A Scheduling Method for IOT-aided Packaging and Printing Manufacturing System

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***Abstract* — To meet the demand of effective control of production in packaging and printing industry, this paper proposes a manufacturing-assist system based on Internet of Things (IOT) techniques. The system is composed of reliable network connection with wireless mesh networks and widely deployed sensor nodes. With smart sensing, transmission and processing for the states of manufacturing facilities, products and production procedures, the system can exert efficient surveillance and control over the manufacturing procedure. Based on this system, this paper further designs a method for scheduling subtasks both among facilities and inside each facility. The method is implemented by Genetic Algorithm for optimization objectives such as minimizing overall production delay and minimizing overall production cost. Simulation and on-spot experiment in enterprise showed the superiority of the method for the optimization objectives.**

Keywords — Package manufacturing; Internet of things; Scheduling; Genetic Algorithm

I. INTRODUCTION

With the rapid development of information technology and industrial automation, the product packaging and printing industry will develop in two directions in the future. One is the functional diversification of packaging and printing machinery. Only the machinery with multiple elastic functions can meet the various demands from diversified market. Another is intelligent control of production procedure. Packaging and printing manufacturing will adopt the automation and information technology for real time, accurate and efficient procedure control [1].

However, currently there exist many problems in packaging and printing manufacturing as follows. 1) There is great loss and waste of raw materials during the production process, and the unreasonable logistics distribution methods lead to low production efficiency. 2) The level of productive forces is still low due to a lot of manual assembling works. 3) There are no effective methods for tracing, controlling and sharing of the stocks, facilities and products [2]. It is necessary to take advanced measures for data acquisition, processing and production optimization in packaging and printing manufacturing.

This paper designs an industrial Internet of Things (IOT) system labeled as PPM-IOT. The system can sense, transmit and process data with IOT techniques in main facilities, so it can obtain the real-time states of facilities operation and incorporate all production procedures for unified management and optimization. Based on this system, we further give elaboration on the principle, optimization objective and implementation of an intelligent subtask scheduling method for different optimization objectives, and make performance comparison among these scheduling schemes with simulation and on-spot experiments in enterprise.

The rest of this paper is as follows. Section II reviews related work. Section III proposes the overall functions and architecture of PPM-IOT. Section IV describes the implementation of scheduling method. Section V demonstrates the evaluation of performance for PPM-IOT. And section VI gives the conclusions.

II. RELATED WORK

Currently there some research works on the scheduling methods for manufacturing. Based on Qos constraints, Zhang [3] proposed a scheduling model for manufacturing services, and designed detailed method based on cloud computing model and ant-colony optimization theory. Laili [4] gave considerations for the computation cost and communication costs in manufacturing unit, describe the time needed for dynamic manufacturing resource allocation, and implemented this allocation method by Genetic Algorithm. [5] proposed cooperative energy-adaptive task-scheduling methods based on immune Genetic Algorithm. The method can not only increase the diversity of searching results with different immune tactics, but also adjust the crossover and mutation probability self-adaptively for a proper balance between diversification and intensification of searching results. Du [6] proposed architecture of cloud-center for robots services, and

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designed cost-minimizing resource-scheduling method for heterogeneous robots. Huang [7] designed an intelligent scheduling procedure based on quality-predication principle. There is a scheduling engine inside it, which contained a sequential evaluation system for final products, a task deployment system and a performance monitoring system. All these works schedule the entire task to a distributed manufacturing unit. However, the complexity of production keeps growing, and one task should be cooperatively handled by several facilities, so task decomposition and cooperation among different manufacturing facilities should also be considered.

Ge [8] proposed a decomposition and allocation method that matches users' demands and resources' capacity. By scheduling subtasks to proper resource-providers, this method can obtain a hierarchical multi-resolution architecture for organizing resources and capacity. With regard to the impact from raw material flow and information flows, Wang [9] decomposed each task into several subtasks and designed a resource-configuration model for optimization objectives such as cost, delay and product quality. He also got solutions of this model based on Max Inherit Optimization method. Wang [10] designed a subtask-scheduling strategy for on-demand workflow. With considerations for the factors that influence resource allocation, such as capacity, cost, credibility and work load in facilities, the method for matching these factors and task-demands were designed. [19] dealt with scheduling in Cloud manufacturing with many enterprises, and considers the performance of four robots deployment methods, including random deployment, robot-balanced deployment, function-balanced deployment and location-aware deployment. Further, three subtask-scheduling strategies are derived for three optimization objectives, including load-balance of robots, minimizing overall cost and minimizing overall processing time. All these works have implemented subtasks decomposition and scheduling among different enterprises. However, our work focuses on scheduling the subtasks to the facilities in one enterprise.

