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An Abductive Reasoning Approach for Energy Saving in Robotic Systems

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Abstract

The velocity and acceleration commands of industrial robots are set to their maximum values to shorten the cycle time of products. However, the excessively high speed and acceleration for movements can cause unnecessary mechanical energy and electricity consumption. This paper proposes an energy-saving approach for robotic systems based on abductive reasoning. Results for different combinations of speed commands and acceleration commands are evaluated based on energy consumption and cycle time. Moreover, a well-designed abduction rule formula is used to achieve a good balance between cycle time and mechanical energy consumption of industrial robots. Simulation results of a Franka robot by ROS, Gazebo, and Moveit verify the effectiveness of the proposed approach.

Keywords: Abductive reasoning, industrial robot, cycle time, energy saving

1. Introduction

To achieve and comply with the goal of sustainable development advocated by the United Nations, industrial and commercial sectors have taken energy saving into account as a major consideration in corporate management. As a result, issues related to Environment, Society, and Governance (ESG) have received much attention from many companies, especially those that consume a large amount of electricity. According to statistical data provided in [1], the energy consumption of industrial robots continues to steadily rise. There are a lot of papers discussing this problem [2 - 5]. In addition, industrial robots are commonly used in automated factories and various work areas. It is not surprising that the cost of electricity consumption and the amount of carbon emissions due to industrial robots are enormous. Since the factories that deploy industrial robots are the users rather than the manufacturers of industrial robots, they can't implement energy saving by modifying the functions of industrial robots. As a result, to reduce electricity consumption for industrial robots, one must take a different approach, from the point of view of saving mechanical energy. In general, the velocity and acceleration commands of industrial robots can be set by their users. To improve the efficiency of the production line to shorten the cycle time of products, normally the velocity and acceleration commands will be set to their maximum values. However, one common scenario involves industrial robots waiting a considerable amount of time for their next move instruction after rapidly arriving at their current target position. In other words, to arrive at the target position in time, industrial robots don't need to move at such a high speed and acceleration [6-7]. Since velocity and acceleration affect the mechanical energy of industrial robots, one can set suitable velocity and acceleration commands to save mechanical energy and reduce electricity consumption.

There are several existing studies focusing on addressing the problems. For instance, Thangaraj and Chelliah used an evolutionary computation algorithm to investigate the energy-saving problem of motor systems [8]. Several previous studies

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[9-10] used long short-term memory (LSTM) and neural networks to accurately predict the energy consumption of industrial robots.

However, the issue discussed in [8] mainly investigates how the changes in motor design and manufacturing can improve energy savings. Namely, the approach proposed in [8] is more suitable for the manufacturer than the user. In addition, the neural networks employed in [9] and [10] to predict energy consumption use graphic process units (GPUs) to shorten the computing time. Nevertheless, for many small and medium-sized enterprises, using GPUs is not a cost-effective solution. Moreover, these existing studies have not investigated the issue concerning the balance between manufacturing efficiency and energy savings. After all, corporate executives are not willing to sacrifice too much manufacturing efficiency for energy savings. To cope with this issue, unlike the approaches developed in previous studies, this paper proposes an abductive reasoning-based approach to find suitable velocity and acceleration commands to achieve a good balance between energy savings and the robot's movement velocity. To verify the effectiveness of the proposed approach, this paper adopts Gazebo, robot operating system 1 (ROS 1), and Moveit to simulate the motion of a Franka robot. Simulation results verify the effectiveness of the proposed approach.

2. Brief Review on Abductive Reasoning

Abductive reasoning was proposed by Peirce [11-12]. Peirce advocated the idea that, in addition to well-known reasoning methods such as inductive reasoning and deductive reasoning, there is another reasoning method called abductive reasoning. Fig. 1 illustrates the relationship between inductive reasoning, deductive reasoning, and abductive reasoning. The first reasoning condition is called "Rule", which is also referred to as "background knowledge" in some papers [13]. The second reasoning condition is called "Observation Result", which is commonly shortened to "Observation" or simply "Result". The third reasoning condition is "Hypothesis", which is also called "premise" in some papers. Generally, inductive reasoning exploits Observation and Hypothesis to derive a Rule. In contrast, deductive reasoning draws a specific observation based on Hypothesis and Rule. Unlike inductive reasoning and deductive reasoning, abductive reasoning seeks the most likely Hypothesis from Observations and Rules.

