The Production Process Can Be Started After Material Coming

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CHAPTER I

INTRODUCTION

1. Background of the Study

The importance of material release time planning in stochastic manufacturing systems has attracted much attention in the last decades. For complex product structures in make to order manufacture, the material will be performed in some different assembly processes during different time periods. The assembly process cannot be started until its subassembly and its material are ready. In the company of this research, the problem arise related to a bogie of a car locomotive which has components with long sequences of manufacturing processes, such as bogie frame, spring plank, upper bolster, and brake equipment. Before being assembled, the material must be provided on time in order to avoid over inventory of material or lateness coming of material, which can effect to assembly process. Based on that case, the optimization of material release time is fully essential in order to minimize the cost that arises from inventory and idle time in machine process. The final product is assembled and tested before delivery to site. It is desirable to design material release times on time, in order to minimize the cost, which is work in process (WIP) holding costs, product earliness and tardiness costs. This is a difficult problem in stochastic situations, where uncertainties in production processes are accumulating and interacting due to the precedence constraints, resource constraints and assembly coordinate requirements (Song, 2006).

Some of previous research work is focused on single machine system. For example, investigated the problem of determining simultaneously material and job ready times and production sequence in a single facility and a flow shop environment subject to the given service level constraints is considered Hodgson et. al., (1997).

Elmagharby (2001) is applied dynamic programming to optimize a common release time for all jobs and the job sequences in a system with a single or multiple parallel machines.

Most of the above work is limited to a single machine. In the multi machine is already done, but most of them considered related to due date without calculating the parameter of its cost. Song (2006) in his research material release time control for complex make-to-order product with stochastic processing time, already applied on complex make to order company and also calculate its cost but its too complicated to applied the method. The method is not only use simulation procedure but also using evolution strategy. In this research will examined complex make to order company, to find on time raw material coming, optimal processing time, in order to minimize the holding costs, product earliness and tardiness costs. Furthermore in this research will be done for some parameters that give influence to the material release time. GA approach is the tool to seek the optimization of its parameter. GA is effective methods for solving complex and global optimization problems such as non-linear integer programming problems. A distinguished characteristic of GA is that a population of possible solutions instead of a single solution is used in the search for the best solution. Each solution candidate is codified as a string of binary or integer numbers, called a chromosome. The objective function is the basis to compare two chromosomes in order to decide which one represents a better solution to the problem. Generations of new individuals (offspring) are obtained using probabilistic operators. By implementing the GA approach, the optimum solution can be achieved and the production cost can be reduced significantly.

1.2 Problem Statement

The production process can be started after material coming. If the materials come on time before being processed, it will minimize the holding cost and idle time machine.

Those cases should be solved in order to minimize the production cost. From the explanation, it can be known the problems that should be solved as follow:

1. When will be the optimum material release time occurred?
2. How much the minimum inventory holding costs and idle time cost in machine?

1.3 Objectives

The objectives of this research are:

1. Determine the optimum material release times.
2. Minimize the inventory holding cost and idle time cost in machine.

1.4 Benefit of Research

The previous research (Song, 2006) will be continued in this research in order to:

1. Develop the improvement of management strategy in generating material release time.
2. Recommend the improvement strategy planning of material release times to decrease the holding cost and idle time in machine.
3. Give the literature study for industrial engineering.

1.5 Research Limitation

The limitation of this research are as follows:

1. The research is done in PT. Industri Kereta Api (INKA).
2. Implementing Song (2006) model and developing model.
3. Determining material release time using GA method applied in *NLI-Gen*® software.

1.6 Outline of Thesis

The structure of thesis as follow:

CHAPTER II **LITERATURE REVIEW**

Contains of concept and basic principal needed to solve the research problem. Also contains of brief description of research result done by previous researcher which has relation with the research doing by now.

CHAPTER III **RESEARCH METHODOLOGY**

Contains of structure and flowchart description, model used, model improvement, tools and materials, research plan, data needed and analytical process.

CHAPTER IV **DATA PROCESSING AND RESULT**

Contains of data explanation during research and then data processing is done based from suitable method.

CHAPTER V **DATA ANALYSIS**

Contain of research analysis from data processing. Data analysis is done with relevant concept.

CHAPTER VI **CONCLUSION AND SUGGESTION**

Contain of conclusion of analysis and suggestion of problems to emphasize future improvement.

