarantee that all components of the spacecraft remain at a safe temperature throughout the mission, the TCS designers implement a variety of cooling methods that account for both internal heat generation and the severe external environment.

Intelligent Techniques

Since the early 1990s, smart technologies have been created that integrate fuzzy logic with conventional PID controllers to enhance their overall performance and surmount their limitations. These controllers are referred to as intelligent because they incorporate numerous techniques under a single name. Table 1, which delineates hardware, software, and supplementary services criteria, illustrates the expansion of the smart controller market. Three diagrams have been generated for four consecutive years, as indicated by the table. [Figure 2] illustrates a comparison between 2017 and 2018, while [Figure 3] illustrates a comprehensive comparison from 2017 to 2020. After analyzing the integrated design of the fuzzy PID controller, scientists have conducted a comprehensive evaluation of fuzzy PD and fuzzy PI. The fuzzy logic rule base functions more like a human for logic calculation, and this combination eliminates the individual faults of fuzzy and PID controllers, resulting in a significantly lower cost than traditional controllers. The results of the operation of a robotic manipulator have been immensely accurate in terms of trajectory tracking and handling uncertainty, as elementary mathematics has been employed to control complex and non-linear systems. The controller has been the subject of extensive research by numerous researchers, and the numerous operations that are necessary in fuzzy controllers are illustrated in [Figure 4]. Table 2 illustrates the disparity in growth rates between traditional and intelligent controllers from 2014 to 2020, suggesting that conventional controllers exhibit lower growth rates than competent controllers [Figure 5].

Table 1: Intelligent controller growth in market in various sectors

PARAMETERS	2017	2018	2019	2020
Hardware	5%	10%	15%	20%
Software	35%	55%	75%	89%
Other Services	40%	50%	60%	70%

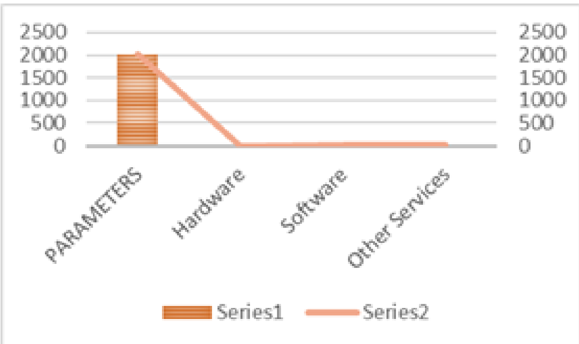

Figure. 2. Graph comparison between years 2017-18

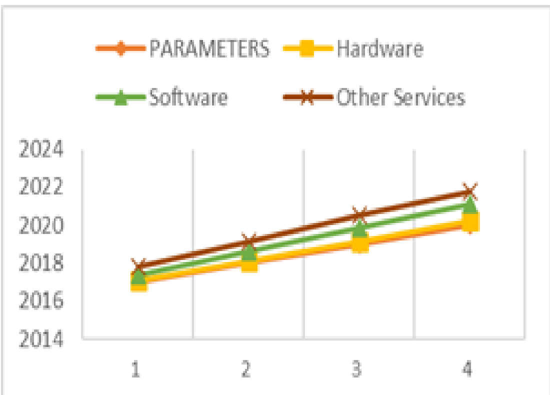

Figure. 3. Graph representing growth in consecutive years

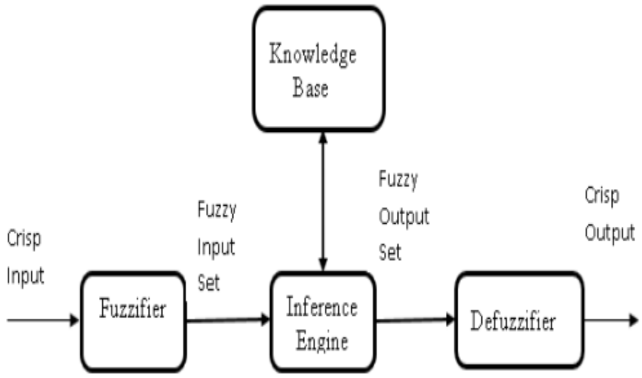

Figure. 4. Steps of Fuzzy Controller

Table 2: Comparison between traditional and intelligent controller

YEAR	Traditional Controller	Intelligent Controller
2014	46%	60%
2015	57%	66%
2016	66%	71%
2017	72%	77%
2018	70%	82%
2019	83%	87%
2020	85%	96%

Table 3: Growth of neural network controller from past era to present.

