Simulation Analysis of Hydraulic Control System of Engineering Robot Arm Based on ADAMS

Haiqing Wu
Department of Mechanical Engineering, Taiyuan Institute of Technology, Taiyuan, Shanxi, 030008, China

***Abstract*—Substantial trenching capacity, communication capabilities, simple configuration, and so on are just a few of the many benefits that make Hydraulic Control Systems (HCS) the context of physical devices used within the geotechnical trench. These characteristics have led to widespread application in developing water conservation and hydroelectric technology, architectural construction, local construction, and other technology. In this article, the engineering robot arm proposed an HCS. Subsequently, a digital version of the functional device is constructed using Anti-Doping Administration and Management System (ADAMS), a simulation program, by incorporating associated restrictions and workload. With the help of a simulation model of the HCS's functioning apparatus, this research obtains the fundamental factors of the excavator's operating range and the pressured condition variation curve of the location of every Hydraulic Actuator (HA). The findings, which provide a conceptual framework and enhancements for the control system equipment, significantly raise the bar on China's excavator architecture, expand digger efficiency, and foster the firm's fast growth. An in-depth examination of the HCS's current operating condition, including an examination of the simulated model's transmission phase, can be determined. The findings provide a theoretical foundation for designing an optimal HCS.**

Keywords*—*Hydraulic control systems; ADAMS; simulation analysis; engineering robot arm

I. Introduction

Being a crucial component of automated control technology, digital electric Hydraulic Control Systems (HCS) have found several uses in numerous industries, including aviation, power generation, and more. An essential component of any digital HCS, electrical hydraulic gates convert low-voltage electric impulses into elevated hydraulic energy, making them essential for any application requiring electrical hydraulic servo control. So, if the electro-hydraulic control circuit valve had failed, the dependability of systems like the electromagnetic flow HCS and the automated control system would have been affected. That's why it's important to focus more on things like doing a technical failure study on the electromagnetic, hydraulic servo valves to make sure the electro-HCS is reliable and will last for the long haul [1]. Demolition robots are cutting-edge tools for the modern deconstruction of reinforced concrete structures. It has several applications in fields as diverse as nuclear energy, disaster response, metalworking, and demolition. The booms arm, which comprises three arm parts and then a crushing hammer mechanism, is the most important part of a destructive robot. Each device contains a hydraulic cylinder connected to a mechanical arm or breaker hammer, depending on the application. The reliability and safety of the building, as well as the profitability and expense of the enterprise, are all impacted by the vibrational properties. Thus, the arm's construction is crucial. As a result, the reliability of components like the automated management system and the digital electric HCS might have been compromised if the electro-hydraulic circuitry valve had failed [2]. Individuals with amyotrophic lateral sclerosis, spinal cord injuries, and other illnesses that cause paralysis from the neck down sometimes wholly or partly lose control of their limbs. Certain activities of daily living, such as getting from one location to another or grasping a glass to drink from, are impossible for paralyzed individuals to do without external support. Providing such aid often requires a nurse or other paramedic, which might take a long time and need many resources. Artificial technologies, such as robotic arms, are often exploited to enable two fundamental and necessary limb tasks for paralyzed people to care for themselves: moving and gripping. Paralyzed people may do everyday chores with a robotic arm that mimics arm motions and restores the patient's ability to hold objects.

In this, a robotic arm was used to pour coffee from a bottle using the patient's motion intents [3]. The primary focus of these control systems is on the robotic arm's redundancy resolution. Plans for the robotic arms and non-holonomic vehicle movements are provided. Priorities of these intersecting paths are described in more detail in the article. If the automobile or the robotic arm has trouble following the desired trajectory, the control algorithm will prioritize which system will complete the job. In this, the authors simulate and execute the dual control of a robotic arm placed on a wheelchair. The redundant arm's calculated configuration is the outcome of an optimization exercise. Hydraulic power robotic manipulators are analyzed and controlled in a separate field [4]. Fig. 1 depicts the Hydraulic Robot System (HRS) block diagram.

