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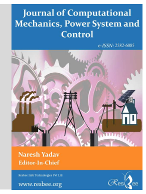

Hybridizing Lion and Dragonfly Algorithm for Robotic Assembly subsets recognition model

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Abstract: Nowadays, a lot of interrelated shape products have been proposed by manufacturing industries for diverse applications in diverse fields like aerospace, defense, as well as space centers. Because of assembly operation, 30 percent of time utilization occurs in manufacturing while comparing with the residual processes in manufacturing. Attaining the optimal sequence is highly complex due to the assembly sequence planning which is a multi-model optimization issue. The probable number of sequences increases exponentially as the number of parts in the assembly raises consequently attaining the optimal assembly sequences which are very complex and have time utilization. To attain the assembly sequences, there subsist numerous mathematical approaches. Nevertheless, current researches affirm that they carry out poorly when it comes to multi-objective optimal assembly sequence. Nowadays, numerous studies have worked on various soft computing-based approaches to solve assembly sequence issues. Here, the assembly subset recognition model is developed. The developed model is used initially to resolve the assembly sequence issues. This approach eradicates aforesaid assembly sets which have numerous directional changes and need high energy. Here, the Lion Mutated and Updated Dragon Algorithm (LMU-DA) is proposed, which is the theoretical hybridization of the Lion Algorithm (LA) and Dragonfly Algorithm (DA). This technique is evaluated with the conventional approaches and it is attained to be efficient in obtaining the optimal assembly sequence for an industrial product.

Keywords: Assembly Sequence, Fitness Function, Optimization Algorithm, Robots, Subset Recognition,

1. Introduction

The assembly process comprises physically multiple elements collectively In order to form novel sub-modules or completed products [1]. This description comprises processes such as riveting as well as welding, a lot of considering the mating act of the elements collectively in the assembly task [6]. Generally, it is considered to be highly complicated while evaluated with the others like material or machine handling so that it characteristically includes multiple tools and processes to entire. The assembly process has traditionally been a physical undertaking given this variety and variability. Infrequently, particular machines are presented to aid as well as make more efficient the assembly procedure more, nevertheless, these all-in-one automated solutions be inclined to be cost is high priced and in-flexible while compliant with changes in product process or design [7].

In laboratory settings, the proof-of-concept robotic solutions have effectively shown the possibility of using "agile robots for the assembly issue", and these technologies are just starting to create their way onto manufacturing lines for decades [11]. Generally, the Assembly does not just part one-by-one connection; it needs numerous features such as assembly setup time, work cell understanding, fixture agreement, and assembly sequence [8]. In order to attain "an optimal sequence is a hard task as ASP is a nondeterministic probability (NP)" hard combinatorial issue. One of the main objectives of the assembly operations is to manufacture processes cost that utilize a high time. It is categorized into the semi-automated assembly, manual assembly, and robotic assembly [9]. From these, robotic assembly acts as an important role in intense automatic industries. By numerous factors, robotic assembly operations are inclined that should be considered like assembly direction, contact type, the shape of the part, as well as part orientation [10].

In assembly lines, the industrial robots are at present deployed are location controlled and programmed to pursue acquired trajectories to conduct the assembly tasks [16]. The known objects are handled by the location-controlled robots within the logical assembly lines marvelously attaining extremely accurate control in velocity and location [3]. Nevertheless, they cannot tackle any unforeseen changes in assembly operations as well as require monotonous reprogramming to become accustomed to

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novel assembly tasks. It is critical to estimate the complementary force-torque profiles in addition to location and direction trajectories, as classic robot assembly operations require making contact with the work pieces to be assembled. A robot requires calculating the work-pieces poses initially to learn the assembly operations execution, as well as subsequently assembly sequences generated by learning from the human exhibition. A few dedicated grippers must be modeled for some specific objects shown in the assembly workspace to seize these parts with several shapes and obtain the force-torque data. Especially, the material to be twisted is unstructured, at the time of a twisting task that creates the control of the rotating angle, which is highly complex. Taking into consideration of aforesaid issues, robotic assembly is a highly challenging issue in the robotics research field, especially in unstructured environments. Conversely, humans have outstanding skills to carry out the assembly tasks which need fulfillment and force control.