REFERENCES

APPENDIX

CHAPTER II

LITERATURE REVIEW

2.1 Theoretical Review

The production process in locomotive company is processed in various machines and it has a complex product structure. This production process consists of production process of material and assembly process. The production process for material is done in welding 1 until welding 4. The assembly process is processing in welding 5 and welding 6. Welding 5 there is an assembly for car locomotive while in welding 6 there is an assembly for bogie. Before being assembled, the material must be provided on time in order to avoid over inventory of material or lateness coming of material, which can effect to assembly process. Based on that case, the optimization of material release time is fully essential in order to minimize the cost that arise from inventory and idle time in machine process. A lot of previous research work is focused on single machine system. For example, Liao (1992) considered the optimal release time for the arriving jobs in a single machine system with stochastic processing times. Hodgson et. al., (1997) investigated the problem of determining simultaneously material and job ready times and production sequence in a single facility and a flow shop environment subject to the given service level constraints. Elmaghraby (2000) extended the above work by including the objective of maximizing an economic gain. A dynamic programming model is applied to a single facility to determine the optimal activity/job start time, Elmaghraby (2001).

The majority of the above work was limited to simple system such as single machine and serial production line. Some of them assumed the fixed production sequences on resources. Little work has been done on material release time planning in general make to order systems with complex products structures, stochastic processing times and multiple resources constraints. The main reason is the extreme complexity of the problem. This is a difficult problem in stochastic situations, where uncertainties in production processes are accumulating and interacting due to the precedence constraint, resource constraints and assembly coordinate requirements.

2.1.1 Material

Materials are substances used in the production or manufacturing of goods. Materials range from man made synthetics such as many plastics to natural materials such as copper or wood.

Raw materials, materials in their unaltered, natural state, are first extracted or harvested from the earth and divided into a form that can be easily transported and stored. The raw materials are then processed to produce "semi-finished materials". These can be input into a new cycle of production and finishing processes to create "finished materials", ready for distribution and consumption.

An example of a raw material is cotton, which can be processed into thread, which can then be woven into cloth, a semi-finished material. Cutting and sewing the fabric turns it into a garment, which is a finished material. Steelmaking is another example, raw materials are mined, refined and processed into steel, a semi-finished material. Steel is then used as an input in many other industries to make finished products.

2.1.2 Product Structure

Product structure is a diagram that shows the sequence in which raw material, purchased parts, and subassemblies are manufactured and assembled to form end-item (Daniel Sipper, 1997). As business becomes more responsive to unique consumer tastes and derivative products grow to meet the unique configurations, BOM management can become unmanageable. Product structure is different with BOM. Product structure contains of list of material that used in product assembly, while

BOM consist not only list of material but also the amount of material and the lead-time.

Advanced modeling techniques are necessary to cope with configurable products where changing a small part of a product can have multiple impacts on other product structure models. Concepts within this entry are all caps locked in order to indicate these concepts.

2.1.3 Work in Process Material

Work in process (WIP) is inventory in the production system waiting to be processed or assembled and may include semi-finished products (a bolt that has been threaded but not coated) or subassemblies (Daniel Sipper, 1997). WIP is the part of inventory, while the inventory is a list for goods and materials, or those goods and materials themselves, held available in stock by a business. Inventory are held in order to manage and hide from the customer the fact that manufacture/supply delay is longer than delivery delay, and also to ease the effect of imperfections in the manufacturing process that lower production efficiencies if production capacity stands idle for lack of materials.

