SCHEDULING IN GARMENT INDUSTRY USING NON-TRADITIONAL OPTIMIZATION TECHNIQUE

A PROJECT REPORT

Submitted By

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KUMARAGURU COLLEGE OF TECHNOLOGY
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JUNE – 2008

Bonafide Certificate

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BONAFIDE CERTIFICATE

Certified that this project report titled **"Scheduling in Garment Industry using Non-Traditional Optimization Technique"** is the bonafide work of **Mr. A. ARUNRAJ (71206507001)** who carried out the research under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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TO WHOMSOEVER IT MAY CONCERN

This is certify that Mr. A. Arunraj 2nd year M.Tech (Apparel Technology and Management) Student of Kumaraguru College of Technology, Coimbatore – 641 006, has done his project on **"Scheduling in Garment Industry using Non-Traditional Optimization Technique"** under the guidence of our organisation during the period from December 2007 to May 2008.

He has taken sincere efforts and shown keen interest in completing the above project successfully. His conduct and character were found good throughout the tenture of the project. We wish him all success in his entire future endeavour.

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This is to certify that Mr/Ms/Mrs A . ARUNRAJ

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in the 2nd National Conference on "ADVANCES IN MECHANICAL SCIENCES" during 27- 28, March 2008.

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Abstract

ABSTRACT

In garment manufacturing industry, the assembly process involves various operations and there is no guarantee that each operation will have the same time. When we assign the operator in the assembly line, some operator will have more work, while other will have to wait for work. To reduce this imbalance in the allocation of work to the operator line balance is done.

In this project genetic optimization technique is applied for the assignment of operator allocation for assembly line-balancing problem. The main aim of this project is to minimize the operator idle time in the production line and also find out the optimal number of task skills an operator should possess in the apparel assembly process. As the variance of operator efficiency is vital to line imbalance in labor intensive industry, a genetic optimization approach is proposed to balance production line through optimal operator allocation with the consideration of operator efficiency.

ஆய்வு சுருக்கம்

ஆடை உற்பத்தி தொழிற்சாலையில், ஆடை வடிவமைப்பு வழிமுறை, பல்வெறு செயல்முறைகளை கொண்டுள்ளது. ஒவ்வொரு செயல்முறைவும் வெவ்வெறு கால அளவை கொண்டுள்ளது. வரைமுறையாக பணியாட்களை, பணியில் அமர்த்தும் போது, சில பணியாட்கள் அதிக கால அளவை எடுத்துக்கொள்கின்றனர். இதனால் மற்ற பணியாட்கள் காத்திருக்க வெண்டியுள்ளது. இந்த வரிசை வேறுபாட்டினை குறைக்க வரிசை சீர்பாடு செய்யப்படுகிறது.

இந்த ஆய்வில், வரிசை வேறுபாட்டினை சீர்செய்ய, பணியாட்களை பணியில் அமர்த்த, ஜெனிடிக் ஆப்டிமைசெஷன் முறையை (Genetic Optimization Technique) கையாளப்பட்டுள்ளது. இந்த ஆய்வின் முக்கிய நோக்கமே பணியாட்களின் காத்திருக்கும் நேரத்தை குறைப்பதும், மற்றும் அவர்கள் ஆடை வடிவமைப்பு வழிமுறையில் எத்தனை செயல்முறையை தெரிந்திருக்க வேண்டும் என்பதை அறிவதே ஆகும். பணியாட்களின் செயல் திறமை வேறுபாடே வரிசை வேறுபாட்டிற்கு முக்கிய காரணியாகும். ஜெனிடிக் ஆப்டிமைசெஷன் முறையை பயன்படுத்தி இக்காரணியை கொண்டு வரிசை சீர் செய்யபடுகிறது.

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ARUNRAJ.A

Contents

CONTENTS

List of Tables

LIST OF TABLES

List of Figures

LIST OF FIGURES

Nomenclatures

NOMENCLUATURE

The following notation is used to search for the optimal operative assignment for an apparel assembly process:

M	set of workstations {1, 2 . . . m}
N	set of tasks {1, 2 . . . n}
O	set of operators {1, 2 . . . o}
S_j	set of workstations that are able to handle tasks j, $Sj \subseteq M$ (j = 1, 2 . . n)
$\lvert S_j \rvert$	total number of workstations at which task j can be processed
x_{ij}	workstation state variable
SI_n	skill inventory, which represents the number of tasks that each operator can handle
α (k)	task skill level of operator k (k = 1, 2, . . . , o)
T_k	set of tasks which can be carried out by operator k
E_k	set of efficiencies which operator k achieves for handling different tasks in T_k
ST_j	standard time of task j, which is the time to complete task j with 100% operator efficiency
$PT_{j \in Tk}$	Processing time of task j by operator k.

Chapter 1

Introduction

CHAPTER 1

INTRODUCTION

1.1 CLOTHING INDUSTRY

Apparel is one of the three basic needs of the mankind. Hence, textiles and apparel have retained an important place in human life starting from historical era to today's modern world. Textile and apparel industry in today's contemporary market place is truly global industry. Apparel industry is no exception to this global phenomenon. Major apparel producing nations are attempting to use modern technology for improving productivity and quality to retain their competitive edge. Apparel production is a type of assembly manufacture that involves a number of processes. Apparel industry tends to generate more production orders, which are split into smaller jobs in order to provide customers with timely and customized products. It is necessary for today's apparel industry to responsive to the ever changing fashion market.

The clothing industry has always been characterized by change and verity, but never so much as today. Until recent times, changes in styles of dress were very gradual and a popular fashion could have a very long life. At the same time, the variety and types of clothing produced were limited by the life-styles and conventions of the day.

During the past three decades or so this situation has undergone a complete turn-around and now reverse is true. Today, fashion changes are dramatic and frequent and they are coupled to an unending verity of cloths for every occasion and activity. As a result the clothing producer has to reconcile the conflict requirements of the market and of his manufacturing faculties in order to stay in business.

The basic needs of market are:

1. Garments with up-to-date fashion appeal;
2. Low forward commitments in order to leave open options to exploit sudden demands during the season;
3. Competitive prices;
4. Acceptable quality standards;
5. Quick response and short delivery times.

But to produce goods efficiently and profitably, the producers requires:

1. A minimum of style and cloth variety;
2. Large orders, well in advance of delivery dates;
3. Adequate time for planning;
4. Time to develop garment and method engineering for 'price sensitive' and other critical types of merchandise;
5. Reasonable level of work in progress.

The key to optimizing this conflict lies in the ability of management to maximize the productivity of available resources and to decrease response time. This can only be achieved by increasing the effectiveness of the operational performance level of every department within the company. In the past moving fashion businesses of today, these performance levels determine success or failure.

In the apparel industry, the assembly process involves a set of workstations in which a specific task in a predefined sequence is processed. Before production, the sewing line supervisors assign one or more sewing operators to each task based on standard time required to complete the task, in order to achieve a balanced line. However, industrial experience shows that it is difficult to achieve a perfectly balanced line because the production rate of each workstation is different. Imbalance occurs due to various factors, including fluctuation in operators' efficiency, frequent changes in product style, order size, prior experience and some unexpected factors, such as absenteeism and machine breakdown. Line balancing control is required to smooth the bottlenecks. According to different system configurations, assembly line can be classified as single-model line, mixed-model line, and multi-model line. Single-model line only assembles one product, while multiple products are assembled in either mixed or multi-model line, but intermediate set-up is required in the latter case. In addition to serial line assembly, flexibility can be improved by the introduction of parallelism, including parallel lines, parallel stations, and parallel tasks. Apparel assembly is an example of a parallel-station line balancing problem.

1.2 SCHEDULING IN GARMENT INDUSTRY

Scheduling is an important tool for manufacturing and engineering, where it can have a major impact on the productivity of a process. In apparel manufacturing, the purpose of scheduling is to minimize the production time and costs, by telling a production facility what to make, when, with which staff, and on which equipment. Production scheduling aims to maximize the efficiency of the operation and reduce costs.

Companies use backward and forward scheduling to allocate plant and machinery resources, plan human resources, plan production processes and purchase materials. Forward scheduling is planning the tasks from the date resources become available to determine the shipping date or the due date. Backward scheduling is planning the tasks from the due date or required-by date to determine the start date and/or any changes in capacity required. Almost many of the garment industries are using backward scheduling.

1.3 LINE BALANCING

The most important element in the history of the garment industry is how to balance the assembly process properly. Line balancing generates up to 50% of production delays due to problems in the line feeding and line balancing. Once the line is set up, it's so important to the staffs of the industrial engineering to evaluate the progress of the line feeding , monitoring the performance, the bundle handling, the methods of evacuation the pieces to the next operation.

