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Multi-objective Shop Floor Scheduling Using Monitored Energy Data

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Abstract

Modern factories will become more and more directly connected to intermittent energy sources like solar systems or wind turbines as part of a smart grid or a self-sufficient supply. However, solar systems or wind turbines are not able to provide a continuous energy supply over a certain time period. In order to enable an effective use of these intermittent energy sources without using temporary energy storages, it is necessary to rapidly and flexibly adapt the energy demand of the factory to the constantly changing requirements of the energy supply. The adaption of the energy demand to the intermittent supply results in different energy-related objectives for the production system of the factory, such as reducing energy consumption, avoiding power peaks, or achieving a power use within the available power supply. Shop Floor Scheduling can help to pursue these objectives within the production system. For this purpose, a solution methodology based on a meta-heuristic will be described for Flexible Job Shop Scheduling taking into account different energy- as well as productivity-related objectives.

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1. Introduction

The energy supply for factories of the future will substantially be based on renewable energies such as wind turbines or solar systems as part of a smart grid or a self-sufficient supply [1]. However, renewable energy sources are only able to provide an intermittent energy supply. In order to enable an effective use of the renewable energy sources without using temporary energy storages, the energy demand of the factory should be able to respond rapidly and flexible to the constantly changing requirements of the energy supply. As a result, reducing energy consumption, avoiding power peaks, or achieving a power use within the available supply will become vital parts of the objectives for the production system of a factory. Shop Floor Scheduling can be used to pursue these energy-related objectives for the production system [2].

In this paper, a method for monitoring and storing energy consumption data streams of the manufacturing equipment will be briefly described for the subsequent application within Shop Floor Scheduling. For specifying the scheduling problem different energy-related objectives for a production system on shop floor level will be defined. These energy-related objectives then will be used in addition to the productivity-related objectives to formulate Flexible Job Shop Scheduling Problem (FJSSP), as a specific class of Shop Floor Scheduling problems. Finally, a meta-heuristic based on a genetic algorithm will be used for solving instances of the FJSSP.

2. Shop Floor Scheduling

Shop Floor Scheduling (SFS) as part of the Production Planning and Control (PPC) ensures the material flow throughout the production system by scheduling all present jobs in terms of their release date [3]. In other words, all jobs are being assigned to manufacturing equipment in a certain sequence and with related processing durations [3,4,5]. Hereby, a job is defined by a certain lot size of a specific product and is often connected to customer orders. It consists of a predetermined processing sequence for the manufacturing operations for the production of the product. This operation sequence can be derived from the work plan in combination with the manufacture bill of material for the certain product. SFS models can be classified according to their constraints [6]. Flow Shop models contain the same machine tool sequencing for every job with no parallel machine tools available and are often used for one piece flow production

systems. Hybrid Flow Shop models have the same sequencing for every job but parallel machine tools are available. Hybrid Flow Shop models represent flexible flow lines and thus have a great significance for the process industry such as chemical, pharmaceutical, oil, food, tobacco, textile, paper, and metallurgical industry as well as for the automotive industry [6]. Within Job Shop models only specific machine tool sequencing exists for every job. Open Shop models do not have a specific sequencing at all. Each job can thus be processed in random sequence on the machine tools.

2.1. Energy-related Job Floor Scheduling

The energy-related Job Floor Scheduling problems in current research can be classified according to their objective functions. The objective functions of energy-related shop floor scheduling problems are addressing the total energy consumption of a production system [7,8], the power peak load [9,10], and electric power costs [11,12]. An approach for connecting the aggregated energy consumption of manufacturing operations with specific Flexible Shop Floor Scheduling Problems has so far not been described in current research.

2.2. Flexible Job Shop Scheduling Models

The Flexible Job Shop Scheduling model can be applied to all different classes of SFS [13]. Usually they are used for the modelling of production systems in industries with high product variety and medium demand for each product. FJSSP includes the assumption that each or some machine tools are capable of offering more than one manufacturing operation. Thus, the machine tool flexibility can be partial or total, referred to as Partially Flexible Job Shop Scheduling Problem (PF-JSSP) or Totally Flexible Job Shop Scheduling Problem (TF-JSSP). PF-JSSP addresses a special case of F-JSSP where each machine tool is not capable to process every operation of a job. TF-JSSP in contrast describes the case, where each machine tool can process every operation of a job [13].