The organization of the paper is as follows: Section 2 explains the literature survey and section 3 demonstrates the system modeling. Section 4 describes the proposed model of the Hybrid Lion and Dragonfly approach. Section 5 describes the result and analysis. Section 6 describes the conclusion of the paper.

2. Literature Survey

In 2019, G Bala Murali *et al* . [1] addressed the issue an assembly sequence planning in order to attain the optimal solution. This paper aspires to exploit the stability graph to produce stable assembly subsets to attain the optimal assembly sequences. In the developed model, the stability graph was considered to minimize the search space as well as to arraign the assembly sequences. In addition, the assembly subset's fitness was estimated based on the user weight at every level prior to proceeding to the superior levels. Because of this, at each phase, the superior fitness value subsets were eradicated by that time of implementation will minimize extremely. In 2020, Gunji Bala Murali *et al.,* [2] worked on “computer-aided design (CAD)-based and knowledge-based techniques” to produce optimal sequences that utilize additional search space throughout the implementation of the approach. To produce an optimal robotic assembly sequence by considering the aforesaid statement as well as the benefits of the artificial intelligence approaches, the fruit fly approach with enhancement was presented. This approach was presently majorly based on how fruit flies can recognize fruits based on their smell. The proposed model was used for diverse industrial products to verify the performance of the approach. In 2018, Jeremy A. Marvel *et al.,* [3] presented a review of multi-robot assembly applications and techniques to explain the inclinations and broad imminent into multi-robot assembly issues for industrial applications. Fixtureless assembly sequences were focused on impacting 2 or more robotic systems. Here, assemblies types can identify which were set up by using multiple robots, the approaches which synchronize the motions of the robot to finish the assembly operations as well as the measures exploited to evaluate the quality as well as assemblies' performance. In 2018, Zuyuan Zhu and Huosheng Hu [4], worked on new research and improvement in the Learning from demonstration (LfD) field. The most important spotlight was positioned on how to show the instance behaviors to the robot in assembly operations. Additionally, the extraction of manipulation features for robot learning and imitative behaviors was generated. To estimate the robot imitation learning performance, different measures were validated. In particular, the LfD application in robotic assembly was a major topic in this work. In 2018, A. Balamurali Gunji *et al.,* [5] worked on the assembly subset recognition technique. To resolve assembly sequence issues, the adopted model was used during the foremost time. This technique eradicates the assembly sets which encompass high directional changes and it necessitates additional energy. The performance analysis of the adopted model was evaluated with more conventional models and was found to be efficient in attaining the optimal assembly sequence.

3. System Modeling

In manufacturing, assembly is the process wherein various models are combined collectively to form a product. As stated before, various studies have been examined concerning diverse techniques to attain optimum assembly sequence. Additionally, to attain the “optimum assembly sequence with a minimum number of iterations” [6], the assembly subsets identification approach is considered. Here, to produce assembly subsets, the parts in a product having contact with one another are grouped. Fig. 1 demonstrates the system modeling of assembly subset recognition.

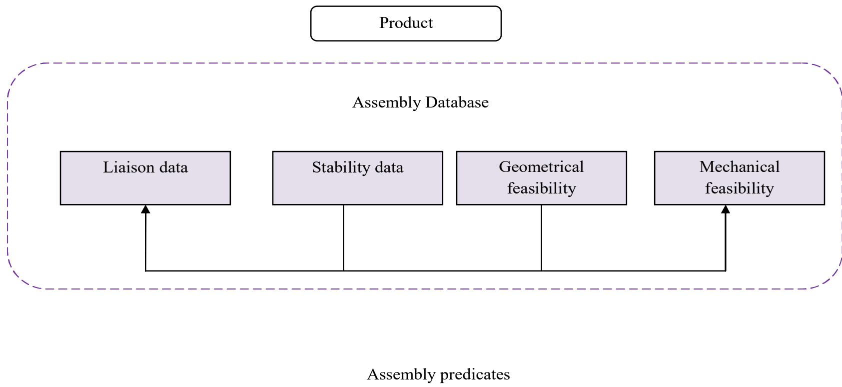

Fig.1. *System modeling of assembly subset recognition*

3.1 Assembly Subsets Recognition Model

By assembly predicates such as stability data, liaison data, geometric feasibility data, and mechanical feasibility data, the assembly subsets are recognized in the assembly subset recognition approach. To attain the optimal assembly sequence, there are numerous techniques are presented. These approaches need a lot of time as well as search space at the time of execution in order to attain an optimal sequence. The adopted hybrid model at first recognizes 2 set assemblies by exploiting the assembly predicates. Subsequently, the generated assembly sets are estimated using the fitness function which is a function of directional changes as well as the energy needed to relocate the parts.