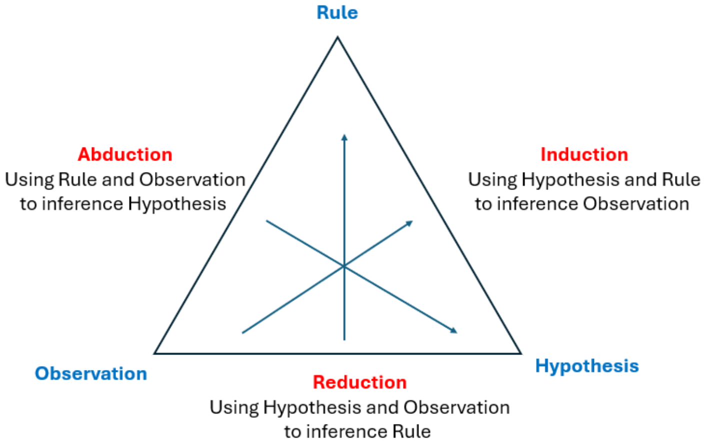

Fig. 1 The relationship among inductive reasoning, deductive reasoning, and abductive reasoning, the red elements represent reasoning methods, and the blue elements represent reasoning conditions

Some existing studies have applied the idea of abductive reasoning to several research fields in computer science, such as natural language processing [14] and artificial intelligence [15-16]. Conventional abductive reasoning is based on logical inference. To apply abductive reasoning in computer science, the presence of modifications is the requisite. Specifically, mathematical formulas are used to provide the most likely premise in abductive reasoning rather than using logical inference. Typically, there are two approaches to using mathematical formulas to provide the most likely premise – cost-function-based [15] and probability-based [17]. Since the cost function-based approach is commonly used in natural language processing, it is adopted in this paper. In particular, the approach proposed in this paper modifies the concept of weight abduction [14, 18] in natural language processing so that it can be used to address the mechanical energy-saving problem for industrial robots. Definitions and acronyms for symbols used in this paper are provided below [13].

R: Rule;

O: Observation;

H: Hypothesis;

P = $\{P_1(x), P_2(x), P_3(x) \ldots\}$: Potential Elemental Hypothesis, where x is the input.

In abductive reasoning, R and O are used to compute H. Input x is the useful information extracted from O. Subsequently, from rule R, one can obtain several axioms consisting of the potential elemental hypothesis (PEH) as described by

$$\mathrm{R}=\mathrm{A}_1 P_1 \wedge \mathrm{A}_2 P_2 \wedge \mathrm{A}_3 P_3 \tag{1}$$

P_1, P_2 and P_3 are potential elemental hypotheses (PEH), while A_1, $A_2$and A_3 are their associated weights and the symbol ^ indicates that a rule utilizes these PEH and weights. With these rules, one can compute the costs. Different observation inputs will yield different costs. The PEH with the highest cost is referred to as the best hypothesis.

3. Energy Saving and Motion Command Planning of Industrial Manipulators Based on Abductive Reasoning

In automatic manufacturing processes, industrial robots are often asked to perform point-to-point motions. In the past, motion planning of the position and velocity commands for industrial robots was conducted to achieve faster point-to-point motions, thereby improving manufacturing efficiency. Recently, issues such as sustainable development, environmental protection, and energy savings have attracted much attention worldwide. Therefore, it is crucial to assess whether the aforementioned motion planning strategy can satisfy the requirement of energy savings as well. However, by simply considering the issue of energy savings while ignoring the need to generate suitable motion commands for faster point-to-point motions, the cycle time of products becomes too long. As a result, it is crucial to balance the cycle time of products and the mechanical energy savings of industrial robots.

