Sustainable flexible flow shop scheduling optimization in flexible packaging industry using genetic algorithm

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Abstract. Flexible flow shop (FFS) scheduling optimization process has a high level of complexity and categorized as an NP-hard problem. X Co is a flexible packaging manufacturer that scheduled FFS manually with a low sustainability level. The objective of this research is to optimize FFS scheduling in X Co using Genetic Algorithm (GA) method to increase the sustainability level and measure its performance. The sustainability parameters contain three main aspects of sustainability. In this optimization process, makespan minimization used as the objective function, and elitism is applied in the GA method to make sure the makespan value is getting smaller in each generation. The result shows an increment of sustainability level in all parameters. Makespan value reduction by 135 hours, zero lateness, idle time reduction by 1755 (hour*machine), machine utility improvement by 5.58%, electricity consumption reduction by 23664 kWh which converted into a reduction of 16731 KgCO₂e greenhouse gas, and also increase employee productivity as much as 0.066 jobs/shift. This research shows an optimal result with a higher level of sustainability in the implementation of optimization on FFS scheduling at X Co.

1. Introduction
Scheduling is an activity of allocating production resources to complete the production process within a specified period by paying attention to the limited resources and constraints that exist, so all work executed properly and feasibly [1, 2]. However, scheduling activities have a high level of complexity, so companies that implement poor scheduling activities can lead to long production times, high delays and idle time, and also low machine utility levels [3]. This circumstance can lead companies into loss in various aspects, so there is a need for scheduling optimization.

Scheduling itself consists of several models by adjusting the type of product produced, one of the scheduling models that is widely used is the Flow Shop (FS) scheduling model. [4]. The more complex form of FS is a flexible flow shop (FFS) or hybrid flow shop (HFS) that has little change by adjusting production conditions, where each production stage consists of several machines in parallel and each order has different type and sequence of work and also different machine compatibility [5, 6].

One method commonly used in FFS scheduling optimization is the Genetic Algorithm (GA) method. According to Sadegheih [7], GA is an excellent method for optimizing various scheduling problems compared to other heuristic methods such as Simulated Annealing from optimization results and computational time. Recently, the optimization process is not only done to find optimal solutions in economic efficiency but also environmental and social efficiency [8]. That concept is a definition of sustainability and has a form of a sustainable manufacturing process where scheduling plays an
important role. According to He et al. [9], sustainable manufacturing is the process of making a product by minimizing negative impacts on the environment while saving energy and other resources. Sustainable manufacturing can also be defined as a branch of sustainability studies that consider economic, environmental and social aspects and objectives in production activities [10]. The implementation of sustainable FFS scheduling which is also part of sustainable manufacturing can be done by measuring several sustainability indicators published by the International Organization for Standardization (ISO) in the form of ISO 14031 in 1999 which have 155 sustainability indicators and indicators published by the National Institute of Standards and Technology (NIST) in the form of a Sustainable Manufacturing Indicator Repository (SMIR) in 2010 that has 212 sustainability indicators.

One example of a company that requires continuous scheduling optimization is X Co. The company is producing flexible packaging by implementing the FFS production model. The production process consists of printing, laminating, slitting and bag making, where each stage of the process consists of several machines that run parallel. The production scheduling process carried out by X Co is still done manually so it can cause losses in economic, environmental and social aspects in the form of long makespans, high delays and idle-time as well as low utilities which have a direct impact on carbon emissions produced and low worker productivity. These problems have been identified during the data collection period in July-August 2018 and in March 2019 as well as being the background for this research. The objective of this paper is to measure the optimization performance of FFS scheduling process at X Co using GA to make its production process more efficient and sustainable.

2. Literature review

2.1. Flexible packaging
Flexible packaging is one type of packaging found in various products on the market. This packaging is a primary, secondary or complementary part of a packaging that has a flexible shape that can wrap and protect packaged products according to the shape of the product or its primary packaging. Flexible packaging can be made using paper materials, plastic films, aluminum foil, metal-coated paper, metal-coated sheets or a combination of these materials [11]. Flexible packaging can be produced with various combinations and adjustments both from the material used, the number of colors, thickness and type of finishing of the packaging such as in the form of a roll, pouch, gusset and bag.

2.2. Flexible flow shop scheduling
FFS production scheme has the definition of working n-orders by m-machines where each order has a work order by different machines [6]. FFS itself is a type of production scheme that is considered challenging to optimize. The FFS scheduling model is an example in the problem of non-deterministic polynomial acceptable problems (NP-hard problems) which is a problem with completion time which will increase exponentially or factorial along with increasing problem size [12]. NP-hard problems will take a very long time and use vast computational resources when searching for the best solution enumerated, namely by evaluating every solution that is in searching space from a problem. The possibility of completing all possible solutions resulting in an FFS problem with the number of n is as much as (n!).