III. OVERALL FUNCTIONS AND ARCHITECTURE OF SYSTEM

The workshops for packaging and printing manufacturing should be able to make full use of the manufacturing facilities to handle multiple simultaneous production tasks. It should also utilize the transportation facilities for efficient delivery of raw materials to workshops and for that of qualified products to warehouses. What's more, raw material can be replenished in time according to the current volume and requirement of raw material supplies.

The PPM-IOT system concerns the states about raw materials, manufacturing facilities, transportation facilities, products and warehouses. The states for raw material include "sufficient and scanty", and are obtained from the electronic label in the package of raw materials. The states for manufacturing facilities include "OFF, ON, idle and maintaining". They can be obtained by the sensors in these facilities or set by the system controller. The states for products include "in processing, entering warehouse, in warehouse and obsolete", and are obtained from the electronic labels in products. The states for warehouses are represented by the number of empty containers, and are obtained by the sensors in these containers. The IOT-based information [11,12] includes state messages from different objects and control messages for these objects. The state messages are processed by the analyzer unit in application layer, and then the control messages are generated, including raw material replenishing and transportation, manufacturing facilities operation and maintaining, products testing and classification, transportation facility operation and maintaining.

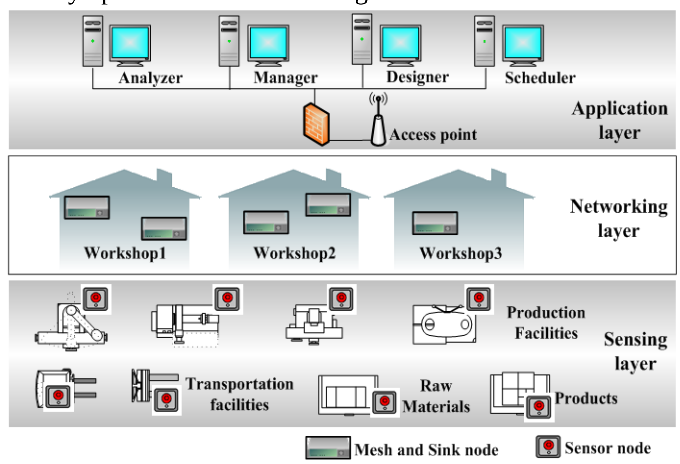


Fig. 1. Architecture of PPM-IOT

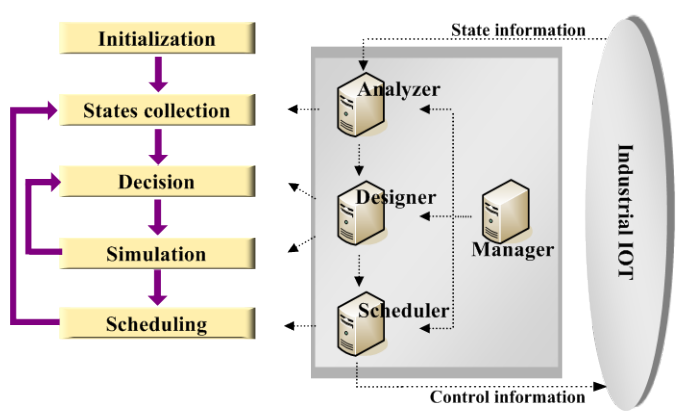


Fig. 2. Handling procedure for subtasks in PPM-IOT

The architecture of PPM-IOT system is shown in Fig. 1. And the handling procedure is illustrated in Fig. 2. There exist four functions in the application layer. The first is the *analyzer* that analyzes the state of relevant elements in the system. The second is the *manager* that operates the basic management functions for the whole PPM-IOT system. The third is the *designer* for manually controlling the production processes and process simulation. And the last is the *scheduler* for dispatching each subtask to relevant facility. In designer, the scheduling decision will be modified if the results from simulation are not satisfactory. The networking layer is based on wireless mesh networks with stable and reliable wireless connections. Each mesh node is also the sink node of local wireless sensor network (WSN). What's more, SIP [13] connections can easily be built in mesh networks for instant communication among staffs. The sensor layer is composed of many local wireless sensor networks, e.g., a WSN for all sensors in a warehouse, or a WSN for all sensors in a manufacturing facility.

