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Pheromone-based Dynamic Coordination for Manufacturing System

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Abstract: Manufacturing enterprises must face increasingly difficult production environments. External factors such as varying product variants and varying quantities as well as internal factors such as reworking and resource breakdowns pose a high challenge for task allocation and control. Inspired by the similarity between ant foraging behavior model and task allocation in manufacturing system, a pheromone-based coordination mechanism for manufacturing system is proposed. The pheromone-based static and dynamic coordination algorithms for task allocation are given. Experimental results demonstrate that not only the relatively optimal processing costs but also balanced use of machines can be achieved by using the proposed algorithm, and that it has high adaptability to the disturbance from inside or outside of manufacturing system. Therefore, it provides a feasible new idea for dealing with an actual allocation problem of production tasks for manufacturing system.

1. INTRODUCTION

The environment within which manufacturing systems operate is characterized by rapid change than ever before. The unforeseen disturbances include: the arrival of new orders, order cancellations, changes in order priority, processing delays, changes in release dates, machine breakdowns, etc. [1, 2]. Hence, such dynamic manufacturing systems require dynamic coordination and control to make full use of system resources, and then improve the system performance. The traditional manufacturing control architectures are not designed to exhibit good agility and adaptation. In fact, their centralized and hierarchical control approaches present good production optimization, but the rigidity and centralization of the control structure implies a weak response to disturbances, therefore, the substitutional heterarchical control architecture has been proposed and investigated [3, 4]. On the other hand, heterarchical manufacturing control architecture presents a good response to change and unpredictable disturbances, but as autonomous manufacturing cells have different information, knowledge, goals and understanding of current situations, and decisions are based on partial knowledge of the system, their action plan may be disparate or even conflictive. Therefore the global production optimization is not guaranteed [5, 6]. Thus an appropriate approach is necessary to coordinate and integrate the behavior of manufacturing system.

Considering the already developed ant colony optimization (ACO) methodology [7], ACO has a powerful capacity to find out good solutions to combinatorial optimization problems, Therefore, ACO has been widely applied to solving various combinatorial optimization problems such as traveling salesman problem (TSP) [8], job-shop scheduling problem (JSP) [9], task allocation problem [10], etc. This paper uses an indirect coordination approach based on pheromone to optimize global performance for manufacturing system.

The remainder of this paper is organized as follows. The pheromone-based coordination mechanism is given in section 2. The pheromone-based static and dynamic coordination algorithms are proposed in section 3. An example is presented to demonstrate the validity of this approach to control task allocation in section 4. Finally, some concluding remarks are given in section 5.

2. PHEROMONE-BASED COORDINATION MECHANISM

Pheromone-based coordination mechanism is inspired by the foraging behavior of real ants. Real ants are capable of finding the shortest path from a food source to their nest without using any direction communication. Instead, they communicate information about the food source via depositing a chemical substance, called pheromone, on the paths. The following ants are attracted by the pheromone. Since the shorter paths have higher traffic densities, these paths can accumulate higher proportion of pheromone. Hence, the probability of ants following these shorter paths would be higher than that of those following the longer ones.

Much to our surprise, just using this simple strategy, an ant colony can find the optimal route from nest to food source quickly in a very complex environment (in contrast with their intelligence) [11].
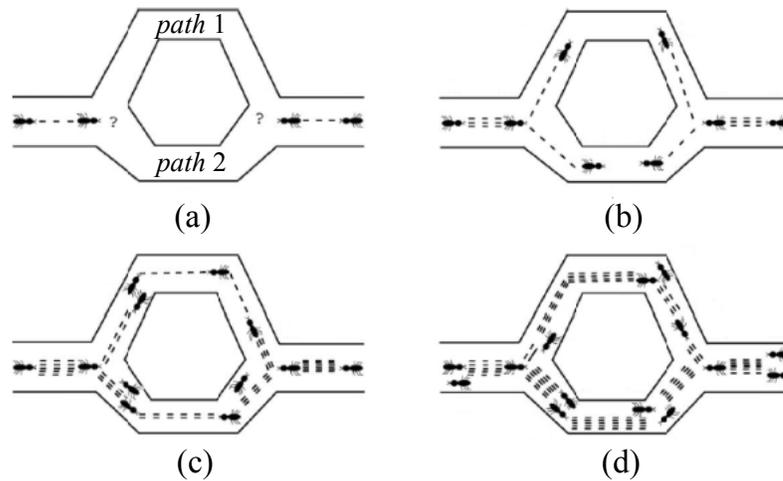
(a) Ants arrive at a decision point. (b) Some ants choose the upper path and some the lower path. The choice is random. (c) Since ants move at approximately constant speed, the ants which choose the lower, shorter, path reach the opposite decision point faster than those which choose the upper, longer, path. (d) Pheromone accumulates at a higher rate on the shorter path. The number of dashed lines is approximately proportional to the amount of pheromone deposited by ants.