For the manufacture sector, the commodity is principally material: raw material, purchased items, semi-finished and finished product, spare part and supplies. Inventory is a “buffer” between two processes, supply and demand. The supply process contributes commodity to the inventory, whereas demand depletes the same inventory. Inventory is necessary because of difference in rates and timing between supply and demand, and this difference can be contributed to both internal and exogenous factors. Internal factors are a matter of policy, but exogenous factors are uncontrollable. Among the internal factors are economies of scale, operation smoothing, and customer service. The most important exogenous factor is uncertainty. Economies of scale may take inventory desirable, even if it is possible to balance supply and demand. There are certain fixed costs associated with production and purchasing, these are set-up cost and ordering cost, respectively. To recover this fixed cost and reduce the average unit cost, many units of an item may be purchased or produced. These large lot sizes will be ordered infrequently and placed in inventory to satisfy future demand. Operation smoothing is used when demand varies over time. An example would be antifreeze or jet skis. Inventory, accumulated in periods of low demand, is used to satisfy higher demand in other periods, which enables the production facility to be operated at a relatively constant production rate, a desirable feature in manufacturing. Customer service is other factor to carry an inventory. Inventory is built up so that customer demand can be met immediately from stock, yielding customer satisfaction. Sometimes the demand is uncertainty and its need to hold more inventory than the forecast demand, which avoid the prospect of running of stock if actual demand exceeds the forecast. This extra inventory is called safety stock. This resupply process is another source of uncertainty that may justify holding safety stock. The lead-time is the time between issuing an order and receiving it. When the lead-time is uncertain, the order may not be received on the planned date. The safety stocks give some protection from a production stoppage due to lead-time uncertainty. The roles of inventory describe so far are operational. There is a totally different reason for carrying inventory market exploitation. Often the vagaries of the market create an economic advantage of maintaining inventory. Price fluctuations in the market may justify acquiring more raw materials than is required for estimated future demand. We emphasize that this is highly speculative and should be left to the financial function in the organization rather than operations management.

The different demand environment types are deterministic or stochastic and independent or dependent. Deterministic means the future demand of inventory item is known with certainty, random future demand is called stochastic. Each of these case is more requires different analysis. The stochastic case is more realistic but also more difficult to handle. Independent demand means demand for an item not related to any other item and primarily influenced by market conditions (Sipper, 1997). Example in clued retail sales and finish goods in manufacturing. Dependent demand is very typical in manufacturing; the demand for one item is derived from the demand of another item. An example would be car, wheels and bolts. Each car requires wheels and each wheels required bolts. The demand for car is independent: wheel and bolts have dependent demand. There is the three level hierarchy here, called product structure. Thus, one car generates demand for four wheels (excluding the spare) and 16 bolts.

Inventory types in production system are classified according to the value added during the manufacturing process. The classifications are raw material, WIP and finished goods. Raw materials include all item required for the manufacturing and assembly process. Typically they are as follow: material needing further processing (flour, woods, steel bars), components that go into the product as is (computer chips, bolts) and supplies (welding electrodes, glue, screw). Finished goods are the outputs of the production process, sometimes called end items, anything from car to shirts to soft drink bottles. The demand for finished goods is usually independent. Also, finished good for one manufacturing organization may be raw materials for another one.

2.1.4 Genetic Algorithm

A genetic algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems. Genetic algorithms are categorized as global search heuristics. Genetic algorithms are a particular class of evolutionary algorithms (also known as evolutionary computation) that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (also called recombination).

Genetic algorithms are implemented as a computer simulation in which a population of abstract representations (called chromosomes or the genotype or the genome) of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

2.1.5 GA History

Genetic algorithms (GA) were first developed by Holland (1975) and they have since been used in many applications including cellular automata, fuzzy logic, image registration, communications network configuration, simulation modeling and optimization, time-tabling, multi-objective workforce scheduling, transportation problem, group technology (GT), and facility planning, time constraint scheduling of limited resources, and location-allocation problems (Gen and Cheng 1994). Gas are computationally simple, powerful with probabilistic transition rules, not limited by assumptions about the search space, and are non-deterministic stochastic search/ optimization methods that use the evolution theories to solve a problem within a complex solution space. In particular, GAs are effective methods for solving complex and global optimization problems such as non-linear integer programming problems.

A distinguished characteristic of GAs is that a population of possible solutions instead of a single solution is used in the search for the best solution. Each solution candidate is codified as a string of binary or integer numbers, called a chromosome. The objective function is the basis to compare two chromosomes in order to decide which one represents a better solution to the problem. Generations of new individuals (offspring) are obtained using probabilistic operators. The most common operators are crossover and mutation. The initial population is usually random generated. Once the initial population is formed, a probabilistic selection procedure defines the parent chromosomes. The old population becomes the new population after selection, crossover, mutation and perhaps a few more operators are applied to the old population.