In the apparel assembly process, the sewing line supervisors assign one or more sewing operators to each task based on standard time required to complete the task, in order to achieve a balanced line. However, industrial experience shows that it is difficult to achieve a perfectly balanced line because the production rate of each workstation is different. Imbalance occurs due to various factors, including

- Fluctuation in operators' efficiency,
- Frequent changes in product style,
- Order size,
- Prior experience
- Some unexpected factors, such as absenteeism and machine breakdown. Line balancing control is required to smooth the bottlenecks.

1.4 OUTLINE OF THE PROJECT

The project work was carried out at "ADARSH KNIT WEAR", TIRUPUR. The company offered technical and personnel support. The project work was initiated on January, 30, 2008. The area chosen for this project work was assembly line in sewing department. We trained the operator who are all involved in the assembly process, for different operation in that assembly process. Based on the skill inventory level of the operators, genetic algorithm was developed to find out the operator sequence in the assembly line. From that we were able to optimize the operators idle time. The project work was completed on 30th may 2008.

1.5 COMPANY DETAILS

ADARSH KNIT WEAR is a well established company specializing in the manufacturing and exporting of high quality garments since 1998. From the beginning, they have been producing wide varieties of clothing for men, ladies and children. Their office is based in Tirupur, India, run by a team of well experienced merchandisers, designers and management staff, supported by three subsidiary factories.

With modern equipment, advanced technology, qualified technicians, skilled workers, and especially with comprehensive quality management system, our production line have the capacity of making over 4, 00,000 pieces of items per month.

ADARSH KNIT WEAR is a Company with high professionalism supported by well defined systems of management. Their products have been exported to many countries worldwide as European Countries, United Kingdom etc., and it has won the prestige from the customers in both local and overseas markets. They are constantly maintained and develop production for better efficiency.

PROFILE

ADARSH KNIT WEAR, Tirupur, Tamilnadu, India, is a leading Manufacturer & Exporter of Knitted Readymade Garments. ADARSH KNIT WEAR currently has production capacity of 400000 pcs basic style per month.

Table 1.1 Company Profile

COMPANY PROFILE	
Name of the Firm	ADARSH KNIT WEAR
Location	S.F.No. 493/1-2, Athimarathottam, Amman Kalyanamandapam Backside, Sirupooluvapatti, Tirupur – 641 601
Contact Phone Numbers	Phone: 0091-98435-09000 Contact Person: Mr.K.Karthikeyan
Email Address	karthick@adarshknitwear.com
Business	MANUFACTURER & EXPORTER OF KNITTED READYMADE GARMENTS
Director	K.Rajendran
Production Capacity	400000 Pcs. per month. Basic style
Product Range	T-SHIRT, POLO SHIRT, CASUAL TOPS, PAJAMA SET, NIGHT WEAR, SHORTS, TROUSERS, E-NECK TOP, ROPMER & BIB.

Chapter 2

Literature Survey

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

Recently different methods have been reported in the literature to optimize the operator allocation in the assembly line using various methods. A number of researchers have dealt with the optimization of operator allocation in the apparel assembly line.

2.2 LITERATUR REVIEW

Ponnambalam et. al., The author proposed a genetic optimization approach to solve the general assembly line balancing problems and compare this method with other heuristic methods. Compare the genetic algorithm with other heuristic method it gives better result.

Jacky et. al., The author addressed an application of a network-based analytical technique of critical path method to schedule for men's shirt manufacturing with progressive bundle system. This paper focus on the problems of dynamic production orders sequencing and resource allocating on the basic of the precedence relationships of assembly operations.

Ibrahim Kattan et. al., The main objective of his thesis is a study of minimizing the maximum completion time or cycle time of the job by using heuristic scheduling techniques. in this paper they are used three hureistic methods.

Mohan Kumar et. al., The author proposed Genetic Algorithm is proposed to workout for an efficient aggregate production plan with long-range policies and resources allocated by long-range decisions of the industries.

Wong et. al., The author addressed, a real-time segmentation rescheduling approach using genetic algorithms to handle production planning and scheduling problem in a dynamic apparel manufacturing environment is proposed. The experimental result shows that the makespan and the influences caused by the change of schedule could be minimized.

Mok et. al., The objective of his paper proposes a genetic algorithms approach to optimize both cut-piece requirements and the makespan of the conventional fabric cutting departments using manual spreading and cutting methods. An optimization model for the manual fabric cutting based on GA was developed.

Kwong et. al., The author deals about, genetic algorithms and fuzzy set theory are used to generate just-in-time fabric-cutting schedules in a dynamic and fuzzy cutting environment. This paper results, genetically optimized schedules improve the internal satisfaction of downstream production departments and reduce the production cost simultaneously.

Guo et. al., The main objective of his thesis, a scheduling problem in the flexible assembly line is investigated. A bi-level genetic algorithm is developed to solve the scheduling problem. Further more, a heuristic initialization process and modified genetic operators are proposed. Result shows that the proposed method can solve the scheduling problem effectively.

Amirthagadeswaran et. al., An attempt has been made to study and solve a penalty involved job shop scheduling problem, under cellular manufacturing environment, using genetic algorithms. The results have been compared with early findings, which results genetic algorithm approach reduces the penalty amount to a great extent.

Raja et.al., This paper addressed the problem of scheduling identical parallel machines with multi-objectives of minimizing the makespan, the total tardiness and earliness. Genetic algorithm technique has been applied for generating multiple schedules with multi objectives. Fuzzy logic is then applied to select the best optimal schedule satisfying the multiple objectives.

Masaru Nakajima, et. al., The author proposed, the line balancing is studied from the view points of high production and fewer workers, and the calculating method of the number of workstations and the cycle time is improved by introducing the concept of unbalanced time.

2.3 ABOUT THE RESEARCHER'S EXPLANATION

The line balancing problem is one of the most traditional problems which have evolved from the concept of division of labour. Line balancing study is still an attractive research topic today due to its relevancy to the everyday manufacturing and the diversity of system configurations. Early research mainly applied the optimization techniques of dynamic programming and integer programming. The Branch and Bound algorithm is one of the heuristic techniques which have the longest history of application in the line balancing problem. Other heuristic techniques, such as simulated annealing, tabu search, and graphical method, have also been applied. The AI-based systems and concluded that the results of most real life problems have not been realized due to the technical problems of implementation, and the "people problem", particularly in the human-centric apparel manufacturing process. Among various AI-domain knowledge, genetic algorithms are the well-adopted technique for line balancing control optimization.

However, in apparel assembly, sewing workstations are tailored for specific tasks and are usually statically configured. Such constraints hindered the direct application of the line balancing research results obtained so far. In fact, the current solution to balance sewing assembly line relies heavily on shop floor expert knowledge, experience and intuition. Experts' decisions may not be consistent under similar conditions, and thus non-optimal. The small order size and frequent changes of style make optimal production control more difficult to achieve. A simulation technique was widely adopted by researchers to provide a scientific solution to control line balancing in apparel manufacture. The above research projects were under a steady state manufacturing environment and considered discrete events which may be unrealistic in practice. These constraints highlight the need for further study in search of effective algorithms to provide an optimal solution to the problem of production control in an apparel assembly process in a systematic manner.

The introduction of a unit production hanger system (UPS), which is capable of automatically delivering a piece of cloth to a target workstation according to a planned work flow schedule, makes the sewing operation configuration more flexible. A sewing assembly line equipped with UPS is similar to traditional parallel stations system. It is essential to develop a "smart" balancing solution for UPS sewing lines in order to take full advantage of its system flexibility. In addition, training the sewing operatives for multi-task handling provides apparel manufacturers with a pool of multi-skilled workers, thus giving the option for task re-assignment in order to achieve a better line balancing result. However, few studies have investigated the effect of skill inventory towards the operation efficiency in sewing assembly. Skill inventory SI_n represents number of task skills each operator should have in the apparel assembly process. The objectives of this study are thus to search online optimal operative assignments in order to minimize the make span using genetic algorithms (GA), and to compare the performance of varying levels of skill inventories SIn on the assembly make span so as to determine the optimal number of task skills an operator should possess in the apparel assembly process.