Fig. (1). The process for real ants to find a shortest path [9].

Fig. (**1**) can explain why an ant colony can achieve such good performance [9]. When an ant is searching for the nearest food source and comes across with several possible paths (path 1 and path 2), it tends to choose the path with the largest concentration of pheromone, with a certain probability. After choosing the path, it deposits a certain quantity of pheromone, increasing the concentration of pheromones in this path. The ants return to the nest using always the same path, depositing other portion of pheromone on the way back. Imagine then, that two ants at the same location choose two different paths at the same time. The pheromone concentration on the shortest way (path 2) will increase faster than the other (path 1): the ant that chooses this way, will deposit more pheromones in a smaller period, because it returns earlier. If a whole colony of thousands of ants follows this behavior, soon the concentration of pheromone in the shortest path will be much higher than the concentration in other paths. Then the probability of choosing any other way will be very small and only very few ants among the colony will fail to follow the shortest path. There is another phenomenon related with the pheromone concentration. Since it is a chemical substance, it tends to evaporate in the air, so the concentration of pheromones vanishes along the time. In this way, the concentration of the less used paths will be much lower than that on the most used ones, not only because the concentration increases in the other paths, but also because their own concentration decreases with time [9].

A further research indicates [12] that the behavior model for ant colony to choose path for food can be presented in (1).

$$p_i = \frac{(k+c_i)^n}{\sum_{j=1}^{m}(k+c_j)^n} \tag{1}$$

Where, p_i is the probability for ant to choose path i for food; c_i and c_j are the quantity of pheromone on path i and j, respectively; k is attractive degree for no pheromone paths; n is a nonlinear coefficient, and we set n to 1 in this paper.

3. PHEROMONE-BASED DYNAMIC COORDINATION

3.1. Pheromone-based Static Coordination Algorithms

In an ants' food foraging process, pheromone is the basic information element and resides in the route it associates. The function of pheromone is to indicate the attraction of its resident route. The prominent characteristic of pheromone is simplicity [12]. Therefore, the task allocation can be looked as ants' food foraging process. Generally speaking, a task can be finished by several routes; in order to make each route have a chance to be selected, so at the beginning, we set an initial value for each route that has the ability to finish the given task, as shown in (2).

$$\rho[i][j] = \begin{cases} c_0 & \text{if work piece } j \text{ can be finished by} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

route i otherwise

When a task needs to select a route to process their work pieces, the work piece firstly perceives the pheromone quantum of each feasible route and selects a process route by route's selecting probability, which can be obtained from (1), as shown in (3).

$$p(i) = \frac{\rho[i][j]}{\sum_{i=1}^{m} \rho[i][j]} \tag{3}$$

Where, i represents one process route and j represents the work piece of the task; $p(i)$ is the selecting probability of process route i and $\rho[i][j]$ is route i's pheromone to work piece j.

After that the selecting algorithm generates a random number and chooses a process route for processing the work piece j according to calculated selecting probability. Then the selected route will get the award, and the "effective pheromone" would be increased. Meanwhile, the involving machine's available processing time on the selected process route will gradually be reduced. Therefore, a pheromone penalty function $P(t)$ ($0 < P(t) < A(c)$ are used to reduce the strength of the pheromone in order to reduce the probability of its being selected again, as shown in (4).

$$\rho[i][j] = \rho[i][j] + A(c) - P(t) \tag{4}$$

Where, c is the total processing cost of the selected route; $A(c)$ is the increased pheromone quantum, and the increment is inversely proportional to the processing cost. $P(t)$ is a decreasing function on the least available time machine of the process route.

When the available time of a certain machine of the process route is less than the corresponding process time processed by this machine for the next work piece, then the pheromone value of the process route automatically becomes zero. Particularly, when a machine's available time is zero, the pheromone value is set to zero for all process routes associated with the machine. The flow chart of pheromone-based coordination algorithm for task allocation is shown in Fig. (**2**).