2.3. Sustainable scheduling
Sustainable scheduling is part of sustainable manufacturing which has the definition of production activities which use processes that can minimize the impact on the environment, save energy and natural resources and safe for workers, communities and the environment and is economically profitable [13].

2.4. Genetic algorithm
GA is an optimization method that works based on a search algorithm combined with a selection and evolution process as well as an evolutionary process that occurs naturally to get better results. Charles Darwin's principle of "survival of the best individuals" became the basis of GA and was developed by
John Holland in the 1960s [14]. Until now, GA has been applied in various processes and has many advantages as follows: GA resolves problems in parallel and multidirectional way, and able to find optimal solutions with a shorter time. GA has an excellent performance in searching for optimal solutions in complex solution landscapes and proven to be able to escape from local optima, GA can solve problems without knowing the problems that must be solved so that it can adjust complex function functions [15].

3. Methodology

3.1. Framework
The optimization process of sustainable flexible flow shop scheduling using the genetic algorithm method begins with collecting data on production components at X Co, then identifying the scheduling system as a method of comparing optimization results. To assess the level of sustainability, both before and after the optimization. Several sustainability indicators will be selected from several published indicator sets. After the sustainability indicator has been chosen, the optimization objective function will be determined that best fits the chosen indicator. Next, an optimization application will be made using the GA method on the IDE Eclipse in java. The finished application will measure performance using the instance library until the performance is as expected and optimization will be carried out using research data to increase the level of sustainability as in figure 1.

3.2. Sustainability level calculation
The process of calculating the level of sustainability is held using indicators that have been selected from the indicator set issued by ISO in the form of ISO 14031-1999 and the indicators published by the NIST in the form of SMIR in 2010. The selection of indicators based on compatibility and the real influence of the indicators selected and based on Akbar and Irohara's research [16] the calculation method was chosen based Tan, et al. research [17]. Some of the sustainability indicators used can be seen in table 1.

Table 1. Data and calculation for sustainable indicators.

| No | Variables                           | Values |
|----|-------------------------------------|--------|
| 1  | Makespan (Hour)                     | (a)    |
| 2  | Total lateness (Hour)               | (b)    |
| 3  | Idle Time (Hour*Machine)            | (c)    |
| Quantity of used machine (Machine) | (d) |
|-----------------------------|-----|
| Quantity of jobs (jobs)     | (e) |
| Shift Duration (Hour)       | (f) |
| Average hourly electricity consumption (kW) | (g) |
| Electricity cost (Rp/kWh)   | (h) |

Environmental aspect

| Electricity consumption (kWh) | (i) = (a) * (g) |
|-------------------------------|-----------------|
| Greenhouse gas produced (KgCO₂e) | (j) = (i) * 0.707 |

Economical aspect

| Machine utility (%) | (k) = ((a)-(c))/((a) * (d)) * 100 |
|---------------------|-----------------------------------|
| Electricity Cost* (Rp) | (l) = (h) * (i) |

Social aspect

| Worker productivity (jobs/Shift) | (m) = (c) / ((a) / (7)) |

Using the variable that already declared above, the makespan calculation could be done by using these models and formulas:

\[ T_{i,j} = P_{i,j} \]

\[ T_{i,j} = 0 \Rightarrow P_{i,j} = 0 \land i \in \{1, \ldots, n\} \land j \in \{1, \ldots, m\} \]  

(2)

\[ T_{i,j} = \max(T_{i,j}, \ldots, T_{i-1,j}) + P_{i,j} \Rightarrow j \in \{1, \ldots, m\} \]  

(3)

\[ T_{i,j} = \max(T_{i,j}, \ldots, T_{j-1,i}) + P_{i,j} \Rightarrow i \in \{1, \ldots, n\} \]  

(4)

\[ T_{i,j} = \max(\max(T_{i,j}, \ldots, T_{i,j-1}), \max(T_{i,j}, \ldots, T_{j-1,i})) \]  

(5)

\[ T_{F_i} = \max(T_{i,j}, \ldots, T_{i,j}) \Rightarrow i \in \{1, \ldots, n\} \land j \in \{1, \ldots, m\} \]  

(6)

\[ M_s = \max(T_{F_i}) \Rightarrow i \in \{1, \ldots, n\} \]  