YEAR	GROWTH (%)
1980	5%
1985	10%
1990	15%
1995	18%
2000	12%
2005	15%
2010	40%
2015	60%
2020	89%

Figure. 5. Graph showing comparative performance of both controller

Neural Network Controller

A multi-layered perceptron is a neural network that is capable of regulating a non-linear plant. It consists of interconnected layers of perceptron's, with the input layer collecting input patterns that can be used to identify categories or output signals in the output layer. Nodes in each stratum operate similarly to those in regression analysis. The figure below illustrates the utilization of a neural network to regulate a discrete-time plant with finite dimensions. . The input to the plant at time k is UK, and ZK is the plant state that maps the current input state to the next input state. When the plant is linear, the state equation is A((Zk, Uk), where F and G are matrices.

$$Z_{K+1} = A(Z_k, U_k) = Fz_k + Gu_k \tag{2}$$

The primary objective is to train a controller using a neural network to achieve the intended state ZK for the plant. Nevertheless, the process of identifying and providing the appropriate input vector to accomplish the objective can be time-consuming when dealing with a linear plant. The strategy employed to resolve this issue is centered on multiple operating points, with the intended state being Zd from the previous year in such cases. Conversely, when the plant is non-linear, we linearize it, necessitating complex computation and a substantial quantity of design effort from academics and engineers. In either scenario, the United Kingdom will ascertain the current state of neural network training time.

Fusion Of Controller (Traditional and Neural)

The efficacy of a control system can be significantly enhanced through the implementation of a hybrid controller. This method can produce optimal outcomes and establish a more dependable and resilient system by integrating the advantages of both classical and intelligent controllers. An effective and persuasive solution for attaining high-quality control in a variety of applications is a hybrid controller, which has the capacity to integrate multiple controllers[10-11].

Neuro fuzzy PID Controller

Fuzzy logic has emerged as one of the most effective controllers for managing a variety of parameters in a real-time system. The uncertainty of the linguistic structure is the issue that arises in fuzzy modeling. Conversely, a neural network [Figure 6] has been implemented. From our biological nervous system. The information that the neural network is learning is difficult to comprehend and decode. A straightforward neural network is illustrated in [Figure 7]. The signals and weights that are present are actual numerical values. The input neurons we provided in this instance did not alter either the input or the output signal. We are providing two input signals, as illustrated in the preceding figure:
the first is X1, and the other is Xn. The first aim of these input signals is to form a product pi by combining with the given weights they are W1 and Wn, and the obtained product pi = Wi xi, i = 1, . . ., n. To collect the information regarding pi, we need to sum up

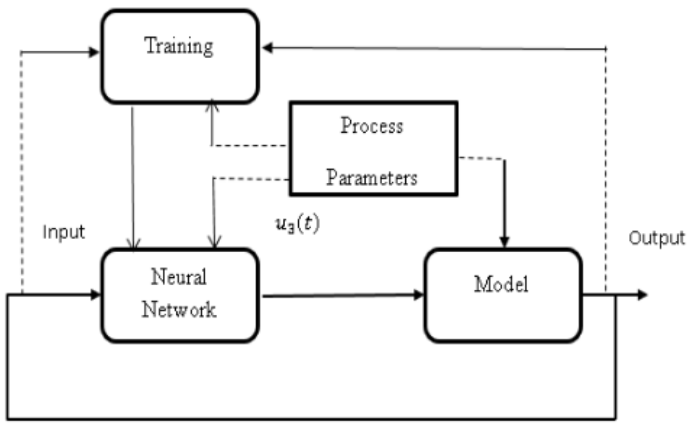

Figure. 6.Neural Network controller

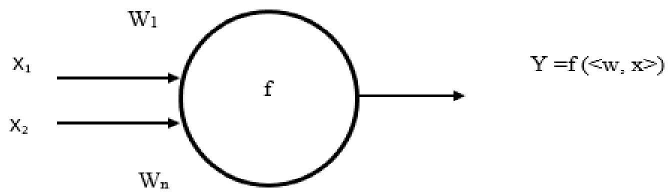

Figure 7. Neural net

$$x = (x1, x2, \ldots . xn) \quad (3)$$
$$w = (w1, w2, \ldots . . wn) \quad (4)$$
$$\mathrm{net} = \mathrm{p1} + \cdots + \mathrm{pn} = \mathrm{w1x1} + \cdots + \mathrm{wnxn} \quad (5)$$

here f represents the transfer function which is being used by the neuron. This transfer function helps to compute the output. Here, the transfer function used is a type of sigmoidal function.