3.2. Pheromone-based Dynamic Coordination

There are many sources of uncertainty in a real-world manufacturing system, which trigger disturbance events in dynamic adaptation manufacturing system control. Generally speaking, there are two types of disturbances, which are resource-related disturbance and source-related disturbance [1, 6].

1) Resource-related disturbance refers to the disturbance caused by unreliability coming from resources (machines) in the shop floor, including machine recovery and machine breakdown.

2) Source-related disturbance refers to the disturbance caused by the changes in orders, including existing order/job cancellation and new order/job arrival.

The resource-related disturbance is considered in this paper.

Fig. (**3**) shows the progress of dynamic coordination by using pheromone-like technique when a machine has a malfunction at time t_0. And the specific dynamic coordination mechanism works as follows:

(1) Set the pheromone value to zero for the malfunction machine.

(2) Find all machines which have the ability to replace the malfunction machine, and calculate pheromone values S_i and the remaining available time T_i for these alternative machines at the current moment.

(3) Calculate the operating pheromone value for each alternative machine, as shown in (5).

$$Q_i = \lambda_1 S_i + \lambda_2 T_i \tag{5}$$

Where, λ_1 and λ_2 are the cost weight and load weight of the machine ($\lambda_1 + \lambda_2 = 1$) respectively.

(4) Transferred the unprocessed work pieces on the malfunction machine to an alternative machine according to task allocation algorithm based on pheromone. The selected probability for each alternative machine is as follows.

$$p_i = \frac{Q_i}{\sum Q_i} \tag{6}$$

(5) The selected machines and the old machines form a new dynamic manufacturing dell.

(6) After the task is completed, the dynamic manufacturing cell will automatically disappear.

4. EXAMPLE AND RESULT

There are three tasks that need to be processed, and there are 9 machines in a manufacturing plant. The production information for these tasks is shown in Table **1**.

Algorithmic parameters are selected as follows: c_0=100, $\alpha(c)$=10000/c, $P(\alpha(t_{min}), A(c))$=$\alpha(t_{min})* \alpha(c)$, where $\alpha(t_{min})$=$D/(D+9 t_{min})$, D=1500.

