Improvement of Production Scheduling Performance using Simulated Annealing Algorithm

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Abstract. Production scheduling aims to minimize processing time, waiting time, and inventory levels, as well as efficient use of facilities, labor, and also equipment. In producing these products there is usually ineffectiveness in the scheduling process, such as sorting jobs that are not optimal so that the production requires a long time to produce products in large quantities. Therefore improving performance in order to increase productivity must be carried out continuously considering tremendously strict competition in the industry and manufacturing sector. This study is aimed to minimize the makespan value by scheduling the job sequence optimally. In this study, simulated Annealing Algorithm is used as one of the algorithms for generic optimization that is then compared to the algorithm used by companies. Based on the data processing, the maximal iteration has been reached with 2 iterations. The last iteration is selected which has the smallest makespan value, namely J2-J4-J3-J1 schedule with makespan value of 18,811.2 minutes. The makespan value obtain by simulated annealing algorithm is considered 9.03% more efficient compared to the companies method.

1. Introduction

Improving performance in order to increase productivity must be carried out continuously considering tremendously strict competition in the industry and manufacturing sector. One way to increase productivity is by scheduling production. In order to gain an optimal result, all production activities must first be planned properly. Production scheduling is strived to manage an effective job assignment at each work station in order to reduce the processing time in a production schedule so that the production results obtained can be maximized. Existence of more effective production scheduling and job processing is required.

Proper scheduling of production processes can reduce idle time in production units and minimize work in process. One measure of performance in scheduling is the completion time (makespan) to a minimum [1].

Scheduling objectives are to increase the effectiveness and efficiency of resource usage, so that total of processing time can be reduced and productivity can be increased, reducing the inventory of semi-finished goods or reducing the number of jobs lining in the queue when the existing resources are still performing other tasks, reducing some delays in work with a deadline to minimize penalty costs, and assisting in making decisions about planning plant capacity and the type of capacity required so that the addition of expensive costs can be avoided [1].
In this study, simulated Annealing Algorithm is used as one of the algorithms for generic optimization that can be applied to find approaches to the global optimum solution of a problem [2]. The advantage of simulated annealing compared to other methods is that its ability to avoid local optimal traps. The algorithm is a random search algorithm, but it does not only accept objective values that always go down.

2. Method
This research was conducted on Butsudan (a household Buddhist altar shelf) production with the following steps:

a. Secondary data collection
   Secondary data used is data that has been prepared by the company. In this case, the data obtained is as follows:
   • Type of machine used
   • Number of machines
   • Engine capacity
   • Types of products
   • Number of constituent parts
   • Dimensions of each product

The data can be seen in Tables 1 and Table 2 which is used to obtain the standard processing time of each product.

| No | Machine       | Code | Number of Machine (Jm) | Machine Capacity (Km) |
|----|---------------|------|------------------------|-----------------------|
| 1  | Panel Saw     | M1   | 1                      | 1                     |
| 2  | Hot Press     | M2   | 1                      | 1                     |
| 3  | Yokosuri      | M3   | 1                      | 1                     |
| 4  | Double Saw    | M4   | 1                      | 1                     |
| 5  | NC Router     | M5   | 2                      | 1                     |
| 6  | Kazaban       | M6   | 2                      | 1                     |
| 7  | Panel Press   | M7   | 3                      | 5                     |
| 8  | Strock Belt Sander | M8 | 2 | 1 |
| 9  | Spray Gun Painting | M9 | 4 | 6 |
| 10 | Body Press    | M10  | 1                      | 1                     |

Table 2. Type of products

| Job | Type of Butsudan | Size | Number of constituent part (Jb) | Demand (P) |
|-----|------------------|------|---------------------------------|------------|
| 1   | Dareto- L        | 18-18| 63                              | 27         |
| 2   | Dareto- L        | 16-48| 51                              | 34         |
| 3   | Dareto- L        | 18-40| 65                              | 20         |
| 4   | Dareto- L        | 18-50| 64                              | 60         |

b. Primary data collection
   Primary data is data directly collected which obtained data as follows:
   • Production Process flow
   • The standard processing time of each constituent and product called as a job.
   Table 3 reveals the primary data which have been collected.
### Table 3. The standard processing data