As mentioned previously, the most significant feature of abductive reasoning is that various hypotheses can be obtained from observations and rules. In this paper, the concept of abductive reasoning is exploited to find a good balance between the cycle time of products and the mechanical energy savings of industrial robots. This paper applies the formula as the rule for selecting parameter values to achieve a balance between cycle time and mechanical energy consumption. This is the best hypothesis once the highest cost is calculated from the formula. Note that the parameters for “Observation” (i.e., input) used in this paper are the moving time of the robot, motor torque, motor speed, etc.

Since this paper mainly investigates the issues of manufacturing efficiency and energy saving, motor speed and mechanical energy are thus adopted under “rule”. As a result, *R* in Eq. (1) is rewritten as

$$R = a_1 e^{P_1(x)} + a_2 e^{P_2(x)} \tag{2}$$

where a_1 and a_2 are the balance parameters set by the user and x is the input, and $P_1(x)$, $P_2(x)$ are potential elemental hypotheses. As indicated by Eq. (3), the sum of the balance parameters must be one.

$$\sum_{i=0}^{n} a_i = 1 \tag{3}$$

Since the best hypothesis yields the highest cost for a rule, the best hypothesis is thus described by

$$H = R_{\max} = \max(a_1 e^{P_1(x)} + a_2 e^{P_2(x)}) \tag{4}$$

Eq. (4) represents the maximum value $R_{\max}$ of rule *R*.

In addition, to facilitate the calculation, as described in Eq. (5), the value of $P_i(x)$ is normalized.

$$0 \le P_i(x) \le 1 \tag{5}$$

This paper focuses on balancing the moving speed of industrial robots (i.e. cycle time) and mechanical energy consumption. It is necessary to construct PEH formulas for both the cycle time and mechanical energy consumption. The PEH of the cycle time is denoted as $C(x)=P_1(x)$ in Eq.(4), while the PEH of the mechanical energy consumption is denoted as $W(x)=P_2(x)$ in Eq. (4). The schematic diagram of the proposed approach is shown in Fig. 2.

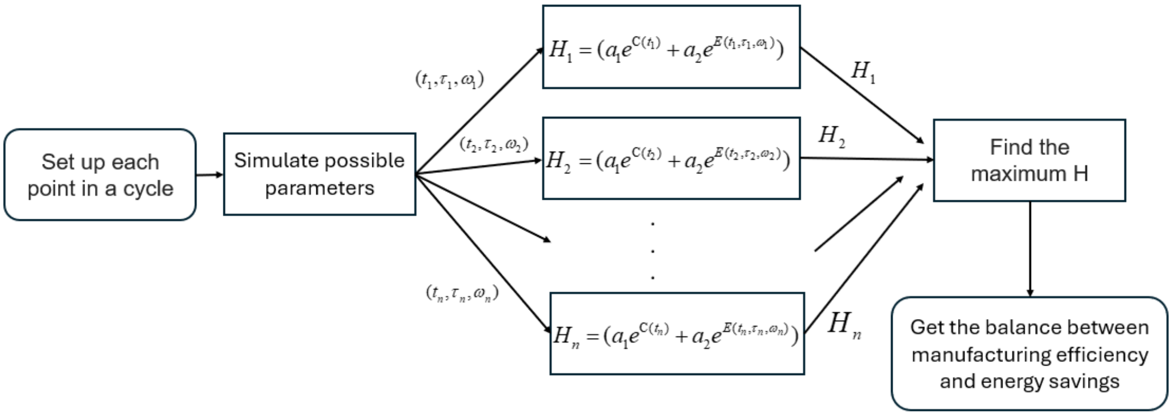

Fig. 2. Schematic diagram of the proposed approach

Since $C(x)$ is a $P_i(x)$ described by Eq. (5), therefore $0 \le C(x) \le 1$. In addition, $C(x)$ is the cycle time of the industrial robot, so for the sake of convenience, $C(x)$ is rewritten as $C(t)$, which is described as

$$C(t) = \frac{T_{\max} - t}{T_{\max} - T_{\min}} \tag{6}$$

where *t* is the moving time of the industrial robot, T_{max} is the maximum moving time, and T_{min} is the minimum moving time. $C(t)$ represents the cycle time, which refers to the time taken for the robot to complete an entire task in a cycle time. This includes the time the robotic arm spends on operation as well as the time waiting for other machines to complete their task.

