Artificial Immune Algorithm for Subtask Industrial Robot Scheduling in Cloud Manufacturing

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Abstract: The current generation of manufacturing industry requires an intelligent scheduling model to achieve an effective utilization of distributed manufacturing resources, which motivated us to work on an Artificial Immune Algorithm for subtask robot scheduling in cloud manufacturing. This scheduling model enables a collaborative work between the industrial robots in different manufacturing centers. This paper discussed two optimizing objectives which includes minimizing the cost and load balance of industrial robots through scheduling. To solve these scheduling problems, we used the algorithm based on Artificial Immune system. The parameters are simulated with MATLAB and the results compared with the existing algorithms. The result shows better performance than existing.

1. Introduction

Industrial robots play a vital role in an automation industry [1]. Industrial robots came into exists in the year 1954, at the same time the basic concepts, requirements and maintenance of industrial robots were also discussed [2]. The main reasons for implementation of Industrial Robots by Manufacturing industry [3] are (i) Task performed by industrial robots are fast compared to manual methods also performs, more number of Tasks because of software and technology. (ii) Industrial robots minimize the usage of time and money compared to traditional methods. (iii) A robot can perform automated tasks/subtasks in a single step by reducing transition time and space availability. (iv) Robots can avoid re-work that happens because several reasons in-turn avoiding productivity loss. (v) High production and profit sale from industrial robot helps in quick recovery of capital expenses. Even though there are many logistic services used by enterprises to improve resource sharing and collaborative work among the enterprises they lack insufficient utilization of manufacturing resources [8] hence there is a need of a model which allows exploiting these resources more effectively.

Cloud Manufacturing (CM) is one of the growing paradigms; the contribution of cloud manufacturing to the success of manufacturing industry is phenomenon. It is a network based manufacturing model which provides information about distribution, description, and registration of exploited shared manufacturing resources [4]. Cloud manufacturing provides an efficient cooperation between the production chain and enterprise cluster. The key characteristics of cloud manufacturing include agility, stretchability and scalability [5]. The backbones of CM are the technologies such as the Internet of things, cloud computing, social media, and Service Oriented Architecture [6]. The heterogeneous nature of manufacturing industries demands an intelligent scheduling model on cloud manufacturing to control the production. Existing task scheduling models fails to allocate the manufacturing resources effectively, this paper made an attempt to provide a subtask scheduling model.
for, minimizing cost and load balance of robots, these objectives are achieved by implementing Artificial Immune Algorithm.

The biological immune system is an adoptive system which protects individual from infections due to foreign agents (bacteria, virus etc) known as Antigens (Ag). An immune system consists of number of cells which recognizes and destroys the Antigens known as Antibody (Ab). The system categorizes all cells into self-cells or not with the help of an intelligent task force action from both local and global, using network of its chemical messengers for communication [16]. This biological process inspired the researchers to develop an Artificial Immune System (AIS) to solve different application problems. Encoding→similarity measure→selection→mutation is the four-decision parameter in AIS. In this paper the scheduling of sub task input to robot referred as antigen and Antibody referred to candidate solution. This paper proposes Immune based Artificial immune algorithm to solve subtask robot scheduling in cloud manufacturing .To measure the performance of the scheduling ,simulation experiments have made and results are obtained using MATLAB and to validate we compared with existing Genetic Algorithm(GA).

The rest of this paper is organized as follows section-2 gives information on cloud manufacturing system and cooperative manufacturing model, section-3 describes formation of tree structure subtasks and example of subtask scheduling, section-4 contains formulation of subtask scheduling strategies, implementation methods and flow chart of the proposed algorithm section-5 provides the settings of the simulation parameters and results. And at the end section-6 gives the conclusion.

2. Cloud Manufacturing System

We present a cooperative manufacturing system figure 1 the stepwise processing procedure of Cloud Manufacturing (CM) system is given below

Step1: CM is introduced to the system by middle wares such as Manager, scheduler, and publisher

Step2: Clients sends a task request to the robot’s scheduler through internet and scheduler starts working accordingly

Step3: Scheduler allocates each subtask to a robot with instructions through internet after analyzing the current state of robot’s process of each task.