| Machine | Job (seconds) |   |   |   |
|---------|---------------|---|---|---|
|         | J1            | J2| J3| J4|
| M1      | 47.02         | 35.97| 42.90| 41.57|
| M2      | 36.34         | 36.19| 36.10| 36.24|
| M3      | 84.44         | 77.18| 79.47| 80.80|
| M4      | 6.70          | 5.11 | 5.05 | 5.41 |
| M5      | 1,842.82      | 1,833.97| 1,836.20| 1,837.89|
| M6      | 1,050.63      | 1,048.89| 1,048.74| 1,049.25|
| M7      | 1,842.82      | 1,833.97| 1,836.20| 1,837.89|
| M8      | 1,050.63      | 1,048.89| 1,048.74| 1,049.25|
| M9      | 115.87        | 104.81| 111.75| 114.23|
| M10     | 2,056.37      | 1,896.28| 1,964.73| 2,010.57|
| **Total** | **8,133.63** | **7,921.28** | **8,009.89** | **8,063.10** |

c. Data Processing

Data processing is performed by using Simulated Annealing Algorithm.

#### 2.1. Simulated Annealing Algorithm

1. The parameters used in Simulated Annealing are as follows [3]:
   a. System state
   System state is defined as a possible solution. For instance, given flow shop scheduling with 4 jobs, so one of the possible scheduling sequence is J4, J1, J3, J2.
   b. Energy
   Energy is defined as how much the minimum objective functions of a combination of system states. In terms of function minimization, suppose that the current solution is x and the function value is f (x), similar to the energy status of a thermodynamic system, energy for flow shop scheduling problems, energy is defined as the value of the makespan of each scheduled solution.
   c. Temperature
   Temperature is a control value that makes the condition move or not. Atoms move freely at high temperatures and become increasingly restricted when the temperature drops. If the temperature is slowly and regularly lowered, the atoms produce crystals with a proper arrangement with minimal energy. Conversely, if the temperature is lowered quickly it will produce polycrystalline (imperfect crystals) with energy that is not minimal. In terms of the flow shop scheduling problem, temperature is defined as a control parameter.
   d. Cooling rate
   In terms of the flow shop scheduling, the cooling rate function is defined as to how quickly the final solution is achieved. The cooling rate is used in the temperature reduction process. Temperature reduction is shown by Equation (1).

   \[ T_b = a \times T_0 \]
   where \( T_0 \) = initial temperature
   \( T_b \) = New Temperature
   \( a \) = temperature reduction factor (\( a < 1 \))

2. Simulated Annealing Algorithm mechanism in flow shop scheduling is defined as follows [3]:
   a. Generating the initial solution
   The initial solution in scheduling is to generate a random schedule. At this stage, the objective value is determined. The result obtained is defined as the best solution for the initial stage.
b. Searching for new solutions
   The next stage is to look for new solutions from the best solutions produced in the previous
   stage which is called the insertion method. New solutions are formed by randomly selecting
   one part of the structure to be moved to another part.

c. Checking the control parameter
   Determination of control parameters reduction is performed to decide if the control
   parameters require to be lowered. If the control parameter is lowered, then proceed to step d.
   Otherwise, step b and c are repeated.

d. Determination of the best new solution
   At this stage, several new solutions are found that are accepted. One of them is next chosen
   to be the best solution. This best solution will be the initial solution if the control parameter
   is changed.

e. Searching for evaluation of new solution
   Evaluation of new solutions is aimed to evaluate whether the new solutions are accepted.
   The evaluation criteria for the solution are shown by Equation (2).

\[
\Delta E = E(X_{i+1}) - E(X_i)
\]  \hspace{1cm} (2)

where \( \Delta E \) = the objective value change
\( E(X_{i+1}) = \) objective value of the new solution
\( E(X_i) = \) objective value of the initial solution

If the objective value of the new solution is less than the objective value of the initial
solution \( (\Delta E \leq 0) \) then the new solution is accepted. Otherwise, then new solutions might
still be chosen with probability [3].

\[
P(\Delta E) = e^{-\Delta E/T} > r
\]  \hspace{1cm} (3)

where \( T \) = control parameter
\( r = \) random value between 0 and 1

f. Control parameter reduction
   To decrease the control parameter is used equation (1)

g. Determination of the maximal iteration
   Determination of the maximum iteration is to decide whether the iteration is complete or
   not. If the maximum iteration is complete, it means the best solution is the optimal solution.
   If the iteration is not optimal then repeat step a to step g.