2.3. Meta-heuristic for multi-objective shop floor scheduling

For the efficient solving of FJSSP problems artificial immune algorithms as specific class of genetic algorithm are often proposed in current research [5,13]. Artificial immune algorithms are adaptive systems used within the evolutionary computation which is a subfield of artificial intelligence (AI). They imitate the behavior of the immune system of living organisms, e.g. if the body recognizes foreign substances and defeats them, in terms of learning and memory. This process is called Antigen-Antibody Reaction. Hereby, antigens located on the foreign substances are recognized by a specific antibody that is used by the immune system to neutralize the substance. The immune system detects the antibodies that offer increased potential in neutralizing antigens and spreads their variations within the next generation of antibodies. The efficiency for neutralizing antigens of an antibody is measured by its affinity value [14].

For adapting artificial immune algorithms to shop floor scheduling problems the following model is applied [13]: (a) Antigen: F-JSSP to be solved; (b) Antibody: feasible schedule established and (c) Affinity Values: productivity- and/or energy-related objectives.

[5] and [13] have proven that cloning selection algorithms as a subtype of artificial immune algorithms are superior to other subtypes. These algorithms consist of two main operations: (a) Cloning selection and (b) affinity maturation. With cloning selection, schedules that are efficient for optimizing the objective function for the scheduling problem are further evolved. Affinity maturation sets the rate of mutation depending on their affinity values. Using the approach proposed in [13] the mutation process itself is executed using simulated annealing (SA) until a stopping-criterion is met. SA can be used for finding a good approximation to the global optimum in a fixed amount of time in a large search space. As a result the meta-heuristic is referred to as hybrid of "Artificial Immune algorithm and Simulated Annealing" (AISA) according to [13].

3. Monitoring strategy and energy-planning database

The monitoring strategy is used for processing the energy data captured from manufacturing equipment. It consists of the (a) *measuring strategy*, (b) *evaluation strategy* and (c) the *energy-planning database* for production systems and is a slightly modified version of the concept carried out in [2].

3.1. Measuring strategy

The measuring strategy represents the starting point for acquiring the energy data from the manufacturing system. An overview for the measurement of energy data for manufacturing equipment is described in [2], [15] and [16]. These measuring methods and procedures are responsible for acquiring the relevant energy data for the data evaluation strategy. The evaluation strategy describes how and which parameters are to be computed from the measured energy profiles for a subsequent storing in the energy planning database [2].

3.2. Evaluation Strategy for Manufacturing Equipment

Figure 1 displays the power consumption profile of a machining center for one hour of production. Two typical operational states for manufacturing equipment in terms of power consumption can be identified in the chart. In the *process* state (1) the manufacturing equipment executes the actual machining cycles or in other words the value creation [2]. Within the *idle* state (2) the equipment is ready for operation but no machining is carried out. A third and fourth operational state where the equipment is in *standby* (3) or *switched on/off* (4) does not appear in the shown profile. The *standby* is similar to the *idle* state, but in this state the equipment is not ready for operation because required components, e.g. auxiliary systems, are turned off. The *on/off* state describes the machine start-up and turn-off.
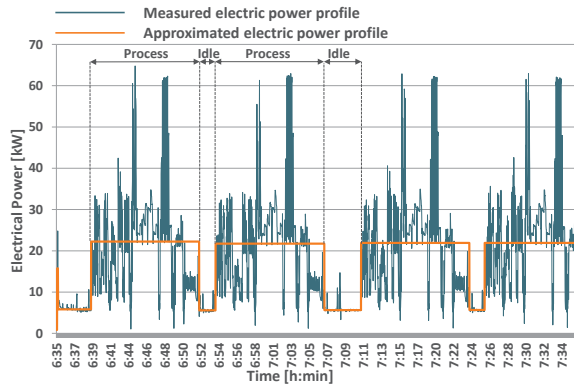
Fig. 1. Evaluation of a power consumption profile of a machining center.

An overview of all four power consumption parameters is given in Table 1.

Table 1. Overview of power consumption parameters [2].