IV. IMPLEMENTATION OF KEY SCHEDULING METHOD

The key of efficient production with PPM-IOT system lies in dispatching simultaneous tasks of different production specifications to proper facilities, and this leads to the necessity of an effective production scheduling method.

A. Design algorithm

The packaging and printing manufacturing is mainly composed of several processing steps for raw materials or intermediate components, including cutting, coloring, sealing, shaping and assembling [14]. These steps cannot be implemented in one facility and should be handled separately, so PPM-IOT decomposes a task into several subtasks, and each subtask is handled in one facility. Considering the diversity of facilities, correlation among subtasks and the total production volume, allocating proper facilities to subtasks is a complex discrete optimization problem. This paper adopts Genetic Algorithm (GA) [15] to solve this problem. GA is good at parallel searching and can avoid the local optimal solution. GA derives from the evolution process in natural biology, and starts from transforming the optimization problem to build a list of genes. The genes are randomly combined to produce a population of chromosomes. Iterative genetic operations for offspring are performed on chromosomes that are randomly selected from the parent population, including fitness value evaluation, population selection, chromosome crossover and gene mutation. As a self-adaptive and multi-directional searching process for global optimization, it can operate on the final results directly with satisfactory robustness.

B. Description of entities in production scheduling

Considering the diversity of facilities' functions, we measure the cost and time needed for various products by a unified metric called Standard Reference Product (SRP for short). For example, the cost for handling a subtask with one facility is equivalent to that for x SRPs. The entities and their relevant properties in production scheduling are described as follows.

The i-th manufacturing facility labeled as $\boldsymbol{E_i}$ ($0 \leq i < ENum$, $ENum$ is the total number of facilities) has the following properties:

1) Current states of E_i (including OFF, ON, idle and maintaining);

2) Unit processing delay ($\boldsymbol{PD_i}$) represents the time needed by E_i to produce an SRP;

3) Unit processing cost ($\boldsymbol{PC_i}$) represents the cost needed by E_i to produce an SRP;

4) Current processing load $\boldsymbol{L_i}$ of E_i is measured by the number of SRPs.

After decompose a task into many subtasks, the subtask of the n-th type labeled as $\boldsymbol{ST_n}$ ($0 \leq n < STNum$, $STNum$ is the total number of types of subtasks) is the minimal unit to be processed in each facility. As shown in Fig. 3, there is M:N function-mapping from ST_n to E_i. If a facility can handle a subtask type, there is a connection between them.

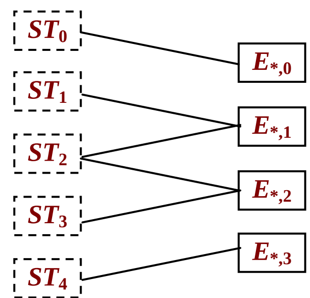


Fig. 3. Function mapping between subtask types and facilities

The production process of the m-th type labeled as $\boldsymbol{P_m}$ ($0 \leq m < PNum$, $PNum$ is the total number of process types) can combine related subtasks into a tree-structure according to specified assembling procedure [16]. And the subtask that is handled last is the root node of process tree. Fig. 4 is an example for two processes.

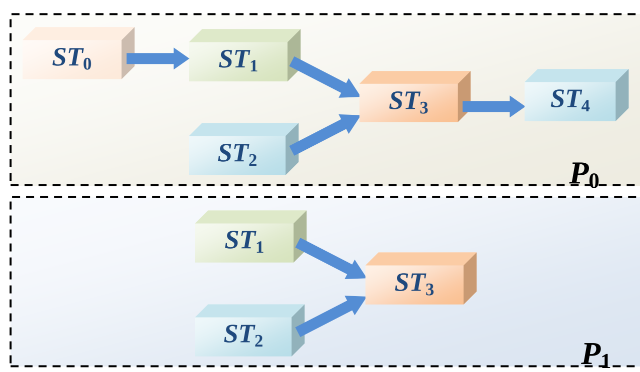


Fig. 4. Formation of process tree with different subtasks

Each subtask is represented by a node in process tree and has the following properties: The production volume $\boldsymbol{PV_{m,n}}$ represents the equivalent number of SRPs that ST_n in P_m amounts to.