Step4: The robots present in each manufacturing centers starts handling the allocated subtasks to them.

![Figure 1. Cooperative manufacturing model](image)

**Table 1.** Notation and Description of subtask scheduling in CM
| S.N | Notation | Description |
|-----|----------|-------------|
| 1   | i) N<sub>wh</sub> | Total number of warehouses. Which Stores the finished products from each task. ii) wh<sup>i</sup> |^<sup>i</sup> th warehouse (0 ≤ t < N<sub>wh</sub>) |
| 2   | i) N<sub>mc</sub> | Total number of manufacturing centres ii) MC<sup>i</sup> |^<sup>i</sup> th manufacturing centre (0 ≤ i < N<sub>mc</sub>) , contains different types of Robots each has the capacity of transporting the raw materials. |
| 3   | T<sub>ti</sub> | Unit Transportation Time, time required to transport the product in MC<sup>i</sup> |
| 4   | T<sub>c,i</sub> | Unit Transportation Cost, represents the cost facilities of transportation available to transport the product in MC<sup>i</sup> |
| 5   | d(a,b) | Distance between location ‘a’ and location ‘b’ |
| 6   | i) N<sub>ro</sub> ii) R<sub>i,j</sub> | Total number of different set (types) of robots Represents robot of j<sup>th</sup> type residing in MC<sup>i</sup> |
| 7   | P<sub>t(i,j)</sub> | Unit Production Time, represents time needed by R<sub>i,j</sub> to produce one URC<sup>*</sup> (Unique Reference Component) **URC**: Considering the complex nature of subtasks a unique metric URC was introduced which measures the relative cost and relative time to handle subtasks (a sample component is selected and assigned cost and time for URC to handle it) |
| 8   | P<sub>C(i,j)</sub> | Unit Production Cost, cost required for R<sub>i,j</sub> to produce one URC |
| 9   | W<sub>t(i,j)</sub> | Workload remaining to handle in R<sub>i,j</sub> |
| 10  | i) N<sub>st</sub> ii) st<sup>n</sup> | Total number of set of (types) subtasks Subtask of n<sup>th</sup> type, minimal component handled in robots |
| 11  | F(N<sub>st</sub>,N<sub>ro</sub>) | Function matrix between ‘st’ and ‘R<sub>i,j</sub>’. Table 2 Defined as F(N<sub>st</sub>,N<sub>ro</sub>) = \( \begin{cases} 1, & \text{if } R_{s,j} \text{ handles } st^n \\ 0, & \text{otherwise} \end{cases} \) |
| 12  | i) N<sub>pr</sub> ii) (N<sub>pr</sub>)<sub>m</sub> | Total number of types of process Process of type m, which provides the relationship between structure of subtask and procedure of finished product |
| 13  | i) N<sub>h</sub> ii) T<sub>k</sub> | Total number of task going to schedule K<sup>th</sup> task |
| 14  | i) (P<sub>r</sub>)<sub>k</sub> ii) (P<sub>r</sub>)<sub>k,n</sub> | Processes type for T<sub>k</sub> Previous subtask type for st<sup>n</sup> in (P<sub>r</sub>)<sub>k</sub> |
| 15  | N<sub>PI</sub> | Total number of product items, refer to MC that st<sup>n</sup> of T<sub>k</sub> is scheduled to target warehouses. |

Table 2. Mapping between subtask and robot types

|        | R<sup>*</sup><sub>1</sub> | R<sup>*</sup><sub>2</sub> | R<sup>*</sup><sub>3</sub> | R<sup>*</sup><sub>4</sub> | R<sup>*</sup><sub>5</sub> |
|--------|------------------|------------------|------------------|------------------|------------------|
| St<sup>1</sup> | 1                 | 0                 | 0                 | 0                 | 0                 |
| St<sup>2</sup> | 0                 | 1                 | 0                 | 1                 | 0                 |
| St<sup>3</sup> | 0                 | 1                 | 0                 | 0                 | 1                 |
| St<sup>4</sup> | 1                 | 0                 | 0                 | 0                 | 1                 |
| St<sup>5</sup> | 0                 | 1                 | 0                 | 0                 | 0                 |