Solved by pheromone-based algorithm, the following results are obtained: n_{11}=25; n_{12}=28; n_{13}=27; n_{21}=19; n_{22}=30; n_{23}=41; n_{31}=26; n_{32}=22; n_{33}=22. n_{ij}=N (i=1, 2, 3; j=1, 2, 3) denotes that N work pieces of P_i will be processed on the route of P_i-R_j (N is less than or equal to the batch size of P$_i$). For example, n_{11}=25 denotes that eighteen work pieces of P_1 are planned to be processed on the P_1-R_1 route.
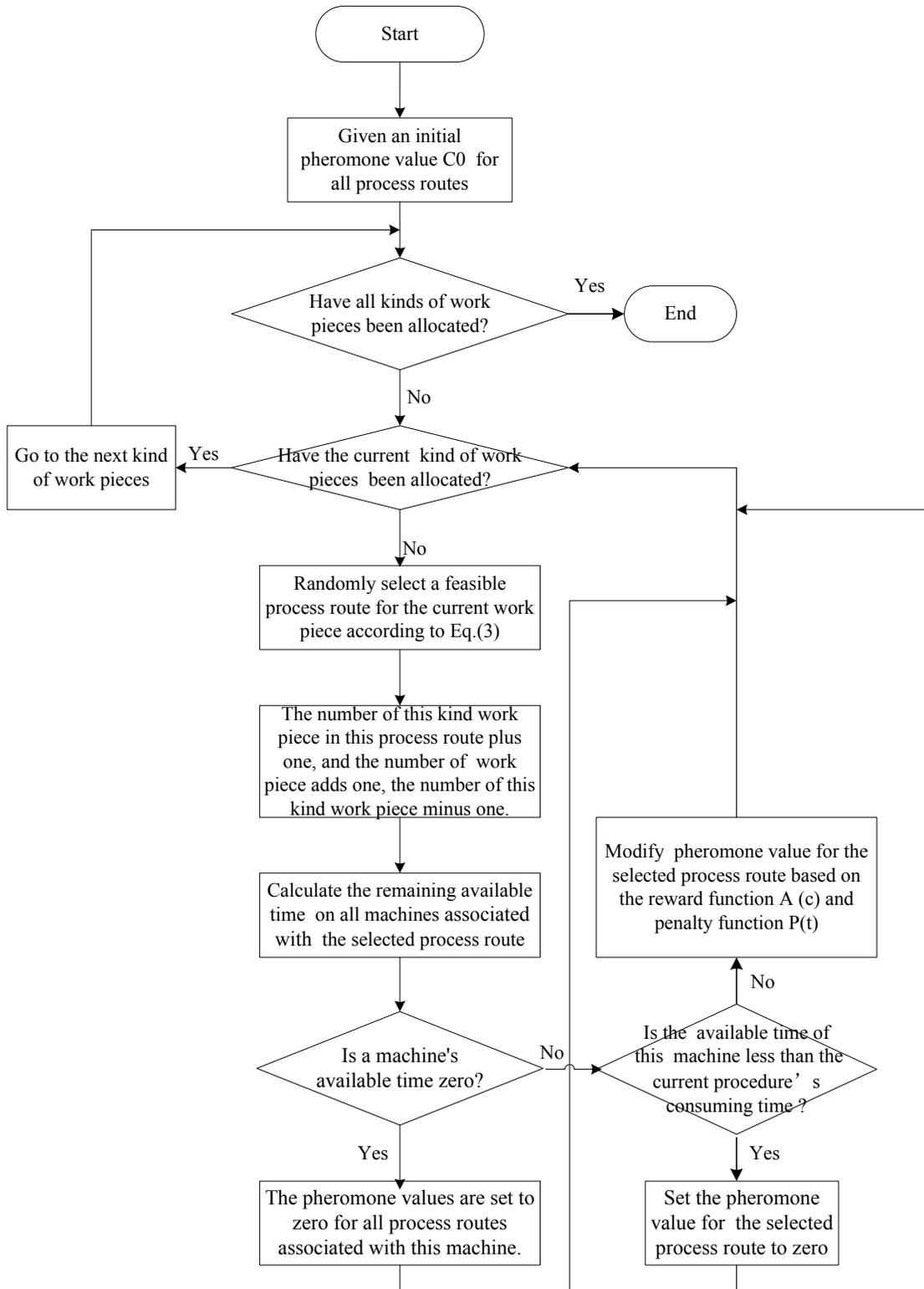
Fig. (2). Pheromone-based static coordination process.
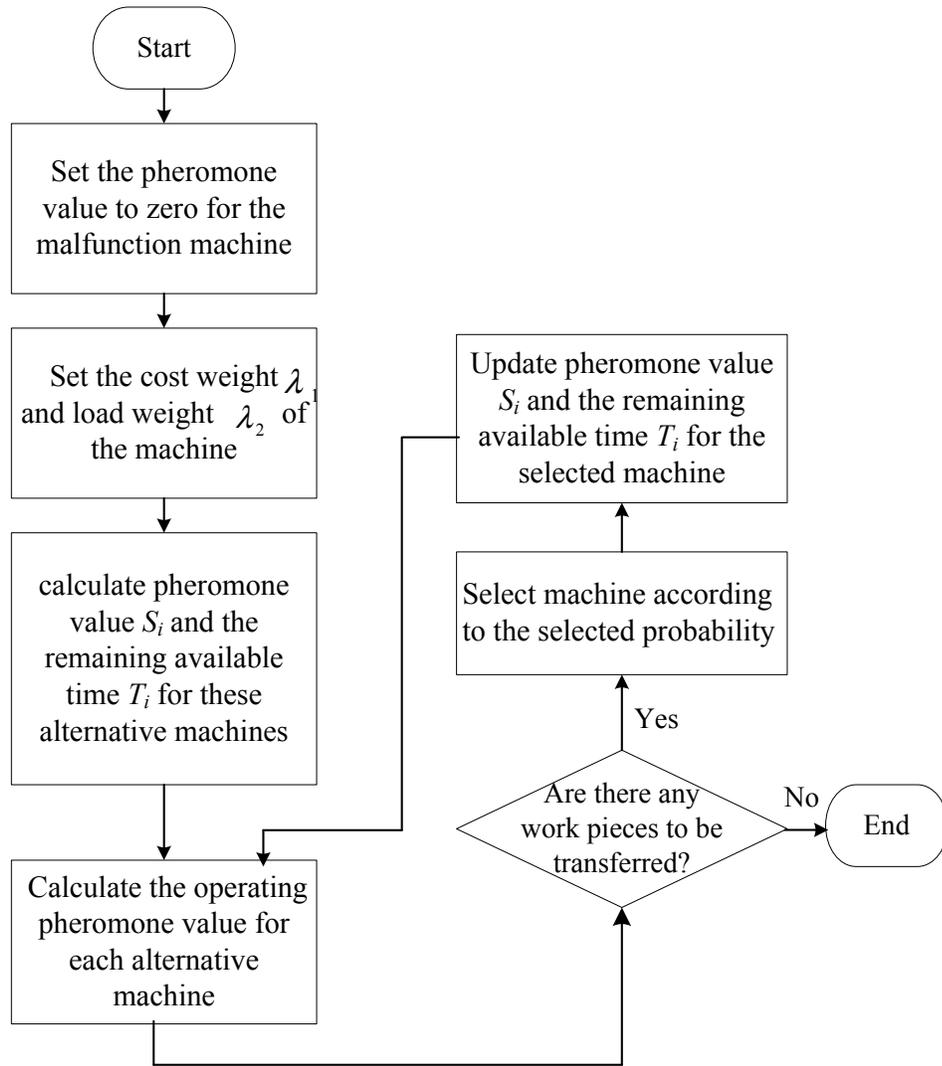
Fig. (3). Pheromone-based dynamic coordination.

