# OPTIMIZATION OF ROBOTIC ASSEMBLY OF PRINTED CIRCUIT BOARD USING EVOLUTIONARY ALGORITHM

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

***Master of Technology***
**in**
**Machine Design and Analysis**

By

**AMIT KUMAR SHRIVASTAVA**


**Department of Mechanical Engineering**
**National Institute of Technology**
**Rourkela-769008**
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**Department of Mechanical Engineering**
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**National Institute Of Technology**
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# CERTIFICATE

*This is to certify that the thesis entitled*, **"OPTIMIZATION OF ROBOTIC ASSEMBLY OF PRINTED CIRCUIT BOARD BY USING EVOLUTIONARY ALGORITHM"** *submitted by* **Mr. AMIT KUMAR SHRIVASTAVA** *in partial fulfilment of the requirements for the award of Master of Technology Degree in* **MACHENICAL ENGINEERING** *with specialization in* **"MACHINE DESIGN AND ANALYSIS"** *at the National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.*

*To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.*

Date

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**Amit Kumar Shrivastava**

# CONTENTS

# Abstract

This research work describes the development and evaluation of a custom application exploring the use of Artificial Immune System algorithms (AIS) to solve a component placement sequencing problem for printed circuit board (PCB) assembly. In the assembly of PCB's, the component placement process is often the bottleneck and the equipment to complete component placement is often the largest capital investment. In printed circuit board (PCB) assembly, the Production rate of the component placement process is dependent on three interrelated problem such as sequence of component placement known as component sequencing problem, assignment of component types to feeders of the placement machine viewed as feeder arrangement problem, and determination of the cycle time i.e. minimum time taken by robot to complete the whole assembly. In the world of PCB manufacturing all the above three issues are playing an important role for increasing the efficiency of production. In case, some components with the same type are assigned to more than one feeder, the component retrieval problem should also be considered. The problem of allocating components to a printed circuit board assembly line, which has several non-identical placement machines in series, is formulated as a mini-type integer programming (IP) model in this report. In order to achieve the best production throughput, the objective of the model is to minimize the cycle time of the assembly line. The model has been proven as NP-complete(non-deterministic polynomial) and a quick solving tool "LINGO" is used to solve small problems.

Due to their inseparable relationship we take feeder arrangement as a fixed i.e. component on feeders are predetermined. We only considered the component sequencing problem, a hybrid Artificial Immune System (AIS) algorithm is adopted to solve this problems for a type of PCB placement machines called the sequential pick-and-place (PAP) machine in this work. The objective is to minimise the total distance travelled by the placement head for assembling all components on a PCB, The results are compared with the other researcher's result used different type of algorithms for same problem.

***Keywords***: Predefine Feeder arrangement, PCB Assembly, AIS Algorithm, and LINGO.

# List of figures

# List of tables

## Abbreviation and Acronym:

***Indices***

| | |
|---|---|
| *i,j* | Components(i,j=0,1,....,n). |
| *t* | Component type (t=1,2,3...μ) |
| *l* | Feeders (f=1,2,.....μ) |
| *seq* | Placement order of placement position(p=1,2,3,...n) |

***Distances-***

| | |
|---|---|
| $d_{ol}$ | Distance travelled from starting point to feeder l. |
| $d_{lj}$ | Distance travelled from feeder l to position of component j on PCB. |
| $d_{il}$ | Distance travelled from position of component i to feeder l. |
| $d_{io}$ | Distance travelled from feeder l to starting point. |

***Sub-tour elimination constraint-***

| | |
|---|---|
| *Ui* | Placement order of component i. |

***Decision variables-***

| | |
|---|---|
| *Xij* | 1 if component i is placed immediately before component j; 0 otherwise. |
| *Xip* | 1 if component i is placed in the *pth* position; 0 otherwise. |
| $y_{til}$ | 1 if component jwith component type t is stored in feeder l; 0 otherwise. |

## Aberrations

| | |
|---|---|
| PCB | Printed circuit board |
| AIS | Artificial immune system |
| PAP | Pick and place machine |
| Antibody | Sequence order of placement of component on board. |
| Population size | Total number of sequence available. |

# Chapter 1

# INTRODUTION

## 1.1 Introduction

Wide applicability of printed circuit boards (PCBs) in many electronic devices such as personal computers, laptops, LCDs, mobile phones, and audio-video equipment has placed an unprecedented demand for PCBs resulting in to explore strategies for low cost production of PCBs. Customers' needs such as smaller product size, greater functionality and reliability have driven the assembly technologies of electronic components and printed circuit boards from manual operations to completely automated ones. That is why the manufacturing industry invests a great amount of resources in order for their processes to be automated by means of integrating electronic systems to their plants, which usually involves having efficient techniques to ease the control of production. A major challenge for any manufacturing industry is to increase its productivity, safety, and quality without significantly increasing unit cost of production. In past few years, *automated* and *flexible* manufacturing systems have received considerable attention from design engineers and researchers [1.1] [1.2] as they provide an alternative to anincreased safety, higher productivity and quality of production. Robots have become an inseparable part of many manufacturing systems, replacing humans, thereby not only increasing the safety of production but also the productivity and quality of production.

Actually, a PCB consists of a pattern of electrical traces etched from copper that is laminated on an insulated base, which is typically rigid fibreglass. The PCB serves as the interconnection device with electrical currents travelling on the board and the different discrete electronic components that are essential to the functioning of an electronic product. Components from a few hundred to some thousands can be assembled on a single Printed Circuit Board. The operation of placement of various electronic components on a PCB is called PCB assembly. It can be classified into two categories:

I. Plated-through-hole (PTH) technology
II. Surface mount technology (SMT).

For products where overall board size is not a serious concern, the PTH technology is applied. The components are inserted into the holes drilled through the PCB. Then, the connections are soldered on the underside of the PCB between the component lead and the PCB pad. However, needs from consumers, such as smaller product size and greater function and reliability, have forced the SMT to switch the PTH technology. The configuration and the size of surface mount components have permitted mounting an outsized range of components on a one PCB.

The assembly of PCBs is a complex task since a PCB may contain many electronic components in numerous shapes and sizes mounted at specific locations on the board. In the few past years, board assembly consisted of inserting component leads through holes in the board and then soldering them into place (Through-Hole assembly). Currently, Surface Mount Technology (SMT) is mostly used in PCB assembly. With SMT, components are attached to a vacant board with solder paste at pre specified location. Then a reflow operation heats the boards inflicting the solder paste to melt and form the proper connections [1.3]. A SMT assembly line mounts the components at faster speeds and with higher precision than a Through-Hole assembly line.

The PCB assembly process within the SMT atmosphere consists of 5 operations. 1st of all, solder paste is applied where the components are going to be placed. Typically, it is applied by screen printing [1.4]. Then, it is followed by the positioning operation of component. A high-speed placement machine is employed to mount tiny components likechip resistors on the PCB 1st. A flexible placement machine is then used to mount massive and large components such as integrated circuits (ICs) on the Printed circuit board. Finally the components areassembled; the PCB is inspected for missing components. Subsequently, the PCB is conveyed through an oven, which makes the solder paste reflow and form the solder joints. Finally, the PCB should be cleaned to remove the contaminants exposed throughout fabrication and assembly.

## 1.2 Assembly Equipments

SMT environment has mainly two sorts of placement machines. Each sort of machine acquires its own peculiarities similarlyas the operation. The first sort of machine is named the sequential pick-and-place (PAP) machine. In PAP machine, components of the similar type are stored in a single stationary feeder, whereas the PCB is placed on a fixed operating table. Throughout the placement operation, the PAP machine head travels to pick up one component at a time from a stationary feeder, and then places it on the stationary board. The PAP machine is able to perform high accuracy. Moreover, it is suitable for operating with massive and large components such as ICs. The Fuji XP-241E machine belongs to current category.

The concurrent chip shooter (CS) machine is second sort of assembly machine. It acquires an X-Y table carrying a PCB, a feeder carrier with many feeders having components, and a rotary turret with multiple assembly heads to pick up and place components. Each assembly head has several nozzles of different sizes and size of head is depends upon the size of component to which head has to carry. A large nozzle is used to pick up and place large components. CS machine is mainly knows for its high speed performance because the pickup and placement operations are performed concurrently which is the major advantage for using the CS machine. However, it is only preferable for operating with small components such as chip resistors. Because the placement of smaller components is given priority, this type of machine is arranged before the PAP machine in the assembly line. The Fuji CP-732E machine belongs to this category.

Although both the PAP machine and the CS machine are SMT placement machines, the configurations as well as the characteristics of both machines are totally different. Table 1.1 summarizes the differences between these two types of placement machines.

**Table 1.1** Differences between PAP and CS Machines

| | *Feeders* | *PCBs* | *No. Of assembly heads* | *Speed* | *Assembly Operation* |
|---|---|---|---|---|---|
| *PAP Machine* | Stationary | Stationary | Single | Moderate | Sequential |
| *CS Machine* | Moveable | Moveable | Multiple | High | Concurrent |

## 1.3 Assembly Process and Machine description

In order to produce additional background information, this section describes the PCB assembly process and also the differingkinds of machines related to the assembly process.The assembly process consists of mounting the electronic components on the PCB. Automated lines, stated to as SMT lines that contain automated board loaders and un-loaders, a screen printer, component placement machines, inspection station and a Re- flow oven are typically used to perform this task. SMT lines are usually organized in a flow line configuration, where all the machines are interconnected by conveyor belts.

There are three main types of component placement machines:

1. Selective Compliant Automated Robotic Arm (SCARA).
2. Cartesian or Gantry machine.
3. Chip shooter machine.

The SCARA is primarily used for the placement of through-hole components. The Gantry machines are used for the placement of large surface mount components. Finally, the Chip Shooter is used for the placement of small surface mount components, which places thecomponents very fast as compared to the other two types of machines[1.5] [1.6] [1.7].

An SMT line may have more than one machine of each type depending on the production capacity requirements. Figure 1.1 shows an example configuration of an SMT line.

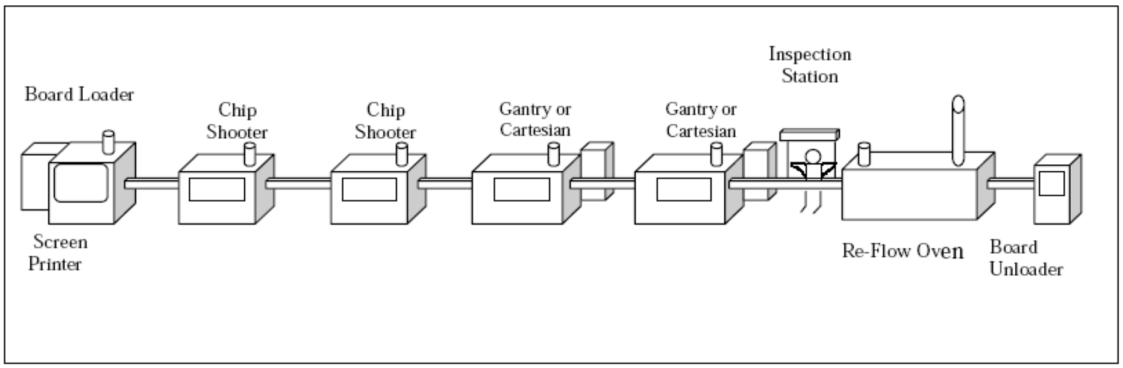



**Figure 1.1** Example of Surface Mount line Configuration [1.13]

The assembly process starts at the board loader, which contains a stack of bare PCBs. A robot arm picks up a PCB and loads it on the input conveyor of the screen printer. The screen printer secures the bare PCB and applies solder paste. When the PCB enters the printer, it is lifted against a stencil. Then a squeegee presses and moves the solder paste across the stencil that has small perforations at the points where the paste is to be placed on the bare PCB. As the squeegee moves across the stencil, the paste is applied to the bare PCB.

Once the paste has been placed on the PCB, a conveyor belt transports the board to a component placement machine. The machine can be a Chip Shooter machine or a Gantry type machine. In the case of a Chip Shooter machine, as the board enters the machine, it is secured on a moving table that positions the PCB as the components are placed in different locations by a turret head. The turret consists of multiple placement heads that contain different suction nozzle sizes. The nozzles are used to transport the components from the feeder carriage (stock of components) in the back of the machine to the PCB table where the components are mounted. Different nozzle sizes are used depending on the size of the component being placed. The turret rotates on a fixed axis. The placement head located at the front of the turret places a component as the opposite placement head picks up a component from the feeders (stock of components) located in the feeder carriage. The feeder carriage holds the component feeders and moves horizontally positioning the correct feeder in the pickup location as the components are needed. Figure 1.2 shows the general configuration of a turret style Chip Shooter machine as viewed from the top.

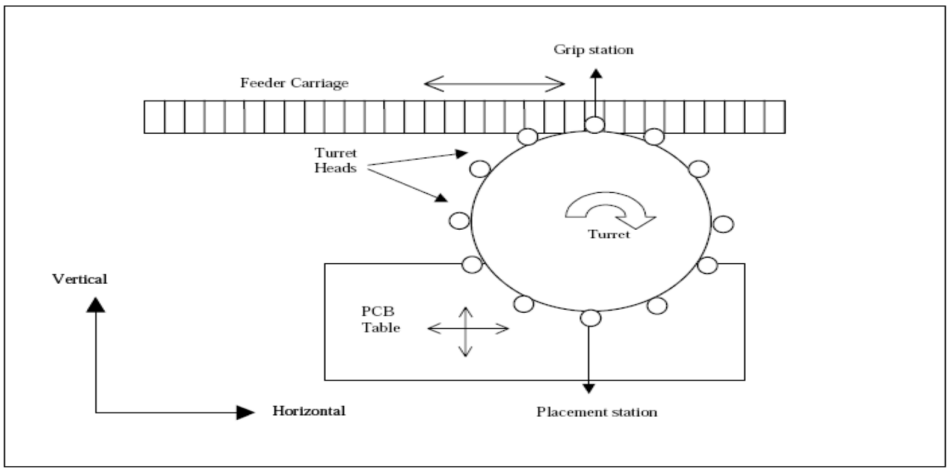



**Figure 1.2** Example of configuration of a Chip Shooter Machine [1.13]

Note that different Chip Shooter machines may have different specifications such as number of placement heads, types of nozzles, number of feeder carriage slots and placement speeds.

