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EXPLORATORY QUANTITATIVE STUDY OF OPTIMAL ADVANCED MANUFACTURING PROCESS PLAN SELECTION USING A SWARM INTELLIGENCE TECHNIQUE

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ABSTRACT

Integration of different phases of production process is one of today's problems in manufacturing. This exploratory study attempts to address this issue by selecting the best manufacturing process plan through the application of swarm Intelligence technique - Ant Colony Optimization (ACO)technique. The problem was simulated and modelled with some assumptions. Series iterations were carried out using the ACO algorithm. The results obtained revealed that an optimal manufacturing process plan selection can lead to optimal time and cost of turning raw materials to finished parts, which directly impacts on the efficiency of any manufacturing organisation.

Keywords: swarm intelligence technique, advanced manufacturing process plans, exploratory study, optimal plan selection.

1. INTRODUCTION

In transforming raw materials into products, a manufacturing function concerned with the identification of technological manufacturing capabilities, is usually referred to as Manufacturing process planning (MPP).It fluctuates in time and space [1]. Non-linear manufacturing process plans is otherwise known as multiple process plans or alternative process plans [2]. Deciding among alternative process plans in a manufacturing system is not an easy one. In manufacturing, the availability of alternative process plans is a key factor for integration of design and process planning as a whole. It can speed up the process of plan generation and results in efficient use of scarce production resources [3].

Swarm intelligence (SI) is a subfield of Artificial intelligence (AI), which is a branch of computer science. AI, which is about is about making computers behave like humans, was coined by John McCarthy, in 1956, at the Massachusetts Institute of Technology [4]. SI is a relatively new. It studies the emergent collective intelligence of groups of simple agents, such as ants. The complete swarm exhibits collective behaviour (intelligence), which provides an efficient solution for complex problems such as the salesman problem [5]. An example of swarm intelligence algorithm is the ant colony optimization. It is a metaheuristic that can be used to find approximate solutions to optimization problems that are very difficult. The observation of ant colonies and their foraging behaviour inspired Marco Dorigo and his colleagues, in 1990's, to develop the first ACO algorithms, which in particular, shows how ants can find shortest paths between food sources and their nest [6]. The indirect communication between the ants via pheromone trails (stigmergy) enables them to find shortest paths between their nest and food sources.ACO is a probabilistic technique useful in problems that deal with discovering optimum paths. It has been used to unscramble many optimization problems such as progressive ordering [7], scheduling [8], constructing line balancing, probabilistic Traveling Salesman Problem (TSP) [9], DNA sequencing [10], 2D-HP protein folding [11], and protein-ligand docking [12]. The main impression is to model the problem to be solved as an examination for the best path in a construction graph, and to use artificial ants to examine for best paths. The biased graph is a graph on which artificial ants repeatedly drop pheromone trails to aid select the graph points of quality paths that match to solution modules. A major idea in the improvement of any ant colony optimization algorithm is to choose the fitness function grounded on which the modules of a problem's construction graph will be compensated with a high-level pheromone trail and to regulate how ants will utilize these assuring components when building new solutions. The fitness function of ACO is repeatedly indirectly expressed as cost minimization of solution components, i.e., the objectives of artificial ants are to travel on the construction graph and choose the points that minimize the complete cost of the solution path.

Quantitative study involves making important deductions about characteristics of a problem of interest without actually solving them [13]. Exploratory research, usually conducted to have a better understanding of an existing problem, is the process of investigating a problem that has not been thoroughly investigated or studied in the past. It doesn't lead to a conclusive result most times [14]. This study is interested in investigating the optimal manufacturing process plan selection, quantitatively, using a swarm intelligent technique - Ant Colony Optimization Algorithm. It describes a methodology for generation of alternative process plans in the integrated manufacturing environment. The Algorithm includes generation of a process plan network. Figure-1 shows the network of different manufacturing process plan sets. The outcome of the procedure is the optimization of the process plan

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network that provides all alternative process plans for the given part [15].