The robotic arm's redundant resolution is the main emphasis of these control systems. Compared to electric motors, they still offer superior power-to-weight ratios and more inherent toughness and rigidity. Academics are paying more attention to creating high-performance controllers for applications such as footed robot control, actuator impedance control, and flight simulator motion control, where precise control efficiency is essential. The data is interpreted by Hydraulic Actuators (HA) as a velocity instruction rather than a force instruction like their electric equivalents, complicating the difficulty of HRS. As a result, the well-researched generic industrial robot approaches cannot be directly used [5].

Typically, robot arms are computationally designed to carry out instructions. Devices like delivery ordering systems, robot arms, and automated guided vehicles may all benefit from being part of a unified network and being directed by AI in an entirely autonomous factory. Some examples of these advantages include higher production and productivity and a better investment return for gear. Microsoft, Amazon, and Google are just a few companies that provide developers with the frameworks, tools, and platforms necessary to train AI [6].

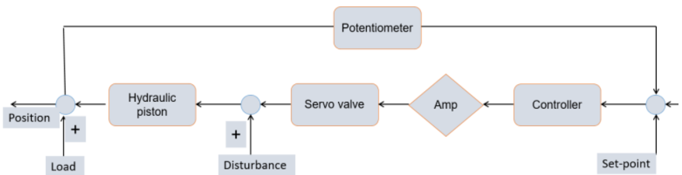

Fig. 1. Block diagram of the HRS.

Compared to contemporary industrial counterparts, non-industrial robotic arms are flexible, have little actuation power, and may include components that display huge variances concerning respective specifications, all of which achieve extensive trajectory tracking and significant difficulty. It restricts the use of flexible or low-cost robots to activities that need great precision or places where circumstances may rapidly change, such as on building sites, where robots are subjected to extreme weather and working circumstances. Operating robots at low speeds, where the dynamics coupling among joints is minimal and is a straightforward solution to cope with such situations, but it comes at the cost of reduced performance and output. Using the maximum potential of cooperative and low-cost robots outlines strategies for improving accuracy and accelerating the process in this objective [7]. Markets for robotics technology are expected to expand rapidly over the next decade, and the introduction of robotics will cause a revolution in the heavy machinery sector, just as it has already done in other areas, such as transportation and manufacturing automobiles. To this day, energy efficiency is still one of the most pressing problems to be addressed in hydraulic systems. The preceding intellectual HRS are inefficient since they use a standard, ineffective valve control. Energy efficiency may be less of a priority during the design phase for fixed installations.

On the other hand, ambulatory robotic systems have a unique challenge because they have very little storage room for their energy sources [8]. Motion sensors attached to the machinery and the human body allow the arm motions and prosthesis to be controlled by inbuilt ultrasonic sensors, somatosensory rhythms, and attempting movements. This approach, however, may lead to significant control errors in the grip and requires frequent changes to the sensor values. As neuromuscular stimulating and intrusive BCIs have advanced in the biomedical field, robotic arms have been programmed to reach out and grab objects. Surface electromyographic and non-invasive EEG inputs have been successfully used for robotic arm gripping [9]. Existing arm-grabbing systems may be classified into non-computer vision-based and machine-learning systems. Robotic arms are often used for grasping. Ultrasonic sensors, central nervous system connections, and electromyograms are only a few of the non-computer vision-based devices that benefit arm gripping. Moving sensors attached to the computer and the human condition allow the arm actions and prosthesis to be controlled by internal ultrasonic sensors and attempting movements.