3. Formation of Tree structure subtasks
Due to heterogeneous relationship between subtasks in a process results too many structures for assembling purpose these structures are transformed into tree structure which gives only aggregation relationship and makes easy to describe the types of the process. For an example let A be a subtask which is divided into two subtasks $A_1$ and $A_2,$ the components of $A_1$ and $A_2$ are used for two successive subtasks B and C and this how tree structure of subtasks is formed. The subtasks which finishes at the end of the process forms the root of the tree as shown in Table 3.

Let’s define a function $G = \begin{cases} 1, & \text{if } s^n \text{ exists in } (N_p)_m \\ 0, & \text{otherwise} \end{cases}$

Let $l_{m,n}$ = number of layers from ‘$s^n$’ to root in $(N_p)_m$ and the mean layer position of ‘$s^n$’ in the process is given below

$$St(l)_n = m = \frac{\sum_{m=0}^{N_p-1} G_{l_{m,n}}}{\sum_{m=0}^{N_p-1} G}$$

Here $s^n$ with greater $st(l)_n$ is handled first in the process

Let $D_{k,n,i,j}$ represents Allocation function that is scheduling of $s^n$ in $T_k$ to $R_{i,j}$ by $G$ in $mc$. And is defined as

$$D_{k,n,i,j} = \begin{cases} 1, & \text{if } s^n \text{ in } T_k \text{ schedule to } R_{i,j} \\ 0, & \text{otherwise} \end{cases}$$

### Table 3. Formation of tree structure of subtask of process

| Layers | Process-1 | Process-2 | Process-3 |
|--------|-----------|-----------|-----------|
| Layer-2 | $s^1$     |           |           |
| Layer-1 | $s^2$     | $s^3$     | $s^4$     |
| Layer-0 | $s^3$     | $s^7$     | $s^5$     |

#### 3.1 Example of subtask Scheduling:
Let $N_{pr}=3, N_{st}=5, N_{ro}=5, N_{mc}=5, N_{wh}=3$

From Table-3, the process types for task-1, task-2, task-3 and task-4 are Process-1, Process-2, Process-2 and Process-3 respectively.

From Figure 3 the Target warehouses for task-1, task-2, task-3 and task-4 are wh-1, wh-2, wh-3 and wh-2 respectively. Also, $s^1$ of task-1 is handled in $R_{1,1}$ hence $D_{1,1,1,1} = 1$ $s^2$ of task-2 is handled in $R_{2,2}$ hence $D_{2,2,2,2} = 1$, $s^3$ of task-3 is not handled in $R_{3,2}$ and in $R_{3,1}$ hence $D_{3,3,3,2} = 0$ and $D_{3,3,3,1} = 0$ and so on.

Robot tree for subtasks is given in the figure 2.
4. Formulation of Optimal Scheduling Objectives

Here we are formulating two optimizing objectives considered in our research namely minimizing overall cost and load balance in robots.

4.1 Optimization of overall cost for $R_{i,j}$:

Let $C_{i,j}$ denotes the overall cost of $R_{i,j}$ which includes production cost denoted as $C_p(i,j)$ and transportation cost $C_t(i,j)$ of $R_{i,j}$

i.e., $C_{i,j} = C_p(i,j) + C_t(i,j)$

And $(i, j) = \sum_{k=0}^{N_h-1} \sum_{n=0}^{N_r-1} D_{k,n,i,j} I_n U_{(pr)k,n} P_c(i,j)$

$C_t(i, j) = \sum_{k=0}^{N_h-1} \sum_{n=0}^{N_r-1} D_{k,n,i,j} V_{(pr)k,n} P_c(i,j)$