In the case of the Gantry placement machine, different machine configurations are possible. However, all of them work similarly. An input conveyor belt transports the PCB into the machine where it is secured to a PCB table that moves in the vertical direction. The Gantry placement machine may have one or two pick and place heads that can pick up and place the components. The heads can hold different size nozzles. The machine has one or two stationary feeder carriages and in some cases a tray holder (used for very large components) where the feeders or trays of components are located. The heads transport the components from the feeders or the tray pickup location to the correct horizontal location while the PCB table brings the PCB to the correct vertical position. The head then lowers and places the component. After all the components have been placed the PCB is released and it is transported by a conveyor to the next machine. Figure 1.3 shows an example configuration of a Gantry type machine viewed from the top. The machine shown in Figure 1.3 contains two pick and place heads and a tray holder.

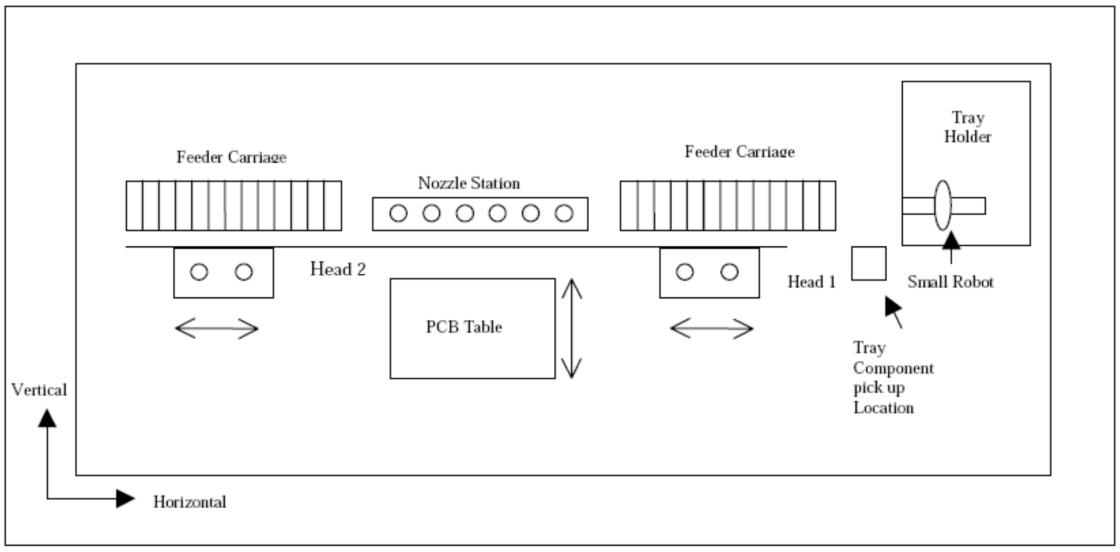



**Figure 1.3** Example Configuration of a Gantry Machine [1.13]

After the component placement machines have placed all the components on the PCB, the PCB then passes through the re-flow oven on a conveyor. The re-flow oven heats the PCB causing the solder paste to melt and form the proper connections between the components and the PCB circuitry. Re-flow ovens have multiple heat zones which are set at different temperatures based on the solder paste being used and the PCB being assembled. When the PCB exits the oven, all the components have been soldered to the circuit of the PCB. Generally, the PCB is then inspected visually by an operator or by a vision machine and stored until needed for the next operation.

In many cases, the next operation is the mounting of through-hole components, which may be done using a SCARA. The SCARA has a robot arm with three joints. Two of the joints allow the robot to move in any direction within a horizontal plane (constant height). The third joint is only used for vertical movement and allows for the pickup and placement of a component [1.8]. Figure 1.4 shows an example configuration of a SCARA robot seen from the side.

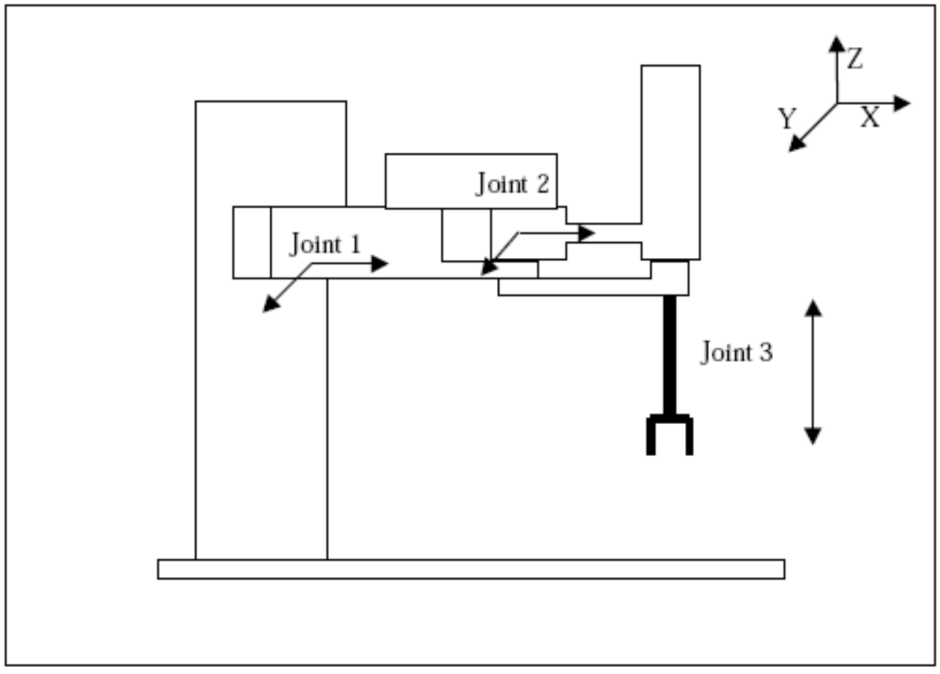



**Figure 1.4** Example Configuration of a SCARA Robot [1.13]

After passing through these processes, the assembly of the PCB is complete. The PCB may proceed to a testing operation before being assembled into the final electronic product. The focus of this research is on the Chip Shooter machine, with emphasis on reducing the placement time required to populate a PCB on the machine.

## 1.5 PCB Assembly Problem

PCB Assembly machines are facing mainly seven types of operational problems during the process. These operational problems are closely related to two issues i.e. Setup Management and Process Optimization [1.4]. Above decision problems are discussed below:

**A. Processes Optimization:**

- *Component allocation*: allocating component types to placement machines;
- *Feeder arrangement*: assigning component types to feeders at each machine;
- *Component sequencing*: determining the sequence of component Placements;

**B. Setup Management:**

- *Machine grouping*: grouping placement machines;
- *PCB sequencing*: sequencing the production of PCBs;
- *PCB grouping*: grouping PCBs into families;
- *Line assignment*: assigning board types to assembly lines;

Among the above PCB assembly operations, the component sequencing is generally the most time-absorbing operation [1.8] [1.9]. In addition, it is frequently a bottleneck in an assembly line and determines the line cycle time [1.10]. Due to the large production volumes, a minor reduction in cycle time will save significant production time. For example, to produce 50,000 boards, a reduction of six seconds in cycle time will save 5,000 minutes, that is, more than 80 working hours. Therefore, to increase the efficiency or minimize the cycle time of the line, the component placement process must be optimized. Optimization of the component placement process includes two interrelated problems: the component sequencing

problem and the feeder arrangement problem. So, the focus of this project work is mainly confined to these two problems.

Generally, the component sequencing problem is alike to the travelling salesman problem (TSP). This is the problem of finding the optimal placement order to visit a set of components and return home with a minimum assembly distance or assembly time for the PAP and the CS machines. On the other hand, the feeder arrangement problem is very like the quadratic assignment problem (QAP). This is the problem of determining the optimal arrangement to assign a set of component types to feeders with a minimum assembly distance or assembly time for both types of machines.

For the PTH technology, the sequence of the insertion operation in the autoinsertionmachine can be simply formulated as the TSP [1.11],and it is not necessary to consider the feeder arrangement problem. However, inthe SMT environment, the efficiency of the component placement process is alsodependent on a feeder to hold which types of components besides the pick andplacement sequence. If the arrangement of components to feeders is not donecarefully, even if the pick and placement sequencing is optimally solved, it cancause significant deterioration in machines performance [1.12]. So, certainly, the component sequencing problem as well as the feeder arrangementproblem should be solved simultaneously.

Chapter 2

# Literature Review

”

## 2.1 Introduction

The literature related to the component placement sequence and feeder assignment problems ispresented in this chapter. Although some researchers treat the problems independently, thecomponent placement sequence and feeder assignment problems are highly related. The firstsections of this chapter present the literature that addresses component sequencing problem and the second section presents the literature that addresses both of these problemstogether. Finally, a summary of the literature is presented.

## 2.2 Placement Sequencing

Many authors have developed heuristics for solving the element placement sequence problem.The question to be answered for this problem is: given a group of components with their corresponding locations on the PCB, determine the component placement sequence that minimizes the overall placement time.

Deo. *et.al.* [2.1] presented a multiple setup PCB assembly planning by genetic algorithm. They developed GA program for optimize component sequencing problem of PCB assembly with the help of a novel sequencing model for PCB and GA approach. Many researchers have modelled the component placement sequencing problem for PCB assembly as a Travelling Salesmen Problem (TSP) or a category of TSP [2.2] [2.3] [2.4]. The TSP is taken into account a Non-Polynomial (NP) complete problem, therefore most researchers use heuristic resolution approaches for finding sub optimal solutions within reasonable amounts of time.

Kho and Ong [2.5] imposed genetic algorithm to unravel the sequencing problem of PCB assembly The approach takes into consideration component insertion priority and sequencing decision rules[2.5]. A polygamy reproduction mechanism with dual mutation has been proposed and implemented. They found that Performance analysis was carried out using the PCB model adopted within the work of Sanchez and Priest. Preliminary analysis shows that an improvement of 19.80% for the total distance travelled by the machine bed was attainable. Further analysis reveals that there was space for still more improvement.

Moyer and Gupta [2.6] address the component sequencing problem for a Chip Shooter machine.This is one among of the few publications that provide a solution approach in which

the component placement sequence for a Chip Shooter machine is optimized. Moyer and Gupta present a close description of the Chip Shooter machine. The distance metric used for the travelling distance between components is the Euclidean metric rather than the Chebyshev metric (maximum of X and Y distance). They present the component sequencing problem as a two-dimensional TSP and ignore the feeder assignment problem. The assumption is that the PCB table movement time is generally more time consuming than the feeder carriage movement time.Thus, minimizing the travelling distance between the components on the PCB has a higher priority in their research.

The algorithm presented is a pair-wise exchange algorithm that requires as input an initial placement sequence and the X-Y coordinates of the components on the PCB. Three alternative methods for generating an initial placement sequence are described. These include generating a component placement sequence based on a random selection, based on an increasing component type identifier, and based on a sorting scheme of increasing X coordinates, and subsequently the increasing Y coordinates of the components [2.14]. Moyer and Gupta present an effective solution time saving methodology. When swapping two components using the pair-wise exchange algorithm, the entire length of the placement sequence is not re-calculated. Instead only the distance between the swapped components and their immediate neighbours in the placement sequence is re-calculated to evaluate any distance savings.

A real case study of a PCB containing 266 components is presented. The component placement sequence for the 266 components is optimized by using the pair-wise exchange algorithm. Three different initial placement sequences were used as input together with the X-Y coordinates of the components. The shortest travelling distance was obtained when using the initial placement sequence based on the component type identifier. The pair-wise exchange heuristic improved the initial random solution by 81%, the initial solution based on the component type identifier by 52%, and the initial solution based on sorting of the components based on the X-Y coordinates by 64%. These results demonstrate that significant improvements can be obtained by using a pair-wise exchange algorithm [2.15].

Other researchers such as Drezner and Nof [2.3], Ball and Magazine [2.2] and Donald and Chan [2.4] have modelled the component sequencing problem for other types of placement machines as a TSP or a class of TSP. Although the machine under study is the Chip Shooter

machine, when ignoring the feeder carriage movement, the component sequencing problems associated with the different types of placement machines become very similar.

Drezner and Nof [2.3] model the component sequencing problem for a pick and place assembly robot as a TSP with predecessor constraints. The robot arm picks up components from different bins and moves them to their corresponding assembly location. The movements of the robot are divided into two categories: loaded arm movement and unloaded arm movement. The loaded arm movements are fixed movements from the bins to the assembly locations. Initially the locations of the bins are determined by solving the Bin Assignment Problem (BAP) which minimizes the distance travelled between the bins and the component assembly locations. The movement time of the unloaded arm is minimized by solving the TSP with predecessor constraints heuristically. An example with numerical results is presented, but no solution procedure steps are presented.

Ball and Magazine [2.2] modelled the component sequencing problem as a Rural Postman Problem (RPP), which is an extension of the TSP. The machine described in this publication is a gantry machine, which works with a stationary feeder carriage and has a pick and place head. To solve the problem, a network of nodes is developed, where the nodes correspond to the feeder slot locations and component locations. The possible movements between the nodes are divided into two types: movements from feeder nodes to component nodes and from component nodes to feeder nodes. The first type of movement is called “required” because once the component types have been assigned to the feeder slots these movements are fixed since the head must move from the feeder containing the component type to each component location. The second type of movement is called “non-required” and depends on the component placement sequence. After defining the network of possible nodes and the types of possible movements, a closed path between the nodes that minimizes the distance travelled by the placement head is found applying an Euler tour algorithm.

Donald and Chan [2.4] also formulate the component sequencing problem for a gantry machine as a TSP. The machine analysed has an independent feeding mechanism that provides the placement head with the components to be mounted. The machine consists of a head that moves in the Z (vertical) direction and a PCB table that moves in the X-Y directions. Donald and Chan [2.4] assume that the feeding mechanism movement time is faster than the PCB table movement time; therefore the problem is modelled as a TSP

governed by the PCB table movement. TRAVEL software, which uses a combination of 2-optimal, 3-optimal and Lin-Kerninghan algorithms, was used to solve the TSP example presented. A production case study was conducted with a single PCB type and an 8% saving for overall processing time was obtained from a 43% reduction on PCB table movement time. This shows that in many cases generating a component placement sequence based on minimizing the PCB table movement can reduce the overall assembly time.