2.1.6 Description of GA

A GA maintains a population of individuals (chromosomes) at generation t Each individual, evaluated to give a measure of 'fitness', represents a potential solution to the problem at hand. A new population (generation t þ 1) is formed by selecting more fit individuals. Some individuals undergo transformations by means of 'genetic' operators to form new solutions. There are mutation transformations that create new individuals by making a random change in an individual, and crossover transformations, which create new individuals by combining parts from multiple individuals. Classic mutation randomly alters a single gene, while crossover exchanges genetic material between two or more parents. After some number of generations, due to selective pressure, the algorithm converges—it is hoped that the best individual in the final population represents a near-optimum solution (Michalewicz 1996). In general, GAs have eight basic components: genetic representation, initial population, evaluation function, reproduction selection scheme, genetic operators, generational selection scheme, stopping criteria and GA parameter settings.

2.1.6.1 Genetic Representation for Potential Solutions

The classic representation for GA is binary digits. However, other representations such as integer and floating point have been found to yield better solutions for different problems. The use of an inappropriate coding scheme has been the cause of many GA failures (Reeves 1997).

2.1.6.2 Initial Population of Solutions

Often initial populations are generated randomly. For problems with small feasible regions, initialization can incorporate problem-specific knowledge to increase the likelihood of having feasible individuals and to generate some good solutions in the initial population.

2.1.6.3 Fitness

Each individual represents a potential solution to a problem. The evaluation function assigns a real number as a measure of fitness to each solution. Usually, the evaluation function is a monotonic function of the problem objective function.

2.1.6.4 Selection

Two popular selection methods are the roulette wheel and tournament. The roulette wheel gives individuals a chance of selection equal to their fitness relative to the population. Tournament selection randomly pits k individuals (k 2) against each other, with the winner contributing to the next generation. An additional method often used is random selection, which is completely arbitrary.

2.1.6.5 Mutation

In each generation, selected chromosomes are exposed to genetic operations: crossover and mutation. Mutation slightly changes an individual. Mutation can be achieved by randomly changing a gene. Figure 1 shows the simplest mutation, flipping a bit. Other mutation operators include swapping the values between two genes, randomly inserting the value of one gene into another location and shifting, etc. Mutation moves the GA to a different neighborhood of the search space (Vose and

Liepins 1991), and is usually called the 'exploration' operator. Crossover is the so-called focusing operator that enables the GA to exploit the current neighborhood and is expected to move the GA to a local optimum. Crossover exchanges genetic material between two or more parents. A one-point crossover exchanges all genes to the left of the cut-point (figure 2), whereas a two-point crossover exchanges genes between two cut-points (figure 3). Cut-points are usually randomly determined.

2.1.6.6 Replacement

Replacement strategies specify how the next generation is to be created. Typically, the child replaces the parents. However, there are many variations to this rule. The Elitist strategy always carries the best individual to the new generation. A tournament strategy, based on a tournament scheme, where the winner of a contest between two or more individuals is used to create the next generation. Yet, another scheme uses each child as a starting point for a local search algorithm and accepts the resulting, and improved, solutions as new children.

2.1.6.7 Stopping Criteria

Setting a fixed number of generations is the most common criterion. Running the GA for fixed duration has also been used as well as time-independent criterion such as population diversity or entropy. In this case, the GA is stopped when the diversity (calculated as an average Hamming distance between pairs) or entropy crosses a specified threshold (Onwubolu and Mutingi 1999). A fourth method is to stop execution when the average or best population fitness has not increased in the last t generations. Rossi and Dini (2000) used a bound on the objective function to stop the GA. When the current population satisfies the bound for the k^{th} time the search stops.

2.1.6.8 Selection of GA Parameters

GA parameter selection includes the setting of values for population size, crossover and mutation rates, and stopping criteria. Despite numerous GA articles, there is no definitive process for choosing these parameters. The practice is to use parameters based on pilot runs or ad-hoc selection.

2.1.7 GA Application

GA has been successfully applied to a variety of optimization problems and are particularly effective in seeking optimal or near optimal solutions in large and complex search spaces. Belonging to the class of meta-heuristics, they ensure the proliferation of solutions of greater expected fitness using probabilistic rules founded on historical information to guide the search. A comprehensive review of work in this area has been published by Gen et. al.,(1997).