Operational state	Power consumption parameter [kW]
On/off	$P_{on/off\,\varnothing}$
Standby	$P_{standby\,\varnothing}$
Idle	$P_{idle\,\varnothing}$
Processing	$P_{process\,\varnothing}$

Within the data evaluation procedure, the power consumption parameters for each operational state are to be computed from the captured power consumption profiles. The temporal *reference interval* for calculating the average power consumption for the state *process* ($P_{process}$) corresponds with the time period of a machining cycle. Due to some random process variations, e.g. caused by the wear of the tools, the mean power consumption may vary slightly for each cycle in the processing state [2]. To address that, the average power consumption parameter ($P_{process\,\varnothing}$) of all measured numbers of machining cycles is calculated [2]. This procedure is analogously used for the other three power consumption parameters. Since there is no temporal reference given that could be used for the state *standby* and *idle*, a reference interval of 60 s is chosen for calculating the power consumption parameters $P_{standby\,\varnothing}$ and $P_{idle\,\varnothing}$ [2]. The *reference interval* for the fourth power consumption parameter $P_{on/off\,\varnothing}$, is defined by the duration of the start-up and turn-off phase of the equipment.

3.3. Energy-planning database

For the effective subsequent use of the evaluated data a comprehensive data management application is required [2]. There are three main determining factors that have an impact on the energy consumption of the manufacturing process: (a) the manufacturing equipment (machine tool), (b) the machining operation and (c) the set of machining parameters. These influencing factors set up the three dimensions of a so-called *EnergyCube*, as a framework for storing the data. The first dimension *manufacturing equipment* (1) defines the

power consumption of the states *idle*, *standby* and *on/off* for the specific machine tool, since the power consumption of these states is in most cases constant for the same equipment. In contrast, the power consumption of the state *process* can significantly vary on a machine tool depending on the second dimension *machining operation* (2) and related third dimension *set of machining parameters* (3). Thus, all three dimensions in combination determine the state *process* for a specific machine tool. Within Figure 2 the *EnergyCube* database is exemplarily shown for a machine tool (Equipment no 1.). Each small *cube* within the *EnergyCube* provides a set of energy planning data.
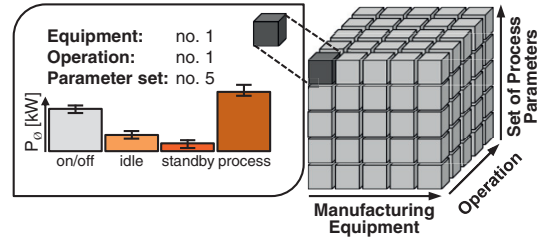

Fig. 2. Energy planning database for the manufacturing system.

4. Energy-related objectives

Energy-related objectives for PPC and in particular for SFS are addressing different energy, power and cost targets:

a. *Energy consumption:*

$$min \sum E := \sum E_i \qquad (1)$$

$$E_i := \sum E_{j,process} + E_{idle} + E_{standby} + E_{on/off} \qquad (2)$$

The aim is to minimize the total energy consumption of all machine tools (1). The energy consumption of a machine tool *i* corresponds to the sum of the energy consumption for the process state for processing a job *j*. In addition, the sum of the energy consumed of the idle and standby state as well as the energy consumption during turning on/off of a machine tool has to be considered (2).

b. *Power peak loads:*

$$min \sum P := \sum_t \sum_i P_{i,t} \qquad (3)$$

$$P_{i,t} := P_{j,process} + P_{idle} + P_{standby} + P_{on/off} \qquad (4)$$

The total power consumption of all machines at one time period should be minimized (3). $P_{i,t}$ is the power consumption of a machine tool *i* in time period *t* (4).

c. *Power use within available supply:*

This objective in terms of SFS is not an objective in the mathematical sense. It is rather an optimization constraint:

$$\sum_i P_{i,t} \leq \overline{P_t} \qquad (5)$$

The power consumption of all machine tools in time period *t* must be equal or below the maximal power supply available for this time period $\overline{P_t}$ (5).

In order to decrease the complexity of the objectives for a better practical implementation, objective (3) can also be represented using (5): The power peak load should always be under a certain threshold value. Thus, objective (3) can be modeled as a constraint in a mathematical sense.