II. Related Works

The best material for the manufacturing robotic arm has to be chosen to achieve the necessary qualities at the lowest possible cost and with the most potential for the intended use. The paper uses the analytical hierarchical process technique to decide which materials to apply in a robotic system [10]. One of the most popular multiple-criteria decision approaches, the Analytic Hierarchy Process (AHP), considers multiple criteria simultaneously. The AHP method's strength lies in its ability to accommodate numerous criteria simultaneously [11]. To solve the challenge of optimizing the design of robot arms for high-speed performance, we offer a surrogate-based evolutionary optimization technique using a global optimization technique, combining the response surface technique with a multi-objective evolutionary computation via decomposition. First, the robot arm's architecture and performance are evaluated using CAD software like Inventor and finite element modelling software like ANSYS [12]. This paper introduces a novel approach to teaching robotics using four components: an algorithm, a virtual experiment, some programming, and a controller.

The authors present an inverse kinematics method with an inexpensive desktop six-axis robotic arm designed for educational purposes. In MATLAB, we implement the inverse solution technique, and in VREP, we create a dynamic model of the desktop robot's arm (V-REP). By moving the virtual robot arm in V-REP to the desired location and orientation using MATLAB's API interface, we can test the efficacy of the robot manipulator technique and ensure its accuracy [13]. The research examines two degrees of freedom (DOF) robot navigation and builds free Cartesian spaces for finding the space available that ensures a collision-free route. An improved Ant Colony Optimization (ACO) method is offered to achieve motion goal-congruent optimum route planning. The improved ACO algorithm's primary purpose is to provide an optimum route based on the precise distance of the D* method. Integrating polynomial equations of the fifth order produces a path with minimal transitional points between the starting and ending points [14]. To improve the trajectory tracking control, the study presents two strategies for dealing with singularities that may arise when a robot arm follows a particular path. The paper uses genetic algorithms, but one is more localized and the other more worldwide. Each approach was tested on polynomial trajectories up to the third degree, and their results were compared based on metrics like trajectory inaccuracy, number of singularities, and computational cost. According to the outcomes, the technique based on the global genetic algorithm performed the best, as it could trace the second and third-degree trajectory with the fewest errors, singularities, and computational costs [15].

They suggested a Deep Learning (DL) model based on multi-directional Convolutional Neural Networks (CNN) with bidirectional Long Short-Term Memory (LSTM). The autocorrelation and the normalization root mean squaring error were used to evaluate the decode performance for different directions in 3D space [16]. The hardware includes the robot's design process, motor selection, and electrical components used to control the robot's joints. The software comprises algorithms that manage the robot's movements to ensure it moves according to specifications and algorithms that transform needed words into proper sequences with target areas. In this scenario, voice recognition software serves as a guide throughout the writing process [17]. Through the use of a small sample of productive results and subsequent actively tendered queries, in which the robot displays a state and starts asking for a label to evaluate whether or not that process and system accomplished the assignment, they propose an approach to eliminate the need for manual designing of reward specific requirements. Instead of expecting the user to personally give the reward signal by labelling every condition encountered during training, our technique only needs labels for a small subset of states, providing a feasible and effective method for learning new abilities without creating incentives [18] manually.

The strategy relies on a sampling approach and has two main components. When a starting point has been found by web search, a greedy approach is used to optimize the route by locally applying adaptive filters to the parts of the path that have particularly severe jerks. Numerical optimization is used to produce the filtered outcome. Developing a collision-indication function expressed as a support-vector machine is more computationally efficient using an adaptable sampling strategy [19]. The study evaluates AL against the most popular data sampling techniques for predicting regression outcomes with reduced sample sizes. The paper provides a unique assessment framework for comparing alternative sampling strategies in a regulated and objective way, despite their varied needs. They examine the sampling efficiency, stability, and predictive value of the resultant ML models from three illustrative use cases (UCs) to determine whether AL or DOE approaches are preferable for data production [20].

III. MATERIALS AND METHODS

A. ADAMS Modeling and Simulation Setup

Using a particular professional environment that may replicate the actual environment down toward the units, gravitation, and operating grids, the HCS design could be loaded into ADAMS. One of the first things to finish after a transfer should be to add restrictions and motor features, including a fixed pair between the land surface and the core, a spinning pair, a block pair, and a roller bearings joint pair at every section of the connection, and a mobility pair between the HA and it is relating engine shaft. Next, users must recognize the step response as the driving factor behind the engineering robot arm. Finally, execute the simulation via the modelling and analysis tool after all the preceding steps. Make sure there are no extraneous restrictions in the system and that there are no free variables.