The most common selection procedure is the Roulette Wheel Procedure explained in Goldberg (1989) in great detail. Crossover and mutation are usually designed according to the problem at hand. However, it is possible to find many standard operators in the literature (Michalewicz, 1996; Goldberg, 1989). In the last 10 years, many papers have been published relating layout design and GA. Most of them are directed to block layout and manufacturing cell layout design. Tam (1992) presents one of the first research projects describing an application of GA to the block layout problem (Eduardo Vila Gonc-alves Filho, Alexandre Jose´ Tiberti, 2005).

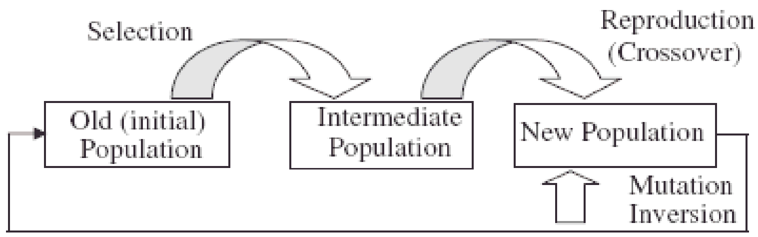

Fig. 1. GA mechanism.

Genetic algorithms find application in biogenetics, computer science, engineering, economics, chemistry, manufacturing, mathematics, physics and other fields.

A typical genetic algorithm requires two things to be defined:

1. a genetic representation of the solution domain,
2. a fitness function to evaluate the solution domain.

A standard representation of the solution is as an array of bits. Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size that facilitates simple crossover operation. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in Genetic programming and graph-form representations are explored in Evolutionary programming.

The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent. For instance, in the knapsack problem we want to maximize the total value of objects that we can put in a knapsack of some fixed capacity. A representation of a solution might be an array of bits, where each bit represents a different object, and the value of the bit (0 or 1) represents whether or not the object is in the knapsack. Not every such representation is valid, as the size of objects may exceed the capacity of the knapsack. The fitness of the solution is the sum of values of all objects in the knapsack if the representation is valid, or 0 otherwise. In some problems, it is hard or even impossible to define the fitness expression; in these cases, interactive genetic algorithms are used.

Once we have the genetic representation and the fitness function defined, GA proceeds to initialize a population of solutions randomly, and then improve it through repetitive application of mutation, crossover, inversion and selection operators (Song, 2006).

CHAPTER III

RESEARCH METHODOLOGY

This chapter explains about research methodology that consists of eight-sub chapter analysis and contains of solving method sequence to make easier in solving the problems.

3.1 Research Object

The research was conducted at PT. Industri Kereta Api (INKA), located in Jl. Yos Sudarso, Madiun, East Java, Indonesia.

3.2 Literature Review

There are two kinds of literature studies, Inductive and Deductive. Inductive study is literature study that keeps the originality of research and usable for researcher to be nowadays research. This study gets from journal, proceeding, seminar, magazine, etc. In inductive study, it can be known the improvement, limitation and problems of previous research, it also can be known the improvement of nowadays methods done by other researcher. Deductive study built conceptual by which the relevant phenomena and parameters is systemized, classified and related so it can be more general. Deductive study is a basic theory that is use as base to solve research problem.

3.3 Model

The model use in this research is the model developed by Song (2006). The notation of model is defined as follows:

J = the entire job set

F = the set of the first job in each branch in each product structure (raw material set).

L = the set of last jobs in each product structure (product set).

Bi = the set of jobs which immediately precede (before) the job i in the product structure. This represents the assembly structural precedence among jobs

f(i) = the job that immediately follows the job i in the product structure. This also represents the structural precedence among the jobs

r(i) = the resources on which the job i is processed

φ(i) = the job which immediately precedes the job i on the resources r(i). This reflects the operational precedence among jobs that is the result of processing at each resources

si = the planned release (or start) time of raw material $i \in F$, which is a decision variable

xi = the processing time of job $i \in J$, which is a decision variable

αi = the actual processing start time of job $i \in J$

ci = the processing completion time of job $i \in J$

di = the due date of product $i \in L$

WHC = work in process holding cost

IC = idle time machine cost

TC = total cost

HC = holding cost

ITC = idle time cost

st = starting time

For a given set of raw material release time, the evolution of the production process can be described by {αi} and {ci} subject to the following constraints:

$\alpha i = \max(\{si\} \cup \{c\varphi(i)\}, i \in F;$ …Eq (1)

$\alpha i = \max(\{c\varphi(i)\} \cup \{cj : j \in \ Bi\}), i \in J/F;$ …Eq (2)

$ci = \alpha I + xi, i \in J;$ …Eq (3)

The formulations above as the parameter constrain in Microsoft Excel software. The constrains are generated for seeking the optimization of random variable in *NLI-Gen*® software to seek the optimum material release time.