(7)

\[ L_i = 0 \Rightarrow T_{F_i} \leq D_i \land i \in \{1, \ldots, n\} \]  

(8)

\[ L_i = D_i - T_{F_i} \Rightarrow T_{F_i} > D_i \land i \in \{1, \ldots, n\} \]  

(9)

\[ T_i = \sum_{i=1}^{n} L_i \]  

(10)

Expression 1 shows that the finished time of the first order in the first machine equals to the processing time of first order on the first machine. Expression 2 shows that the finished time of order-i on machine-j equals to zero if the processing time in that specific order and machine is zero. Expression 3 shows that the finished time of first order in every machine equals to maximum finished time from the previous machine added by processing time on that machine. Expression 4 shows that the finished time of every order in the first machine equals to maximum finished time of the previous order in the first machine added by the processing time of that order on the first machine. Expression 5 shows that the finished time of order-i on machine-j equals to maximum time from maximum finished time on a previous order in that machine and maximum finished time of the previous machine on that order then added by the processing time of order-i on machine-j. The finished time of processing order-i can be calculated using Expression 6 that shows the finished time of order-i is a maximum time of finished...
processing time of order-i on every machine. Makespan is also using the same concept as calculating finished time in every order with some differences. Expression 7 is used for calculating makespan by finding the maximum time of finished time from every order. Expression 8 shows that lateness of order-i is zero if the deadline value is greater than the finished time of the order and Expression 9 shows that lateness is the result of subtracting finished order time by deadline for calculating the idle time if the finished order time is greater than deadline value. The total lateness is calculated using Expression 10 that sum up all lateness value in every order. Idle time (\( c \)) calculation could be done by using this formula.

\[
It = \sum_{j=1}^{N} (Mc - \sum_{i=1}^{n} P_{i,j}) \Rightarrow i \in \{1, \ldots, n\} \land j \in \{1, \ldots, m\}
\]  

Expression (11) could be seen as the way of calculating idle time by sum up the result of subtraction between makespan and the total time of machine that used on that specific j-order.

3.3. Optimization software design

The software with this interface has been designed with various main parts, namely a dialogue management system that can interact directly with users and centralized processing systems consisting of a model base management system (MBMS) and database management system (DBMS). MBMS is used as a tool to solve calculations from equations and algorithms used in the optimization process. DBMS is used as a provider and place to store data needed in the calculation process and optimization process by software. The configuration of the software design system can be seen in figure 2.

Figure 2. Scheduling optimization software configuration design.

Models designed in system configuration are implemented using genetic algorithm optimization methods. Software development itself is done using the Java programming language with the help of the Eclipse IDE. The device is built with input data on engine specifications for each type of order (capacity, speed, and energy consumption) and produces the best output data based on genetic algorithm methods. Previously, class diagrams are created using SAP Power Designer software version. 16.6. Which will be useful in determining the interaction between data used in the software optimization model. In addition, MySQL-based database is developed. The other parts of the software act as interfaces to carry out the optimization process using the GA method. In this section, the GA method parameter input data is inputted and the results of scheduling optimization results are displayed.

3.4. System verification

Models have gone through the implementation process so that the optimization software will be obtained through the verification phase. The verification phase is useful to find out whether the model in the
software works well as it has been designed and carried out equations input into the system [19]. In this study, a system verification was carried out by comparing the results of the model calculations and the equations performed by the system with calculations using the help of Microsoft Excel 2013 software.

3.5. System validation
The system that has been created goes through the validation stage. This stage is useful for knowing the behavior of the system that has been made in solving problems that have been made and demonstrating the problem-solving process. According to Sargent [20], validation can be done by comparing the results of software calculations with known problems. In this study, several instances of the library will be used in the form of several TSP problems and calculate how much the performance of the software system in finding the optimum results from these problems. In addition, the comparison of optimization results with several literature results will be used without following the parameters used to determine the maximum reliability of the software among several existing research results and know the advantages.

