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The optimization of energy consumption in product manufacture has analyzed

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***Abstract*---**A scheme is given for optimizing the movement of the robotic arm with the help of AHP so that the minimum energy consumption criteria can be achieved. As compared to Direct Kinematics, Inverse Kinematics will evolve two solutions out of which the best-fit solution will be selected with the help of AHP and is kept in search space for future use. The importance of sustainable manufacturing has been widely discussed. The optimization of energy consumption in product manufacture has been deeply analyzed, mainly focusing on the energy directly absorbed by the manufacturing process. On the contrary, this paper focuses on the analysis and optimization of the energy consumption related to the robot arm, probably the most mathematically complex robot anyone could ever build, and we will present an optimized solution for the movement of a three-arm manipulator using the Analytical Hierarchy Process (AHP).

***Keywords*---**Robotic arm, Analytical Hierarchy Process (AHP), Energy consumption, Sustainable.

Introduction

Many industrial countries witnessed an increase in the prices of both electricity and fuel during the last decade. According to recent statistics one of the large consumers of energy is the manufacturing industry. The majority of the energy is usually consumed by robots used in the manufacturing industry. In addition, the optimal usage of energy in robots plays an important role in minimizing CO2 emission in the production stage of a product's lifecycle. During the last years, the rapid increase of the energy price together with strictly international and national policies has pointed out the problem of energy efficiency, moving companies' awareness from the reduction of the production time to the identification of an optimal trade-off between production time and energy consumption [2]. The robotic arm is commonly used in industries. In many field

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applications where technical support is required, manhandling is either dangerous or is not possible.

In such situations, three or more arm manipulators are commonly used. They are of great demand to speed up the automation process. Three-link manipulators are the fundamental robotic arms according to [3], for many industrial processes, e.g. the robotized spot-welding assembly; the consumption can be cataloged as “process energy” or “auxiliary energy”. The process energy, generally representing the majority of the consumption, is the energy directly used in the manufacturing of the products, e.g. the assembly welding energy. The auxiliary energy is the energy required by the operations that allow the execution of the process, e.g. robotic energy consumption. Even if several papers cope with the reduction of the process energy [2], auxiliary energy plays a relevant role and deserves to be studied. According to [4], there is a need to optimize the movement for energy consumption and various mechanical and control related attributes like friction, settling time, etc., which will improve the performance. The total energy consumed by the robot is usually affected by the required torque on each joint and inertia tensors of each link.

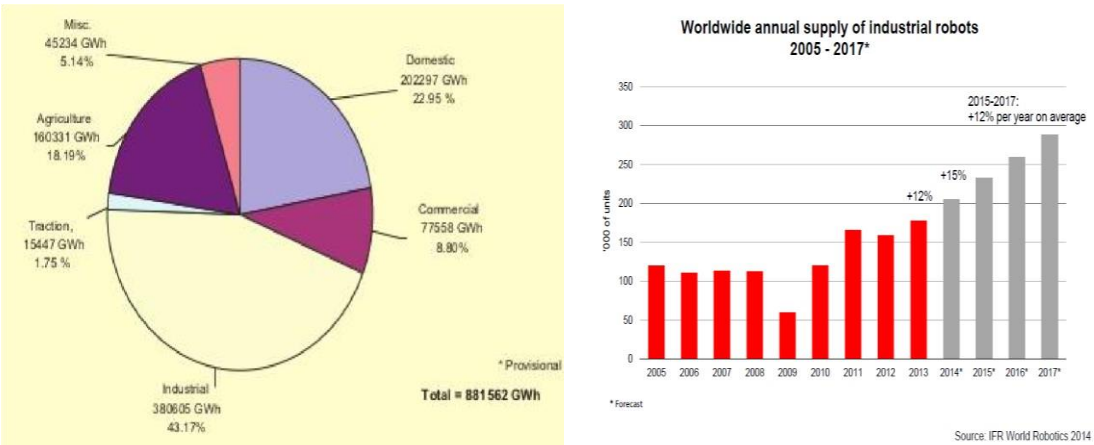

Fig 1. Shows the Energy Consumption of Different Sectors and Increase in Supply of Robots