2.4 PROBLEM FORMULATION

In the apparel industry, sewing operators are usually trained to be multi-skilled. In other words, each operator is trained to master the skills for a set of tasks in which the operator's efficiency depends on his/her skill level and previous experience. In this project, task set T_k and efficiency set E_k are determined by the skill inventory SI_n.. The operators are cross-trained with multi-skills, an operator may not achieve 100% efficiency at every task. Therefore, the actual task processing times vary among operators. For example, when operator k processes a task he/she is good at, $\alpha(k)$ =1, he/she can achieve 100% efficiency (**e** $_{\alpha (k)}$= 100%), and the task processing time is the same as the task standard time, PT_j = ST. When operator k is processing a task with less competency, $1 < \alpha(k) \leq SI_n$, he/she can only achieve a lower efficiency, **e** $_{\alpha (k)}$< 100%. As a result, the task processing time is longer than the task standard time, $PT_j > ST_j$. The task j processing time by operator k can be calculated by:

$$PT_{j \in Tk} = \frac{ST_j}{e_{\alpha(k)}} \tag{2.1}$$

Chapter 3

Optimization Techniques

CHAPTER 3

OPTIMIZATION TECHNIQUES

3.1 NEED FOR OPTIMIZATION

Optimization algorithms are becoming increasingly popular in engineering design activities, primarily because of the availability and affordability of high-speed computer. They are extensively used in those engineering problems where the emphasis is on maximizing or minimizing a certain goal. For example, optimization is routinely used in aerospace deign activities to minimize the overall weight of the aircraft. Thus the minimization of the weight of the aircraft components is of major concern to aerospace designers. Chemical engineers, in the other hand, are interested in designing and operating a process plant for an optimum rate of production. Mechanical engineers design mechanical components for the purpose of achieving either a minimum manufacturing cost or a maximum component life.

Production engineers are interested in designing optimum schedule of the various machining operations to minimize the ideal time of machines and the overall job completion time. Civil engineers are involved in designing buildings, bridges, dams and other structures in order to achieve a minimum overall cost or maximizing safety or both. Electrical engineers are interested in designing communication networks so as to achieve minimum time for communication from one node to another.

All the above-mentioned task either minimization or maximization (collectively known as optimization) of an objective requires knowledge about the working principles of different optimization methods.

3.2 TYPES OF OPTIMIZATION TECHNIQUES

i. Single or multi variable optimization
ii. Single or multi objective optimization
iii. Constrained or unconstrained optimization
iv. Linear or non-linear optimization
v. Non-traditional optimization algorithms
   - Genetic algorithm
   - Particles swarm optimization
   - Neural networks
   - Simulated annealing
   - Fuzzy logic

3.3 OPTIMIZATION TECHNIQUES - AN OVERVIEW

Most traditional optimization methods used in industrial engineering problems can be divided into two broad classes: Direct search method and Gradient search methods. In which direct search method requires only the objective function values and gradient search method requires gradient information either exactly or numerically. One common characteristic of most of this method is that they all work by point-by-point basic. An algorithm starts with an initial point (usually supplied by the user) and depending on the transition rules used in the algorithm a new point is determined. Essentially, algorithms vary according to the transition rule used to update a point.

Among the direct search method, pattern search method and conjugate direction method have been extensively used. In pattern search methods at every iteration a search direction is related according to a combination of exploratory search locally and a pattern search regulated by some heuristics rules. Often this method gets terminated prematurely and degenerates to a sequence of exploratory moves. In conjugate direction methods, a set of conjugate directions are generated using the history of a previous few iterations. Even though this method has been very popular, the common problem with this method is that often the search directions become independent and occasional restarts are necessary. Moreover this algorithm has a convergence proof of well-behaved, unimodel functions. Box's direct search method is different from these methods in that the algorithm works with a number of points instead of a single point.

The algorithm resumes with an evenly distributed set of points. At every iteration a new set of points is created around the best point of the previous iteration. Since no information about the rejected points is used in choosing new points in subsequent iterations, the method is slow and inefficient; but the waiting time to obtain the global solution may be too large to make the search useful in real world problems. Simplex search method uses a simplex point to create a new simplex according to some rules depending on the objective function values at all points of the simplex. The essential idea is to generate the whole space cannot be spanned, the simplex search is blind and cannot general find the global solution.

Besides, some random search techniques are also used extensively especially in problems where no knowledge about the problem is known or where the search is large or where none of the traditional methods has worked. These methods are also used to find a feasible starting point especially if the number of constraints is large. It is to be mentioned here that this discussion is not to say that these traditional are useless, infact they have been extensively used in many engineering optimization problems. The suggestion here is that if the solutions obtained by some traditional methods are satisfactory, there is no problem. But if the solutions obtained are not satisfactory or some known methods can not be applied, then the user either has to learn and use some other optimization methods suitable to solve that problem.

Chapter 4

Genetic Optimization Technique

CHAPTER 4

GENETIC OPTIMIZATION TECHNIQUE

4.1 INTRODUCTION

A genetic algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems. It is a directed search algorithms based on the mechanics of biological evolution. It was developed by John Holland, University of Michigan (1970's).It provide efficient, effective techniques for optimization and machine learning applications and widely-used today in business, scientific and engineering circles.

4.2 BASIC STRUCTURES OF GENETIC ALGORITHM

Genetic Algorithm is population-based search techniques that maintain populations of potential solutions during searches. A string with a fixed bit-length usually represents a potential solution. In order to evaluate each potential solution, GAs need a payoff (or reward, objective) function that assigns scalar payoff to any particular solution. Once the representation scheme and evaluation function is determined, a GA can start searching. Initially, often at random, GAs creates a certain number, called the population size, of strings to form the first generation. Next, the payoff function is used to evaluate each solution in this first generation. Better solutions obtain higher payoffs. Then, on the basis of these evaluations, some genetic operations are employed to generate the next generation.

To gain a general understanding of genetic algorithms, it is useful to examine its components. Before a GA can be run, it must have the following five components:

1. A chromosomal representation of solutions to the problem.
2. A function that evaluates the performances of solutions.
3. A population of initialized solutions.
4. Genetic operators that evolve the population.
5. Parameters that specify the probabilities by which these genetic operators are applied.

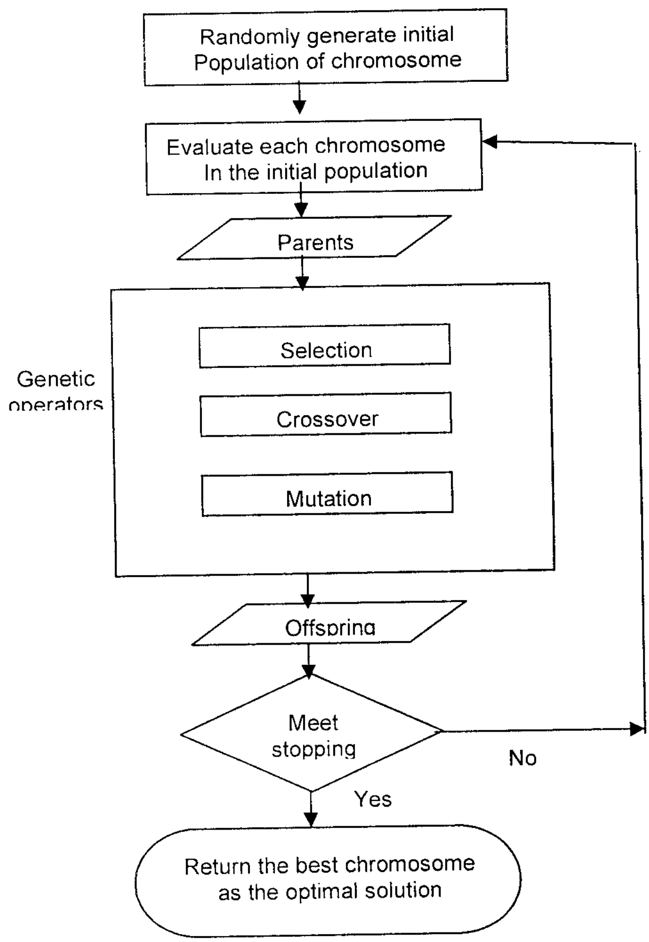


Fig.4.1. Flow Diagram of Genetic Algorithm

4.2.1 Representation

Usually, only two components of GA are problem dependent: the representation and evaluation functions. Representation is a key genetic algorithm issue because genetic algorithms directly manipulate coded representations of problems. In principle, any character set and coding scheme can be used. However, binary character set is preferred because it yield the largest number of schemata for any given parameter resolution, thereby enhancing the implicit parallelism of genetic searches. Note that, in most GAs, the individuals are represented by fixed-length binary strings that express a schema as a pattern defined over alphabet {0, 1, *}, and describe a set of binary strings in the search space.