3.4 Model Development

Model development is developed based on the model of Song (2006). By those model as the parameter, it can develop the formula to calculate total work in process (WIP) holding cost (WHC), idle time machine cost (IC) and total cost (TC). The model development can be stated as follow:

$$WHC = HC(st_i - si) + HC(st_{i+1} - si + 1) + HC(st_{i+2} - si + 2) + ...+ HC(st_n - sn)$$

$$WHC = \sum_{i \in J/L}^{n} HC\left(st_{(i)} - si\right) \qquad \text{…Eq. (4)}$$

$$IC = ITC(st_{i+1} - c_i) + ITC(st_{i+2} - c_{i+1}) + ...+ ITC(st_{n+1} - c_n)$$

$$IC = \sum_{i \in L}^{n} ITC(st_{i+1} - c_i) \qquad \text{…Eq. (5)}$$

$$TC = WHC + IC \qquad \text{…Eq. (6)}$$

The objective is to find the optimal material release times that minimize the expected sum of holding costs, earliness cost and tardiness cost.

3.5 Data Collecting

There are two kinds of collecting the data. Those are primary data and secondary data. Primary data consist of product structure, raw material holding cost, raw material penalty cost and material flow of each machine. Secondary data consist of data that collect from outside of company's environment, the data are tutorial source correlating with the research and existing data from the internship report.

3.6 Algorithms

The algorithm for data calculation can be described as follow:

Step 1: Provide the data input, those are name of material, material release time (decision variable), stochastic processing time, starting process time and finishing process time.

Step 2: Define the Gene, which is the initial release time as a decision variable.

Step 3: Define the Fitness, which is the cost that wants to be minimized.

Step 4: Open the *NLI-Gen*® Generator software

Step 5: Set the location of Fitness.

Step 6: Find Fitness closest to 0.

Step 7: Add gene groups, Type of Genes in group : Integer, Crossover Operator : Two Point crossover, range Lowest Value : 0, Highest Value 48 (initial due date).

Step 8: Number of generation 1000.

Step 9: OK then Run.

3.7 Optimization Using GA Approach

GA is one of some tools of optimization. The optimization using GA need some steps to initialize the problem and process it until the optimum solution can be achieved. In this research, the GA is used for double loop. The first loop is idle time holding cost as a chromosome, which has the starting time of each job in the production process for the gene. The second loop is WIP holding cost as a chromosome, which has production time of each for the gene. The optimum solution for the first loop will become the input or the parent representation for the second loop in order to find the optimum material release time as a result. There are some steps in GA.