Genetic algorithms are often viewed as function optimizers, although the range of problems to which genetic algorithms have been applied is quite broad. An implementation of a genetic algorithm begins with a population of (typically random) chromosomes. These structures evaluate and allocate reproductive opportunities in such a way that those chromosomes, which represent a better solution to the target problem are given more chances to reproduce than those chromosomes which are poorer solutions [4]. Analytical Hierarchy Process is a pragmatic way of reaching the best solution from a given search space without modifying the solution. This method is intensively used for solving corporate problems related to finance, marketing, etc. AHP has proved itself to be one of the best available methods to find the ranks of fitness values based on the application objectives [4].

Problem Statement

The paper focuses on robot energy consumption in pick-and-place tasks. A task consists of the grabbing or release of an object in a specific position, thus representing a constraint to the robot configuration during the task execution. As an example, the ABB -IRB140 industrial robot has been chosen.

Consider 3 links of the robot with 350mm, 360mm, 380mm lengths respectively, which has 50 of freedom and has a carrying capacity of 5kg, with a weight of 98 kg, power specification of 200-240 V AC ±10%, 50/60 Hz, 4.5 kVA; it can give accurate results within the range of 5-400C ambient temperature and 45-95 % (non-condensing) humidity and with a max. Reach of 810mm.

Methodology

The proposed approach is based on 4 steps, where, Inverse kinematics is applied on the 3 links to find link angles. For each link angle, we have obtained two solutions (step 1). AHP is applied for the different factors to obtain the fitness function (step 2). Three links each having two solutions in total gives six angles. These six angles are fed into GA such that they form different combinations. These combinations/solutions from the Genetic Algorithm, which generate the new population (step 3). Finding the optimized value from the previous step which fits the criteria (step 4) the block diagram of the system is shown below [4].