4.2.2 Evaluation Function

Along with the representation scheme, the evaluation function is problem dependent. Genetic Algorithm is search techniques based on feedback received from their exploration of solutions. The judge of the GA's exploration is called an evaluation function. The notion of evaluation and fitness are sometimes used interchangeably. However, it is important to distinguish between the evaluation function and the fitness function. While evaluation functions provide a measure of an individual's performance, fitness functions provide a measure of an individual's reproduction opportunities. In fact, evaluation of an individual is independent of other individuals, while an individual's fitness is always dependent of other individuals.

4.2.3 Initial Population

Choosing an appropriate population size for a genetic algorithm is a necessary but difficult task for all GA users. On the one hand, if the population size is too small, the genetic algorithm will converge too quickly to find the optimal solution. On the other hand, if the population size is too large, the computation cost may be prohibitive.

4.2.4 Operators

From a mechanistic point of view, a GA is an iterative process in which each iteration has two steps, evaluation and generation. In the evaluation step, domain information is used to evaluate the quality of an individual. The generation step includes a selection phase and a recombination phase. In the selection phase, fitness is used to guide the reproduction of new candidates for following iterations. The fitness function maps an individual to a real number that is used to indicate how many offspring that individual is expected to breed. High-fitness individuals are given more emphasis in subsequent generations because they are selected more often. In the recombination phase, crossover and mutation perform mixing. Crossover reconstructs a pair of selected individuals to create two new offspring. Mutation is responsible for re-introduction inadvertently "lost" gene values. Most research has focused on the three primary operators: selection, crossover, and mutation. While selection according to fitness is an exploitative resource, the crossover and mutation operators are exploratory resources. The effectiveness of a GA depends on an appropriate mix of exploration and exploitation. The following describe these three operators in detail.

Selection: The selection phase plays an important role in driving the search towards better individuals and in maintaining a high genotypic diversity in the population.

Crossover: In order to explore other points in the search space, variation is introduced into the intermediate population by means of some idealized genetic recombination operators. The most important recombination operator is called crossover. A commonly used method, called one-point crossover, selects two individuals in the intermediate population which then exchange portions of their representation.

Mutation: When individuals are represented as bit strings, mutation consists of reversing a randomly chosen bit. For example, assume that the individuals are represented as binary strings. In bit complement, once a bit is selected to mutate that bit will be flipped to be the complement of the original bit value.

4.2.5 Parameters Running a genetic algorithm entail setting a number of parameter values. However, finding good settings that work well on one's problem is not a trivial task. There are two primary parameters concern the behavior of genetic algorithms: Crossover Rate (Cr) and Mutation Rate (Mr). The crossover rate controls the frequency with which the crossover operator is applied. If there are N individuals (population size=N) in each generation then in each generation N*Cr individuals undergo crossover. The higher crossover rate, the more quickly new individuals are added to the population. If the crossover is too high, high-performance individuals are discarded faster than selection can produce improvements. However, a low crossover rate may stagnate the search due to loss of exploration power. Mutation is the operator that maintains diversity in the population. A genetic algorithm with a too high mutation rate will become a random search. After the selection phase, each bit position of each individual in the intermediate population undergoes a random change with a probability equal to the mutation rate Mr. Consequently, approximately Mr*N*L mutations occur per generation, where L is the length of the chromosome. A genetic algorithm with a too high mutation rate will become a random search.

4.3 SOME APPLICATION OF GENETIC ALGORITHM

Table 4.1 Application of Genetic Algorithm

Domain	Application Types
Control	Gas pipe line, pole balancing, missile evasion, pursuit
Design	Semiconductor layout, aircraft design, keyboard configuration, communication networks.
Scheduling	Manufacturing, faculty scheduling, resource allocation.
Robotics	Trajectory planning
Machine Learning	Designing neural networks, improving classical algorithms, classifier systems
Signal Processing	Filter design
Game Playing	Poker, checkers,
Combinatorial Optimization	Set covering, traveling salesman, routing, bin packing, graph colorings, partitioning.

Chapter 5

Methodology

CHAPTER 5

METHODOLOGY

5.1 WORK MEASUREMENT

Work measurement techniques find the time required to do a job by qualified operator working at a standard pace and using the standard method. The time thus calculated is known as Standard Time. The method to do the job is normally standardized by using Motion study procedures before carrying out work measurement or time study. The various commonly employed Work Measurement techniques are:

1. Stop Watch Procedure of Time Study.
2. Predetermined-Motion Time Systems (PMTS).
   or Elemental-Motion Time Systems(EMTS).
   or Basic Motion Time Systems (BMTS).
3. Synthesis-Synthesized Time Standards
4. Analytical Estimating
5. Work Sampling or Activity Sampling or Ratio-Delay Study.

5.2 STOP WATCH TIME STUDY

5.2.1 Time study

Time study is a work measurement technique for recording the times and rates of working for the elements a specified condition, and for analyzing the data so as to determine the time necessary for carrying out the job at a defined level of performance.

Time study was developed by F.W. Taylor and also is called stop watch time study as a stop watch is used for making time observations. Time study is the original technique of work measurement and it is concerned with the direct observation of work while it is being done. Since one subject of work measurement is to enable target times to be set with which to compare the results subsequently achieved and there by exercise control, direct time study is only of use for repetitive work, that is to say for any job which is subsequently going to be repeated under the circumstances which applied and by the method used while the study was being taken. An important feature of time is the way in which the accuracy of the results obtained improves as the number of occasions upon which the operation is observed increases. In other words, the accuracy of time study increases with the number of observations conducted to make the study.

5.2.2 Essentials for time study

The following are the four essential for the time study of any job:

1. An accurate specification of where the job begins and where it ends, and of the method by which is to be carried out, including details of materials, equipment, conditions etc.
2. Systems of recording the observed (actual) time taken by workers do to the job while under the observation.
3. A clear concept of what is meant standard rate of working.
4. A means of assessing the amount of rest and other allowances which should be associated with the job.

5.2.3 Time study procedures

1. Identify the job to be time studied and the operations to be timed.
2. Obtain the improved procedure of doing the job from the method study department.
3. Select the workers for study.
4. Take the workers as well as the supervisors into confidence and explain to them the objectives of study.
5. Collect the equipments and arrange machinery required to conduct the time study and ensure their accuracy.

6. Explain the worker the improved working procedure and the use of tools and other attachments to do the job.
7. Break the job into operations and operations into elements and write them on proper form. Also separate constant elements from variable elements.
8. Determine the number of observations to be timed for each element.
9. Conduct the observations (of the timing elements) and record them the time study form.
10. Also rate the performance of the workers during the step (9) above.
11. Repeat steps (9) and (10) for taking more than one observations.
12. Compute observed time from the measure of central tendency.

Standard time may be defined as the amount of time required to complete a unit of work, under an existing working conditions, using a specified method and machinery by an operator, using a specified method and machinery, by an operator able to do the work in a proper manner, and at a standard time. In this project we are considered standard time as the best time of each operation by an operator.

5.2.4 Application of time study

Stop watch time study is employed:

1. For checking time standards obtain by other methods.
2. For timing repetitive operations employed in manufacturing different jobs.
3. Where it become necessary to break down an activity in detail and study.
4. For determining schedules and planning work.
5. For determining standard costs and as an aid in preparing budgets.

determining selling price.

7. For determining machine effectiveness, the number of machines which one person can operate, and as an aid in balancing assembly lines.
8. For determining time standards to be used as a basis for the payment of a wage incentive to direct labour and indirect labour.
9. For determining time standards to be used as a basis for labour cost control.

Table 5.1 Time Study Form

Time Study Form											
Product: Date:	Operator: Time study engineer:										
Operation	Observed Time (Stop watch reading)										Averaged Observed Time
	1	2	3	4	5	6	7	8	9	10	
1											
2											
3											
4											
5											
6											
7											
8											

5.2.5 Selecting the job to be time studied

One or more of the following reasons may justify the conduct of time study.

1. If it is a newly created job.
2. A change in material or method of working has been made towards improvements and a new time standard is required.
3. A complaint has been received from a worker or union about the unjust time standard for an operation.
4. Standard times are required prior to the introduction of a incentive scheme.
5. When cost of a particular job appears to be excessive.
6. To compare the efficiency of two proposed methods.
7. To investigate the utilization of a piece of plant the output of which is low.