4. Result and discussion

4.1. Current sustainability level
To see how the level of sustainability of the results of manual scheduling has been done by X Co PPIC staff, the calculation is done using sample order data as attached in attachment 2 and calculated using manual iterations with the formulation contained in the FFS method section. Calculation of indicators is done sequentially in the sample data starting from the first to the last sequence (number 40). This calculation is done to simulate a simple scheduling process using FCFS rules so that the results of sustainability calculations can be seen in table 2.

| Indicator                              | Value  |
|----------------------------------------|--------|
| Makespan (Hour)                        | 826    |
| Total Lateness (Hour)                  | 123    |
| Idle time (Hour*Machine)               | 7579   |
| Machine utility (%)                    | 29.42  |
| Electricity consumption (kWh)          | 144790 |
| Greenhouse Gas produced (KgCO₂ e)      | 102367 |
| Worker productivity (jobs/shift)       | 0.34   |

From the sustainability level calculation without optimization, it can be seen that the process of manually scheduling 40 orders still produces 123 hours of total delay (compared to the overall deadline of 720 hours/30 days). Total idle time can also be said to be still high, amounting to 7579 hours * engine and engine utility by 29.42%. The level of efficiency in the environmental aspect shows that electricity consumption is 144790 kWh as long as the entire makespan is run and converted into 102367 Kg of greenhouse gas production equivalent. The level of efficiency in social terms shows that worker productivity in each shift can carry out 0.34 orders. The poor level of sustainability obtained by manual scheduling and calculation occurs because of the inability of humans to be able to solve problems that are difficult to describe and use complex calculations.

4.2. System verification and validation
The created system has gone through a verification and validation stage to determine whether the methods and functions that have been implemented in the software having a correct calculation following the desired rules and stages. The verification process has been carried out with manual calculations using Microsoft Excel in the explode order function, calculation of makespan, idle time and utility values. While the stages of software validation are compared with other models [20]. In this study, the TSP problem library is used using TSPLIB which has the most optimum value. This stage of
validation is also done to meet the objective of measuring performance optimization and comparing it with the methods that have been developed in journals and other studies and produce performances in table 3.

**Table 3. Software library testing performance.**

| Library | Searching space | Optimum Value | Best Result | Performance |
|---------|-----------------|---------------|-------------|-------------|
| EIL51   | $1.55 \times 10^{66}$ | 426           | 431         | 98.8%       |
| KroA100 | $9.33 \times 10^{157}$ | 21282        | 23150       | 91.9%       |

The validation process is carried out using two libraries, namely EIL51, which has 51 problem points with search spaces $1.55 \times 10^{66}$ and KroA100, which have 100 problem points with a search space of $9.33 \times 10^{157}$. Testing of EIL51 produced performance of 98.9% and testing of KroA100 produced performance of 91.9%. To be able to ensure that the software has novelty and can compete with other software, a literature study is conducted on some of the research software results that use similar libraries. The results of the literature study can be seen in table 4.

**Table 4. Performance comparison between literatures.**

| Library | Literature | Best Result | Performance |
|---------|------------|-------------|-------------|
| EIL51   | [21]       | 431         | 98.8%       |
| EIL51   | [22]       | 436         | 97.7%       |
| EIL51   | [23]       | 441         | 96.6%       |
| KroA100 | [24]       | 30856       | 68.9%       |

The results of performance comparisons show that the GA model and software developed in this study have the ability to compete and can be proven that the performance is higher compared to some optimization software developed in the literature research.

4.3. Optimization result

The scheduling optimization process is carried out on 40 sample data and will be compared with calculations without optimization in table 2. In the experiment, the GA parameter in the form of a population of 1000, the target generation of 10000 generations, a PC value of 0.9 and PM value of 0.2. The use of these parameters is based on the book Genetic Algorithms: Theory and Applications for Business and Industry by Arkeman et al. [25]. Optimization result has been compared with the results before optimization and contained in table 5 and have been calculated against the indicator indicators that have been set and repeated as many as 15 iterations where each iteration consists of sub-repetitions of 10 times.

**Table 5. Optimization result.**

| Indicator                         | Before Optimization | After Optimization | Improvement | Objective Status |
|-----------------------------------|---------------------|--------------------|-------------|------------------|
| Makespan (Hour)                   | 826                 | 691                | -135        | Accomplished     |
| Total lateness (Hour)             | 123                 | 0                  | -123        | Accomplished     |
| Idle time (Hour*Machine)          | 7579                | 5824               | -1755       | Accomplished     |
| Machine utility (%)               | 29.42               | 35.0               | +5.58       | Accomplished     |
| Electricity consumption (kWh)     | 144790              | 121126             | -23664      | Accomplished     |
| Greenhouse Gas produced (KgCO$_2$e) | 102367             | 85636              | -16731      | Accomplished     |
| Worker productivity (jobs/shift)  | 0.339               | 0.405              | +0.066      | Accomplished     |

The results of FFS scheduling optimization in table 5 show the achievement of increasing the level of sustainability in all parameters used. There was a reduction in makespan of 135 hours, a decrease in delays of 123 hours so that there was no delay. An idle time reduction of 1755 units of time (Machine *
hours), an increase in machine utility by 5.58%; the decrease in electricity consumption was 23664 kWh which was later converted to a reduction in greenhouse gas production of 16731 KgCO$_2$ and an increase in worker productivity by as much as 0.066 jobs/shift. These results show that optimal results are obtained which have a higher level of sustainability after the FFS scheduling optimization process. Although the level of sustainability in every aspect is improved, we do not categorize the sustainability level using Monte Carlo and multi dimensions scaling (MDS) methods as conducted at Marimin et al [26] research.