2. PROBLEM FORMULATION

2.1 Assumptions

For easy mathematical computation and brevity, the following assumptions are made in this study:

a) There are only four alternative feasible process plans to select from
b) Each feasible process plan has four steps of activities
c) All the feasible process plans have the same starting step and finishing step
d) The alternative process plans can be modelled as network as shown in Figure-1
e) Time required to complete an activity is directly proportional to its cost
f) In addition to efficient process planning, by a well-running manufacturing process, there is cost effectiveness
g) The tasks are performed by skilled persons.
h) The probability of the shortest route is equivalent to the probability of the optimal advanced manufacturing process selection plan

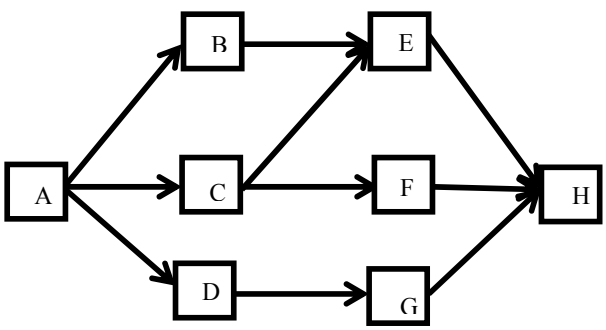

Figure-1. Network showing different manufacturing process plan sets.

Table-1. Simulated real time cost for each process step.

S. No	EDGE	VALUE
1	$A \to B$	9
2	$B \to E$	4
3	$E \to H$	5
4	$A \to C$	9
5	$C \to E$	3
6	$C \to F$	3
7	$F \to H$	7
8	$A \to D$	3
9	$D \to G$	7
10	$G \to H$	5

The four alternative manufacturing process plans one can select from, with starting point and end point A and H respectively, as shown in Figure-1, are as follows:

$$A \to B \to E \to H$$
$$A \to C \to E \to H$$
$$A \to C \to F \to H$$
$$A \to D \to G \to H$$

3. ACO MODELING

Let
τij(t)represent the intensity, at time t, of pheromone trail on edge (i,j)
Q/Lk represent the quantity of deposited trail by each ant on every visited edge (i,j)
Δ τijrepresent the sum of all newly deposited trail
Following trail deposition by all ants, the trail value is updated using
τij(t + n) = p × τij(t) + Δ τij, where p is the rate of trail decay per time interval

Two factors that drive the probabilistic model are visibility and trail, which are respectively denoted as; η ij and τij(t)

Where,
η ij = 1/dij, and
dij is the length of edge (i,j)

The Probabilistic Transition Function is given as follows:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}} & \text{if } k \in allowed_k \\ 0 & otherwise \end{cases}$$

All ants perform the local pheromone update, to the last edge traversed, after each construction step.
$\tau_{ij}=(1-\varphi)\cdot\tau_{ij}+\varphi\cdot\tau_0$,
where φ∈(0,1] is the pheromone decay coefficient, and τ_0 is the initial value of the pheromone.

The amount of pheromone on the path with vaporization can be calculated using;

$$\tau_{kl}(t+1) \leftarrow (1-\theta) * \tau_{kl}(t) + \sum_{n=1}^{m} \Delta\tau_{kl}^{n}(t), \forall k,l \in A, 0 \le \theta \le 1$$

The amount of pheromone on the path without vaporization can be calculated using;

$$\tau_{kl}(t+1) \leftarrow \sum_{n=1}^{m} \Delta\tau_{kl}^{n}(t), \forall k,l \in A$$

Where,

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$$\Delta\tau_{kl}^{n}(t)=\begin{cases}\dfrac{1}{C^{n}(t)}, \text{ if arc}(k,l)\in T^{n}(t)\\ 0, otherwise\end{cases}$$

is the mathematical model of the pheromone level on the ground

$\Delta\tau$ is the amount of pheromone that an ant deposit.

k,l is the edge connecting the node k and l.

n is the nth ant.

$\Delta\tau_{kl}^{n}(t)$ shows the amount of pheromone deposited by the nth ant on the edge connecting the node k with l at the tth iteration.

$C^{n}(t)$ is the length of the path. It is also the complete cost function of the tour $T^{n}(t)$ created by the nth ant at the tth iteration.

$T^{n}(t)$ is the set of all arc that ant n has paid a visit to at the iteration t.

θ is a constant that allows you to define the vaporization rate.

$\theta=0$ means there is no vaporization.

$\theta=1$ is when the vaporization is at the maximum level.

In this study attention was paid to the amount of pheromone on the path without vaporization bearing in mind that the shorter the path, the more pheromone deposited by the ant.

4. ADOPTION OF ANT COLONY OPTIMIZATION ALGORITHM

The adoption of the ACO model in achieving optimal plan selection was done by finding the probability of the shortest route using the above network.