A study was taking in a garment industry (ADARSH KNIT WEAR) at Tirupur. The manufacturer is produced collar T-shirt, we are going to demonstrate the genetic line balancing optimization procedure for this collar t-shirt assembly process. There are eight assembly processes (front & back join with twill. tape, sleeve attach with Body, collar rib attach, neck tape attach, neck tape closing with label, side seam, sleeve peek, bottom hem) involved, preparation process are separated. The assembly process of each garment consists of the above mentioned eight operation tasks, denoted N = {1 2 3 4 5 6 7 8}. Each task description with standard time is given in Table 5.2. In total, 13 operators are assigned to complete this production order. Based on the standard time of each operation, the theoretical number of operators for each operation can be calculated, and the actual number of operators can be assigned. The operators' skill levels in the trained tasks and achievable efficiency are shown in Table 5.3, while the flow diagram of the assembly process is shown in Figure 5.1.

Table 5.2 Collar Rib Neck with Half-Sleeve T-Shirt (Outer) - Operation Breakdown

operation (j)	Operation description	Standard time ST_j (sec)	Theoretical no. of operator assignment	Actual no. of operator assigned	Theoretical operator assignment
1	Front and back joint with poly. tape	30	1.06	1	1
2	Sleeve attach with Body	55	1.96	2	2,3
3	Collar rib attach	50	1.77	2	4,5
4	Neck Tape attach	50	1.77	2	6,7
5	Neck Tape closing with Label	55	1.96	2	8,9
6	Side seam	60	2.14	2	10,11
7	Sleeve Peek	30	1.06	1	12
8	Bottom hem	35	1.26	1	13
Total cycle time		365	12.96	13	

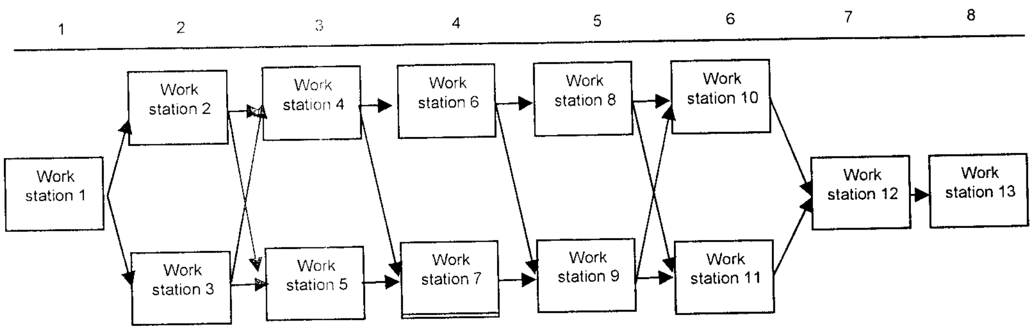


Figure 5.1 Flow Diagram of an Apparel Assembly Process

5.2.6 Selection of worker for time study

Until and unless, the workers, the workers union and the shop supervisor, all are taken into confidence and explained to them the utility of work study, they are very remote chances of success of a work study engineer. The purpose pf method study is usually obvious to everyone: it is to improve the method of doing job. It will relive the workers of fatigue or unpleasant work. The purpose of time study is less obvious, and unless it is very carefully explained to every one concerned, its object may be completely misunderstood, with consequent unrest and even strike.

- The work study engineer should first get the worker's representative and supervisors together and explain in simple terms what he is going to do and why. All their questions should be answered frankly and truthfully.
- It is better to ask the foreman and worker's representative to suggest the most suitable workers to be taken for conducting time study. Such a worker should be a competent, study person. His rate of working should be average or slightly better than average. Temperamentally unsuitable workers should be avoided at all costs.
- In time study practice, a distinction is made between a representative worker and a qualified worker. A representative worker is one whose skill is the average of the group under consideration. He is not necessarily a qualified worker. A qualified worker one who is accepted as having the necessary physical attributes, who posses the required intelligence and education, and has acquired the necessary skill and knowledge to carry out the work in hand to satisfactory standards and safety, quantity and quality.
- In time study there is a reason for insistence on selecting a qualified worker. In setting time standards, especially when they are to be used for incentives , the standard to be aimed at its one which can be attained by the qualified worker and which can be maintained without causing him undue fatigue. The study on slow or very fast workers will tend to result in the setting of time standards either unduly loose or unduly tight; this will unfair towards the management or the workers and will probably be the subject of complaints later.
- Once the proper worker has been selected, he should be carefully explained the purpose of study. He should be asked to work at his

usual pace; taking whatever rest he is accustomed to take. He should be invited to explain any difficulties he may encounter.

- In case a new / improved method has been installed the worker must be allowed plenty of time to settle down before he is timed. The work study engineer, while timing a worker should remain at a place where he can see everything the worker does, without interfering with his movements or distracting his attention.
- On no account should any attempt be made to time the worker without his knowledge, from a concealed position or with the watch in the pocket. It dishonest and if noticed by workers will create problems.

Table 5.3 Operator's Skill Level (Trained Task with Estimated Efficiency) for Different Level of Skill Inventory

Skill level	α (k) = 1	α (k) = 2	α (k) = 3	α (k) = 4	α (k) = 5	α (k) = 6	α (k) = 7	α (k) = 8
EFFICIENCY / OPERATOR	100%	95%	90%	85%	80%	80%	80%	80%
1	1	2	3	4	5	6	7	8
2	2	1	7	5	8	4	3	6
3	2	6	6	4	4	3	2	3
4	3	6	5	2	5	4	1	2
5	3	8	2	3	6	5	5	2
6	4	2	3	5	1	7	6	4
7	4	7	6	6	3	5	2	1
8	5	4	1	8	7	3	6	3
9	5	5	8	6	2	1	3	6
10	6	4	5	3	3	2	5	4
11	6	3	4	7	6	2	4	5
12	7	5	2	2	4	8	8	7
13	8	3	4	1	2	6	4	5

5.4 PRODUCTION LINE BALANCING BY GENETIC OPTIMIZATION

The algorithms are implemented using the computer programming language "C". The program developed is used for solving different problems of varying constraints such as sequence of operations, line balancing and others with the crossover probability is 0.7 and mutation probability 0.3.

In this project, genetic algorithms (GA) are used to optimize operator assignment in assembly so that line balancing can be achieved through the minimization of overall operator idle time. The proposed method re-adjusts the operator assignment after every fixed time interval, according to the most updated production status in order to smooth out the bottlenecks in the assembly line. The total time to complete a production order can be shortened eventually by minimizing the operator idle time. In solving and optimization problem with GA, it is usually assumed that a potential solution to the problem may be represented as a set of variables. These variables ("genes") are joined together to form a string of values ("chromosome"). A fitness function is then defined to measure relative merit of each string in solving the particular optimization problem. In genetic evolution, an initial population of chromosomes can be set by random initialization. Genetic variation is brought into the current population by the application of two genetic operators: crossover and mutation. Chromosomes are then selected as survivors of next generation; such selection is made that reflects the fact that fitter individuals have higher tendency to be selected. The evolution process is continued such that the qualities of the individual solutions are improving in successive populations. In this way, GA can move to a successful outcome without the need to examine every possible solution to the problem in a drastically small time.

The line balancing optimization problem makes the following assumptions:

1. We should not correlate the effect of one operation task of an operator, when he shifts to another.
2. Let us nullifying the all operations initially.

3. Number of machines for each operation is always sufficient.

5.4.1 Chromosome syntax

Although the binary representation is the most widely accepted representation, solution strings are not restricted to binary in GA. integer and real number strings are commonly used in various optimization studies. The choice of representation in GA is related to the nature of the problem. In the line balancing optimization problem, each operator possesses limited skills, which implies each is only capable of handling limited tasks. For example, SI_n = 2 implies each operator is trained to master the skill of two tasks.

In this project, integer chromosome representation is used. In an integer string, each gene represents the skill level, $\alpha i(k)$, k = 1, 2, . . ., n, of each operator's current task, and the length of the chromosome is the number of operators. Therefore, the whole genetic code which represents all operators' task skills is shown by the following equation:

$$\alpha h = [\alpha h\ (1)\ \alpha h(2)\ . . .\ \alpha h\ (o)], \qquad (5.1)$$

Where h = 1, 2. . . μ (population Size).

Each operator's current task skill level, αh (k), is not unconstrained and must be within a range from 1 to SIn. For instance:

$$1 \leq \alpha i(k) \leq Sin.$$

For example, five operators (o = 5) are required to complete a production order. When the skill inventory is three, SIn = 3, chromosome α = [2 1 3 1 1] implies that operator 1 should work on his/her second competent task, operator 3 should work on his/her third competent task, and operators 2, 4 and 5 should work on their most competent task. Once skill levels (α) are defined, the operator's tasks and the corresponding operation efficiency are obtained from the predefined look-up table provided by the training department, as shown in Table 3.