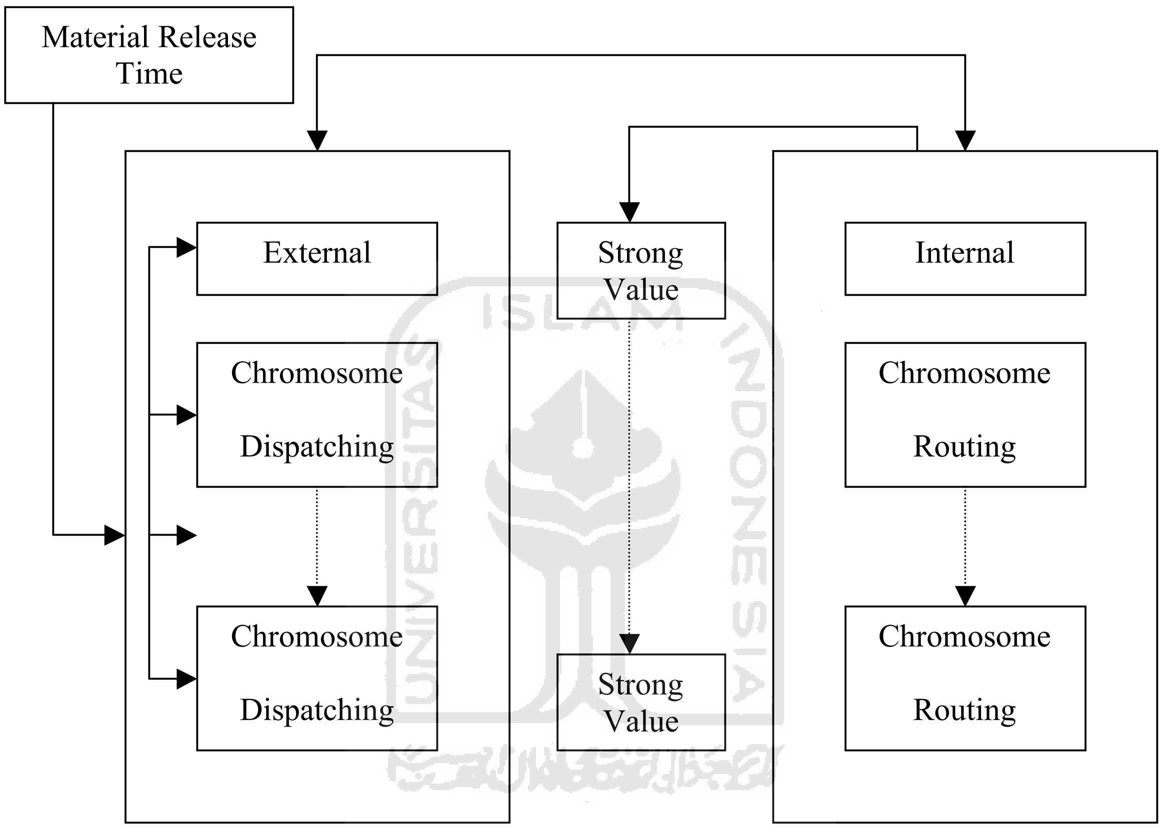

Figure 3.1 Double Loop GA

3.7.1 Initialization

The initial parent population can be randomly or specifically generated. In this paper, for each individual in the initial parent's population, the release time of each material is generated uniformly between zero and the product's due date. The parent representation for the first loop consist of starting time as a gene and become the WIP holding cost as a chromosome. The parent representation for the second loop consists of production time as a gene and the idle time cost in machine as a chromosome.

First loop:

Parent 1

St1	St2	St3	St4	St5	St6	St7	St8

Parent 2

St9	St10	St11	St12	St13	St14	St15	St16

Second loop:

Parent 1

Pt1	Pt2	Pt3	Pt4	Pt5	Pt6	Pt7	Pt8

Parent 2

Pt9	Pt10	Pt11	Pt12	Pt13	Pt14	Pt15	Pt16

Figure 3.2 Parent Representation

3.7.2 Chromosome Representation

Material release time is represented as gene individual which fusion that become chromosome. Those parameters are connected and integrated each other with the variables of total material holding cost, tardiness cost and earliness cost of each machine. So it is suitable with the habit of this representation, so starting time and completion time can be represented using integer. Meanwhile process time is generated randomly between zero and the product’s due date and also represented using integer.

3.7.3 Selection

The initial chromosome as a beginning generation will do selection by concerning on the fitness of each chromosome. The high fitness chromosomes will have more chance to do selection and duplication than the less fitness chromosomes, this method is called by roulette wheel selection (Gen and Cheng, 1997; 2000).

3.7.4 Crossover

Crossover is done to create one or two new chromosomes, which called offspring. Offspring is created from two parents chromosome based on process selection. The mechanism of this method is to determine crossover randomly, then keep the sequence of initial gene until that crossover to be offspring in the child chromosome. Then fill the empty room in the child chromosome with gene from second parent that has not available yet except by first parent. The example of crossover is described as follow:

First loop:

Parent 1 (Starting Time)

3	5	6	8	4	3	6	4

Parent 2 (Starting Time)

5	3	7	1	5	7	3	4

Offspring 1 (Starting Time)

3	5	6	7	4	3	7	4

Offspring 2 (Starting Time)

5	3	6	1	5	8	3	4

Second loop:

Parent 1 (Starting Time)

3	5	6	7	4	3	7	4

Parent 2 (Starting Time)

5	3	6	1	5	8	3	4

Offspring 1 (Production Time)

3	5	6	7	4	4	6	4

Offspring 2 (Production Time)

5	3	7	1	5	8	3	3

Figure 3.3 Crossover Representation

3.7.5 Mutation

Mutation process is done by changing two genes element randomly in order to avoid premature generation of crossover. Mutation chance adjusted in very small measurement, between 0.001 - 0.005. In this research gene changes is happened between two selections in random.