Table 1. Production information for tasks.

Task	Quantity	Routes	Machine/Processing Time /Cost Per Time Unit			
P_1	80	1-1	1/12/4	3/18/3	4/15/2	6/15/8
		1-2	2/12/5	5/10/5		
		1-3	8/15/6	2/12/5		
P_2	90	2-1	2/10/5	5/5/5	8/10/6	1/6/4
		2-2	4/8/2	3/15/3	9/10/2	7/15/12
		2-3	1/8/4	4/8/2	6/5/8	
P_3	70	3-1	8/6/6	9/10/2	7/25/12	
		3-2	6/12/8	1/10/4	3/5/3	
		3-3	5/10/5	2/8/5	8/15/6	

Table 2. Pheromone quantum on each machine.

Machine ID	Machine Type	Released Pheromone
M1	lathe	829
M2	milling machine	936
M3	machining center	540
M4	grinding machine	811
M5	lathe	695
M6	planning machine	837
M7	boring machine	315
M8	grinding machine	758
M9	drilling machine	141

Table 3. Task allocation results for remaining 30 work pieces.

Machine ID	Machine Type	Allocated Number
M3	machining center	19
M7	boring machine	11

The pheromone quantum on each machine is shown in Table **2**.

Assume that M9 is failure at time t_0, and then the remaining 30 work pieces can't be processed on M9. The alternative M3 and M7 can processed them. Set the cost weight λ_1 to 0.6 and load weight λ_2 to 0.4 for M3 and M7 respectively.

According to the dynamic coordination of the above steps, the obtained allocated work pieces on each alternative machine M3 and M7, as shown in Table **3**.

The tasks can be well allocated between different alternative machines by adjusting the weight factors λ_1 and λ_2. It not only ensure that the relatively low-cost and alternative machines can be well selected to process the remaining work pieces, but also take into account the full use of the idle machines' processing capabilities. Therefore, the manufacturing system can be fully utilized as soon as possible. A new virtual dynamic manufacturing cell can be formed by adding the new machines to the original manufacturing cell. Therefore, some tasks can be well allocated by coordinating among several machines or manufacturing cells, which can learn from each other, in order to optimize the system's overall performance.

CONCLUSION

Inspired by social insects, a new pheromone-based dynamic coordination for manufacturing system is presented in this paper. According to that, a pheromone-based task allocation algorithm is proposed. Based on pheromone technique, an example is given and experimental results confirm that the proposed approach is feasible for dynamic coordination problems.

Pheromone-based dynamic coordination approach has following characteristics: (1) Tasks allocation and resources optimization can be combined effectively, and (2) The approach is not only simple, but also feasible.

The application of pheromone-based coordination approach in manufacturing system is focused on basic task allocation problems and is only tested by using computer, therefore, it is still preliminary and further research work is needed. Future work will consider the following issues: (1) applying the proposed coordination approach to real industrial cases, (2) further exploring ant agent coordination for dynamic re-scheduling coordination control which can provide a schedule immediately and efficiently, and (3) improving the proposed coordination algorithms so as to improve allocation efficiency.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

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