5.4.2 Initial population

Initial population is generated randomly in this study. The initialization process is detailed as follows:

Step 1 Initialize parameters: index $h = 1$, a population size μ and population P.

Step 2 Randomly produce an integer-number string,

$\alpha h = [\alpha h\ (1)\ \alpha h\ (2). . .\alpha h\ (k). . .\alpha h(o)]$,

where $\alpha h\ (k)$ is the skill level of operator k, and $1 \leq \alpha h\ (k) \leq SI$.

Step 3 If αi is feasible, go to step 4; else return to step 2.

Step 4 If $h = \mu-1$, then $P = \{\alpha 1,\ \alpha 2. . .\ \alpha\mu-1\}$ is the initial population and stop; else return to step 2.

Step 5 Set $\alpha\mu$ = skill levels of theoretical operator assignment (which is calculated based on the standard time of different tasks),

$P = \{\alpha 1, \alpha 2, . . . ,\alpha\mu-1, \alpha\mu\}$.

In step 5, the theoretical operator assignment is maintained in the initial population in order to speed up the optimization process. In the line balancing problem, the feasibility of each individual operator assignment is subject to various constraints. In the above routine, an individual is defined as feasible solution in step 3 only when the following constraints are satisfied:

for $\alpha h = [\alpha h\ (1)\ \alpha h\ (2) . . . \alpha h(o)]$ □ P,

if Nt □ $T\alpha h$ (5.2)

then $\alpha h = [\alpha h\ (1)\alpha h\ (2) . . .\alpha h(o)]$ is feasible,

else $\alpha h = [\alpha h\ (1)\alpha h\ (2) . . . \alpha h(o)]$ is not feasible.

In constraint Eq. 3,

Nt is the set of in completed tasks of the current production order at time t,

$T\alpha h$ is the task set of all operators with their current skill level setting,

$\alpha h = [\alpha h(1)\ \alpha h(2) . . . \alpha h\ (o)]$.

If constraint Eq. 3 is not satisfied, it implies that $\alpha h = [\alpha h\ (1)\ \alpha h\ (2) . .\alpha h(o)]$ could never complete the production order since there are some tasks in Nt that are not processed by any of the operator in set O. In addition, the total number of workstations employed for each task j (j □ $T\alpha h$) of the current skill setting, αh, must not exceed the available workstations for the corresponding task j. For instance:

$$\sum x_{ij} \leq |S_j| \quad x_{ij} \square M \qquad (5.3)$$

5.4.3 Fitness function

In GA, fitness function is defined as the measure for the fitness of each individual chromosome so as to determine which will reproduce and survive into the next generation. Thus, given a particular chromosome, the fitness function returns a single numerical score, "fitness", which is proportional to the "ability" of the individual that the chromosome represents. The fitness score assigned to each individual in the population depends on how well that individual solves a specific problem. In this line balancing optimization problem, minimizing operator idle time, which is equivalent to cycle time minimization, would be the prime objective. Let P denote the set of feasible solutions. For a given sequence α □ P, fitness Φ (α) can be defined as:

$$\phi(\alpha) = \frac{T_{target}}{T_{cycletime(\alpha)}} \qquad (5.4)$$

Where fitness Φ (α) decreases as the T cycle time (α), increases. In Eq. 5, T target is the target cycle time. In GA, genetic operators such as crossover and mutation are responsible for bringing in genetic variation to the population. However, applying these genetic operators may cause lost features in some genes and result in infeasible solutions. In case an infeasible solution results, that is a solution that does not satisfy constraints, then the solution fitness is zero,

$$\Phi(\alpha) = 0. \qquad (5.5)$$

5.4.4 Genetic operators

In GA, crossover and mutation are the two major genetic operators which provide genetic variation in the population by initiating chromosomal changes. Crossover, as the name implies, exchanges information ("genes") among chromosomes. Mutation randomly alters some genes in chromosomes. In this paper, traditional single-point crossover [29], which is a powerful algorithm for both binary and integer chromosomes, is employed.

5.4.4.1 Single-Point Crossover

Single-point crossover has the following procedures:

Step 1 Randomly select two parents for mating from the population.

Step 2 Generate a random integer within a range of [0, l−1]

(where l is the length of the chromosome).

Step 3 Both parents are split at this point, thus producing two "head" segments and two

"tail" segments.

Step 4 The tail segments are then swapped over to produce two new full length chromosomes.

The two offspring each inherit some genes from each parent from this single-point crossover. Figure 5.2 shows a single-point crossover that occurs after the third bits of two ten-bit parental chromosomes. Crossover is not usually applied to all pairs of individuals selected for mating. Indeed, the crossover task is a random process with application likelihood, called the probability of crossover. A typical probability of crossover is between 0.6 and 1.0.

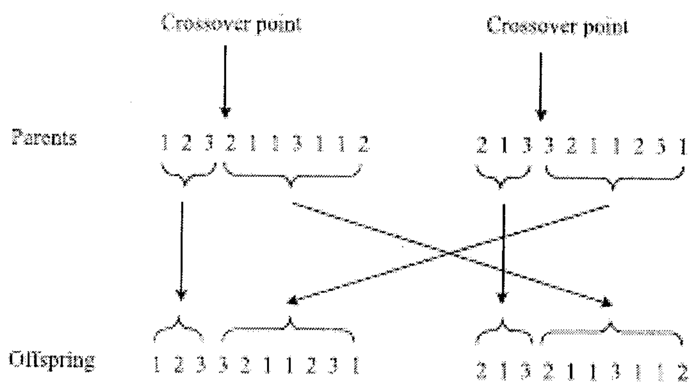


Figure 5.2 Single-Point Crossover

5.4.4.2 Random resetting mutation

In GA, mutation is another genetic operator that is applied to each offspring. As compared to crossover, mutation is only seen as a "background" operator in GA. However, research has shown that although mutation is generally of a low probability of use (the typical value is between 0.0015 and 0.03), it is still a very important operator as it becomes more productive, and crossover becomes less productive, when the population converges. In this line balancing optimization problem, random resetting mutation is used. Under random resetting mutation, with some small probability, a new gene value is chosen at random from the set of permissible values in each position. Thus, for example, Figure 5.3 shows an illustration where the third gene is mutated that a new gene value 1 replaces the original gene value 3.

	Mutation point
Offspring	1 2 3 2 1 1 3 1 1 2
Mutated Offspring	1 2 1 2 1 1 3 1 1 2

Figure 5.3 Random Resetting Mutation

5.4.5 Parent selection

In nature, different individuals compete for resources in the environment. Some are better than others. Those that are better are more likely to survive and propagate their genetic material. This process of natural selection is mimicked in GA by selection schemes in which parental chromosomes with high fitness have a greater chance than those with low fitness of producing offspring. One of the most widely used selection schemes is called the "biased roulette wheel scheme", in which each current string in the population has a roulette wheel slot sized in proportion to its fitness. The biased roulette wheel scheme can be described as follows:

Step 1 Sum the fitness of all the population members; call the resulting total

Fitness $\Phi_{total} = \sum \Phi$.

Step 2 Generate a random number, θ, between zero and total fitness,

Step 3 Return the first population member whose fitness, when added to the fitness of the preceding population members are greater than or equal to θ.

Step 4 Repeat steps 2 and 3 until μ strings are selected from the parent pool.

In roulette wheel selection, the chance of a parent being selected is directly proportional to its fitness. In the example of Figure 5.4, from a population of ten chromosomes with a set of fitness evaluations totaling 80, six individuals are selected by the biased roulette wheel scheme according to six random numbers generated from the interval of 0 and 80.