5	3	7	1	5	8	3	3

8	5	3	7	1	5	3	3

Figure 3.4 Example of Mutation

3.7.6 Selection

The objective function of selection is to get the best finishing result in the shortest time, to avoid the premature chromosome generation that caused premature convergence, to get global finishing result so that population diversity can be kept.

3.7.7 Replacement

Genetic algorithm generator software is used in this research. The number of n-population in the last generation will be used to reposition the worst population from previous generation by stopping criteria at 1000 generations.

3.7.8 Software

The problem is stated briefly in Microsoft Excel software, together with the states of gene, fitness and another constraint integrated with genetic algorithm. GA optimization is built using *NLI-Gen*® software that works in windows operating system to realize the model.

3.7.9 Result, Conclusion and Recommendation

Research result is from data processing and analyzing then discuss to find research result.. Conclusion is stated in the final step of this research after doing some analysis. Conclusion answers the objective of research that already stated. Recommendation is providing to give suggestion of case solving method on researched system. Suggestions also given for future research to make model development and algorithm to solve more complex cases but with the same characteristic as the case in this research.

3.8 Flowchart

The steps of research should be arranged systematically and grouped in some steps with flowchart that described as follow:

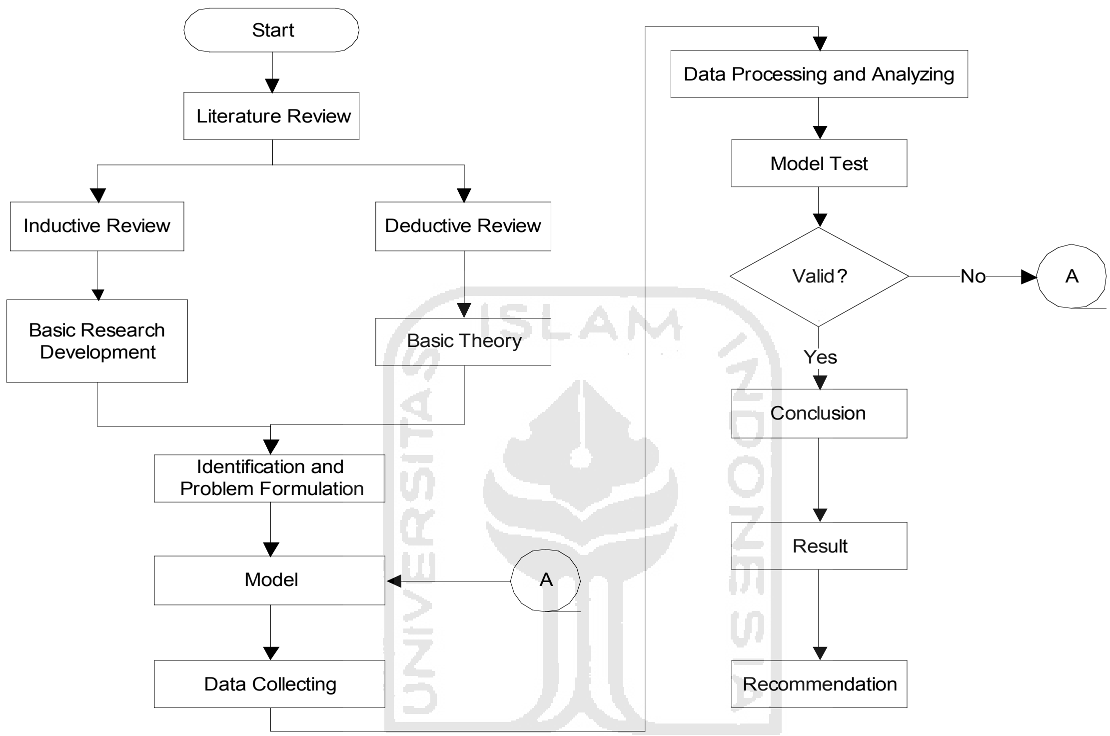

Figure 3.5 Research Flowchart