5. Application of the meta-heuristic

The functioning of the energy-related AISA meta-heuristic is described on the basis of a simplified practical planning problem in order to enable a full comprehension. This problem consists of three jobs and two machine tools. The power consumption of a specific operation ($P_{process\,\varnothing}$) for and for the idle state ($P_{idle\,\varnothing}$) of a machine tool is derived from the EnergyCube. The planning problem is outlined in Table 2:

Each job J_j consists of a set of operations $O_{j,l}$. All operations of a job j must be processed in the given sequence $\{O_{j,1}; O_{j,2}; O_{j,3}; ...\}$ on an eligible machine tool M_i. The eligibility parameter takes value 1, if machine tool i can process $O_{j,l}$ and 0 otherwise. For processing an operation a machine tool needs a specific process time as well as a specific average power consumption ($P_{process\,\varnothing}$). Furthermore the average power consumption of machine tool i for being in the idle state ($P_{idle\,\varnothing}$) is considered.

Table 2. PF-JSSP planning problem (Antigen).

Machine tool		Eligibility [0;1]		Process times [s]		Average power consumption [kW]	
Jobs	Operations	M_1	M_2	M_1	M_2	M_1	M_2
J_1	$O_{1,1}$	0	1	-	5	-	10
	$O_{1,2}$	1	0	3	-	8	-
	$O_{1,3}$	1	1	4	3	6	3
	$O_{1,4}$	1	1	6	5	9	12
J_2	$O_{2,1}$	1	0	5	-	15	-
	$O_{2,2}$	1	0	4	-	6	-
	$O_{2,3}$	0	1	-	3	-	8
J_3	$O_{3,1}$	1	1	4	4	7	11
	$O_{3,2}$	1	0	5	-	9	-
				Idle state		2	3

In the following paragraph the AISA algorithm in conformity with [13] will be described:

Step 1: An initialization of antigens is used for a random generation of size N of schedules from the feasible region. *Step 2:* Initialize a new mutating pool of size N. *Step 3:* An affinity value is assigned to each schedule according to the defined objectives. *Step 4:* The schedule with the highest affinity value in this generation is transferred to the new mutating pool. *Step 5:* N-1 schedules are selected via binary tournament, i.e. by comparing the affinity value of always two schedules and transferring the superior schedules into the new mutating pool. *Step 6:* Each schedule in the mutating pool undergoes an affinity maturing procedure via Simulated Annealing (SA) until a stopping criterion is met. *Step 7:* Repeat 2-7 for the new mutating pool until a stopping criterion is met.

In order to enable a better understanding of the algorithm, the initialization for the schedules, the affinity value assignment, and the affinity procedure via SA will be described in the following.

5.1. Initialization of schedules

An initial random operations sequence represented by integer values is assigned to a random number between 0 and 1. Hereby, the chronological order of the integers refers to the corresponding operation of a job, e.g. the first disposed integer *1* refers to the first operation of job *1* and the second disposed integer *1* refers to the second operation of job *1* and so on. The random values are sorted in a non-rising pattern (Table 3). Thus, the operation integer values are sorted regarding their assigned random values. This sorted integer string is the initial feasible sequence for the schedule.

Table 3. Initial sorted sequence [13].

Random value [0,...,1]								
0,82	0,70	0,67	0,61	0,58	0,58	0,34	0,26	0,15
Random operations sequence (integer form)								
2	1	2	3	1	1	2	1	3

This integer string corresponds to the following operations sequence: $\{O_{2,1}; O_{1,1}; O_{2,2}; O_{3,1}; O_{1,2}; O_{1,3}; O_{2,3}; O_{1,4}; O_{3,2}\}$. Each operation is then assigned to a random integer value for a machine tool (Table 4). The maximum of the integer value is corresponding to the quantity of eligible machine tools for a specific operation, e.g. for $O_{1,1}$ the only possible integer value for the machine tool assignment is 1. Hereby, a 1 corresponds to the first eligible machine tool for an operation, a 2 for the second and so on, e.g. the 1 for $O_{1,1}$ refers to M_2. For each operation and machine tool the resulting process time and power consumption can be assigned. As a result the corresponding affinity value for the schedule can be calculated. This initialization procedure is repeated until the population size of N schedules is achieved [13].

Table 4. Initial representation of an antibody [13].