The k-th task to be handled labeled as $\boldsymbol{T_k}$ ($0 \leq k < TNum$, $TNum$ is the number of tasks to be processed this time) has the following properties:

1) $\boldsymbol{Prc_k}$ is the process type for this task;

2) $\boldsymbol{Prn_{k,n}}$ is the subtask type for the previous node of ST_n of T_k in process tree;

3) $\boldsymbol{TM_k}$ is the total number of production items for this task;

4) $\boldsymbol{E_{k,n}}$ is the facility for ST_n of T_k.

If T_k consists of ST_n, and ST_n of T_k is scheduled to E_i, we set allocation sign $U_{k,n,i}$=1, and 0 otherwise. Based on Fig. 3 and Fig. 4, we propose an example of scheduling scheme in Fig. 5, and have *PNum*=2, *STNum*=5 and *ENum*=4. Among 3 tasks to be processed, the process types for T_0, T_1 and T_2 are P_0, P_1 and P_1 respectively. ST_0 of T_0 is scheduled to E_0 and we have $U_{0,0,0}$=1. ST_2 of T_1 is scheduled to E_2 and we have $U_{1,2,2}$=1. The chains of facilities for $task_0$, $task_1$ and $task_2$ are $E_0 \rightarrow E_1 \rightarrow E_0 \rightarrow E_0 \rightarrow E_3$, $E_1 \rightarrow E_2 \rightarrow E_2$ and $E_1 \rightarrow E_2 \rightarrow E_2$ respectively. The subtasks from different tasks are distinguished by different frame styles of cuboids. Considering that many facilities can handle a subtask, there exist many scheduling schemes that lead to different chains of facilities and performance [17].

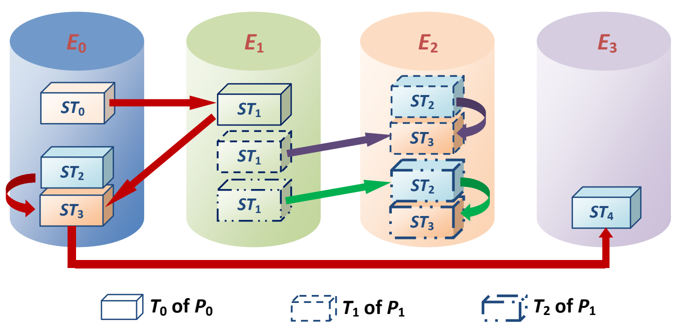


Fig. 5. Example of subtask scheduling and handling

C. Subtasks scheduling inside facility

A facility should arrange the order of its subtasks properly to achieve the minimal overall processing time. For the general case, the minimal overall handling time in that facility is achieved by handling the subtask with the shortest processing time first. But in our case, there are complex dependant relations among subtasks from different facilities. So the subtask with the shortest processing time may not be handled first, and the minimal processing time in one facility cannot lead to the optimal performance for the whole system. For the same reason, ordering these subtasks in one facility by the deadlines of the corresponding tasks is also unreasonable.

Assign Boolean variable $STF_{m,n}$=1 if ST_n exists in P_m and $STF_{m,n}$=0 otherwise, and let $L_{m,n}$ be the number of layers from ST_n to the root of process tree in P_m. Taking P_0 in Fig. 4 as an example, ST_4 is at layer 0 and ST_1 is at layer 2. So the average layer position for ST_n in all relevant processes is

$$aveL_n = \frac{\sum_{m=0}^{N_P-1} STF_{m,n} L_{m,n}}{\sum_{m=0}^{N_P-1} STF_{m,n}} \tag{1}$$

Obviously the ST_n with larger $aveL_n$ tends to be handled earlier in process. The $aveL_n$ in the process tree embodies the relative order of subtask handling, so we adopt the tactic that sorts the subtasks in a facility by the decreasing order of their $aveL_n$.