As for the PEH of mechanical energy consumption, the mechanical energy consumed by the industrial robot is considered as

$$E(t, \tau, \omega) = \int \tau \times \omega dt \tag{7}$$

where $E(\tau, \omega)$ is the mechanical work provided by the industrial robot, τ is the torque, and ω is the rotational speed. In addition, the maximum mechanical work is denoted as E_{max}, while the minimum mechanical work is denoted as E_{min}. The PEH of the mechanical energy consumption $w(x)$ is rewritten as $w(\tau, \omega)$, which is described by Eq. (8).

$$w(t, \tau, \omega) = 1 - \frac{E_{\max} - E}{E_{\max} - E_{\min}} \tag{8}$$

With equations Eq. (3), Eq. (4), Eq. (6), and Eq. (8), one can perform the calculations of balancing the cycle time of products and mechanical energy consumption.

4. Simulation Setup and Results

Gazebo, ROS 1, and Moveit are used in this paper to simulate the motion of a Franka robot. In the simulation, the Franka robot performs a point-to-point motion that moves from joint point (0, 0, 0, -90, 0, 90, 0) to joint point (0, -21, 0, -140, 0, 120, 0), shown in Fig. 3 to Fig. 5. The maximum rotational speed and the maximum rotational acceleration for each joint are listed in Table 1.

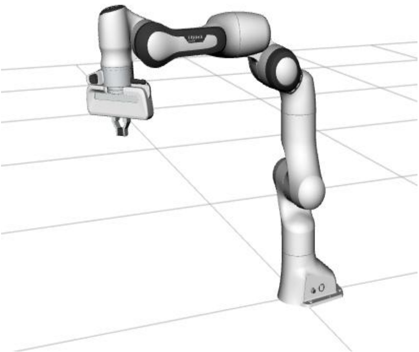

Fig. 3 The robot's initial joint position (0, 0, 0, -90, 0, 90, 0)

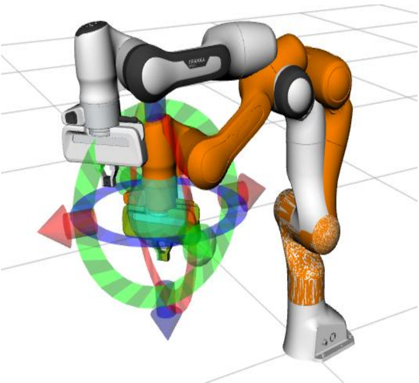

Fig. 4 The robot is moving from the initial position to the final position, the orange color robot is in the final position

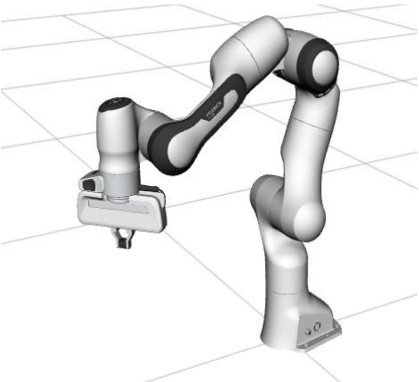

Fig. 5 The robot's final joint position (0, -21, 0, -140, 0, 120, 0)

Table 1 Maximum rotational speed and maximum rotational acceleration

joint	Maximum rotational speed v_{max}	Maximum rotational acceleration a_{max}
1	2.175 rad/sec	3.75 rad/sec^2
2	2.175 rad/sec	1.875 rad/sec^2
3	2.175 rad/sec	2.5 rad/sec^2
4	2.175 rad/sec	3.125 rad/sec^2
5	2.61 rad/sec	3.75 rad/sec^2
6	2.61 rad/sec	5 rad/sec^2
7	2.61 rad/sec	5 rad/sec^2

As mentioned previously, in many factories, the velocity and acceleration commands are set to their maximum values. However, sometimes the industrial robots will wait a considerable amount of time for their next move instruction after rapidly arriving at the target position. This kind of arrangement certainly is not energy-efficient.