Where,

- $(Pr)_k$: Process type for $T_k$
- $(P_{r})_{k,n}$: Types of previous subtask of st$^n$ in $(P_{r})_{k,n}$
- $I_n$: Total number of Items
- $U_{m,n}$: Subtask unit production output
- $V_{m,n}$: Subtask unit transportation volume
- $S_{k,n}$: mc containing st$^n$ of $T_k$ scheduled to target warehouse

Objective is to minimize the overall cost of $R_{i,j}$

i.e., minimize $\left(\sum_{i=0}^{N_{mc}-1} \sum_{j=0}^{N_{ro}-1} C_{i,j}\right)$ s.t $0 \leq i < N_{mc}$, $0 \leq j < N_{ro}$

4.2. Load Balance Scheduling:

Let $L_{B(i,j)}$ be load of $R_{i,j}$ defined as

$L_{B(i,j)} = \sum_{k=0}^{N_h-1} \sum_{n=0}^{N_r-1} D_{k,n,i,j} I_n U_{(pr)k,n}$

Objective is to minimize the standard deviation of the loads for $R_{i,j}$

i.e., minimize $\left(\text{std } L_{B(i,j)}\right)$ s.t $0 \leq i < N_{mc}$, $0 \leq j < N_{ro}$
### 4.3 Implementation of AIS for Optimal Scheduling

Robot subtask scheduling is NP-hard problem. From literature there exist many heuristic algorithms to solve this assignment problem. In this paper we implemented AIS based algorithm to this problem. The fitness functions of the considered objectives and the flow chart for AIS Algorithm is given below

Fitness functions for optimization objectives considered are

\[
\text{Fit}_1 = \frac{1}{\sum_{j=0}^{Nro-1} c_{ij}} \quad \text{and} \quad \text{Fit}_2 = \frac{1}{\text{std}(L_B)}
\]

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**Figure 4.** Flow Chart of the proposed Algorithm
5. Simulation Parameters
The simulation of flowchart we use the following parameter and fixed the value of the parameter is as
follows

Table 4. Parameter Setting for Simulation

| Parameters | Values | Parameters | Value Range       |
|------------|--------|------------|-------------------|
| $N_{mc}$   | 10     | $d(a,b)$   | [500,2000]        |
| $N_{ro}$   | 12     | $T_{c,i}$  | [50,80]/$(ton.100km)$ |
| $N_{wh}$   | 05     | $P_{c(i,j)}$ | [20,50]$       |
| $N_{st}$   | 16     | $P_{t(i,j)}$ | [30’60] min    |
| $N_p$      | 16     | $U_{m,n}$  | [1,6] times of URC |
| $I_n$      |        |            | [50,100]         |

To solve the problem the number of task consider as 20, 30, 40, 50, 60. And 20 different types of robots
randomly had chosen. The threshold fixed as 40 to 120 and conducts the simulation using MAT LAB
and considers the performance as standard deviation of robot load balancing and overall cost. The same
performed with GA for validate the result as shown below.

Table 5. Performance of AIS

| Number of subtasks | AIS | GA |
|--------------------|-----|----|
| Load balance       | Overall cost | Load balance | Overall cost |
| 20                 | 950  | 350 | 952   | 349   |
| 30                 | 1250 | 560 | 1251  | 558   |
| 40                 | 1500 | 700 | 1499  | 699   |
| 50                 | 1650 | 500 | 1650  | 499   |
| 60                 | 1700 | 850 | 1701  | 850   |

The performance of scheduling shows optimal performance that is minimal standard deviation of robot
load with low cost for CM. The table values shown that the overall cost grows as the load increases and
it depends on distance and cost of transportation. The workload is high, there is a congestion of subtask
in robot.

6. Conclusion
This Paper presented AIS for subtask scheduling of industrial Robots based on cloud manufacturing
model for cooperative manufacturing cluster. This paper addressed two scheduling optimizing strategies
such as minimizing overall cost and load balance in robots. The simulation results shown optimal
performances on above said optimizing strategies. Future research can be done on other parameters of
subtask scheduling in a robot such as Arriving pattern of task, Inventory costs.

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