Random value [0,...,1]								
0,82	0,70	0,67	0,61	0,58	0,59	0,34	0,26	0,15
Random operations sequence (integer form)								
2	1	2	3	1	1	2	1	3
Random integer for machine tool assignment from the feasible region								
1	1	1	1	1	1	1	2	1
Machine tool assignment								
M_1	M_2	M_1	M_1	M_1	M_1	M_2	M_2	M_1
Process time [t]								
5	5	4	4	3	4	3	5	5
Power consumption [kW]								
15	10	6	7	8	6	8	12	9

5.2. Assignment of affinity values

Since the mutation of antibodies (feasible schedules) depends strictly on the affinity value, the affinity value of the AISA corresponds directly to the objective function [13]. The greater the affinity value gets, the higher is the rate of mutation of the antibody. Thus, antibodies with greater affinity values evolve superior compared to those with lower affinity values. Typical productivity-related objectives, e.g. makespan, have to be minimized. In order to make them available for being used as affinity value for the meta-heuristic the reciprocal value is calculated – affinity value = 1/makespan. For an AISA with multi-objectives to be minimized, e.g. makespan and total energy consumption, the objectives have to be transformed to one affinity value – as

shown in (6) – (9). For comparing the antibodies regarding the different objectives the ranking method (6) is used. The ranking method is a well-known approach for solving multi-objective optimization problems [7,17].

$$F(x) = \sum_a w_a \frac{f_a(x) - min_{f_a}}{max_{f_a} - min_{f_a}} \qquad (6)$$

This function results in the following ranking function by considering the same weight for both objectives for a schedule *s* in terms of the two objectives *makespan* and *total energy consumption*:

$$F(s) = 1/2 \cdot \frac{C_{max}(s) - min_{C_{max}}}{max_{C_{max}} - min_{C_{max}}} + 1/2 \cdot \frac{E(s) - min_E}{max_E - min_E} \qquad (7)$$

Thus, the affinity value of an antibody corresponds to:

$$A(x) = 1/F(x) \qquad (8)$$

For each schedule *s* in the population of N schedules the affinity value is calculated:

$$A(s_1) = 1 \Big/ {\frac{1}{2} \cdot \frac{C_{max}(s_1) - min_{C_{max}}}{max_{C_{max}} - min_{C_{max}}} + \frac{1}{2} \cdot \frac{E(s_1) - min_E}{max_E - min_E}}$$
$$\vdots \qquad (9)$$
$$A(s_N) = 1 \Big/ {\frac{1}{2} \cdot \frac{C_{max}(s_N) - min_{C_{max}}}{max_{C_{max}} - min_{C_{max}}} + \frac{1}{2} \cdot \frac{E(s_N) - min_E}{max_E - min_E}}$$

where:

- min_E Minimum of total energy consumption within the decision vector for all s
  $min_E = min_{s_1,...,s_N} E(s)$
- max_E Maximum of total energy consumption within the decision vector for all s
  $max_E = max_{s_1,...,s_N} E(s)$
- $min_{C_{max}}$ Minimum of makespan within the decision vector for all s
  $min_{C_{max}} = min_{s_1,...,s_N} C_{max}(s)$
- $max_{C_{max}}$ Maximum of makespan within the decision vector for all s
  $max_{C_{max}} = max_{s_1,...,s_N} C_{max}(s)$

5.3. Affinity maturing procedure via SA:

For affinity maturing the SA is applied in combination with a SHIFT operator [13]. The SHIFT Operator generates a new sequence of operations for an incumbent schedule *s*. E.g. randomly the eighth of the operations values is selected (Table 5). Subsequently, a new random value between 0 and 1 is generated for the selected random value. In our case the 0,26 changes to 0,52. Thereafter, the random numbers are sorted in a non-rising pattern.

Table 5. Random selection of an operation [13].

Random value [0,...,1]								
0,82	0,70	0,67	0,61	0,58	0,59	0,34	**0,26**	0,15
Random operations sequence (integer form)								
2	1	2	3	1	1	2	**1**	3

For this sequence a predefined number of 10 different machine assignments are randomly generated and the one with the highest affinity value *A* is selected and referred to as $s_{mutated}$. This machine assignment for one schedule is exemplarily shown in Table 6.

Table 6. Randomly generated machine assignment for the new schedule [13].