Because of the similarity between the TSP and the component sequencing problem given a fixed feeder assignment, further literature review addressing the TSP is presented in this section. Mandl [2.7], Smith [2.8] and Lawler *et al.* [2.9] present algorithms to solve the TSP. The solution approach proposed by Mandl [2.7] is a branch and bound method that will not be discussed any further due to its high solution time.

Smith [2.8] presents two solution approaches to the TSP. These include an approximate method called the two optimal methods and an exact solution approach known as Little's algorithm. However, Little's algorithm will not be discussed due to its large computational time. The two optimal methods require as input an initial path between the locations of the cities (components).

This initial path can be created using a construction heuristic such as the nearest neighbour algorithm, which consists of choosing an initial city and then travelling from one city to the next closest city until all the cities are included in the travelling path. Once an initial path exists, the two optimal methods systematically swap two cities in the travelling sequence. If the total travelling distance is reduced, then the swap is accepted and the swapping process is repeated starting again from the first city in the travelling path. Otherwise, the swap is not conducted and another interchange is proposed. This process is repeated until all possible swaps of two cities are tried and no further reduction of the total travelling distance is obtained.

Lawler *et al.* [2.9] presents several heuristics to solve the TSP. These heuristics include the, furthest insertion point, nearest neighbour algorithm, arbitrary insertion point, two optimal, three optimal, and or-optimal. The authors describe each of the heuristics briefly and compare the quality of their solutions.

The nearest neighbour algorithm, furthest insertion point, and arbitrary insertion point are construction heuristics. The nearest neighbour algorithm consists of choosing an initial starting point or city and then travelling to the nearest city until all cities are included in the path. The furthest insertion point consists of choosing a starting city and then adding to the tour the city located the furthest away. Once two cities are in the tour, the next city chosen is the one with the minimum furthest distance away from each of the cities in the tour. The chosen city is then inserted in the tour between the two cities that minimize the increase in the tour length. This procedure is repeated until all cities are assigned. The arbitrary insertion point consists of choosing a starting city and then arbitrarily choosing another city to form an initial tour. The length of the initial tour is calculated. Then another city is selected arbitrarily and added to the initial tour in the position where the tour length increases the least. This procedure is repeated until all the cities are included in the tour. Two optimal, three optimal and or-optimal are improvement heuristics that require an initial tour. Given an initial tour the two optimal and three optimal perform two and three city exchanges in the tour respectively. If the tour length improves by exchanging the order of the cities in the tour, then the exchanged is performed otherwise the exchange is not performed. This procedure is repeated until no further reduction in the tour length is obtained. The or-optimal is a modified version of the three optimal, which considers only a small percentage of exchanges that would be considered by a regular three optimal. The or-optimal considers only those exchanges that would result in a string of one, two, or three currently adjacent cities being inserted between two other cities [2.15].

The tests show that for the construction heuristics, arbitrary insertion point outperforms the furthest insertion point heuristic, and the furthest insertion point outperforms the nearest neighbour heuristic. For the set of improvement heuristics two optimal outperforms the three optimal when using equivalent run times, the or-optimal algorithm was not included in the comparison.

Ayob and Kendell presents A survey of surface mount device placement machine optimisation: Machine classification , they surveyed the characteristics of the various machine technologies and classifies them into five categories (dual-delivery, multi-station, turret-type, multi-head and sequential pick-and-place), based on their specifications and operational methods.[2.10].Van Breedam [2.11], Otten and Van Ginneken [2.12], Press *et al.* [2.13], and Golden and Skiscim [2.14] present the application of Simulated Annealing (SA)

to the TSP. Although the algorithms they present vary slightly, they all work under the concept of SA. SA consists of moving from an existing solution (a travelling path or component placement sequence) to a proposed solution (another possible travelling path or placement sequence) based on probability. The algorithm keeps track at all times of the best solution found. When a solution is generated (using pair-wise exchange or other methods) from the current solution, two possible cases exist. The first case is the case in which the proposed solution is better than the current solution and the proposed solution (travelling path or placement sequence) is accepted, thereby replacing the current solution. If the proposed solution is also better than the best solution then the best solution is also replaced. The second scenario is the one in which a worse solution than the current solution is found. For this case, the Boltzmann density function is used to calculate the probability of accepting the proposed solution to replace the current solution [2.12]. Boltzmann density function is a function of the proposed solution objective function value (total travelling distance between cities or components), the objective function values of the past solutions, and the annealing temperature, which is a function of the number of iterations performed. The outcome of this calculation is a number between zero and one, which is then compared to a randomly generated number between zero and one. If the calculated number is less than or equal to the randomly generated number, then the proposed solution is accepted and replaces the current solution. Otherwise, the proposed solution is rejected. This process allows escaping from local minimum solutions. As the number of iterations increases, the annealing temperature decreases therefore decreasing the probability of accepting bad solutions or escaping from local minimum, leading to a final solution where no improvements are found. Van Breedam [2.11] obtained better results using SA to solve the TSP as compared to improvement algorithms, which always end at the first local minimum.

Golden and Skiscim [2.14] applied SA combined with the two reverse algorithm to resolve the TSP and compare their results to those obtained using different heuristics. The two reverse algorithms are analogous to the two optimal algorithms. The underlying difference between the two optimal and also the two reverse algorithm presented within this publication is that in the two reverse algorithm only two arcs are modified within the route of the TSP. This can be achieved by reversing the order of the cities in a portion of the travelling salesman tour. In the regular two optimal four arcs are changed when the order of two cities is swapped in the route. The two reverse procedure used to generate new solutions in the SA routine, tends to generate solutions more similar to the current solution than with the two

optimal since only two arcs are changed in the route instead of four. The SA used with the two reverse to generate solutions is compared to the two reverse by itself and also to the CCAO heuristic. The CCAO heuristic is a hybrid procedure that uses a starting sub tour of cities and inserts cities to the sub tour using cheapest insertion criteria (least increase in travelling distance). Then the initial solution is improved using a branch-exchange heuristic and the or-optimal heuristic. The results show that the CCAO heuristic and the two reverse algorithms by itself performed better than SA using the two reverse to generate new solutions for the TSP.

## 2.3 Placement Sequencing and Feeder Assignment

Several authors have also developed heuristics for solving the component sequencing problem and the feeder assignment problem considering the inter relationship between them. As mentioned previously, the placement time of a set of components is highly dependent on both the placement sequence and the feeder assignment. In the previously described papers, each of these problems has been addressed separately under the strong assumption that the total placement time is mainly dependent on either the component sequencing or the feeder assignment.

Although this assumption may hold valid for some of the placement machines, it generally does not hold for the Chip Shooter machine since both the PCB table and the feeder carriage can potentially delay the placement of a component.

McGinnis *et al.* [2.16] provide a formal description of the feeder assignment and placement sequencing problem and describe the related literature. The authors emphasize the importance of considering the relationship between the problems for concurrent type machines, such as theChip Shooter machine.

This section presents the articles that have focused on solving both of these problems as related problems. Some authors such as Gupta and Moyer [2.6], Leu *et al.* [2.17] and Kumar and Li [2.18] have developed mathematical and heuristic approaches to solve these problems On the other hand, De Souza and Lijun [2.19] and Huang *et.al.* [2.20] has developed knowledge-based solution approaches.

Gupta and Moyer [2.6] present an efficient solution approach for determining the component placement sequence and the feeder assignment for a Chip Shooter machine. The algorithm

consists of a one-step iterative process between the component sequencing and the feeder assignment problems. The algorithm starts by generating an initial placement sequence using the nearest neighbour algorithm. The solution is improved using a pair-wise exchange until all the possible pair-wise exchanges have been attempted or a pre specified maximum numbers of non-improving solutions are reached. The solution approach keeps at all times a list with a predetermined number of the best placement sequences obtained throughout the improvement process. Once a final list of placement sequences has been generated, a feeder routine, which m constructs and improves a feeder assignment for each of the placement sequences, is used. The initial feeder assignment is constructed based on the component indicator number, and although it provides an initial solution, this may not be the best way to do it. The feeder assignment routine combines the initial feeder assignment data with the first placement sequence on the list and the placement time is calculated. For each of the placement sequences under study, a pair-wise exchange heuristic is applied to the initial feeder assignment to improve the placement time. The feeder assignment pair-wise exchange routine stops either when all the possible exchanges have been performed or a pre specified numbers of non-improving solutions are reached. The feeder assignment routine is then applied to the next placement sequence in the list. At the end of the process the placement sequence and feeder assignment combination that yields the smallest placement time is chosen as the final solution.

An important feature of the component sequencing routine is that when a proposed placement sequence is worse than the best placement sequence by a pre specified percentage, the longest link in the proposed component placement sequence is saved in tabu list so that it would not be used in future solutions. The algorithm was tested against those proposed by Leu *et al.* [2.17] and De Souza and Lijun [2.19]. The results of the algorithm proposed by Gupta and Moyer [2.6] outperform both of these although they do not assume a cyclic system in which the placement time of a component is dictated by the slowest of the three machine mechanisms (turret head, PCB table and feeder carriage).

Leu *et al.* [2.17] presents a solution approach for the component sequencing problem and the feeder assignment problem using genetic algorithms. They present genetic algorithms to solve both of these problems for three different types of placements including the Chip Shooter machine. The genetic operators used to create new solutions based on the parent solutions include a modified crossover operator, mutation operator, inversion operator, and

rotation operator. The algorithms allow setting of parameters that specify the number of solutions to be created at each iteration using each of the genetic operators. Moreover, they optimize both the placement sequence and feeder assignment simultaneously using two links: one being the placement sequence and the other the feeder assignment. These two links are then combined to calculate the overall placement time. The distance metric used for the movement of the PCB table is the Chebyshev metric and for the feeder carriage movement the Euclidean metric distance is used although the feeder carriage is supposed to move on a single axis. The algorithm is tested with 50 components, assuming values for the PCB table speed, the feeder carriage and the turret head rotation time. The results stated in the publication appear inconsistent with the results shown in the plots and the placement path shown.

Kumar and Li [2.18] formulate the placement sequencing problem and the feeder assignment problem for an automated assembly machine consisting of a robotic arm, a stationary PCB table, and a stationary feeder carriage as a combination of the TSP and the minimum weight matching problem (MWMP). By decomposing the problem into a TSP assuming a feeder assignment and a MWMP assuming a placement sequence they determine an upper bound. Then they suggest finding lower bounds using relaxation techniques such as linear programming relaxation or Lagrangian relaxation. The bonds are found in order to evaluate any possible solutions. The authors present an experiment in which the placement sequence and feeder assignment for ten different PCB configurations with 100 components are optimized. They use a software package called SAS/OR to solve the MWMP in polynomial time and use their own software (UK-TSP) which employs heuristics such as nearest neighbour, nearest insertion, furthest insertion and random generation to generate an initial placement sequence. The software then uses two optimal and three optimal to improve the initial placement sequence. The results obtained are tested against those obtained by using the S shape method and greedy algorithm. The proposed solution approach performed on average 24.11% and 25.35% better than the S shape method and the greedy algorithm respectively.

De Souza and Lijun [2.19] developed a knowledge-based system to address the component sequencing and feeder assignment problems for the Chip Shooter machine. The components are separated into different groups based on the component size and quantity. Then the arrangement of the feeders is conducted based on the component size groups and the location of the components on the PCB. A TSP module is then used to determine the placement

sequence of two, three or even more type components from the same group. The TSP module uses a minimum spanning tree (MST) combined with a knowledge-based heuristic that yields results of guaranteed worst-case performance. An example is presented in which the placement sequence and feeder assignment for a PCB with 14 components is optimized. The results obtained are compared to those obtained using the heuristic in the multi-head concurrent operation (MCO) placement machine. The MCO heuristic gives a total placement time of 5.67 seconds versus 4.10 seconds when using the knowledge-based system. However, no clear conclusions regarding the performance of the knowledge base solution approach can be made from an experiment with only one replication.

Huang *et al.* [2.20] also focus their efforts on developing a knowledge-based system to solve the component sequencing problem and the feeder assignment problem for multiple batches of PCBs. The machine under study is the gantry machine with two mounting heads, a moving PCB table, and stationary feeder carriages. The expert system generates a feeder assignment in which the component types that are mounted with the highest frequency are assigned to the feeder slots that are the closest to the PCB table. Once the feeders have been assigned to the feeder slots using the feeder location arrangement module of the knowledge-based system, the tooling and nozzle calculation module generate alternative placement sequences using a hill-climbing algorithm, which requires short computation time. This generates placement sequences that minimize the nozzle changes and possible contingencies between the two heads. The travelling path evaluation module then evaluates the component placement sequences and the best sequence is selected. The main advantage of the expert system is that it takes into account the possible constraints that are encountered in the assembly of PCBs and relaxes many of the assumptions made by other authors.

## 2.4 Summary of Literature Review

The literature reviewed in this chapter described the component sequencing problem individually and as inter related with feeder assignment problems for different types of placement machines. Because of the similarity between these two problems and the TSP and QAP respectively, publications dealing with the TSP and QAP were also described.

The publications dealing with the component sequencing problem and the feeder assignment problem provided construction heuristics such as nearest neighbour, furthest insertion point,

arbitrary insertion point, greedy algorithm, etc. Most publications also propose improvement heuristics such as pair-wise exchange, two optimal, three optimal and some variation of tabu search to improve upon the initial solutions obtained using the construction heuristics. One of the publications proposed genetic algorithms as a solution approach. All of these solution approaches iterate searching for a better solution as long as improvements can be achieved and better solutions can be obtained. However, the publications that specifically addressed the component sequencing problem and the feeder assignment problem for the Chip Shooter machines did not take into account some important characteristics of the assembly process.

PCB table is not constant, but instead it is a function of the distance travelled and the type of components mounted on the PCB. Not all component feeders occupy a single feeder slot, but may occupy more than one feeder slot because of the size of the component. This adds additional travel distance and capacity requirements on the feeder carriage mechanism. All of the publications assumed that the PCB table velocity and the feeder carriage velocity are constant when they are not. Assuming a constant velocity for these mechanisms provides a misleading placement time estimate, which in many cases is used as the performance measure of the solution approaches described in the publications reviewed.