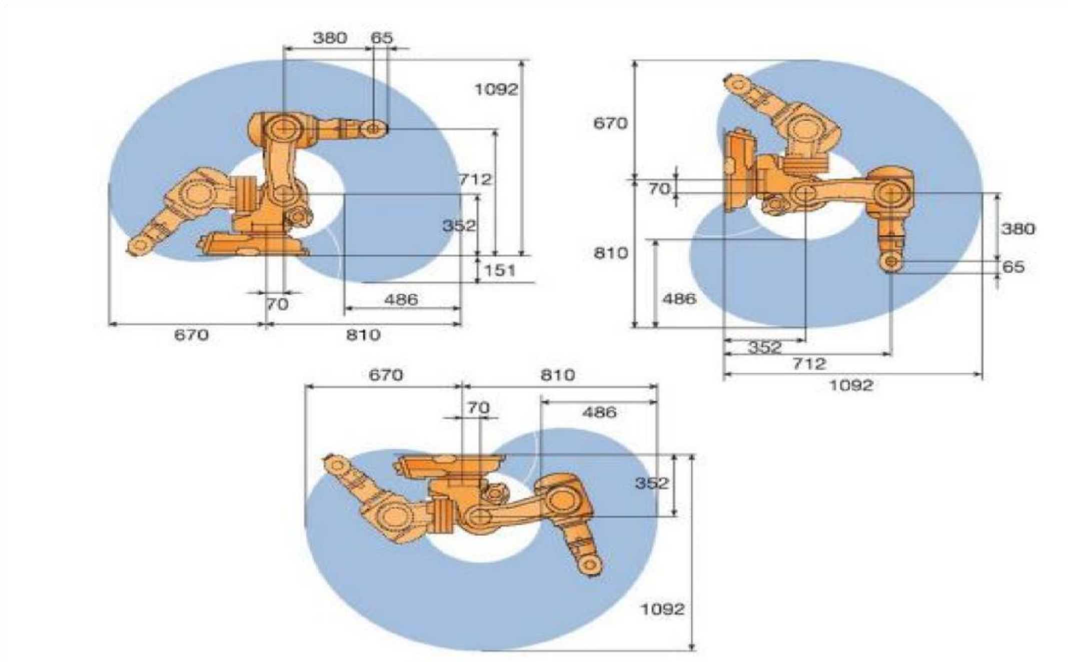

Fig. 2. Robot's frame

Kinematics of the Manipulators

In order to program the tool motion, we must first formulate the relationship between the joint variables, position, and orientation of the tool. This is called Kinematics Transformation. Kinematics can be done in two ways:

1) Direct kinematics
2) Inverse kinematics

Direct kinematics

A manipulator is composed of serial links that are affixed to each other revolute or prismatic joints from the base frame through the end-effectors. Calculating the position and orientation of the end-effectors in terms of the joint variables is called forward kinematics. In order to have forward kinematics for a robot mechanism in a systematic manner, one should use a suitable kinematics model. Denavit-Hartenberg's method that uses four parameters is the most common method for describing the robot kinematics. These parameters ai-1, αi-1, di, and θj are the link length, link twist, link offset, and joint angle, respectively. A coordinate frame is attached to each joint to determine D-H parameters. Zi axis of the coordinate frame is pointing along with the rotary or sliding direction of the joints [7].

Inverse Kinematics

The inverse kinematics problem of serial manipulators has been studied for many decades. It is needed in the control of manipulators. Solving the inverse kinematics is computationally expansive and generally takes a very long time in the real-time control of manipulators. Tasks to be performed by a manipulator are in the Cartesian space, whereas actuators work in joint space. Cartesian space includes orientation matrix and position vector. However, joint space is represented by joint angles. The conversion of the position and orientation of manipulator end-effectors from Cartesian space to joint space is called an inverse kinematics problem. There are two solutions approaches, [7]

a. Geometric
b. Algebraic used for deriving the inverse kinematics solution, analytically In this paper we are solving the Inverse kinematics using Geometric approach.

System development

Solving the inverse kinematics of the robot is an important step for calculating the inverse dynamics of the robot in the forthcoming steps. It is archived under the assumption that the first three joints are responsible for the end-effectors position and the last three are responsible for its orientation. With the given position and orientation of the target location, the position of the wrist is calculated. The previous assumption provides a simplification for the calculations therefore it is widely used for solving the inverse kinematics of the serial- chain manipulators. The calculations of link angles (θ1, θ2, θ3) are made geometrically. Requirements for manipulator having three-link and end effectors are [5]:

a. Link and Actuated joint
b. End effectors

c. Joint coordinates $\theta_1, \theta_2, \theta_3$
d. Reference point
e. End effectors coordinates x, y, ϕ
f. Link lengths.

Geometrical Equations

$x = l_1 \cos\theta_1 + l_2 \cos(\theta_1+\theta_2) + l_3 \cos(\theta_1+\theta_2+\theta_3)$ -------- (1)
$y = l_1 \sin\theta_1 + l_2 \sin(\theta_1+\theta_2) + l_3 \sin(\theta_1+\theta_2+\theta_3)$ -------- (2)
$\Phi = \theta_1+ \theta_2+ \theta_3$ --------- (3)

After rewriting and squaring and adding the equations, we will get one unknown θ_1, in the form of P cosα + Q sinα + R = 0

Where,

$P = - 2l_1x'$
$Q = - 2l_1y'$ α = θ
R = x´2 +y´2+l12-l2 2

Now finding the $\theta_1, \theta_2, \theta_3$

$$\theta_1 = \gamma + \sigma \cos^{-1}\left(-\frac{(x'^2+y'^2+l_1^2-l_2^2)}{2l_1\sqrt{x'^2+y'^2}}\right)$$

$$\theta_2 = atan2\left[\frac{y' - l_1 sin\theta_1}{l_2}, \frac{x' - l_1 cos\theta_1}{l_2}\right] - \theta_1$$

θ3 = ϕ – θ1 - θ2.