Random value [0,...,1]								
0,82	0,70	0,67	0,61	0,58	0,59	**0,52**	0,34	0,15
Random operations sequence (integer form)								
2	1	2	3	1	1	**1**	2	3
Random integer for machine tool assignment from the feasible region								
1	1	1	**2**	1	2	**2**	1	1
Machine tool assignment								
M_1	M_2	M_1	M_2	M_1	M_2	M_2	M_2	M_1
Process time [t]								
5	5	4	4	3	3	5	3	5
Power consumption [kW]								
15	10	6	11	8	3	12	8	9

The new schedule $s_{mutated}$ from the incumbent schedule s is accepted if the ranking function from the new mutated schedule is superior to the original schedule [13]:

$$\Delta F = F(s_{mutated}) - F(s) \leq 0 \qquad (10)$$

If this is not the case the new mutated schedule is accepted with a probability of [18]:

$$P(\Delta F) = exp(-\frac{\Delta F}{t_i}) \qquad (11)$$

where the temperature t_i decreases according to the geometric cooling schedule [18]:

$$t_i = \alpha \cdot t_{i-1}; \text{ at each temperature i} \qquad (12)$$

Commonly used values of α are between 0,8 and 0,99. The initial temperature t_0 is a critical parameter for the success of SA and depends on the range of ΔF. The initial temperature must enable the acceptance of almost any schedule during the first iteration. If the schedule $s_{mutated}$ is still not being accepted a new iteration will proceed, starting again by applying the SHIFT operator to the incumbent schedule s. At each temperature *i* a quantity of 15 schedules of *s* is generated by the SA and the search is stopped if after seven consecutive temperatures still no improvement in terms of $F(s_{mutated})$ is made [13]. After a schedule $s_{mutated}$ is accepted or the SA is stopped for the schedule *s*, the whole affinity maturing procedure is applied to the next schedule in the mutating pool.

6. Practical implementation and industry case

The application of an energy-related meta-heuristic for a shop floor scheduling problem has been tested in the automotive industry for a production line with 10 machine tools.

As input the real-time measured power consumption data of the machine tools has been used. The real-time data has then been evaluated using the EnergyCube data management concept. Figure 3 shows exemplarily the average power consumption data for the different operational states of a

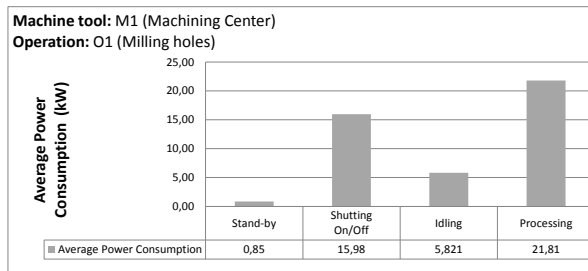machining center for a specific manufacturing operation (milling holes).

Fig. 3. Set of energy planning data for a machining center.

By applying an energy-related meta-heuristic, 15% annual energy savings have been achieved for the production line. Figure 4 shows the simulated, annual energy-saving potential on machine tool level for the production line.
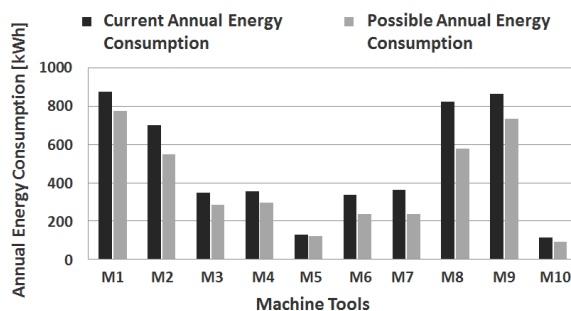

Fig. 4. Energy-saving potential for the machine tools

7. Summary and conclusion

Within this paper a methodology for multi-objective shop floor scheduling taking into account energy consumption data of machine tools has been presented. Therefore, the following key-contents have been described:

- The EnergyCube concept for the evaluation of monitored energy data gained from the machine tools
- Different energy-related objectives for a company formulated on the basis of the available data
- The AISA meta-heuristic for solving flexible job shop scheduling problems taking into account different energy- as well as productivity-related objectives
- The potential of the EnergyCube concept and of energy-related meta-heuristics for a real production line in the automotive industry

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