4.1 Total Real Time Cost of the Plan

$R_1: A \to B \to E \to H$

$(9) \to (4) \to (5) = 18$

$R_2: A \to C \to E \to H$

$(9) \to (3) \to (5) = 17$

$R_3: A \to C \to F \to H$

$(9) \to (3) \to (7) = 19$

$R_4: A \to D \to G \to H$

$(3) \to (7) \to (5) = 15$

4.2 Calculating Pheromone Level Without Vapourization

$$\tau_{kl}(t+1)=\sum_{n=1}^{m}\Delta\tau_{kl}^{n}(t)$$

Assuming the pheromone level is 1.

$$\tau_{kl}(R_1)=\frac{1}{18}=0.056$$

$$\tau_{kl}(R_2)=\frac{1}{17}=0.059$$

$$\tau_{kl}(R_3)=\frac{1}{19}=0.053$$

$$\tau_{kl}(R_4)=\frac{1}{15}=0.067$$

4.3 Probability of Choosing the Route Without Vaporization

The probability of selecting a route, in this case a plan, without vaporization is given as follows:

$$P_{kl}^{n}(t)=\frac{[\tau_{kl}(t)]^{\alpha}\times[\eta_{kl}(t)]^{\beta}}{\sum\left([\tau_{km}(t)]^{\alpha}\times[\eta_{km}(t)]^{\beta}\right)}$$

Assuming α , β = 1

Probability of R_1 :

$$P_{kl}(R_1)=\frac{1\times0.056}{(1\times0.056)+(1\times0.059)+(1\times0.053)+(1\times0.067)}$$

$$P_{kl}(R_1)=\frac{0.056}{0.235}=0.238.$$

Probability of R_2 :

$$P_{kl}(R_2)=\frac{1\times0.059}{0.235}=0.251.$$

Probability of R_3 :

$$P_{kl}(R_3)=\frac{1\times0.053}{0.235}=0.226.$$

Probability of R_4 :

$$P_{kl}(R_4)=\frac{0.067}{0.235}=0.285.$$

The best iteration calculated, which is R_3: $A\to C\to F\to H$. It is the shortest route and has a total weight of 19 with a probability of 0.226 (i.e. 22.6 %.).

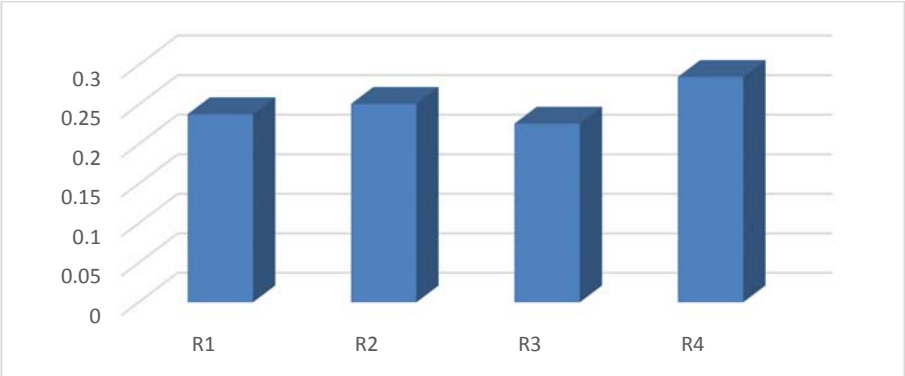

Figure-2. Probabilities of alternative selection plans of an advanced manufacturing.

5. RESULTS AND DISCUSSIONS

Figure-2 clearly shows the probability of all the available alternative process selection plans, with the third selection plan, $R_3 : A \to C \to F \to H$, having the smallest probability of 0.226. The other alternative selection plans have the following probability:

$$R_1 : A \to B \to E \to H = 0.238$$
$$R_2 : A \to C \to E \to H = 0.251$$
$$R_4 : A \to D \to G \to H = 0.285$$

The possible optimal process alternative selection plan in this study is assumed to be determined by the probability of the shortest route obtained by the application the ant colony optimization algorithm. So, R3 is the shortest route probability, followed by R1, then R2, while R4 has the probability of longest route. This implies that the best process selection plan of the advanced manufacturing is R3 and the worst is R4.

6. CONCLUSIONS

A four alternative advanced manufacturing process selection plans was modelled in this study. Ant colony optimization techniques were adopted in the selection of the optimal advanced manufacturing process selection plan, by calculating the probability of each of the alternative selection plan. The process selection plan associated with the shortest route of the route network developed was taken to be equivalent to the optimal part of the system. The route with the probability of shortest route therefore is equivalent to the process selection plan of the advanced manufacturing. The selection plan is $R_3 : A \to C \to F \to H$, with probability 0.226.

Conflict of Interests

The authors hereby declare that, regarding the publication of this paper, there is no conflict of interests whatsoever.

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