Eq. (1) can be indicated as the total number of directional changes, K indicates the total number of parts in an assembly, $d.c_{j\cdot j+1}$ represents a directional change for 2 successive assembly operations throughout the assembly of the product. The energy needed to progress the part formulation is computed based on eq. (3).

$$\sum_{j=1}^{k-1} d.c_{j\cdot j+1} \tag{1}$$

$$d.c_{j\cdot j+1} = \begin{cases} 0 & \text{if } d.c_j = d.c_{j+1} \\ 1, & \text{otherwise} \end{cases} \tag{2}$$

$$E = x \times \rho \times v \times g \tag{3}$$

The energy formulation stated in eq. (3), the individual part is computed, i.e., density, mass, and volume are considered. By exploiting the digital mockup optimizer toolbar, it is due in "computer-aided 3-D interactive application (CATIA V5 R17)" they are produced robotically throughout the bounding box technique. In eq. (3), x represents the distance traveled by a part in an assembly, E (Joule) represents the energy needed to transmit the part for the assembly, and ρ represents part density, g represents acceleration because of gravity, and v represents part volume. From the bounding box, the density is used which is attained "from CATIA V5 R17 for a given product in the energy formulation".

On the basis of the directional changes a fitness function is used and at each level, the part energy to evaluate the generated assembly subsets. When modeling fitness formulation, the energy must be divided as directional changes are unit minimum, by any constant number that is high for instance 1 × 1011.

Eq. (4) represents the fitness function, where α_1 and α_2 represents user-defined weights for directional changes and energy, which range from 0 to 1.

$$f = \sum_{j=1}^{k-1} \left(\alpha_1 \times d \cdot c_{j\cdot j+1} + \alpha_2 \times \left(x_{j\cdot j+1} \times \rho \times v \times g \right) \right) \tag{4}$$

The weights selection is "left up to the industrial engineer". The adopted model uses the directional changes, as well as the energy as a fitness function; it eradicates the subsets, which are possessing maximum fitness values. To produce the superior-level subsets, the qualified subsets are exploited, and to produce the superior-level subsets, the superior subsets are estimated for fitness value. This procedure carries on until the subset length is equivalent to the assembly length. In three industrial products, the adopted model is used like simple transmission assembly; gear assembly; and De Fazio transmission assembly. Gear Assembly predicates such as stability data, liaison data, mechanical feasibility data, and geometrical data are needed to produce the assembly subsets. In CATIA V5 R17, by running the macros, the predicates extraction is performed automatically. In general, macros are the same as the VB script coding, where in writing the code, VB script commands are exploited.

a) Liaison Data for Gear Assembly:
It is indicated in the matrix form that presents the information regarding the parts contact [5].

b) Stability Data
It presents information regarding the stability of the contacting part: also the two parts are in permanent or partial stability.

c) Geometric Feasibility
In 6 directions, the feasibility of the parts is examined to identify which direction is feasible to assemble the part, not including the interference. Also, it is named an interference matrix. During assembly, it aids to find the number of directional changes of end-effectors.

d)Mechanical Feasibility:
It presents the information regarding the amalgamation of 2 kinds with physical connectors in the attendance of another part. In general, it comes into continuation while any physical connectors are considered as the most important parts.

4. Proposed Model: Hybrid Lion and Dragonfly approach

The adopted model to attain the optimal assembly sequence is described in this section. This technique exploits the LMU-DA [14] model to estimate the fitness of the subassemblies prior to happening to produce the superior-level subsets. Not like other approaches, the adopted model minimizes the time and search space, as this model attains the assembly sequence issue solution. Primarily, by assembly subsets recognition, the minimizations of iteration are attained, and at each phase, the fitness is evaluated. This technique eradicates the subsets that have maximum fitness value amid the reasons for the minimization in iteration count [15].