This research will focus on developing a solution approach for the component sequencing problem with fix feeder arrangement for the Pick and Place machine using construction and improvement Artificial immune system algorithm. Furthermore, the proposed solution approach will relax the assumptions previously mentioned.

Chapter 3

# TECHNIQUES FOR OPTIMIZATION OF PCB ASSEMBLY

## 3.1 Introduction

Assembly of printed circuit board is a based on the principle of Travel Salesman Problem (TSP). The Travelling Salesman Problem or the TSP is a representative of a large class of problems known as combinatorial optimization problems. In the ordinary form of the TSP, a map of cities is given to the salesman and he has to visit all the cities only once to complete a tour such that the length of the tour is the shortest among all possible tours for this map.In general, the TSP includes two different kinds, the Symmetric TSP and the Asymmetric TSP [3.1]. In the symmetric form known as STSP there is only one way between two adjacent cities, i.e., the distance between cities A and B is equal to the distance between cities B and A (Fig. 3.1). But in the ATSP (Asymmetric TSP) there is not such symmetry and it is possible to have two different costs or distances between two cities. Hence, the number of tours in the ATSP and STSP on n vertices (cities) is (n-1)! and (n-1)!/2, respectively

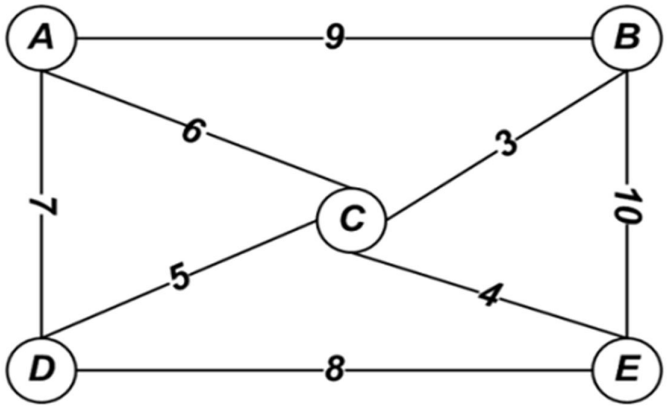



**Fig. 3.1** The tour with A=>B =>C =>E =>D => A is the optimal tour [3.1]

There are different approaches for solving the TSP. Solving the TSP was an interesting problem during recent decades. Almost every new approach for solving engineering and optimization problems has been tested on the TSP as a general test bench. First steps in solving the TSP were classical methods. These methods consist of heuristic and exact methods. Heuristic methods like cutting planes and branch and bound [3.2], can only optimally solve small problems whereas the heuristic methods, such as 2-opt [3.3], 3-opt, Markov chain [3.4] simulated annealing [3.5] and tabu search are good for large problems. Besides, some algorithms based on greedy principles such as nearest neighbour, and spanning

tree can be introduced as efficient solving methods. Nevertheless, classical methods for solving the TSP usually result in exponential computational complexities. Hence, new methods are required to overcome this shortcoming. These methods include different kinds of optimization techniques, nature based optimization algorithms, population based optimization algorithms and etc. In this chapter we discuss some of these techniques which are algorithms based on population.

Population based optimization algorithms are the techniques which are in the set of the nature based optimization algorithms. The creatures and natural systems which are working and developing in nature are one of the interesting and valuable sources of inspiration for designing and inventing new systems and algorithms in different fields of science and technology. Evolutionary Computation [3.6], Neural Networks [3.7], Time Adaptive Self-Organizing Maps [3.8], Ant Systems [3.9], Particle Swarm Optimization [3.10], Simulated Annealing [3.11], Bee Colony Optimization [3.12] and DNA Computing [3.13] are among the problem solving techniques inspired from observing nature.

In this chapter population based optimization algorithms have been introduced. Some of these algorithms were mentioned above. Other algorithms are Intelligent Water Drops (IWD) algorithm [3.8], Artificial Immune Systems (AIS) [3.14] and Electromagnetism-like Mechanisms (EM) [3.15]. In this chapter, every section briefly introduces one of these population based optimization algorithms used for solving the TSP in past researches.

## 3.2. Evolutionary algorithms

### 3.2.1 Introduction:

Evolutionary Algorithms (EAs) imitates the process of biological evolution in nature. These are search methods which take their inspiration from natural selection and survival of the fittest as exist in the biological world. EA conducts a search using a population of solutions. Each iteration of an EA involves a competitive selection among all solutions in thepopulation which results in survival of the fittest and deletion of the poor solutions from the population. By swapping parts of a solution with another one, recombination is performed and forms the new solution that it may be better than the previous ones. Also, a solution can be mutated by manipulating a part of it. Recombination and mutation are used to evolve the population towards regions of the space which good solutions may reside.

Four major evolutionary algorithm paradigms have been introduced during the last 50 years: genetic algorithm is a computational method, mainly proposed by Holland [3.15]. Evolutionary strategies developed by Rechenberg [3.16] and Schwefel [3.17]. Evolutionary programming introduced by Fogel [3.18], and finally we can mention genetic programming which proposed by Koza [3.19]. Here we introduce the GA (Genetic Algorithm) for solving the TSP. At the first, we prepare a brief background on the GA.

### 3.2.2 Genetic algorithms:

Genetic Algorithms focus on optimizing general combinatorial problems. GAs have long been studied as problem solving tools for many search and optimization problems, specifically those that are inherent in NP-Complete problems. Various candidate solutions are considered during the search procedure in the system, and the population evolves until a candidate solution satisfies the predefined criteria. In most GAs, a candidate solution, called an individual, is represented by a binary string [3.20] i.e. a string of 0 or 1 elements. Each solution (individual) is represented as a sequence (chromosome) of elements (genes) and is assigned a fitness value based on the value given by an evaluation function. The fitness value measures how close the individual is to the optimum solution. A set of individuals constitutes a population that evolves from one generation to the next through the creation of new individuals and deletion of some old ones. The process starts with an initial population created in some way, e.g. through a random process. Evolution can take two forms:

**Crossover:** Two selected chromosomes can be combined by a crossover operator, the result of which will replace the lowest fitness chromosome in the population. Selection of each chromosome is performed by an algorithm to ensure that the selection probability is proportional to the fitness of the chromosome. A new chromosome has the chance to be better than the replaced one. The process is oriented towards the sub-regions of the search space, where an optimal solution is supposed to exist [3.20].

**Mutation:** In mutation process, a gene from a selected chromosome is randomly changed. This provides additional chances of entering unexplored sub-regions. Finally, the evolution is stopped when either the goal is reached or a maximum CPU time has been spent [3.20].

In the following the GA operation pseudo code has been written:

1. Start

2. Population initialization

3. Repeat until (satisfying termination criteria)

   • Selection

   • Cross over

   • Mutation

   • Making new population with the fittest solutions

   • Evaluation

   • Checking the termination criterion

4. Take the best solution as output

5. End

## 3.3 Ant colony optimization (ACO)

The ACO (Ant Colony Optimization) heuristic is inspired by the real ant behaviour (fig.3.2) in finding the shortest path between the nest and the food [3.21]. This is achieved by a substance called pheromone that shows the trace of an ant. In its searching the ant uses heuristic information which is its own knowledge of where the smell of the food comes from and the other ants' decision of the path toward the food by pheromone information [3.22].

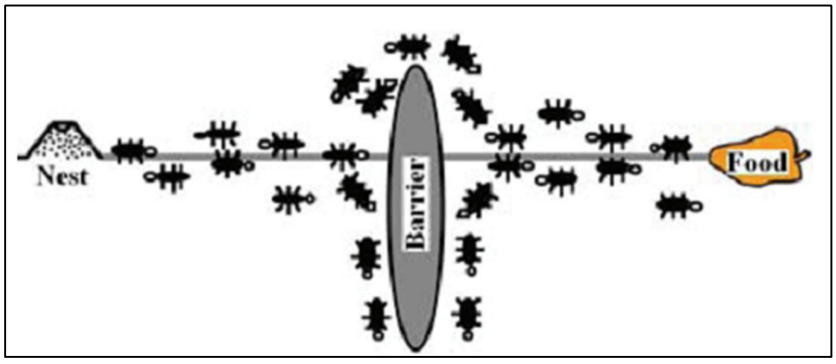



**Fig. 3.2.** Real ant behaviour in finding the shortest path between the nest and the food [3.1]

In fact the algorithm uses a set of artificial ants (individuals) which cooperate to the solution of a problem by exchanging information via pheromone deposited on graph edges. The ACO algorithm is employed to imitate the behaviour of real ants and is as follows:

Initialize

Loop

Each ant is positions on a starting node.

Loop

Each ant applies a state transition rule to incrementally build a solution and a local pheromone updating rule.

Until all ants have built a complete solution.

A global pheromone updating rule is applied.

Until end condition

## 3.4 Particle swarm optimization (PSO)

Particle Swarm Optimization (PSO) uses swarming behaviors observed in flocks of birds,schools of fish, or swarms of bees (figure 3.3), and even human social behavior, from whichintelligence emerges [3.23].The standard PSO model consists of a swarm of particles. They move iteratively through the *feasible* problem space to find the new solutions. Each particle has a position represented bya position-vector $\overrightarrow{x_1}$($i$ is the index of the particle), and a velocity represented by a velocity-vector $\overrightarrow{v_1}$. Each particle remembers its own best position so far in a vector $\overrightarrow{x_i^{\#}}$ and its $j$-th dimensional value is $\overrightarrow{x_{ij}^{\#}}$. The best position-vector among the swarm heretofore is thenstored in a vector $x^*$ and its $j$-th dimension value is $x^*j$ .The PSO procedure is as follows:

**Fig.3.3**. Birds or fish exhibit such a coordinated collective behavior [3.1]

***Algorithm 1*** Particle Swarm Algorithm

01. Begin
02. Parameter settings and swarm initialization
03. Evaluation
03. ***g***= 1
05. While (the stopping criterion is not met) do
06. for each particle
07. Update velocity
08. Update position and local best position
09. Evaluation
10. EndFor
11. Update leader (global best particle)
12. ***g***+ +
15. End While
13. End

The PSO algorithm has several phases consist of Initialization, Evaluation, and Update Velocityand Update Position.

## 3.5 Intelligent water drops

### 3.5.1 Introduction

The last work on the population based optimization algorithms inspired by nature is a novelproblem solving method proposed by Hamed Shah-hosseini [3.7]. Thismethod is called “Intelligent Water Drops” or IWD algorithm which is based on theprocesses that happen in the natural river systems and the actions and reactions that takeplace between water drops in the river and the changes that happen in the environment thatriver is flowing. Here we prepare a complete description on this new and interestingmethod. To start with, the inspiration of IWD, natural water drops, will be stated. After thatthe IWD system has been introduced. And finally these ideas are embedded into theproposed algorithm for solving the Traveling Salesman Problem or the TSP.

### 3.5.2 Natural water drops

In nature, we often see water drops moving in rivers, lakes, and seas. As water drops move,they change their environment in which they are flowing. Moreover, the environment itselfhas substantial effects on the paths that the water drops follow. Consider a hypotheticalriver in which water is flowing and moving from high terrain to lower terrain and finallyjoins a lake or sea. The paths that the river follows, based on our observation in nature, areoften full of twists and turns. We also know that the water drops have no visible eyes to beable to find the destination (lake or river). If we put ourselves in place of a water drop of theriver, we feel that some force pulls us toward itself (gravity). This gravitational force as weknow from physics is straight toward the center of the earth. Therefore with no obstaclesand barriers, the water drops would follow a straight path toward the destination, which isthe shortest path from the source to the destination. However, due to different kinds ofobstacles in the way of this ideal path, the real path will have to be different from the idealpath and we often see lots of twists and turns in a river path. In contrast, the water dropsalways try to change the real path to make it a better path in order to approach the idealpath. This continuous effort changes the path of the river as time passes by. One feature of awater drop is the velocity that it flows which enables the water drop to transfer an amountof soil from one place to another place in the front. This soil is usually transferred from fastparts of the path to the slow parts. As the fast parts get deeper by being removed from soil,they can hold more volume of water and thus may attract more water. The removed soilswhich are carried in the water drops are unloaded in slower beds of the river. There

areother mechanisms which are involved in the river system which we don't intend to considerthem all here.

In summary, a water drop in a river has a non-zero velocity. It often carries an amount ofsoil. It can load some soil from an area of the river bed, often from fast flowing areas andunload them in slower areas of the river bed. Obviously, a water drop prefers an easier pathto a harder path when it has to choose between several branches that exist in the path fromthe source to the destination.

### 3.5.3 Intelligent water drops

Based on the observation on the behavior of water drops, we develop an artificial waterdrop which possesses some of the remarkable properties of the natural water drop. ThisIntelligent Water Drop, IWD for short, has two important properties:

1. The amount of the soil it carries now, Soil (IWD).
2. The velocity that it is moving now, Velocity (IWD).

This environment depends on the problem at hand. In anenvironment, there are usually lots of paths from a given source to a desired destination,which the position of the destination may be known or unknown. If we know the position ofthe destination, the goal is to find the best (often the shortest) path from the source to thedestination. In some cases, in which the destination is unknown, the goal is to find theoptimum destination in terms of cost or any suitable measure for the problem.

We consider an IWD moving in discrete finite length steps. From its current location to itsnext location, the IWD velocity is increased by the amount nonlinearly proportional to theinverse of the soil between the two locations. Moreover, the IWD's soil is increased byremoving some soil of the path joining the two locations. The amount of soil added to theIWD is inversely (and nonlinearly) proportional to the time needed for the IWD to pass fromits current location to the next location. This duration of time is calculated by the simplelaws of physics for linear motion. Thus, the time taken is proportional to the velocity of theIWD and inversely proportional to the distance between the two locations.

Another mechanism that exists in the behavior of an IWD is that it prefers the paths withlow soils on its beds to the paths with higher soils on its beds. To implement this behavior ofpath choosing, we use a uniform random distribution among the soils of the available pathssuch that the probability of the next path to choose is inversely proportional to

the soils ofthe available paths. The lower the soil of the path, the more chance it has for being selected by the IWD.