Now we choose to move the end effectors from reference point (0,0,0) to the destination point (63,36,32.4^0).
From the above values, solve using the inverse kinematics equation. We get:

θ_1 = 146.991°,
-80.953°

θ_2 = -62.987°,
110.593°

θ_3 = -51.911°,
2.7565°

From the above six solutions, we arrange them in eight combinations.

Genetic Algorithm

A Genetic algorithm (GA) is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. The algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution.

Analytical Hierarchy Process (AHP)

The analytic hierarchy process is a process that Structure a problem as a hierarchy or as a system, elicit judgments that reflect ideas, feelings, and emotions, represent those judgments with meaningful numbers, synthesize results, and analyse sensitivity to changes in judgment. [4]

The purpose of AHP is to structure complexity in gradual steps from the large to the small, or the general to the particular so that we can relate them with greater accuracy according to our understanding. Because experience is too vast to lay it out in a single network structure, we are satisfied with piecemeal decompositions and with occasional linkages of them.

The purpose is to improve our awareness by the richer synthesis of our knowledge and intuition. AHP is a learning tool. It is not a means to discover the TRUTH because the truth is relative and changing. In the AHP, next to setting up a STRUCTURE to represent a problem, the reciprocal property is the most fundamental aspect for creating a SCALE. [4]

A hierarchy is an efficient way to organize a complex system, and functionally, for controlling and passing information down the system. Unstructured problems are best grappled within the systematic framework of the hierarchy or a feedback network. In our case Fitness of each chromosome depends upon many factors like acceleration, jerk, the weight of the links, Forces acting on the links, Friction, etc.,

We will consider four mains factors on which the fitness function will be calculated by applying the Analytical Hierarchical Process. These four main factors are Movement (F1), Friction (F2), Least Settling Time (Min. Vibration) (F3), Forces acting on the links (F4). First, we will decide the importance and value of these four attributes for each angle separately. Table 1 for angle $\theta 1$ which is the angle moved by link-1 Similarly Table 2 and Table 3 for the angles $\theta 2$ & $\theta 3$.

Table 2
Importance and Value of the Four Attribute For Θ_1

Factor	Importance	Value (total 1)
F1	High	0.4
F2	Low	0.1
F3	Medium	0.2
F4	Medium	0.3

Max. Eigen value $\boldsymbol{\lambda_1}$ *= 4.23* **C.*i*** *= 0.07 (≤ 0.1).*

Table 3
Importance and Value of the Four Attribute For Θ_2

Factor	Importance	Value (total 1)
F1	Medium	0.2
F2	High	0.4
F3	Low	0.1
F4	Medium	0.3

Max. Eigen value $\boldsymbol{\lambda_2}$ *= 4.25* **C.*i*** *= 0.08 (≤ 0.1).*

Table 4
Importance and Value of the Four Attribute For Θ_3

Factor	Importance	Value (total 1)
F1	Medium	0.2
F2	Medium	0.2
F3	High	0.4
F4	Medium	0.2

Max. Eigen value $\boldsymbol{\lambda_3}$ *= 4.24* **C.*i*** *= 0.08 (≤ 0.1).*

Now, we have the Eigen values of the matrices corresponding to the three angles, thus it is possible to construct the Objective function or Fitness function. The Fitness function is shown in the equation below:

$$f(x) = \theta_1 \times \lambda + \theta_2 \times \lambda + \theta_3 \times \lambda$$

Results and Discussion

By considering the above flow charts we fed the fitness function into GA by giving the lower and upper bounds for each variable that affect the energy consumption of the robot. In this study, we assessed four components viz., Movement, Friction, Least Settling Time, and Forces acting on the links. In our assumption, these four factors are very important, play an important role to optimize the energy consumption. Follows optimized results prove the same. When we iterated the function we obtained the fitness value asset of combination. The graphs for the above results, which show the behaviour, follow as now we obtained the values from GA; we also want to calculate result from AHP to compare both the result, so that we can predict the best method to find the optimized solution. The inverse kinematics had yielded link angles based on a strict mathematical model. The mathematical model fails to accommodate the effects of various internal and external parameters concerning the three-link robotic arm.