B. Parameters of a Functional Hydraulic Cylinders Motion

The lifting arm hydraulic cylinder length L1, the buckets pole hydraulic cylinder lengths L2, and the bucket hydraulic cylinder length L3 all play a role in establishing the precise geometries of a spade. After L1, L2, and L3 are set in stone, it's clear where the anti-shovel mechanism will be placed. Anti-shovel hydraulic cylinder motion characteristics are shown in Table I.

C. Movement Function and Trajectory Simulations of a Hydraulic Cylinder

The following is a motion simulator of a crane hydraulic cylinder, a bucket rod hydraulic cylinder, and a bucket hydraulic press.

1) Hydraulic cylinder boom motion model: Full-shrinkage adjustment cylinder bucket rod position. Make sure the cylinder is set to full contraction before adjusting the bucket. The hydraulic cylinder's motion function allows the boom to extend and retract. To play back simulation results and create curves, you must transfer ADAMS/Post-processed Modular. Trace Marker could trace the path of the excavator's bucket's tooth marking points, and the resulting trajectory chart is shown in Fig. 2.

2) Hydraulic cylinder and bucket rod model in motion: If the bucket tooth is a direct line, then the Moving function entails changing the connection between the boom and the bucket rod and the connection between the bucket rod and the bucket. To play back simulation results and create bends, it must convert ADAMS/Post-processed components.

3) Hydraulic cylinder movement simulator for a bucket: The excavation work trajectory of a resource extraction bulldozer is a circular arc, with the steak between the bucket and rod the bucket serving as the middle of the plot line and the proximity from the tendon to the bucket tooth serving as the radius; the wrap edge the arc length are both calculated by the stroke of the bucket hydraulic cylinder.

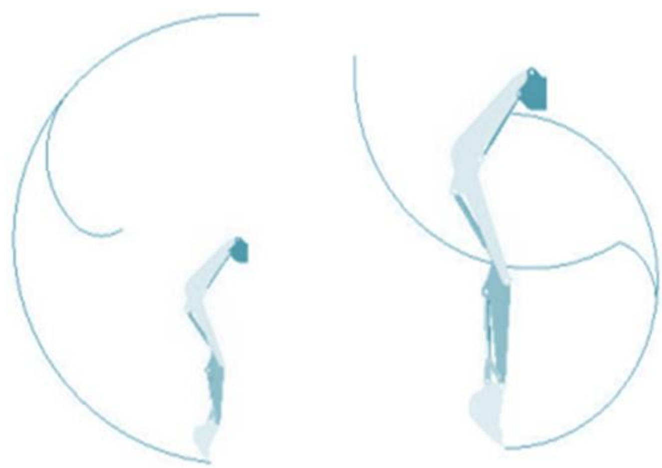

Fig. 2. An animated model of manipulating arms and a model of a bucket rod.

D. Dynamic Simulation Analysis

Regarding excavators, the primary area of investigation is the force fluctuation at the bucket's teeth and hinge point, which may be gleaned through a simulation model of the machine's mechanical power relations when subjected to different external loads. The goal is to guarantee that the design will work as intended.

1) Estimating Work in a Complicated Mining Procedure: Friction and soil resistance is not considered. Throughout its time spent underground, an excavator is subjected to those mentioned above primary external loads:

a) Mines that provide normal and tangential resistance: Mining resistance may be considered operating just on top of the bucket tooth in two directions: the tangential direction, which is perpendicular to the tracks, and the regular direction, which is perpendicular to the track. The following is their EQU (1) based on experience:

$$W_1 = K_0 bh \qquad W_2 = \psi W_1 \tag{1}$$

The resisting ratio of k_0 mining is representative of the overall resistance encountered by bucket-style excavating tools underground. Failure of the soil, soil loading, and friction all contribute to the overall resistance. The SI unit for k_0 N/cm^2 Miniature excavators often functions best on flat ground. Based on a table, we get a k0=15N/cm2 b-cutting width value as unit cm. Based on this model, *b=60 cm*. The unit for h-cutting depth is centimetres. On average, *h=0.2 b=12 cm*. ψ resistant to Mining Parameters. Accessing a lookup table reveals, $\psi = 0.6$. The following information is obtained by plugging the figures as mentioned above into EQU (2), and computing

$$W_1 = 10800, N = 10.8KN \qquad W_2 = 0.5, W_1 = 5.4KN \tag{2}$$

b) Resistance to lifting: After excavating is complete, hoisting resistance mainly pertains to the gravitation of the elements in the bucket. It is attributed to the bucket's centroid as normal and always moves vertically downwardly.

$$G = \rho V_g = rV \tag{3}$$

The capacity of a V-Bucket: $V = 0.28m^2$ in line with the value of the specification. Level dirt has a density of $1.8\times10^4 kg/m^2$. Based on the gravity setting in ADAMS, it is given by $g = 9.8m/s^2$. The gravitational value of the components may then be determined around *5KN.*

c) Load up the vehicle and enter ADMAS: The acute and normal directions of the bucket teeth match the tangential and normal directions of resistance. It demonstrates that these forces all act in the same direction. We can calculate the variations in the force of each cylinder at every hinge point whenever it works in the deep position by applying a typical complicated motion in excavation as a work circle. We may also get the excavation's kinetic models without considering the response times and the length of the working cycle, which includes excavation and unloading. The pace of bucket digging often determines how long it takes to excavate. The running speed is set to 0.5 m/s, the digging speed to 0.75 m/s, and the unloading time to 2s to make the simulation easier.

We split a cycle into three parts and determined the overall cycle duration to be 8s according to the results above:

(i) The bucket phase that descends: We adapt the working device's digging point to the broadest possible digging diameter, which entails reducing the size of the bucket rod and boom cylinder. We presume no additional loads are being imposed throughout this operation.

(ii) The phase of digging: The bucket and bucket rod cooperate to fill the bucket with earth. It denotes the end of the digging process. The load in this operation is the normal and tangential digging resistance. They start off increasing as the bucket angle rises. Digging resistance increases the most while digging the deep and decreases when the bucket angle increases.

(iii) Phases of hoisting and unloading: During the hoisting phase, we first set the boom cylinder to its full shrinking position while adjusting the bucket cylinder to guarantee that items are not dispersed throughout the ascent in the bucket. Then finish emptying, and adjust the bucket rod and cylinder to the complete shrinkage condition. The primary burden in the mining process is the weight of the material, and the boom-raising stage does not change as the weight of the material increases.

IV. Result And Discussion

To provide the required HCS, the HCS first pumps the hydraulic fluid, which then circulates across the device. The hydraulic mechanism allows the bigger versions of the commercial or hydraulic robotic arm to carry substantial weights; hence, the arms are typically metal. Findings from the engineering robotic manipulator for the ADAMS model are analyzed below. Metrics such as accuracy, precision, recall, mobility, and energy transformation are compared with the conventional methods. The conventional methods are Artificial Intelligence (AI) [21] and DL [22]. The findings are listed below.

A. Accuracy

As a measure of a device's accuracy, it refers to how closely calculated values align with the real thing. It has been shown that the proposed approach is more precise than the existing method. We provide our results in terms of the percentage of accuracy. In Fig. 3, the recommended system's accuracy is shown. AI has achieved 75% accuracy, but ML has only reached 83%. The proposed method has 95% of accuracy. It demonstrates that the proposed method is superior to the traditional methods. Table I represents the accuracy.