3. Result and Discussion
   Calculating the processing time of each product by considering the number of product demands,
   number of constituent parts of each product, number of machines, machine capacity and the standard
   processing time of each product with the following equation:

\[
TM = \frac{P \times Wb \times Jb}{Jm \times Km}
\]  \hspace{1cm} (4)

\( TM_n \) = processing time of product \( n \) on machine \( m \)
\( P \) = number of demand of product \( n \)
\( Wb \) = Standard processing time of product \( n \)
\( Jb \) = number of constituent parts of product \( n \)
\( Jm \) = number of machine \( m \)
\( Km \) = machine capacity
\( n \) = type of jobs; 1, 2, 3, 4
\( m \) = type of machines; 1, 2, 3, ……10
The values of $P$, $Wb$, $Jb$, $Jm$ and $Km$ for the calculation of product processing time 1 on machine 1 can be seen in tables 1 and 2, while the calculation is as follows;

$$TM = \frac{P \times Wb \times Jb}{Jm \times Km}$$

$$TM = \frac{27 \times 63 \times 47.02}{1 \times 1}$$

$$TM = 79,981.06 \text{ seconds or equal to } 1,332.92 \text{ minutes}$$

The following Table 4 reveals the calculation results of processing time for the whole products on each machine.

| Machine | $J1$ (Minute) | $J2$ (Minute) | $J3$ (Minute) | $J4$ (Minute) |
|---------|---------------|---------------|---------------|---------------|
| TM1     | 1,332.92      | 1,039.41      | 929.45        | 2,904.51      |
| TM2     | 206.03        | 209.18        | 156.41        | 463.86        |
| TM3     | 2,394.01      | 2,230.63      | 1,721.85      | 5,171.03      |
| TM4     | 189.85        | 147.60        | 109.47        | 346.36        |
| TM5     | 414.63        | 519.63        | 306.03        | 918.94        |
| TM6     | 472.78        | 594.37        | 349.58        | 1,049.25      |
| TM7     | 328.48        | 302.91        | 242.12        | 731.08        |
| TM8     | 976.93        | 972.92        | 728.81        | 2,164.31      |
| TM9     | 161.74        | 156.13        | 119.12        | 355.39        |
| TM10    | 925.36        | 1,165.19      | 685.38        | 2,056.27      |

3.1. Simulated Annealing Algorithm

Scheduling completion steps using the Simulated Annealing algorithm are briefly described as below:

a. Generating an initial solution

In this stage, determination of the initial solution is performed by calculating the smallest makespan value using 3 methods [4]:

- FCFS (First Come First Serve),
- SPT (Shortest Processing Time),
- LPT (Longest Processing Time)

Based on the calculation result obtained by the methods, it is found out LPT method produce the smallest makespan value which is 18,936.94 minutes with job sequences of $J4$-$J1$-$J2$-$J3$. The value then serves as the initial solution.

b. Generating new solution

Generation of a new solution is performing by using the insertion method. In this method, the number of exchanges (replication) is determined. In this study, replication is carried out 5 times based on several references followed. The replication value is a number indicating the number of loops which must be done before decreasing the control parameters. Job sequences obtained from the replication results are:
Among 5 job sequences shown on Table 5, it is found out that the new best solution is the job sequence of J2-J4-J1-J which can be performed in 18,811.2 minutes. The makespan value serves as the new solution which is then compared to the initial solution consuming time of 18,936.94 minutes gained by Equation 2.

\[
\Delta E = E(X_{i+1}) - E(X_i) \\
= -125.7 \\
\text{where } E(X_{i+1}) = 18,811.2 \text{ and } E(X_i) = 18,936.9
\]

As the criteria if \( \Delta E \leq 0 \) then the new solution is accepted. Because of \( \Delta E = -125.5 \) means that the new solution is accepted.