$$f(t) = \frac{1}{1+e-t} \quad (6)$$

For computing the output, the equation can be

$$y = f(net) = f(w1x1 + \cdots + wnxn) \quad (7)$$
$$\mathrm{x} = (\mathrm{x1}, \mathrm{x2}, \ldots . \mathrm{xn}) \quad (8)$$
$$\mathrm{w} = (\mathrm{w1}, \mathrm{w2}, \ldots . . \mathrm{wn}) \quad (9)$$

Adaptive Neuro fuzzy Interference System

The interference system contains a collection of imprecise IF-THEN rules. The learning capability of these principles enables them to approximate a nonlinear function. This system is also referred to as a universal estimator. The second fuzzification layer provides the input for this layer. This layer assists in the determination and calculation of the firing intensity of each rule. The constant development of this controller is evident in Table 3, which illustrates the increase in neural network growth from the previous era to the present. This inline form is illustrated in [Figure 8], which displays the percentage in the respective years, and it is represented in bar graph form in [Figure 9]. If the plant is nonlinear, the function will be nonlinear. Selecting and providing an appropriate and acceptable input vector to transition a linear plant from its current or initial state to the desired state from the previous year is a challenging task. The resolution of this issue is contingent upon numerous operational factors.

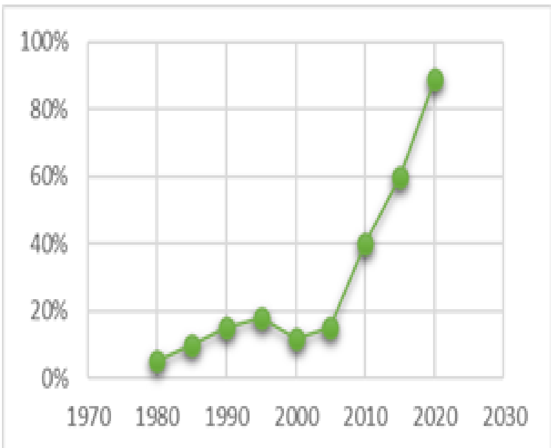

Figure. 8. Neural network growth in graph form

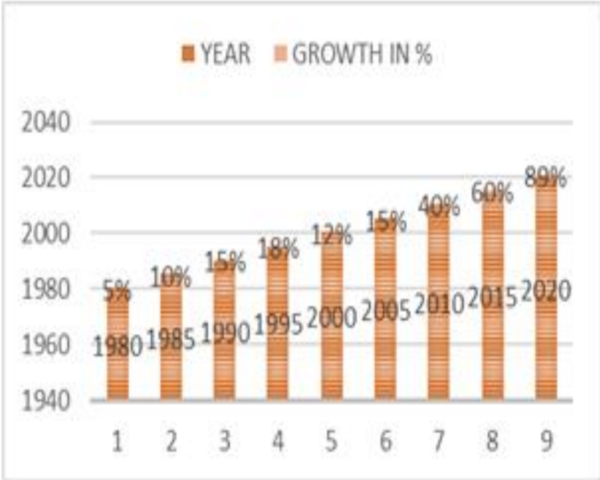

Fig. 9. Neural network growth in bar graph form

Conclusions

Individuals aspiring to enhance the resilience of their controllers are encouraged to examine this study. It incorporates a diverse array of control systems, commencing with the development of traditional personal computers and advancing to the application of fuzzy logic within conventional PID controllers. The heuristic methodology of fluid logic is of paramount significance for the advancement of the PID controller. The incorporation of fuzzy logic enhances the intelligence of the PID controller, resulting in an extended runtime and a decrease in development time. Neuro-controllers have established a prominent position in the field of control systems due to their computational capabilities, which allow them to perform multiple tasks simultaneously.

In contrast, the amalgamation of neuro-PID and neuro-fuzzy controllers produced significant results. The utilization of an adaptive neuro-fuzzy inference system significantly enhances the flexibility of the controller through the effective modulation provided by neuro-fuzzy techniques. In addition to the evolutionary algorithm and particle swan optimization, other optimization methodologies may also be implemented to optimize gain tuning. This research provides a comprehensive overview for control engineers and scholars, delivering significant insights into the integration of control methodologies for the development of effective and robust controllers.

Disclosure Statement

The authors report there are no competing interests to declare.

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