In numerous studies, the conventional Dragonfly algorithm (DA) [13] is used because of its ease and important static and dynamic behavior. However, it lacks obstruction such as pre-mature convergence as well as getting no trouble trapped into the local minima. Conversely, conventional LA [12] is highly consistent and robust in performance. However, the time utilized to perform territorial defense is large. In this paper, a hybridized form of these 2 optimization approaches is developed to pack with the aforesaid disadvantages, called LMU-DA [14]. In reality, the theoretical changes of DA are performed by maintaining the LA approach logic.

While compared with other conventional approaches, this technique has one more benefit in that there is no requirement to generate an arbitrary assembly sequence. The probability of a feasible one is minimum if the sequence is produced arbitrarily, therefore needs a higher number of iterations is needed. The process of the adopted model pursued in the solution updating is stated below:

By exploiting the mutation process of LA, the DA separation (Sa_g) is updated. Specifically, exploiting Eq. (5), Sa_i indicates the separation, and exploiting the variable X and X_j location of the current swarm and its neighbour is shown. It is updated with Eq. (6), rather than updating the search agent separation. In LA, the mutation formulation is formulated in Eq. (6) and Eq. (7). Moreover, the number of elements and mutation point are expressed as NP and MP, r indicates a random number correspondingly.

$$Sa_i = \sum_{j=1}^{N} X - X_j \tag{5}$$

$$MP = \text{round}(1 + NP(\text{new cub} - 1) \cdot r \tag{6}$$

$$\text{new cub} = \min(MP) - (\max(MP) - \min(MP)) * r \tag{7}$$

By exploiting the nomadic lion distance update, the Distance of DA is updated. Generally, the DA updates its distance with the support of Eq. (8). Nevertheless, in the proposed model, the search agents update their distance with Eq. (9). Moreover, I represents chromosome size and $a-b$ indicates diversity amid the solution sizes.

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{8}$$

$$\text{Distance} = \sqrt{\frac{1}{I * \text{sum}(a-b)^2}} \tag{9}$$

At first, 2 sets of assemblies are produced by exploiting the assembly predicated. In order to estimate the fitness of 2 set assemblies, aforesaid subsets are transmitted to the proposed model.

5. Result and Analysis

In this section, the experimentation of the adopted technique over the conventional techniques such as "Genetic Algorithm (GA), Ant colony optimization algorithm (ACO), and fruit fly algorithm was presented". Fig 2 exhibits the analysis of the adopted model over the existing models regarding the motor drive assembly for the original assembly subsets. Fig. 3 demonstrates the computational time of the adopted model over the existing techniques. Fig 4 represents the performance analysis of the adopted model over the existing techniques as regards transmission assembly. Moreover, the overall analysis demonstrates the adopted model is superior to the existing techniques.

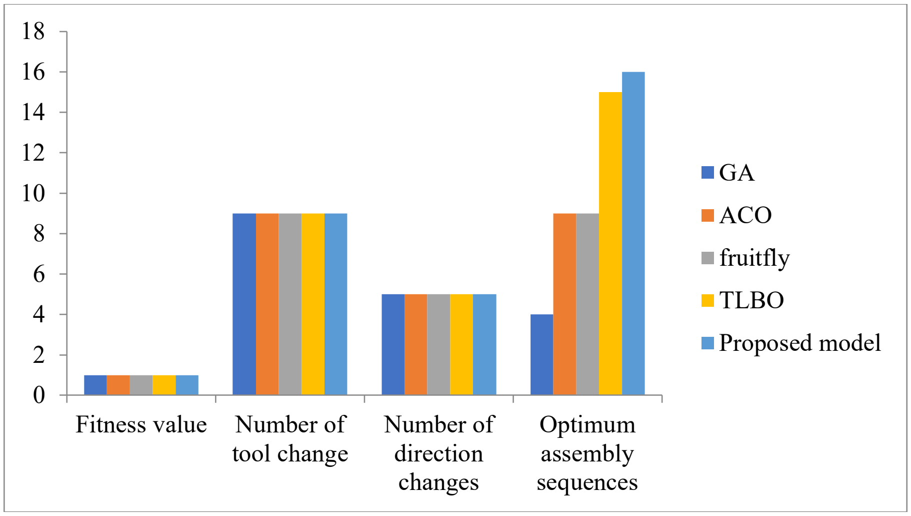

Fig.2. *Analysis of the adopted technique over the existing techniques regarding the motor drive assembly*