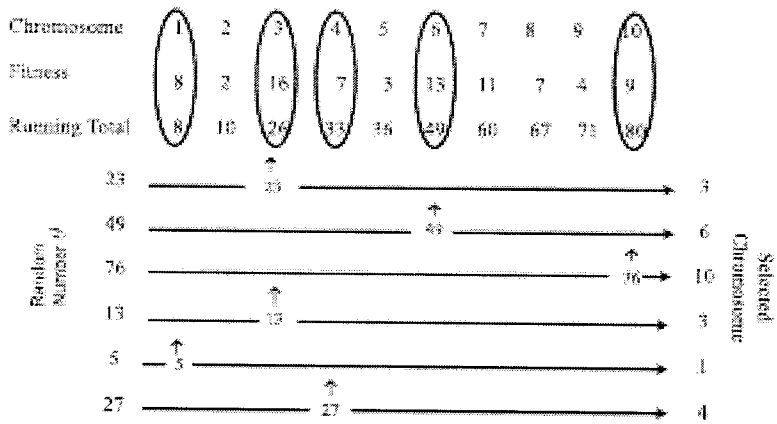


Figure 5.4 Biased Roulette Wheel Selection

5.4.6 Elitism

Even though the biased roulette wheel selection procedure is based on the principle of "the survival of the fittest", there is no guarantee that some fit individuals will be selected because they are random processes. In order to improve the selection mechanism, we are proposed "elitism" in this job sequencing problem. Elitism is an addition to the many selection methods that forces the GA to retain some of the best individuals in each generation. This elitist strategy copies the best individuals of each generation directly into the succeeding generation. Such individuals might otherwise be lost if they are not selected to reproduce, or if they are destroyed by crossover or mutation. This elitist strategy can increase the speed of domination of populations by the best individuals and provide an improvement of the GA performance.

5.4.7 Evolution and termination criterion

After initialization, evolution occurs in accordance to the standard genetic operations of crossover, mutation and selection. The evolutionary process is allowed to continue until no significant further increase is obtained in the fitness of the fittest string, or the defined maximum number of generations is reached. Thus, the fittest string generates the operator assignment which can finish the current production order with the minimized idle time and assembly cycle time. The described genetic optimization procedure is repeated for every fixed time interval so as to readjust the operator assignment according to production status. Such online rescheduling by GA is used to minimize the assembly cycle time.

This projects aims to investigate whether genetic optimized operator assignment can reduce the apparel assembly process time when compared with the theoretical operator assignment. Moreover, it will compare the performance of different levels of skill inventory SIn on the makespan such that the optimal number of task skills an operator should have in the assembly process can be determined. The proposed method is applied to adjust the operative assignment in every hour so that the assembly makespan $T_{makespan}$ is minimized.

- Population size μ = 10
- Maximum number of generation = 20
- Crossover probability = 0.7
- Mutation probability = 0.03

Chapter 6

Results and Discussion

CHAPTER 6

RESULTS AND DISCUSSIONS

6.1 OPERATOR ALLOCATION IN THE ASSEMBLY LINE BY USING GENETIC ALGORITHM

The operator sequence is developed by using the genetic algorithm for different skill inventory level. The algorithms are implemented using the computer programming language “C”. Below results show that the operator sequence for the assembly line for all skill inventory level.

6.1.1 C Program: Results

```
enter 1 operation timing= 30
enter 2 operation timing= 55
enter 3 operation timing= 50
enter 4 operation timing= 50
enter 5 operation timing= 55
enter 6 operation timing= 60
enter 7 operation timing= 30
enter 8 operation timing= 35

enter the initial sequence1 2 2 3 3 4 4 5 5 6 6 7 8

******AT SKILL INVENTORY LEVEL = 2*******

******OPERTOR SEQUENCE IS******
1--3
2--6
3--5
4--8
5--6
6--5
7--7
8--2
```

9--1

10--4

11--2

12--3

13—4

******AT SKILL INVENTORY LEVEL = 3*******

******OPERTOR SEQUENCE IS******

1--4

2--3

3--2

4--8

5--6

6--5

7--4

8--5

9--3

10--2

11--6

12--7

13—1

******AT SKILL INVENTORY LEVEL = 4*******

******OPERTOR SEQUENCE IS******

1--5

2--3

3--2

4--1

5--7

6--6

7--4

8--5

9--4

10--3

11--6

12--8

13—2

******AT SKILL INVENTORY LEVEL = 5*******

******OPERTOR SEQUENCE IS******

1--5

2--4

3--3

4--2

5--8

6--6

7--5

8--6

9--4

10--3

11--7

12--1

13—2

******AT SKILL INVENTORY LEVEL = 6*******

******OPERTOR SEQUENCE IS******

1--6

2--4

3--5

4--2

5--1

6--7

7--3

8--5

9--6

10--4

11--8

12--3

13—2

******AT SKILL INVENTORY LEVEL = 7*******

******OPERTOR SEQUENCE IS******

1--6

2--5

3--4

4--2

5--3

6--8

7--6

8--5

9--7

11--1

12--2

13—3

******AT SKILL INVENTORY LEVEL = 8*******

******OPERTOR SEQUENCE IS******

1--7

2--6

3--1

4--2

5--6

6--5

7--2

8--3

9--4

10--3

11--5

12--4

13--8

6.2 COMPARISON OF DIFFERENT SKILL INVENTORY LEVEL

Based on the operator sequence, for different skill inventories the operators are arranged in the assembly line. The mean completion value of genetically optimized operator assignment with different level of skill inventories are listed in Table 3 and shown in the figure 6.1. Genetic optimization procedure can improve the assembly makespan because all makespans of the genetically-optimized results are less than that of the theoretical operator assignment, as shown in Table 3. Skill inventory SIn = 3 generates the shortest assembly completion time among all other skill inventories. In other words, operators who have mastered the skills of more than three tasks could not improve the system performance. Therefore, the optimal number of task skills each operator should have in apparel assembly process is three.

Table 6.1 Mean Makespan Value of Genetically Optimized Operator Assignment with Different Level of Skill Inventories for 300 Garments.

Skill inventory SI_n	1	2	3	4	5	6	7	8
Makespan ($T_{makespan}$)	9300	9180	8840	9020	8950	8970	8910	8880
Fitness improvement	---	1.29%	4.94%	3.01%	3.76%	3.54%	4.19%	4.51%

Figure 6.1 Makespan Values at Different Skill Inventory Level

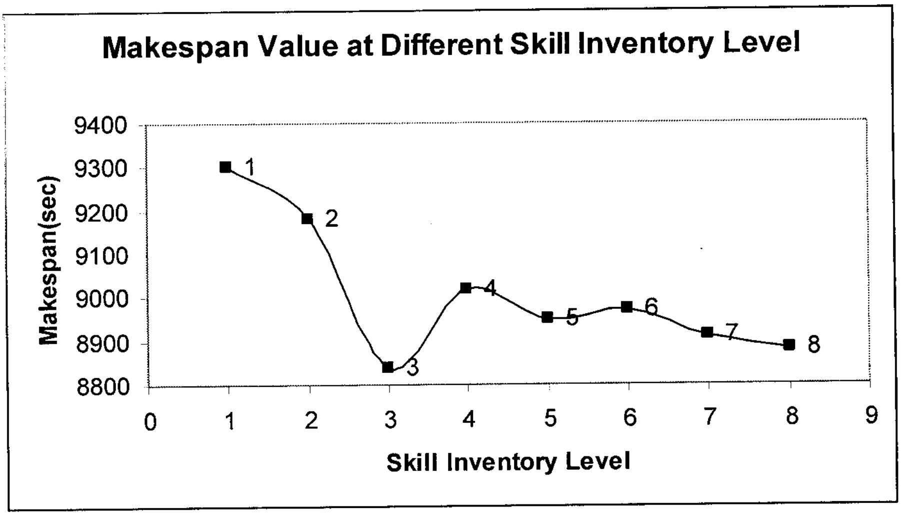
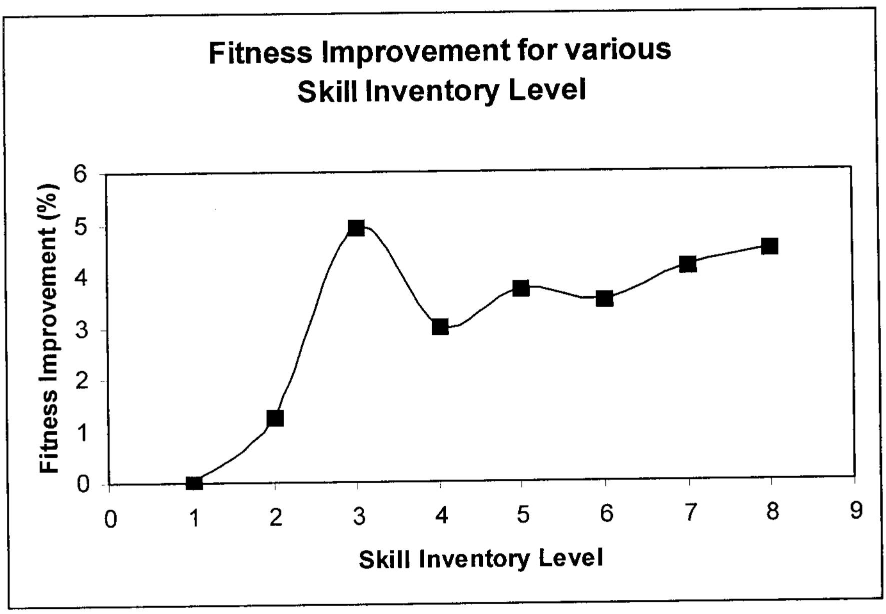


Figure 6.2 Fitness Improvement for various Skill Inventory Level



Chapter 7

Conclusions

CHAPTER 7

CONCLUSIONS

In this project, genetic algorithms (GA) are used to optimize the operator assignment so that overall idle time, and thus makespan, can be minimized. The makespan of operator assignment based on different skill inventories, SIn, is compared in which skill inventory SIn = 3 generates the shortest assembly makespan. It has shown that the genetic optimization procedure can improve the assembly makespan since all makespans of the genetically optimized results are less than that of the static theoretical operator assignment. It can also be concluded that the optimal number of operation skills each operator should have is three. The implications for apparel manufacturers is that more resources put on training the sewing operator to handle more than three operations does not further improve the line balance and makespan of the apparel assembly process.