To investigate this issue, in the simulation, five different rotational speeds — 20% v_{max}, 40% v_{max}, 60% v_{max}, 80% v_{max}, 100% v_{max} — and five different rotational accelerations — 20% a_{max}, 40% a_{max}, 60% a_{max}, 80% a_{max}, 100% a_{max} — are used. Therefore, a total of 25 different combinations of speed commands and acceleration commands are used in the simulation. The associated simulation results of the cycle time of the products are shown in Table 2.

Table 2 Cycle time

Time (sec)	20% a_{max}	40% a_{max}	60% a_{max}	80% a_{max}	100% a_{max}
20% v_{max}	2.79	2.352	2.186	2.09	2.08
40% v_{max}	2.43	1.782	1.53	1.43	1.33
60% v_{max}	2.43	1.733	1.43	1.23	1.182
80% v_{max}	2.43	1.728	1.43	1.24	1.132
100% v_{max}	2.43	1.726	1.44	1.24	1.134

Based on the simulation results shown in Table 2, one can find that the cases of 100% a_{max} and 80% v_{max} yield the shortest cycle time. The cycle time for the case of 100% a_{max} and 100% v_{max} is slightly longer (2 msec longer), which is possibly due to measurement noise. These two cases are considered to have both yielded the shortest cycle time.

Using Eq. (7), one can compute the mechanical energy consumed by the industrial robot. The simulation results corresponding to 25 different combinations of velocity commands and acceleration commands are shown in Table 3.

Table 3 Mechanical energy consumption

Mechanical energy	20% a_{max}	40% a_{max}	60% a_{max}	80% a_{max}	100% a_{max}
20% v_{max}	10.05	10.03	9.29	10.01	10.2
40% v_{max}	10.01	10.11	10.2	9.75	9.45
60% v_{max}	9.93	10.19	10.12	10.29	9.9
80% v_{max}	10.04	10.13	10	9.99	9.95
100% v_{max}	10.04	10.15	10.23	10.09	10.02

Based on the simulation results shown in Table 3, one can find that the cases of 60% a_{max} and 20% v_{max} consumed the least mechanical energy, which can save about 7.29% of mechanical energy. However, the cycle time for this case is 2.186 seconds, which is almost 93.1% longer than the minimum cycle time.

To cope with the problem, the proposed abductive reasoning-based approach is used. Firstly, the cycle time listed in Table 2 is converted into Table 4 using (6), where T_{max} =2.79 and T_{min} =1.132. Subsequently, the consumed mechanical energy listed in Table 3 is converted into Table 5 using Eq. (8).

Table 4 Normalized cycle time to be used in the proposed approach

$C(t)$	20% a_{max}	40% a_{max}	60% a_{max}	80% a_{max}	100% a_{max}
20% v_{max}	0	0.264174	0.364294	0.422195	0.428227
40% v_{max}	0.217129	0.607961	0.759952	0.820265	0.880579
60% v_{max}	0.217129	0.637515	0.820265	0.940893	0.969843
80% v_{max}	0.217129	0.640531	0.820265	0.934861	1
100% v_{max}	0.217129	0.641737	0.814234	0.934861	0.998794

Table 5 Normalized mechanical energy consumption to be used in the proposed approach

$w(t,\tau,\omega)$	20% a_{max}	40% a_{max}	60% a_{max}	80% a_{max}	100% a_{max}
20% v_{max}	0.24	0.26	1	0.28	0.09
40% v_{max}	0.28	0.18	0.09	0.54	0.84
60% v_{max}	0.36	0.1	0.17	0	0.39
80% v_{max}	0.25	0.16	0.29	0.3	0.34
100% v_{max}	0.25	0.14	0.06	0.2	0.27