D. Implementation of subtask scheduling among facilities based on Genetic Algorithm

Each chromosome from the Genetic Algorithm provides a complete scheme for scheduling the subtasks in all tasks. The ST_n in T_k corresponds to a gene, which is indexed by k*$STNum$+n. If ST_n in T_k is allocated to facility E_i, then the gene is assigned with value i. If ST_n is not in T_k, then the gene is assigned with negative value -1. Based on the scheduling scheme in Fig. 5, the chromosomes for the three tasks are coded in Fig. 6.

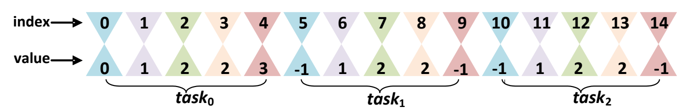


Fig. 6. Example of chromosome initialization

According to different optimization objectives [18], we build different fitness functions. For minimizing the overall production cost, first we calculate the production cost of each subtask in E_i, then we get the sum of these individual costs of E_i among all tasks.

$$C(i) = \sum_{k=0}^{TNum-1} \sum_{n=0}^{STNum-1} U_{k,n,i} TM_k PV_{\mathrm{Prc}_{k,n}} PC_i \tag{2}$$

The optimization objective of system's overall Cost Optimization Scheduling (COS for short) is

$$\text{Minimize}\left(\sum_{j=0}^{RNum-1} C(i)\right) \tag{3}$$

The corresponding fitness function is

$$\mathrm{F}_{COS} = \frac{1}{\sum_{j=0}^{RNum-1} C(i)} \tag{4}$$

Among a batch of tasks, the overall production delay depends on the subtask that finishes last. Due to the complex dependency of subtasks in a process, current subtask cannot be handled until the previous subtasks in the process are handled by other facilities. So it is hard to describe the exact production delay. In the case of ideal scheduling, the facility that finishes last should handle all its subtasks without idle waiting, and all relevant previous subtasks are ready when the subtask in this facility is to be handled. So the ideal system production delay is the sum of individual production time of each subtask and current load.

$$D_M(i) = \sum_{k=0}^{TNum-1} \sum_{n=0}^{STNum-1} U_{k,n,i} TM_k PV_{\mathrm{Prc}_k,n} PD_i + L_i PD_i \quad (5)$$

The optimization objective of system’s overall Delay Optimization Scheduling (DOS for short) is

$$\mathrm{Minimize}(\mathrm{Max}(D_M(i))) \quad (6)$$

The corresponding fitness function is

$$\mathrm{F}_{DOS} = \frac{1}{\mathrm{Max}(D_M(i, j))} \quad (7)$$

At the beginning, we generate N chromosomes as the initial population by randomly allocating facilities to subtasks, and N is within range of [40,120].

The steps in each iteration are as follows. First, evaluate the values of fitness functions for each chromosome. Second, selection chromosomes with high values and make crossover for new chromosomes. Third, execute gene mutation for new chromosomes. These operations iterate for new generations until the fitness value converges or the number of generations is large enough.

V. Evaluation of the Scheduling Method in Packaging and Printing Manufacturing System

The PPM-IOT system has been applied in a packaging and printing manufacturing enterprise. First we get the characteristics of 38 manufacturing facilities of 9 types, 12 process types and 11 subtask types with the measuring experiments in IOT platform, including detailed composition of process trees, function mapping relations, PC_i and PD_i for different facilities, and $PV_{m,n}$ for each subtask. Based on these characteristics, we execute the Genetic Algorithm in Matlab for the optimal chromosome of each optimization objective, and conduct simulation experiments based on the scheduling schemes from these chromosomes.

In simulation we set 9 task scenarios. Each scenario consists of several tasks of random chosen process types, and the production volume of tasks scenario increase from 1000, 2000 … to 9000 SRPs. For Random Scheduling (RAN for short), DOS and COS, we get three performance indexes including overall production delay, overall production cost and average utilization rate of facilities in a given time. The results are shown from Fig. 7 to Fig. 9.

In the case of actual production, we divide a batch of production tasks into 3 equal parts, and adopt RAN, COS and DOS scheduling for each part respectively. The performance results are shown in Fig. 10.

From above results, we observe that DOS scheduling leads to the shortest production delay and the highest production efficiency, and COS scheduling yields the minimal production cost. Both COS and DOS yield high utilization rate of facilities. However, RAN scheduling performances the worst.