The process of optimizing FFS scheduling using software also runs in a relatively short time, which is for 1 minute to get a possible solution of 10 million possible solutions. This result is far better than the use of the enumerative method that has been done previously. In the enumerative method, the optimization process can only be performed on 10 orders which have 3 million workaround solutions, but it takes around 3 minutes and uses a very high amount of computation resources. This certainly provides benefits and is an advantage of the genetic algorithm method because it can carry out the optimization process with a much faster time and by using smaller computational resources. Advantages of using the GA method with enumerative methods can be seen in table 6.

| Parameter          | Genetic Algorithm | Enumerative       |
|--------------------|-------------------|-------------------|
| Searching Coverage | <1%               | 100%              |
| Computation time   | 10 million solutions / minute | 3 million solutions / minute |
| RAM usage          | 15 million solutions / GB  | 750 thousand solutions / GB |

From table 6, it can be seen that GA has a far better advantage than enumerative methods, in terms of saving computational time and RAM usage, the GA method outperforms the enumerative method, but in searching coverage the enumerative method is much better because it is able to know every solution that is available to get the best or the most optimal solution. However, the enumerative method cannot be done on problems with a very large number of solutions because it can require computational time and unreasonable computational resources. The optimization results show that there are many optimum solutions in the solution landscape that have X Co FFS scheduling problems. With the combination differences obtained, it can be said that the optimization process is not trapped in the local optima. However, regardless of whether or not the optimization process at local optima is trapped, the solutions obtained have shown an increase in the level of sustainability and have met the research objectives.

4.4. Managerial implication

The process of optimizing flexible packaging production scheduling on X Co with an FFS production system can be done using the genetic algorithm method to increase the expected level of sustainability in the entire production process. The scheduling process that was done manually by PPIC staff can now be done more easily and more precisely by using a DSS in the form of a software application that will produce a near-optimal scheduling solution. The use of DSS is also quite easy and does not require in-depth capabilities in the use of computers.

This software can also double the task of recording orders because it is equipped with a database that will be added to each input of the scheduled orders. With the use of this software, it can increase the sustainability level of X Co and benefit the company in economic, environmental and social aspects. In the economic aspect, X Co can save production costs that can increase profits. Whereas in the environmental aspect, the company can be more environmentally friendly and improve the company image. As well as on social aspects, companies can increase the productivity of their workers.
5. Conclusions and Recommendations

5.1. Conclusions
Currently, the X Co production scheduling process still has a low level of sustainability and can potentially disadvantage the company. DSS software has been developed that can optimize FFS X Co. scheduling. DSS software uses the basic GA method in performing optimization combined with additional selection methods in the form of elitism. Software has passed the verification and validation stages with satisfactory performance even better than some studies. The optimization results using software showed a reduction in makespan of 135 hours, a decrease in delay of 123 hours so that there were no delays, a decrease in idle time of 1755 units of time (Machine * hours), an increase in engine utility by 5.58%; the decrease in electricity consumption was 23664 kWh which is later converted to a decrease in greenhouse gas production of 16731 KgCO2e and an increase in worker productivity by as much as 0.066 jobs/shift. These results show that optimal results are obtained which have a higher level of sustainability after the FFS scheduling optimization process.

5.2. Recommendations
It is necessary to measure the effect of GA parameter parameters on the performance of FFS scheduling optimization. So there is no need to do an experiment by trial and error in every search for the optimum solution. GA operators can also be developed with a stochastic method so that it can improve the overall optimization performance of GA. It is also necessary to integrate applications with enterprise resource planning (ERP) software owned by companies so that the optimization process can be more realistic in accordance with the conditions of raw materials and can be implemented more easily and quickly because it is integrated. Dynamic scheduling should also be considered in further study to accommodate real-life situation when orders comes in anytime. The optimization method has to also be developed so that the PPIC staff does not need to manually assign machines. The machine assignment process should be done automatically by the software that can be developed in further studies.

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