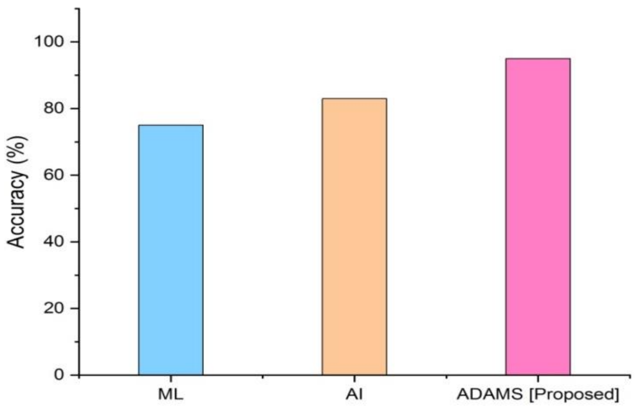

Fig. 3. Accuracy.

TABLE I. ACCURACY MEASUREMENT

Techniques	Accuracy (%)
ML	75
AI	83
Proposed ADAMS	95

B. Precision

Precision, often called positive prediction value, is the percentage of correct opinions among the retrieved instances. Precision is a determinant of value, which it may determine. Precision measures how likely it is that a specific recovery will occur. The proposed work has significantly higher accuracy than the current methods. Fig. 4 shows the results of comparing the precision of conventional and proposed methods. Conventional methods achieve the following levels of accuracy; therefore, ML has attained 77%, and AI has reached 83%. As a result, the proposed system offers the highest potential outcome of 95%. The precision value is shown in Table II.

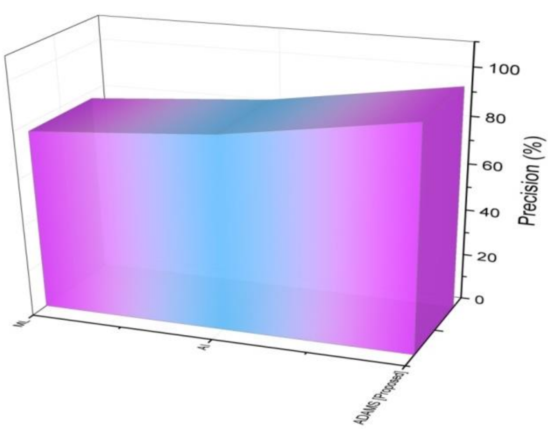

Fig. 4. Precision.

TABLE II. PRECISION VALUE

Techniques	Precision (%)
ML	77
AI	83
Proposed ADAMS	95

C. Recall

Fig. 5 compares the proposed technique and the existing method for recall. The recall is the fraction of relevant events which have been retrieved. One other name for sensitivity is recalled. The proposed method has the greatest recall of all the conventional systems. Conventional methods' recall for predicting performance is as follows: ML achieves 73%, AI achieves 85%, and the proposed method achieves 97%. It shows that the intended work will be completed effectively. The recall analysis is shown in Table III.

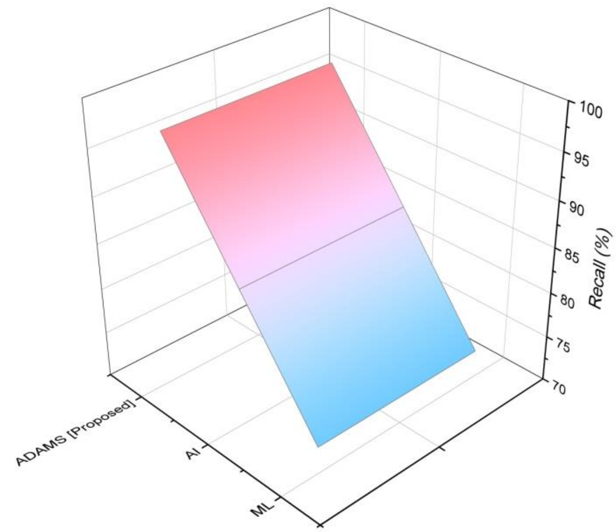

Fig. 5. Recall.