The angles so obtained from inverse kinematics were more theoretical in nature and less pragmatic. GA software is used to get real solutions due to its high successive rates. The success rate of GA depends upon crossover and mutation. The main reason to use a genetic algorithm is there are multiple local optima, the numbers of parameters are very large, and the objective function is noisy or stochastic. AHP is a pragmatic method of mathematically ranking the various available alternatives (which get evolve during the execution of GA in various test runs/iterations) along with approximate reasoning. In this paper, we selected AHP in place of conventional techniques like Roulette Wheel, Rank Selection to reduce the ambiguity of the equations. However, there are innumerable optimization methods, the above factors driven us to use these techniques, which meet our requirement. By solving using GA we got the following graphs.

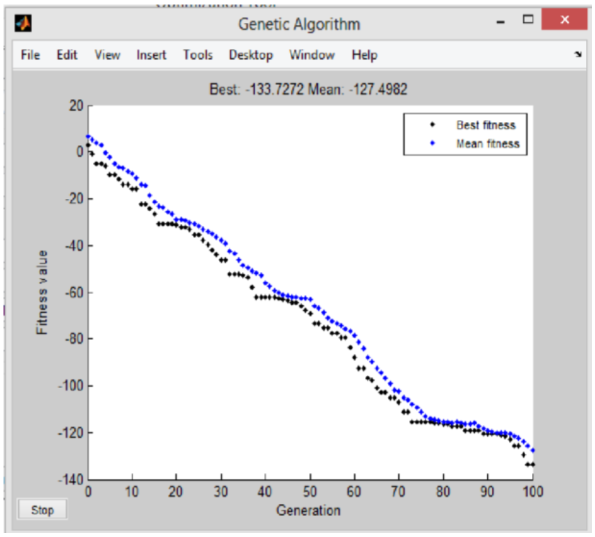

Fig. 3. Best fitness graph

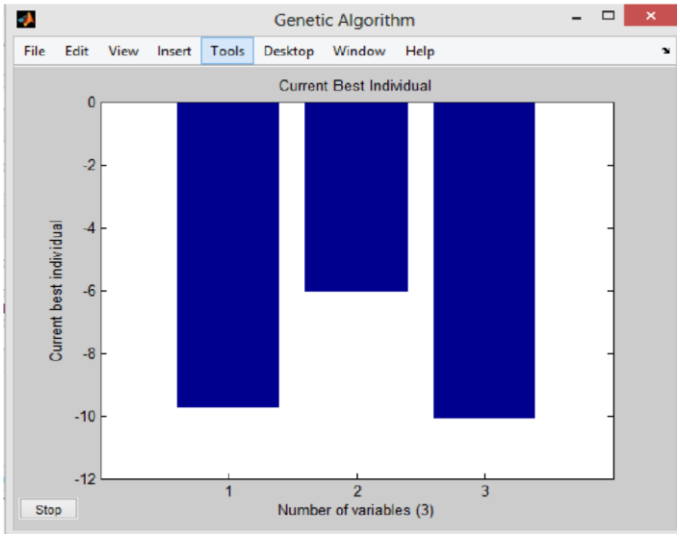

Fig.4.Best Individual

Conclusion

In this paper, we have focused on the analysis and optimization of the energy consumption related to the robot arm. We used the GA method and the AHP method for optimization. We have used GA and AHP separately and found the best fitness and best individual graphs. But we get the best-optimized solution by using GA and AHP together.

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