Appendix

APPENDIX 1

PROGRAM

```
#include<stdio.h>
#include<math.h>
main()
{
int
op[13],op1[13],op2[13],op3[13],op4[13],op5[13],op6[13],op7[13],ot[13],ot1[13]
,ot2[13],ot3[13],ot4[13],ot5[13],ot6[13],ot7[13],ot8[13],i,t[8];
char data[100];
FILE *fp;
clrscr();
fp=fopen("a.txt","w");
for(i=1;i<=8;i++)
{
printf("\nenter %d operation timing=",i);
scanf("%d",&t[i]);
fprintf(fp,"\nenter %d operation timing= %d",i,t[i]);
}
/********INITIALIZATION***********/
printf("\n\nenter the initial sequence");
fprintf(fp,"\n\nenter the initial sequence");
for(i=1;i<=13;i++)
{
scanf("%d",&op[i]);
//5
fprintf(fp,"%d ",op[i]);
ot[i]=op[i];
```

```
}
/********ITERATION CUM CROSSOVER AND MUTATE**********/
/*---first----*/
ot1[13]=op[6];
ot1[11]=op[3];
ot1[9]=op[1];
ot1[7]=op[12];
ot1[5]=op[10];
ot1[3]=op[8];
ot1[1]=op[5];
ot1[12]=op[4];
ot1[10]=op[7];
ot1[8]=op[2];
ot1[6]=op[9];
ot1[4]=op[13];
ot1[2]=op[11];
/*---second---*/
ot2[13]=op[1];
for(i=1;i<=12;i++)
{
op1[i]=op[i+1];
}
ot2[3]=op1[1];
ot2[4]=op1[12];
ot2[1]=op1[6];
ot2[2]=op1[3];
ot2[5]=op1[10];
ot2[6]=op1[8];
ot2[9]=op1[4];
ot2[10]=op1[2];
ot2[7]=op1[5];
ot2[8]=op1[7];
ot2[11]=op1[9];
```

```
ot4[8]=op3[7];
ot4[9]=op3[4];
ot4[10]=op3[2];
ot4[11]=op3[9];
ot4[12]=op3[11];
/*----fifth-----*/
ot5[12]=op3[1];
ot5[13]=ot4[4];
ot5[4]=ot4[4];
for(i=1;i<=12;i++)
{
op4[i]=op3[i+1];
}
ot5[1]=op4[6];
ot5[2]=op4[3];
ot5[3]=op4[5];
ot5[5]=op4[10];
ot5[6]=op4[8];
ot5[7]=op4[1];
ot5[8]=op4[4];
ot5[9]=op4[7];
ot5[10]=op4[2];
ot5[11]=op4[9];
/*-----sixth-----*/
ot6[5]=ot5[7];
ot6[13]=op4[1];
ot6[12]=ot5[4];
ot6[4]=ot5[4];
for(i=1;i<=12;i++)
{
op5[i]=op4[i+1];
}
ot6[1]=op5[6];
```

```
ot6[2]=op5[3];
ot6[3]=op5[1];
ot6[6]=op5[8];
ot6[7]=op5[5];
ot6[8]=op5[4];
ot6[9]=op5[7];
ot6[10]=op5[2];
ot6[11]=op5[9];
/*------seventh------*/
ot7[12]=op5[1];
ot7[13]=ot6[6];
ot7[4]=ot6[4];
ot7[7]=ot6[4];
ot7[10]=ot6[5];
ot7[1]=ot6[9];
ot7[2]=ot6[1];
for(i=1;i<=12;i++)
{
op6[i]=op5[i+1];
}
ot7[3]=op[1];
ot7[5]=op[10];
ot7[6]=op[8];
ot7[8]=op[4];
ot7[9]=op[7];
ot7[11]=op[9];
/*ot8[13]=op[6];
ot8[11]=op[3];
ot8[9]=op[1];
ot8[7]=op[12];
ot8[5]=op[10];
ot8[3]=op[8];
ot8[1]=op[5];
```

```
/*printf("\nThe new sequence is"); */
/*for(i=1;i<=12;i++)
{
op7[i]=op6[i+1];
ot7[i]=op7[i];
}
ot8[13]=ot7[1];*/
/*printf("\nThe new sequence is");*/
/*for(i=1;i<=12;i++)
{
op8[i]=op7[i+1];
ot8[i]=op8[i];
} */
/*ot9[13]=ot8[1];*/
/*printf("\nThe new sequence is");    */
/*for(i=1;i<=12;i++)
{
op9[i]=op8[i+1];
ot9[i]=op9[i];
}
ot10[13]=ot9[1];*/
/*printf("\nThe new sequence is");*/
/*for(i=1;i<=12;i++)
{
op10[i]=op9[i+1];
ot10[i]=op10[i];
}
ot11[13]=ot10[1];*/
/*printf("\nThe new sequence is");    */
/*for(i=1;i<=12;i++)
{
op11[i]=op10[i+1];
ot11[i]=op11[i];
```

```
}
ot12[13]=ot11[1];*/
/*printf("\nThe new sequence is");*/
/*for(i=1;i<=12;i++)
{
op12[i]=op11[i+1];
ot12[i]=op12[i];
} */
fprintf(fp,"\n******AT SKILL INVENTORY LEVEL = 2*******");
fprintf(fp,"\n\n******OPERTOR SEQUENCE IS****** ");
for(i=1;i<=13;i++)
{
fprintf(fp,"\n\n%d--%d",i,ot1[i]);
}
fprintf(fp,"\n******AT SKILL INVENTORY LEVEL = 3*******");
fprintf(fp,"\n\n******OPERTOR SEQUENCE IS****** ");
for(i=1;i<=13;i++)
{
fprintf(fp,"\n\n%d--%d",i,ot2[i]);
}
fprintf(fp,"\n******AT SKILL INVENTORY LEVEL = 4*******");
fprintf(fp,"\n\n******OPERTOR SEQUENCE IS****** ");
for(i=1;i<=13;i++)
{
printf("\n\n%d--%d",i,ot3[i]);
fprintf(fp,"\n\n%d--%d",i,ot3[i]);
}
fprintf(fp,"\n******AT SKILL INVENTORY LEVEL = 5*******");
fprintf(fp,"\n\n******OPERTOR SEQUENCE IS****** ");
for(i=1;i<=13;i++)
{
fprintf(fp,"\n\n%d--%d",i,ot4[i]);
}
```

```
fprintf(fp,"\n******AT SKILL INVENTORY LEVEL = 6*******");
fprintf(fp,"\n\n******OPERTOR SEQUENCE IS****** ");
for(i=1;i<=13;i++)
{
fprintf(fp,"\n\n%d--%d",i,ot5[i]);
}
fprintf(fp,"\n******AT SKILL INVENTORY LEVEL = 7*******");
fprintf(fp,"\n\n******OPERTOR SEQUENCE IS****** ");
for(i=1;i<=13;i++)
{
fprintf(fp,"\n\n%d--%d",i,ot6[i]);
}
fprintf(fp,"\n******AT SKILL INVENTORY LEVEL = 8*******");
fprintf(fp,"\n\n******OPERTOR SEQUENCE IS****** ");
for(i=1;i<=13;i++)
{
fprintf(fp,"\n\n%d--%d",i,ot7[i]);
}
getch();
}
```

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