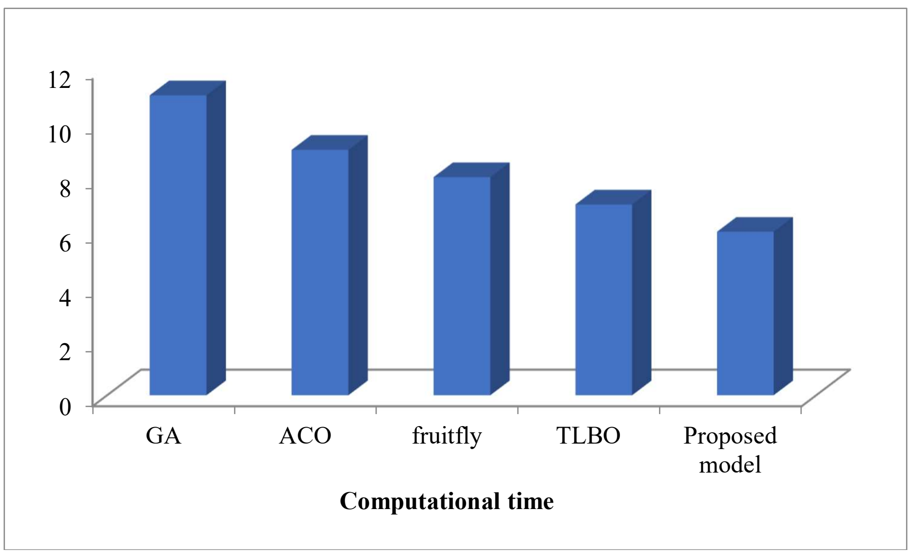

Fig.3. *Computational time of the adopted technique over the existing techniques*

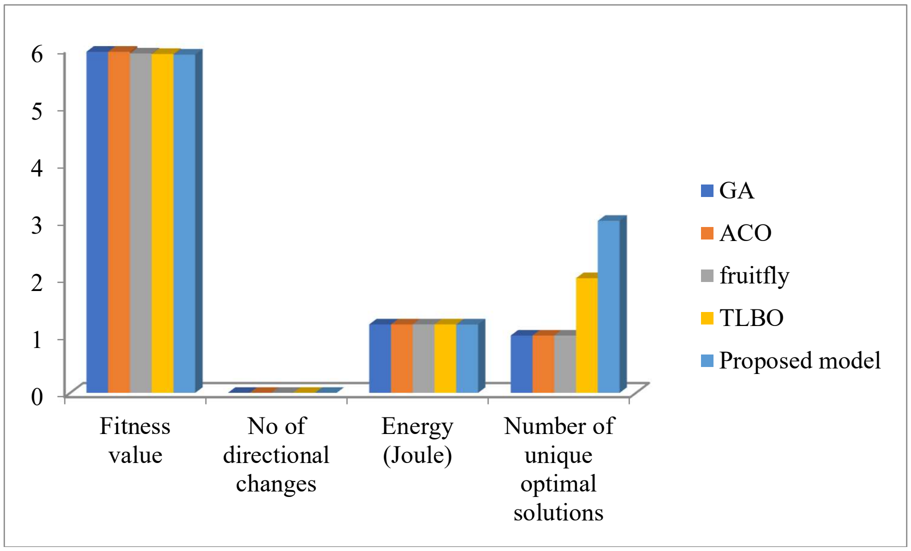

Fig.4. *Analysis of the adopted technique over the existing techniques regarding transmission assembly*

6. Conclusion

By exploiting the LMU-DA approach, the adopted assembly subset recognition, to obtain optimal assembly sequence planning, was effectively demonstrated in diverse industrial assemblies. From the predicate criterion, the adopted model recognizes the sub-assemblies to obtain the optimal assembly sequence rather than the random assembly sequence generation consideration. It enhances the execution time and obtains the solution rapidly compared with the other optimization approaches. Before happening to higher subsets, this approach estimates the fitness function subsequent to each subset generation. This technique exploits the method of generating the assembly subsets, and by that, more distinctive solutions were attained.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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