In this part, we specifically express the steps for solving the TSP. The first step is how torepresent the TSP in a suitable way for the IWD. For the TSP, the cities are often modeled bynodes of a graph, and the links in the graph represent the paths joining each two cities. Eachlink or path has an amount of soil. An IWD can travel between cities through these links andcan change the amount of their soils. Therefore, each city in the TSP is denoted by a node inthe graph which holds the physical position of each city in terms of its two dimensionalcoordinates while the links of the graph denote the paths between cities. To implement theconstraint that each IWD never visits a city twice, we consider a visited city list for the IWDwhich this list includes the cities visited so far by the IWD. So, the possible cities for an IWDto choose in its next step must not be from the cities in the visited list.

## 3.6 Bee colony optimization

### 3.6.1 Introduction

Similar to other natural inspired and collective intelligence based algorithms such as PSOwhich is taken from the bird's life and ACO based on the ant colony social life, another kindof artificial intelligence systems that can be useful in solving many engineering,management, control and computational problems, is an algorithm inspired from Beecolonies in nature. The Bee Colony Optimization (BCO) algorithms are interesting meta-heuristic algorithms that represent another direction in the field of swarm intelligence.Here, firstly we introduce the bee system and bee colony optimization briefly and then somerecent works on the TSP which have used bee systems are investigated.

### 3.6.2 Bee colony optimization

The bee colony's function according to nature is as follows. At first, each bee belonging to acolony looks for the feed individually. When a bee finds the feed, it informs other bees by dancing. Other bees collect and carry the feed to the hive. After relinquishing the feed to thehive, the bee can take three different actions.

1. Abandon the previous food source and become again uncommitted follower.
2. Continue to forage at the food source without recruiting the nest-mates.
3. Dance and thus recruit the nest-mates before the return to the food source.

With a certain probability that is dependent on the obtained feed quality, its distance fromthe hive and the number of the bees which are now engaged with this feed resource, a bee selects one of the stated actions and follows its work in a similar repetitive form [3.24]. This behavior can be applied to many complicated engineeringproblems including computational, control, optimization, transportation, etc. In thefollowing we study such a method that focuses on the TSP solving.

### 3.6.3 BCO application

The BCO algorithm can be a significant method in local search applications. One of the mostprimary works on the bees and their life is [3.25]. In this study, the authorsapplied bee system along with GA and introduced a modified and improved form of theconventional GA. Based on this fact that the regular GA lacks the global search ability; theimprovement is regarding to overcome this shortcoming. Hence, a new GA inspired by thebee colony's function has been presented, the authors called it, bee system. The mainpurpose of this modified GA (bee system) is to improve the local search ability of Gaswithout degrading the global search ability. In the proposed bee system, firstly global searchis performed using the simple GA structure. Through this global search step, somechromosomes with reasonable high fitness produced which are called superiorchromosome. These superior chromosomes are kept for the local search procedure and eachof them corresponds to a local population. At the beginning of the local search all of thechromosomes in each local population make couple (crossover) with its population superiorchromosome. This crossover is named concentrated crossover which tries to search concentratearound the related superior chromosome. Another difference between thebee system and ordinary GA is migration among the population. In this method, the beesystem selects one individual per predetermined generation, and transfers it to the neighboring population which is called migration. All of the mentioned operators are in the local searchpart. After passing the predetermined generations, the local search stops. If the best solutionfound so far does not suffice the ending condition, the global search starts again and the algorithm is repeated [3.25]

Chapter 4

# THEORY OF ARTIFICIAL IMMUNE SYSTEM

## 4.1 Introduction

Recently, there was an increasing interest within the field of Artificial Immune System (AIS) and its application for solving numerous issues specifically for the TSP [4.1], [4.2]. AIS is impressed by natural immune mechanism and uses immunology method in order to improve systems capable of performing variety of tasks in various areas of research and analysissuch as diagnosis, pattern recognition, fault detection, and a number of other research area as well asoptimization. Here we would like to know the AIS utterly. To begin with, it would be helpful to become more acquainted with natural immune system.

Natural immune systems comprises the structures and processes within the living body that offer a defence system against invaders and conjointly altered internal cells that cause disease. During a glance, immune system's main tasks are often divided into three parts; recognition, categorization and defence. As recognition half, the immune system firstly needs to identify the invader and foreign antigens e.g. bacteria, viruses and etc. Oncerecognition part completes, classification should be performed by immune systems, this is the second half. And acceptable kind of defence must to be applied for each class of foreign aggressive phenomenon as the third half. The most important facet of the immune systems in mammals is learning capability. Namely, the immune systems will grow throughout the life time and is capable of using learning, memory and associative retrieval so as to resolve mentioned recognition and classification tasks. Additionally, the studies show that the natural immune systems are helpful mechanisms in data processing and might be helpful in inspiration for problem solving and numerous optimization problems [4.3].

## 4.2 Artificial immune system

Like the natural immune systems the AIS is a group of techniques that attempt to algorithmically mimic natural immune systems' behaviour [4.4]. As mentioned earlier, the immune system is vulnerable to all of the invaders, additionally the outer influences, like vaccines which are artificial ways of raising individual's immunity. Vaccines are other factors that can stimulate the immune system's susceptibility. This feature is the key point of the AIS structure. The vaccines in the AIS are abstracted forms of the preceding information. Vaccination modifies genes based on the useful knowledge of the problem to achieve higher fitness in comparison to the fitness that obtained from a random process when for example a classical GA is applied. Once again it is necessary to point out that, vaccines contain some

important information about the problem and in consequence the vaccination process employed in a right manner can be very useful in the performance of the algorithm. Like classical GA and based on its structure the AIS can work. The GA operators (crossover and mutation) search the problem space randomly and hence they don't have enough capability of meeting the actual problem at the local level. GAs are known as incapable of search fine local tuning because they are global search algorithms. Immune method through vaccination tries to overcome such blindness of crossover and mutation [4.3]. After vaccination, the immune method might leads to deterioration. This case happens when vaccination leads to smaller fitness values than previous ones. Hence, another important part of immune algorithm is prevention of deterioration when inserting vaccine. In short, immune operators perform in four steps: firstly, an individual is selected, randomly. Now as the second step, the vaccine is inserted at the individual's randomly chosen place. Vaccine insertion might leads to deterioration, the third step is checking for deterioration. And finally the forth step is discarding every individual that shows degeneration right after vaccine. This way of checking could be dangerous for diversity and could result in algorithm's inability to avoid local optima, especially when combined with small populations. The studies show that the use of immune systems resulted in fasterconvergence when population is large enough and diversity is secured. The combination of immune algorithm and GA, form the immune genetic algorithm (IGA). Many of previous works that are performed on the TSP used IGA. Now, we first investigate the IGA and its structure in detail and after that we have a look at some previous works around the TSP [4.5].

In summary, the IGA consists of these steps:

1. Creation of initial population in some way, e.g. through a random process
2. Abstract vaccines according to the former information
3. Checking the termination criterion (if it is satisfied go to step 10 and else go to next step)
4. Crossover on the randomly selected individuals
5. Mutation on the produced children
6. Vaccination on the former step outcome
7. Deterioration checking

8. Discarding every individual that shows degeneration right after vaccine

9. Go to step 3

10. End

As it is obvious from the ten steps which have been mentioned above, the IGA is very similar to the conventional GA, but they are different in operators.

## 4.3 Theories of AIS

The study and design of the artificial immune systems (AIS) is a relatively new area of research that tries to build computational systems that are inspired by the natural biological immune system. As we mentioned in subsection 3.3 there are many desirable computational feature in BIS that can be used to solve computational problems. A typical AIS model/algorithm implements one or more of these features. The books [4.4] and [4.6] provides the detail of the modelling and applications of AIS. The four forms of AIS algorithm reported in the literature are immune network model, negative selection, clonal selection and danger theory.

### 4.3.1 Immune Network Model

The immune network model was proposed by Jerne [4.7]. This theory proposed that the immune system maintains aidiotypic network of interconnected cells for antigen recognition. These cells both stimulate and suppress each other in a certain way that leads to stabilization of network.

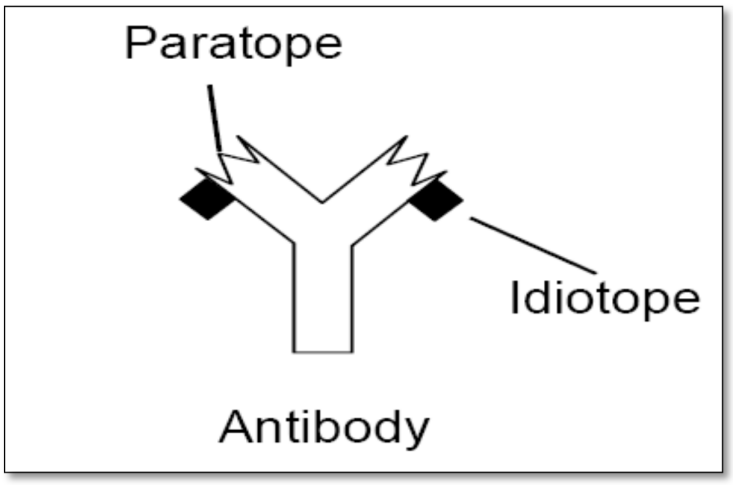



Fig. 4.1 Presence of paratope and idiotope on antibody [4.5]

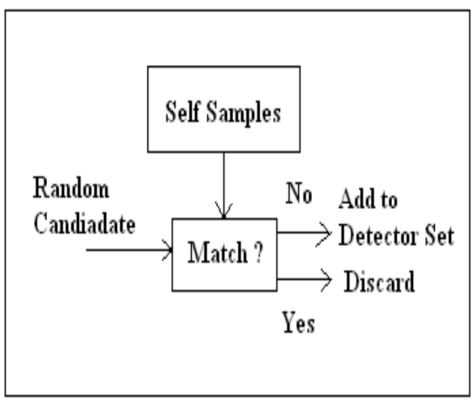
The formation of such a network is possible by the presence of paratope and idiotope on the each antibody cell. The paratope present on one B-cell is recognized by other B-cells idiotopes so each cell recognizes as well as recognized. In this network two cells are connected if the affinities they share exceed a certain threshold and the strength of the connection is directly proportional to the affinity they share.

In network formation point of view two things are very important: antigen-antibody binding and antibody-antibody binding. This idiotypic network can also be thought of as having cognitive capabilities that makes it similar to a neural network [3.15].

## 4.3.2 Negative Selection Algorithm:

The purpose of negative selection is to provide tolerance for self-cells. It deals with the immune system's ability to detect unknown antigens while not reacting to the self-cells [4.8]-[4.24]. During the generation of T-cells, receptors are made through a pseudo-random genetic rearrangement process. Then, they undergo a censoring process in the thymus, called the negative selection. There, T-cells that react against self-proteins are destroyed; thus, only those that do not bind to self-proteins are allowed to leave the thymus. These matured T-cells then circulate throughout the body to perform immunological functions and protect the body against foreign antigens. This algorithm is given by Forest et al. [4.8], [4.9] whose main steps are:

Step 1. In generation stage, the detectors are generated by some random process and censored by trying to match self samples as shown in Fig 4.2(a).



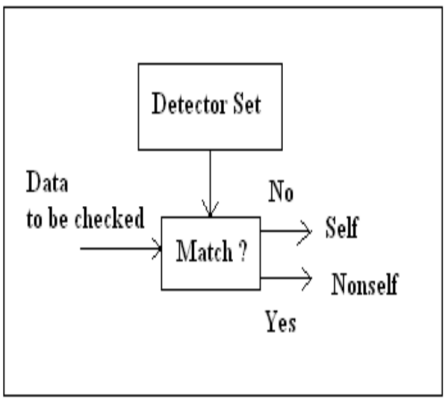




Fig. 4.2(a) Censoring Stage. Fig.4.2(b) Monitoring Stage

Fig. 4.2 Basic of Negative Selection Algorithm **(a)** Censoring Stage **(b)** Monitoring Stage [4.5]

Step 2. Those candidates that match are eliminated and the rest are kept as detectors.

Step 3. In the detection stage, the collection of detectors (or detector set) is used to check whether an incoming data instance is self or non-self as shown in Fig. 4.2(b).

Step 4. If it matches any detector, then it is claimed as non-self or anomaly.

### 4.3.3 Clonal Selection Algorithm

The clonal selection principle of AIS describes how the immune cells eliminate a foreign antigen and is simple but efficient approximation algorithm for achieving optimum solution. The basic algorithm is first applied by Charsto et al. for solving optimization problems [4.10]-[4.11]. The steps involved in the clonal selection algorithm are:

Step 1. Initialize a number of antibodies (immune cells) which represent initial population size.

Step 2. When an antigen or pathogen invades the organism; a number of antibodies that recognize these antigens survive. In Fig.4.3 only the antibody C is able to recognize the antigen3 as its structure fits to a portion of the pathogen. So fitness of antibody C is higher than others.

Step 3. The immune cells recognize antigens undergo cellular reproduction. During reproduction the somatic cells reproduce in an asexual form, i.e. there is no crossover of genetic material during cell mitosis. The new cells are copies (clones) of their parents as shown for antibody C in Fig.4.3.

Step 4. A portion of cloned cells undergo a mutation mechanism which is known as somatic hyper-mutation as described in [4.10].

Step 5. The affinity of every cell with each other is a measure of similarity between them. It is calculated by the distance between the two cells. The antibodies present in a memory response have on average a higher affinity than those of early primary response. This phenomenon is referred to as maturation of immune response. During the mutation process the fitness as well as the affinity of the antibodies gets changed. In each iteration after cloning and mutation those antibodies which have higher fitness and higher affinity are allowed to enter the pool of efficient cells. Those cells with low affinity or self-reactive receptors must be efficiently eliminated.

Step 6. At each iteration among the efficient immune cells some become effecter cells (Plasma Cell), while others are maintained as memory cells. The effecter cells secrete

antibodies and memory cells having longer span of life so as to act faster or more effectively in future when the organism is exposed to same or similar pathogen.

Step 7. The process continues till the termination condition is satisfied else steps 2 to 7 are repeated.