Table 6 Simulation results of hypothesis

H	20% a_{max}	40% a_{max}	60% a_{max}	80% a_{max}	100% a_{max}
20% v_{max}	1.1627	1.2991	2.2068	1.404	1.2703
40% v_{max}	1.2909	1.453	1.5118	1.938	2.3547
60% v_{max}	1.357	1.4198	1.6196	1.6249	1.9412
80% v_{max}	1.2674	1.4631	1.7103	1.8287	1.9303
100% v_{max}	1.2674	1.4501	1.5401	1.7516	1.872

Moreover, in the simulation, it is assumed that the user wants to achieve a balance between energy consumption and cycle time but prefers to emphasize energy consumption slightly more. Therefore, the parameters are set as $a_1 = 0.6$ and $a_2 = 0.4$ are used in Eq. (2), while P_1 is $w(t,\tau,\omega)$ and P_2 is $C(t)$. Using Eq. (4), one can compute hypothesis H. The simulation results are shown in Table 6. Based on the simulation results shown in Table 6, one can find that the cases of 100% a_{max} and 40% v_{max} yield the best hypothesis, namely the best solution, with a value of 2.3547 (rounded to the fourth decimal place). In particular, with this choice, the cycle time is 1.33 sec (from Table 2), and the mechanical energy consumption is 9.45 (from Table 3). Comparisons among different approaches are listed in Table 7.

One can further calculate the cycle time difference between the proposed abductive reasoning-based approach and other approaches that were also tested in the simulation. The comparison results are listed in Table 8.

In addition, one can also calculate the mechanical energy consumption difference between the proposed abductive reasoning-based approach and other approaches that were also tested in the simulation. The comparison results are listed in Table 9.

Table 7 Comparisons among different approaches

Approach	Acceleration and velocity command	Cycle time	Mechanical energy consumption
Shortest cycle time	100% a_{max} and 80% v_{max}	1.132 sec	9.95
Least mechanical energy consumption	60% a_{max} and 20% v_{max}	2.186 sec	9.29
Proposed abductive reasoning-based approach	100% a_{max} and 40% v_{max}	1.33 sec	9.45

Table 8 Cycle time difference between the proposed abductive reasoning-based approach and other approaches also tested in the simulation

Approach	Cycle time	Cycle time difference compared with the proposed approach
Shortest cycle time	1.132 sec	−0.198 sec (−14.89%)
Least mechanical energy consumption	2.186 sec	0.856 sec (+39.16%)
Proposed abductive reasoning-based approach	1.33 sec	0 sec (0%)

Table 9 Mechanical energy difference between the proposed abductive reasoning-based approach and other approaches that were also tested in the simulation

Approach	Mechanical energy consumption	Mechanical energy consumption difference compared with the proposed approach
Shortest cycle time	9.95	0.5 (+5.03%)
Least mechanical energy consumption	9.29	−0.16 (−1.69%)
Proposed abductive reasoning-based approach	9.45	0 (0%)

5. Conclusions

This paper proposes an abductive reasoning-based approach to find suitable velocity and acceleration commands to achieve a good balance between energy savings and the robot's movement velocity. Gazebo, ROS 1, and Moveit are adopted in this paper to simulate the motion of a Franka robot. Simulation results indicate that the proposed abductive reasoning-based approach can provide a decent balance between the cycle time of products and the mechanical energy consumption of industrial robots. Compared with the shortest cycle time method, the proposed approach reduces mechanical energy consumption by 5.03%. In addition, compared with the least mechanical energy consumption method, the proposed approach saves 39.16% of cycle time. The proposed abductive reasoning-based approach can be applied to other parameter selection problems that require a good balance among several parameters.

Conflicts of Interest

The authors declare no conflict of interest.

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