TABLE III. RECALL

Techniques	Recall (%)
ML	73
AI	85
Proposed ADAMS	97

D. Mobility

Robotics designed for long-distance transportation are called Mobility Systems. The ability to move freely is crucial for automated systems to carry out their missions in challenging and intricate settings. Wheels, feet, hops, and other forms of mobility may all be used by robotic systems. The mobility contrast is demonstrated in Fig. 6. Established methods like ML have attained 75% mobility, while AI has reached 81% mobility. According to the findings, the proposed system is mobility towards the extent of 93%. The results of the mobility research are presented in Table IV.

TABLE IV. MOBILITY

Techniques	Mobility (%)
ML	75
AI	81
Proposed ADAMS	93

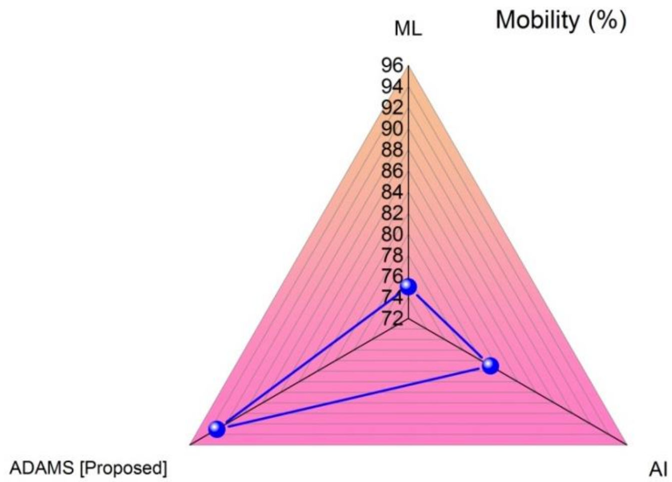

Fig. 6. Mobility.

E. Energy Transmission (ET)

Converting one type of resource into another is termed ET. The contrast between the two forms of ET is seen in Fig. 7. Existing methods, such as ML, have attained a mobility rate of 73%, and an AI of 88% in the ET. The results show that the proposed method can convert energy for robotics technology by a significant percentage is 97%. The analysis of ET is shown in Table V.

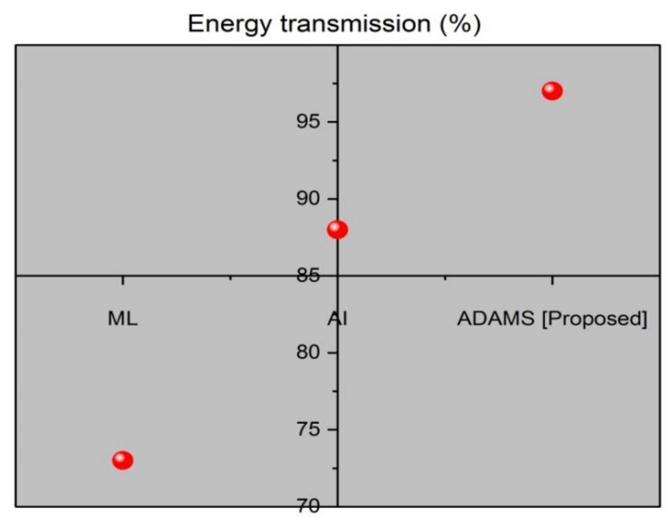

Fig. 7. Energy transmission.

TABLE V. ENERGY TRANSMISSION

Techniques	ET (%)
ML	73
AI	88
ADAMS [Proposed]	97

V. CONCLUSION

This study uses ADMAS software's robust analysis feature to examine the engineering robot's simulation Hydraulic Control System (HCS)'s functioning device. We have determined the scope of this research work and the significant fundamental characteristics of accuracy, precision, recall, mobility, and Energy Transmission (ET), and we have acquired the defined points and the force curve of a Hydraulic Actuator (HA) via a simulation model. This study obtained a model simulation study of the HCS's operational state, and our findings may be used as a theoretical foundation for the development and optimization of engineering robots' HCS.

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