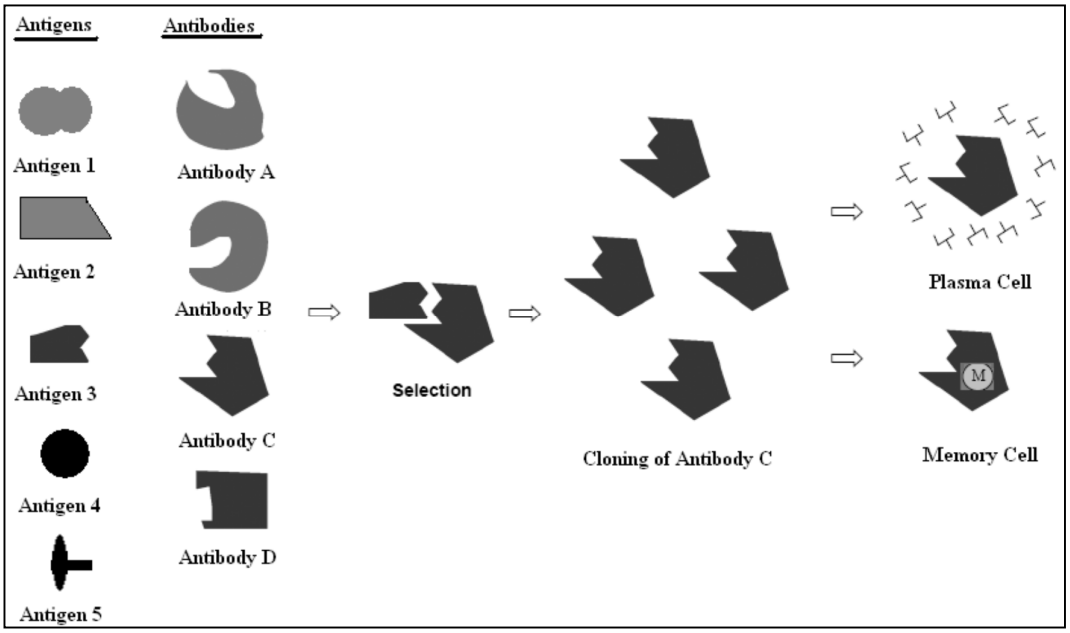



Fig. 4.3 Basic of Clonal Selection Algorithm [4.5]

The clonal selection algorithm has several interesting features such as population size is dynamically adjustable, exploration of the search space, location of multiple optima, capability of maintaining local optima solutions and defined stopping criteria.

## 4.3.4 Danger Theory

This theory is given by Matzinger in 1994 [4.12]. The immune system in order to function properly, it's very important that only the "correct" cells are matched as otherwise this could lead to a self-destructive autoimmune reaction. Classical immunology stipulates that an immune response is triggered when the body encounters something non-self or foreign. It is not yet fully understood how this self–nonself discrimination is achieved, but many immunologists believe that the difference between them is learnt early in life. In particular, it is thought that the maturation process plays an important role to achieve self-tolerance by eliminating those T- and B-cells that react to self. In addition, a "confirmation" signal is required: that is, for either B-cell or T- (killer) cell activation, a T- (helper) lymphocyte must

also be activated. This dual activation is further protection against the chance of accidentally reacting to self.

In accordance to danger theory there must be discrimination happening that goes beyond the self–non-self distinction described above. For instance:

1. There is no immune reaction to foreign bacteria in the gut or to the food we eat although both are foreign entities.
2. Conversely, some auto-reactive processes are useful, for example against self molecules expressed by stressed cells.
3. The definition of self is problematic—realistically, self is confined to the subset actually seen by the lymphocytes during maturation.
4. The human body changes over its lifetime and thus self changes as well. Therefore, the question arises whether defences against non-self-learned early in life might be auto-reactive later.

Other aspects that seem to be at odds with the traditional viewpoint are autoimmune diseases and certain types of tumours that are fought by the immunesystem (both attacks against self) and successful transplants (no attack against non-self). The Danger Theory takes care of “non-self but harmless” and of “self but harmful” invaders into our system. The central idea is that the immune system does not respond to non-self but to danger. Practically there is no need to attack everything that is foreign, something that seems to be supported by the counter-examples above. In this theory, danger is measured by damage to cells indicated by distress signals that are sent out when cells die an unnatural death. As shown in Fig.4.4 a cell that is in distress sends out an alarm signal, whereupon antigens in the neighbourhood are captured by antigen-presenting cells such as macrophages, which then travel to the local lymph node and present the antigens to lymphocytes [4.13]. Essentially, the danger signal establishes a danger zone around itself. Thus B-cells producing antibodies that match antigens within the danger zone get stimulated and undergo the clonal expansion process. Those that do not match or are too far away do not get stimulated.

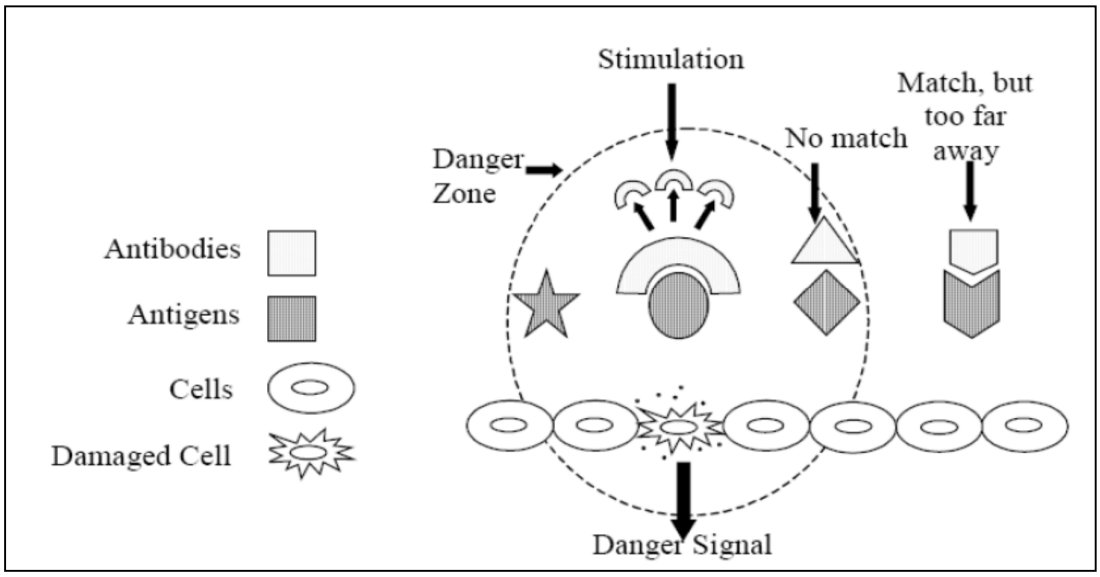



Fig. 4.4 Principle of Danger Theory [4.5]

In accordance with Danger theory Bretscher and Chon proposed a two signal model. According to this

Signal1: this is used for antigen recognition. Basically to determine the cell is a foreign cell.

Signal2: this is used for co-stimulation. This refers that the cell is really dangerous. So in accordance to the two signal model the danger theory operates by 3 steps

Step 1. Become activated if you receive signals one and two together. Die if you receive signal one in the absence of signal two. Ignore signal two without signal one.

Step 2. Accept signal two from antigen-presenting cells only. Signal one may come from any cell.

Step 3. After activation revert to resting state after a short time.

The challenge is clearly to define a suitable danger signal. The danger signal helps to identify which subset of feature vectors is of interest. A suitably defined danger signal overcomes many of the limitations of self–non-self selection. It restricts the domain of non-self to a manageable size, removes the need to screen against all self, and deals adaptively with scenarios where self (or non-self) changes over time.

## 4.4 Recent uses of AIS based Modelling

In recent years the area of Artificial Immune System (AIS) based modelling has drawn attention of many researchers due to its broad applicability to different fields. Some of the significant application areas include optimization problem [4.10]-[4.11], [4.14], computer security [4.15], design of intrusion detection [4.16], fault detection [4.17], fault tolerance, pattern recognition, distributed learning, sensor network, Job-shop scheduling, design of recommendation system etc. The AIS is relatively young and emerging as an active and attractive field involving models, techniques and applications of great diversity.

## 4.5 Summary

This chapter presents the functionality of BIS that is how the body restricts itself from the invasion of external microorganisms. It also outlines how the artificial immune system (AIS) is developed by following the principle of BIS. The four forms of AIS algorithm are discussed and the application areas are highlighted. In the present the clonal selection principle is chosen to be used for various applications as it is simple and easy to implement.

Chapter 5

# Problem Description

## 5.1 Types of PCB assembly used

Several researchers optimize the printed circuit board assembly problem by using different type of assemblies. This is generally categorized on the basis of position of feeder available, types of placement head, position of assembly board. Some of following are detailed below:

In a type-1 machine, a single feeder F1, possibly in the form of a magazine, provides components to a single assembly head H (there is no turret) at a fixed location in the horizontal X-Y plane. The head H also deposits components onto the PCB at a fixed point in x-y. The table T moves in the X-Y plane so that components are placed at the desired locations on the PCB. This type of assembly machine is the simplest and is normally adopted when only one type of components has to be placed [5.1]**.** As shown in fig (5.1).

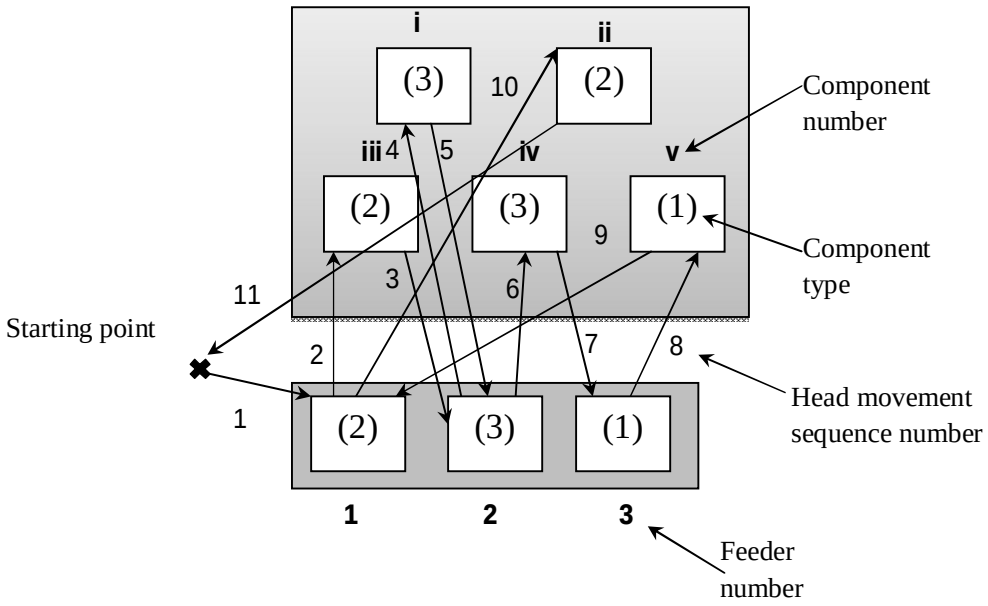



**Fig 5.1** The assembly sequence of PCB with one set of feeder

In a type-2 machine, the two feeder (or feeder array) and the table are stationary (and hence the PCB is also in a fixed location). The single assembly head H (again, there is no turret) moves in the X-Y plane to carry components to the correct placement positions on the PCB. If an array of feeders is adopted, the machine can be used to place components of different types onto a PCB.As shown in fig (5.2).

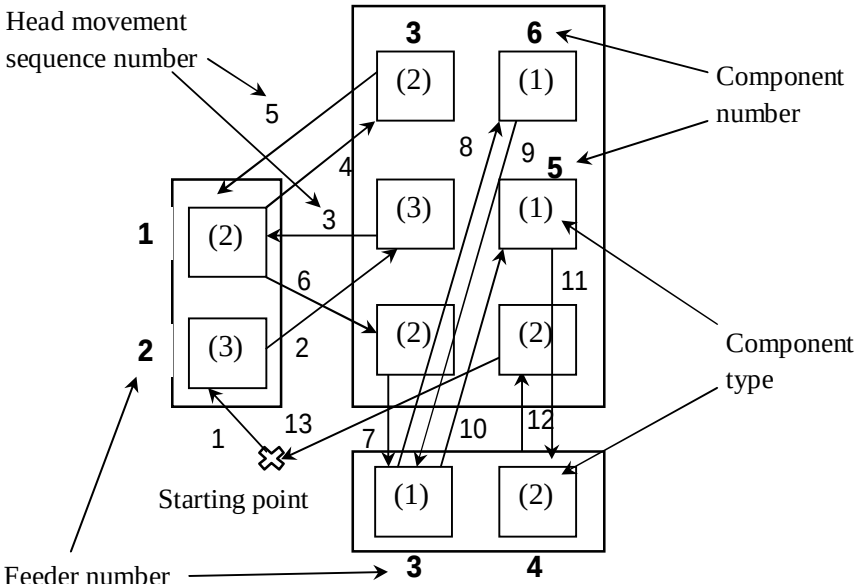



**Fig.5.2** The assembly sequence of PCB with two set of feeder

Components are placed to correct placement positions on the PCB. If an array of feeders is adopted, the machine can be used to place components of different types onto a PCB.

A type-3 machine has a turret carrying multiple pick-up/placement assembly heads H. The centre of rotation of the turret is fixed in the X-Y plane. A feeder array F2 moves along the X-axis to bring the feeder with the required component to the fixed pick- up location. The table T moves in the X-Y plane to position different points of the PCB, in sequence, at the fixed component placement location. Component pick-up and placement occur simultaneously after the correct feeder and the table has reached their designated positions and the turret has completed indexing the appropriate pick-up and placement heads. This type of machine can also place components of different types. PCB assembly planning involves two types of tasks: set-up management and process optimization. In the context of planning for a single assembly machine with an array of feeders, set-up management can include arranging the allocation of components among the different feeders or, alternatively, the relative positioning of the feeders in the array, to help reduce assembly cycle times.