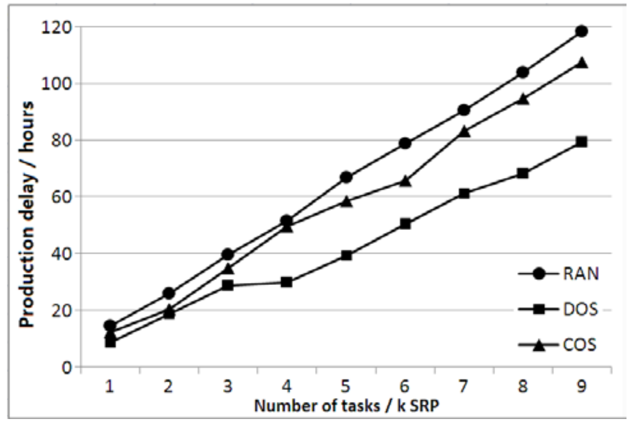


Fig. 7. Overall production delay

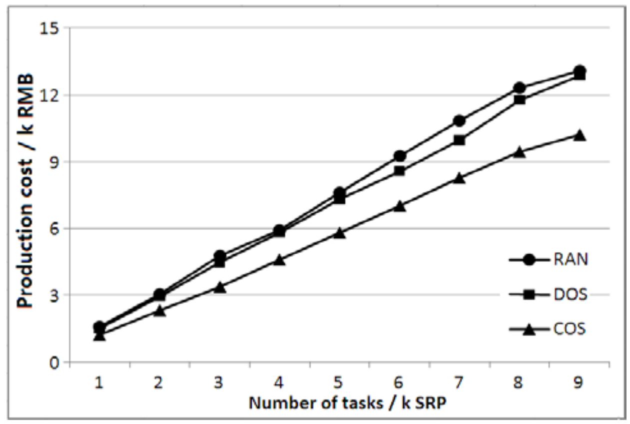


Fig. 8. Overall production cost

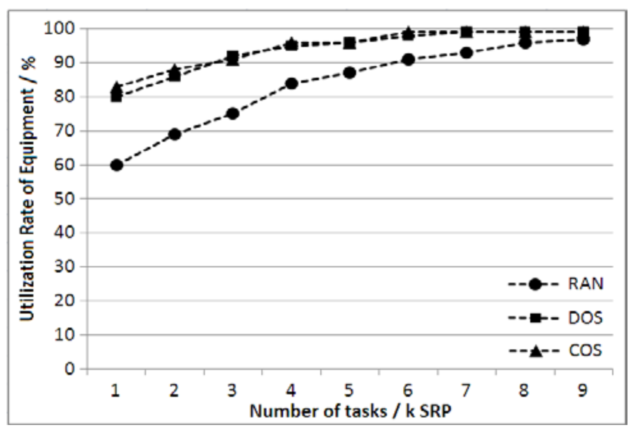
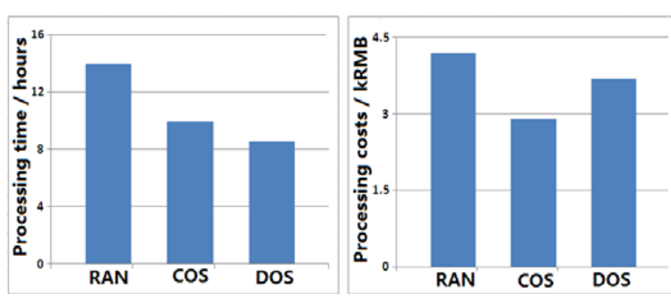


Fig. 9. Average utilization rate of facilities



(a) Overall production delay (b) Overall production cost

Fig. 10. Comparison among different scheduling methods in production

VI. Conclusions

Based on IOT techniques, this paper proposes a manufacturing-assist system for packaging and printing production with multiple simultaneous tasks. The system can sense the states and features of relevant objects in real-time production, and behave with proper actions in time. For different optimization objectives such as minimizing overall production cost and minimizing overall production delay among all manufacturing facilities, we implement an intelligent subtask scheduling method based on Genetic Algorithm.

Future works include effective analysis and utilization of the gathered information from all sensors, and intelligent scheduling of transportation facilities for raw materials and products.

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