c. Control parameter value reduction

Reduction of control parameters is carried out to obtain the possibility of makespan values smaller than the new solution. The initial predetermined is 100 with a reduction factor of 0.45. A reduction factor is a number used to decrease parameters in a gradual and controlled manner, with the following results:

| Number of iteration | Control Parameter | Job seq. | Makespan (minute) |
|---------------------|-------------------|----------|-------------------|
| Iteration 1         | 100               | 4 3 1 2  | 18,936.9          |
|                     | 1 4 2 3           | 19,344.5 |
|                     | 2 4 1 3           | 18,811.2 |
|                     | 3 4 2 1           | 19,181.0 |
|                     | 2 3 1 4           | 20,387.7 |
| chosen solution     |                   | 2 4 1 3  | 18,811.2          |
| Iteration 2         | 45                | 2 1 3 4  | 20,387.7          |
|                     | 1 3 4 2           | 19,612.6 |
|                     | 3 2 4 1           | 19,055.2 |
|                     | 4 2 3 1           | 18,936.9 |
|                     | 2 4 3 1           | 18,811.2 |
| Chosen solution     |                   | 2 4 3 1  | 18,811.2          |

d. Evaluation of the new solution

In the state of 100 control parameter value, the new solution selected is the schedule sequence with a makespan of 18,811.2 minutes. This solution is compared to the initial solution namely makespan of 18,936.94 minutes. The new solution produced is better than the initial conditions so that the initial solution is accepted to be the new solution of job schedule J2-J4-J1-J3 with a makespan value of 18,811.2 minutes.
e. Determination of the maximal iteration

The maximal iteration has been reached, namely 2 iterations so that the iteration has been fulfilled. From the overall sequences obtained, the last iteration is selected which has the smallest makespan value, namely $J_2 - J_4 - J_3 - J_1$ schedule with 18,811.2 minutes makespan value.

**Table 7.** Makespan value using simulated annealing algorithm

| Job | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 |
|-----|----|----|----|----|----|----|----|----|----|-----|
| J2  | Start | 0 | 1,039.41 | 1,248.59 | 3,479.22 | 3,626.82 | 4,146.44 | 4,740.81 | 5,043.73 | 6,016.65 | 6,172.78 |
|     | End   | 1,039.41 | 1,248.59 | 3,479.22 | 3,626.82 | 4,146.44 | 4,740.81 | 5,043.73 | 6,016.65 | 6,172.78 | 7,337.97 |
| J4  | Start | 3,943.92 | 4,407.78 | 9,578.82 | 9,925.18 | 10,844.12 | 11,893.37 | 11,624.46 | 14,788.76 | 15,144.16 |
|     | End   | 3,943.92 | 4,407.78 | 9,578.82 | 9,925.18 | 10,844.12 | 11,893.37 | 12,624.46 | 14,788.76 | 15,144.16 | 17,200.42 |
| J3  | Start | 4,873.38 | 5,029.79 | 11,300.66 | 11,410.13 | 11,716.17 | 12,065.75 | 12,866.57 | 15,517.58 | 15,636.69 | 17,885.80 |
|     | End   | 4,873.38 | 5,029.79 | 11,300.66 | 11,410.13 | 11,716.17 | 12,065.75 | 12,866.57 | 15,517.58 | 15,636.69 | 17,885.80 |
| J1  | Start | 6,206.30 | 6,412.33 | 13,694.67 | 13,884.52 | 14,299.16 | 14,771.94 | 15,100.42 | 16,494.51 | 16,656.25 | 18,811.16 |
|     | End   | 6,206.30 | 6,412.33 | 13,694.67 | 13,884.52 | 14,299.16 | 14,771.94 | 15,100.42 | 16,494.51 | 16,656.25 | 18,811.16 |

Figure 1 reveals Gantt chart of Scheduling by Simulated Annealing algorithm.

![Scheduling using Simulated Annealing method](image)

**Figure 1.** Gantt Chart using Simulated Annealing Algorithm

The simulated annealing algorithm is used to find approaches to the global optimum solution of production scheduling. In this case, simulated annealing algorithm provides a solution in terms of makespan.

4. Conclusion

It can be concluded that the first based on data processing performed by using the Simulated Annealing Algorithm method (4 jobs and 10 machines), the optimal makespan obtained is 18,811.2 minutes. The second comparison analysis of the makespan value of the Simulated Annealing Algorithm method to the company method is as follows, which is included with the Simulated Annealing Algorithm method obtained 18,811.2 minutes of makespan value which is 9.03% more efficient makespan compared to the Gupta algorithm which is used by companies, and the optimal job
sequence of the Simulated Annealing Algorithm method is $J_2-J_4-J_3-J_1$. Therefore, Simulated Annealing algorithm is powerful and could be recommended to be used in companies to increase the productivity.

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