Process optimization for an assembly machine is usually a componentsequencing problem. The aim of component placement sequencing is to optimize the movements of the table (in a type-1 machine) or the assembly head (in a type-2 machine).as shown in fig.(5.3).

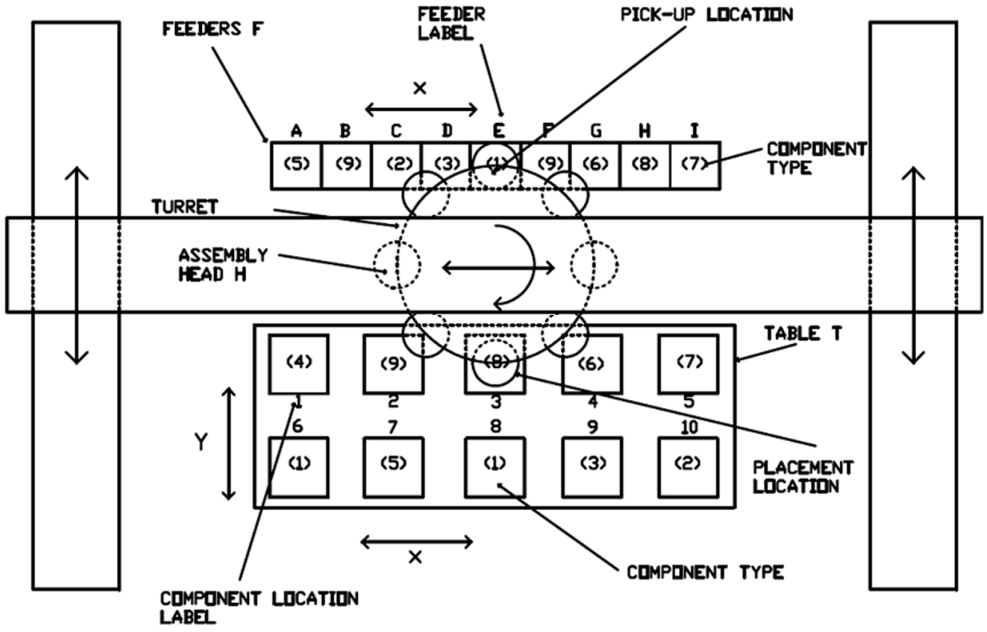



**Fig.5.3** The assembly sequence of PCB with turret arrangement [5.1]

## 5.2 Proposed PCB assembly

This work totally focuses on the sequential PAP machine. In this type of machines, the components are stored in multiple stationary feeders. The placement head travels to pick up a component from a feeder at a time, and then place it on the stationary board. The PAP machine is able to achieve high accuracy, and suitable to operate with large components such as integrated circuits (IC). The Operation sequence of PAP machine is that the placement head starts from its original location (starting point or home position), moves to a feeder that carries components, picks up a component from the feeder, and then moves to the desired placement location on the stationary board, and places it there. After that, the head moves back to the previous feeder if the next component is the same type with the previous one or moves to another feeder to pick up the next component if it is different from the previous one and place it on the board [5.2]. The head repeats this operation procedure until all

components are placed on the board and returns to its starting point, waits for the next board, as illustrated in Fig. (5.4).

Consider a PCB to be assembled by a PAP machine. The PCB has 10 components with 6 different types. Each component type can be stored in any feeder, and a feeder can only store a unique type of components, so 6 feeders are required. The objective of integrated problem is to minimize the total travel distance of placement head, which includes the distance from the starting point to a feeder at the beginning (i.e. $d_{0f}$), the distances from a feeder to a component's position on the PCB (i.e., $d_{fc}$), the distances from a component's position to a feeder (i.e., $d_{cf}$), and the distance from the last component's position to the starting point (i.e., $d_{i0}$). Suppose we have a sequence *starting point-f3-c2-f3-c3-f2-c9-f2-c4-f1-c5-f1-c10-f6-c8-f6-c7-f5-c6-f4-c1-starting point* where f and c denotes feeder and component respectively. So the sequence of component on PCB according to component number results as 2-3-9-4-5-10-8-7-6-1, this sequence is called as antibody for artificial immune system and by using this sequence, one can calculate the total travel distance of placement head by using the distance calculating formula between two points i.e.

$$d_{1,2} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Here $x_1$, $y_1$are the coordinates of first point whereas $x_2$, $y_2$ are the coordinates of second point and so on. The coordinates of all placement position on PCB and the predetermined component arrangement in the feeders are tabulated in the Table. 1. The coordinates are taken from the reference of starting point having coordinates (0, 0).

All the positions on PCB and feeders having a unique type of component are predefined and fixed. We use above equation (1) to calculate all distance for example, According to the above sequence, the head will move from starting point to the feeder 3, to pick type 1component and then place this component on 2nd number of component on PCB and coordinates according are (0, 0) , (10, 20) and (30, 30) respectively then the distance travel by placement head to pick 1 type of component from starting point to the feeder 3 (i.e. f3) is calculated as follows.

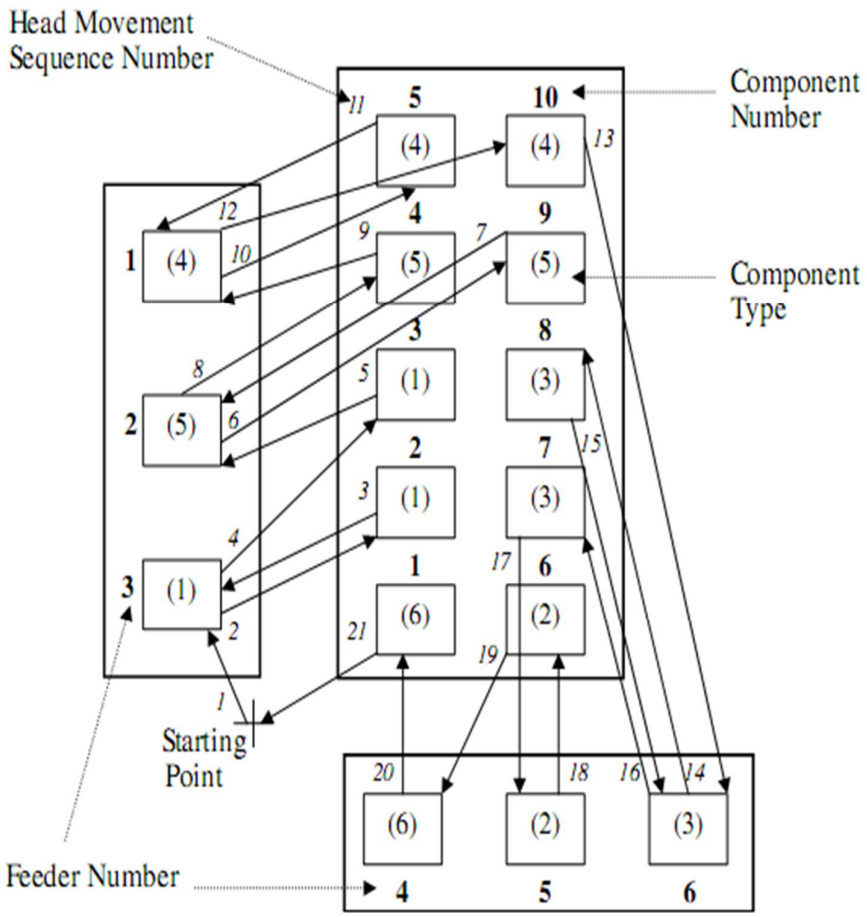



**Fig.5.4** The assembly sequencing of placement head [5.2]

So Total distance

As shown in above example, all distance can be calculated by equation (1) with the help of Table.1. The Total distance travelled by head is called here as a fitness value for every sequence we calculate. There are some more PCB assemblies have been taken to account

Table.5.1Data of integrated problem with 10 components and 6 types [5.2]

| component | type | Coordinates(mm) | | feeders | Coordinates(mm) | |
|---|---|---|---|---|---|---|
| | | *x* | *y* | | *x* | *y* |
| 1 | 6 | 30 | 20 | 4 | 10 | 50 |
| 2 | 1 | 30 | 30 | 5 | 10 | 35 |
| 3 | 1 | 30 | 40 | 1 | 10 | 20 |
| 4 | 5 | 30 | 50 | 6 | 30 | 10 |
| 5 | 4 | 30 | 60 | 2 | 50 | 10 |
| 6 | 2 | 50 | 20 | 3 | 70 | 10 |
| 7 | 3 | 50 | 30 | | | |
| 8 | 3 | 50 | 40 | | | |
| 9 | 5 | 50 | 50 | | | |
| 10 | 4 | 50 | 60 | | | |

Table. 5.2 Component type and coordinates of different type of assembly problem [5.1][5.2]

| Problem type | component | Type | Coordinated(mm) | | feeders | Coordinates (mm) | |
|---|---|---|---|---|---|---|---|
| | | | *x* | *y* | | | |
| 4x2 problem | 1 | 1 | 30 | 20 | 1 | 10 | 30 |
| | 2 | 2 | 30 | 30 | 2 | 10 | 20 |
| | 3 | 2 | 50 | 20 | | | |
| | 4 | 1 | 50 | 30 | | | |
| 4x4 problem | 1 | 4 | 30 | 40 | 1 | 10 | 30 |
| | 2 | 3 | 30 | 60 | 2 | 10 | 20 |
| | 3 | 1 | 50 | 60 | 3 | 20 | 10 |
| | 4 | 2 | 50 | 40 | 4 | 30 | 10 |
| 6x4 problem | 1 | 2 | 30 | 20 | 4 | 10 | 35 |
| | 2 | 1 | 30 | 30 | 1 | 10 | 20 |
| | 3 | 1 | 30 | 40 | 2 | 30 | 10 |
| | 4 | 3 | 50 | 20 | 3 | 30 | 10 |
| | 5 | 3 | 50 | 30 | | | |
| | 6 | 4 | 50 | 40 | | | |

similar to above assembly 10x6 problem like 4x4, 4x2 and 6x4. The component arrangement and the allocation of component on feeders and assembly are board tabulated in Table. 2

## 5.3 Mathematical Model

As we already knows component sequencing and feeder arrangement problem are integrated to each other without the solving one we cannot solve other problem so that for modelling of mathematical model component sequencing problem, suppose the assignment of component types to feeder is solved beforehand, the component sequencing model can then be formulated for finding the optimal total travelling distance of placement head. In order to achieve objective a decision variable has to be define as:

$$x_{ij}\begin{cases} 1 \text{ if component i is placed immediately before component j;} \\ 0 \text{ otherwise:} \end{cases}$$

Actually, PAP component sequencing problem is totally based on TSP principle and somewhat similarto the TSP also, except the objective function. For the PAP machine, theobjective is not to minimize the distance between component iand component j because the placement head is unable to placethe next component on the PCB immediately without picking up acomponent from a feeder first. Therefore, the objective for thePAP machine should be to minimize the summation of different distancesincluding [5.2]:

- The distance between the position of component i on the PCB and feeder l (if i = 0, it is the distance between the starting pointat the beginning and feeder l).
- The distance between feeder l and the position of the next component.
- The distance between the position of the last component i andthe starting point at the end.

The component sequencingproblem can be formulated as:

$$minimize\ dist = \sum_{i=0}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n}\sum_{l=1}^{\mu}(d_{il} + d_{lj}) + \sum_{i=1}^{n} d_{i0}x_{i0} \qquad (1)$$

Subjected to

$$\sum_{i=0}^{n} x_{ij} = 1 \ for\, j = 0,1,\dots\dots,n; i \neq j. \qquad (2)$$

$$\sum_{j=0}^{n} x_{ji} = 1 \ for\, j = 0,1,\dots\dots,n; j \neq i. \qquad (3)$$

$$u_i - u_j + nx_{ij} \leq n-1 \quad for\, i,j = 0,1,\dots\dots,n; i \neq j. \qquad (4)$$

Equation (1) is an objective function which is formed to minimize the total travel distance from placement head. If we assumed that PAP head is placing the components with constant speed then the objective function will be change from travel distance to placement time for assembling hole component on board. Equation (2) shows first set of constraint which ensure that only one component must be placed immediately before *j*component. Equation (3) shows second set of constraint ensure that exactly one component must be place immediately after *i*component. Above two constraint sets are not sufficient. Although the above two set of constraint are satisfied by solution but solution may still be infeasible due to presence of sub-tours. Therefor the third set of constraint added in above model, in order to remove sub-tours. Due to the Placement head start assembly from starting point therefor it is redundant to include *i* and/ or *j* = 0.

It is found form above model, objective function is a minimise type of non-linier integer programming (NLP) model. It is very hard to solve by manually that is why we used one LP commercial solver package LINGO to solve above NLP problem. This commercial package gives an optimal solution which is compared with the global optimal solution got from the artificial immune system algorithm.

## 5.4 Development of AIS algorithm

An evolutionary algorithm evolves its population in a way that makes individuals more and more adapted to the environment. In other terms, the fitness function is minimized/ maximized. Real-life applications are of course much more complex, with the main problem being to adapt, or even create operators that correspond to the problem at hand. The flow chart of the AIS algorithm is shown in fig. 2. The operative mechanisms of immune system are very efficient from a computational standpoint [5.3].

An AIS starts with an initial set of random solutioncalled population. Each solution in

population is called chromosome, which represent of point in the search space. The AIS search process is one essential genetic operation: exploration (or diversification). Generally the mutation operators explore the wide range of search space. The antibodies evolve through successive iterations, called generations. During each generation the antibodies are evaluated using some measures of fitness. The fitter the antibodies, the higher the probabilities of being selected to perform a genetic operation (i.e. mutation). In the mutation phase, the mutation operation maintains the diversity in population to avoid being trapped in local optima. A new generation is formed by selecting some of the parents and offspring according to their fitness value, and by rejecting others so to keep the population size constant. After the predetermined number of generation is performed, the algorithm presents the best antibodies, which hopefully present optimal solution or may be sub-optimal solution to the problem [5.4].

As per as genetic algorithm AIS has also a great level of flexibility. It can be hybridized with other heuristics in order to improve the solution further. The flowchart of AIS for the PAP problem is shown in fig 5.5. The procedure of the AIS for PAP is listed as follows:

Step 1. Set the initial parameters like population size (*pop*), the number of iteration (*max_iter*).

Step 2. Generate *pop*initial antibodies with one link encoding discussed in Section 5.3.1. For each chromosome, the link is generated by randomly generation.

Step 3. Evaluate the fitness value *dist*as illustrated *in* section 5.3.2 for all antibodies in the population.

Step 4. After the evaluation of *dist,* calculatethe affinity illustrated in section 5.3.3 for all antibodies on the basis on which the cloning of antibodies will be carryout.

Step 5. Follow the selection procedure to select antibodies to perform the heuristic mutation operation is section 5.3.4.

Step 6. Compare all clone with the antibodies in the population by the fitness value *dist*. Retain the best *pop* antibodies in population.

Step 7. Population size after the mutation operations gone increased so that some presents of population size are deleted any add new antibodies to achieve predetermined population size called receptor editing described in section 5.3.5.

Step 8. Determine the best chromosome at each iteration. Repeat Step 3 to Step 8 until *max_iter* iterations are performed.

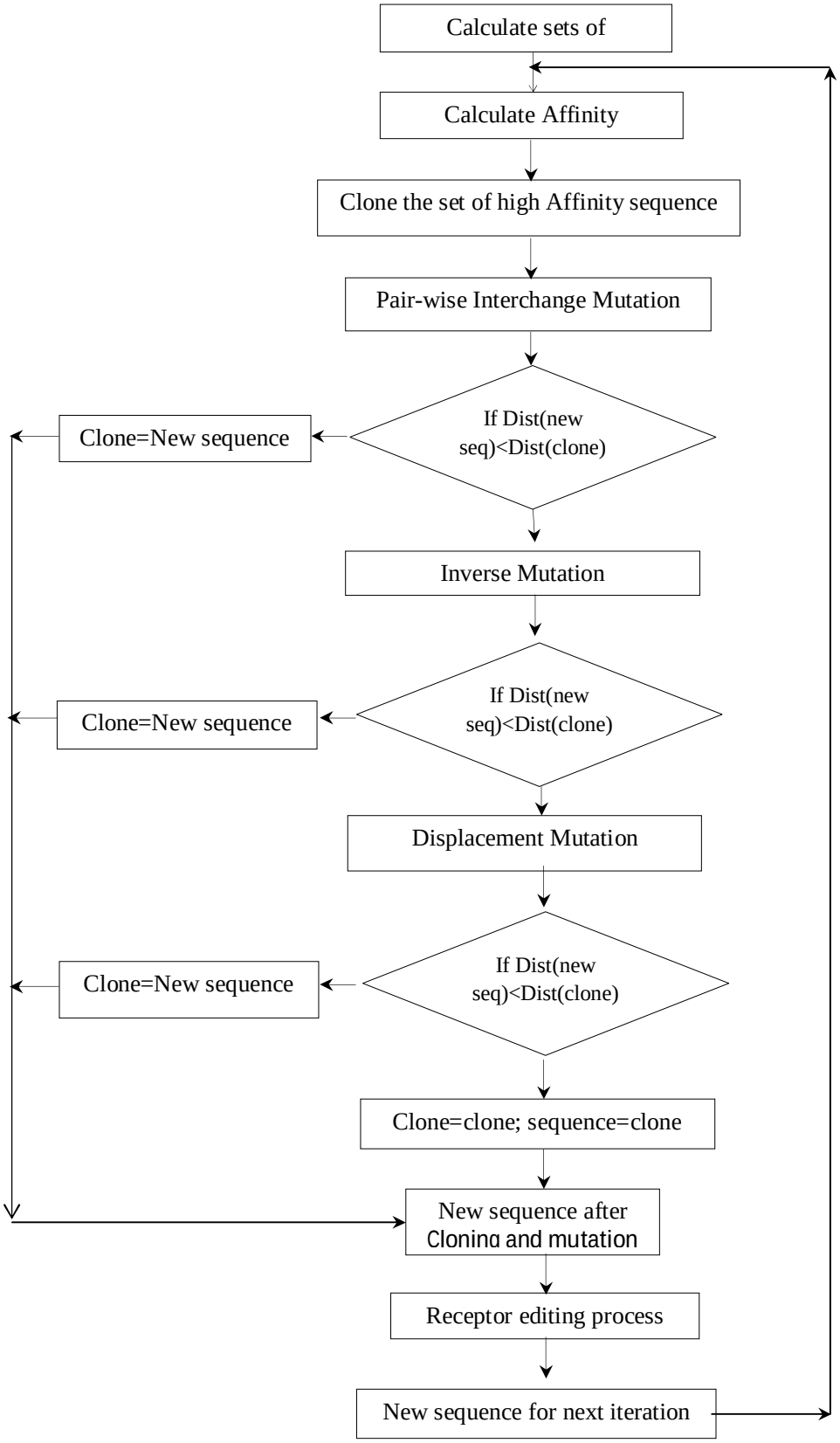



**Fig. 5.5** The Flow chart of artificial immune system algorithm for PCB assembly.

### 5.4.1 Encoding

An antibody is illustrated in Fig. (5.6) encoding of PCB and feeder representation, in which the number inside the bracket in PCB represents the component type. For example, if the sequence of placements starts with component 2, then component 3, component 9, component 4, component 5, component 10, component 8, component 7, component 6 and finally component 1. Its sequence can be represented as (2 3 9 4 5 10 8 7 6 1), that is, the sequence of component on PCB, as shown in Fig. 5.6(a)

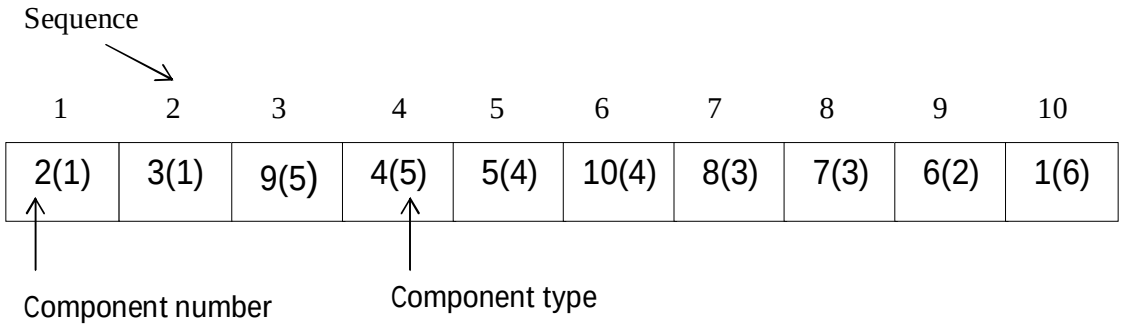



**Fig. 5.6** (a) Encoding of given sequence of component is on PCB.

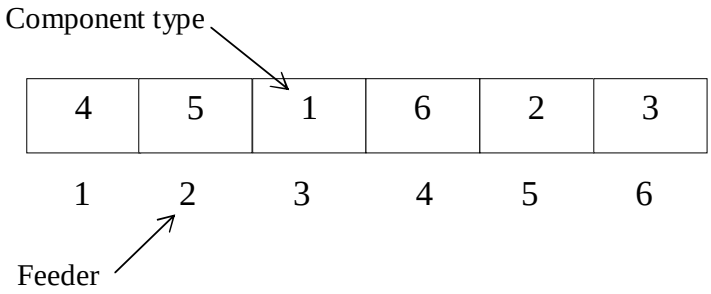



**Fig 5.6(b)** Encoding of feeder components.

If the ten components are from six component types, and type 4 is assigned to feeder 1, whereas types 5, 1, 6, 2 and 3 are assigned to feeders 2, 3, 4, 5, 6 respectively, then the feeder arrangement can be represented as (4 5 1 6 2 3). Sometimes, the number of feeders available is more than that of component types required. Some components with the same

type can therefore be assigned to more than one feeder. Nevertheless, it was observed that no more than two feeders with the same component type could be used on an assembly line. Therefore, at most a particular component type can be stored in two feeders at the same time. Not surprisingly, component types with greater use should have the priority to be assigned to surplus feeders. In the above example, it is assumed that no one surplus feeder is available. One type component is stored in only one of feeder. The feeder arrangement is now encoded as (4 5 1 6 2 3), as illustrated in Fig. 5.6(b).

### 5.4.2 Evolution of fitness function

The fitness function used for PAP problem is total distance travelled by the placement head. Fitness function calculates the total distance the head travelled. Its includes the distance from original location i.e. starting point to a feeder at the beginning, the distance from a feeder to a component on assembly board and the distance from last component to the original location. Lets *Dist($x_i$)* be the fitness function for antibody $x_i$ in PAP problem, and *D(a,b)*represent the distance between point *a* and *b*, then

$$Dist(x_i) = D(0, f(1)) + \sum_{i=1}^{n} D(f(i), c_i) + \sum_{i=1}^{n-1} D(c_i, f(i+1)) + D(c_n, 0) \qquad (5)$$

Where n is the number of component; *f(i)* is the feeder location for the *i*th component; $c_i$ is the location of component at assembly board and *0* is the original location i.e. starting point.

Here, *f(i)*represent the feeder location for *i*th component. For example, for component 2, it is stored in feeder 5, so *f(2)* = 5, that is $f_5$ in the previous discussion.

### 5.4.3Clone Selection Principle

Each schedule (antibody) has a fitness value that refers to the affinity value of that antibody. Affinity value of each schedule is calculated from the affinity function. The affinity function is defined as:

$$Affinity(p) = \frac{1}{Fitness\ value} \qquad (6)$$

From this relation, a lower fitness value gives a higher affinity value. Further the cloning of antibodies is done directly proportional to their affinity function values. Therefore, there will be more clones of antibodies that have lower fitness value than those with higher fitness values in the new generated clone population. An immune based approach to minimize fitness value on parallel processors has been presented in [5.5]. An affinity function is defined based on fitness values of the schedules [5.6] [5.7] Also they have given a function to calculate the number of clones that would be proliferated [5.8] [5.9].

### 5.4.4. Affinity mutation principles

The affinity maturation principle consists of three methods namely mutation and receptor editing. Mutation a two phased mutation procedure which used for the generated clones [5.4].

a) Pair wise interchanges mutation.
b) Inverse mutation.
c) Displacement mutation.

#### *5.3.4.(a) Pair wise Interchange Mutation:*

Given a sequence *s*, let *i* and *j* be randomly selected two positions in the sequence *s*. A neighbour of *s* is obtained by interchanging the jobs in positions *i* and *j*. If the fitness value of the mutated sequence (after pair wise interchange mutation) is smaller than that of the original sequence, then store the mutated one in the place of the original one, as shown in fig. 5.7.

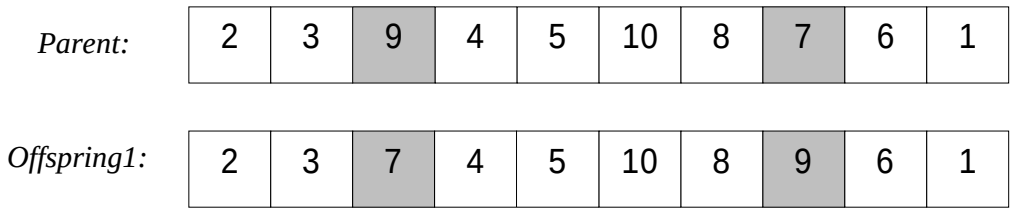



**Fig. 5.7**The Pair wise interchange mutation operation.

#### *5.3.4.(b) Inverse Mutation:*

For a sequence *s*, let *i* and *j* be randomly selected two positions in the sequences. A neighbour of *s* is obtained by inversing the sequence of jobs between *i* and *j* positions. If the fitness value of the mutated sequence (after inverse mutation) is smaller than that of the original sequence (a generated clone from an antibody), then the mutated one is stored in the place of

the original one. Otherwise, the sequence will be mutated again with random pair wise interchange mutation. As shown in fig. 5.8.

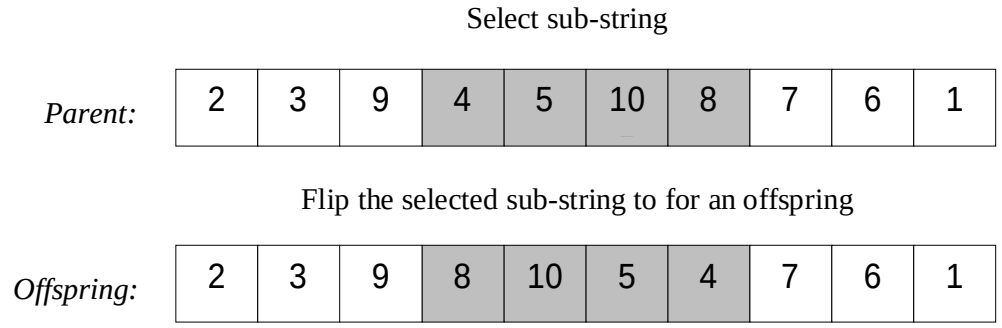



**Fig .5.8** The Inverse mutation operations.

### *5.3.4(c) Displacement Mutation:*

In this method a sub tour is selected in random and it is removed from the tour and inserted it in a randomly selected position. However the sub tour is inserted in reverse order as shown in fig. 5.9.

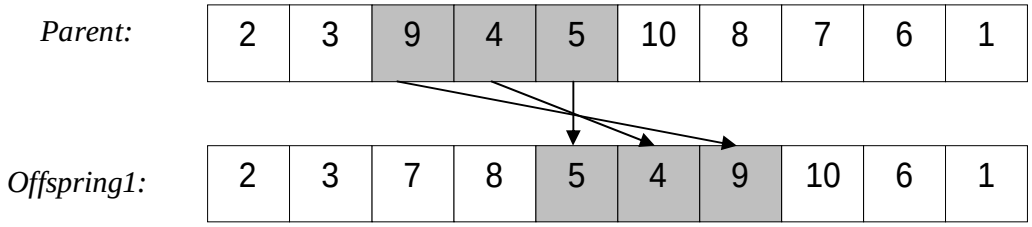



**Fig. 5.9** The Displacement mutation operation.

By using all above mutation techniques we got a very impressive and large variety of antibodies in predefine population size.

### 5.4.5 Receptor Editing:

After cloning and mutation processes, a percentage of the antibodies (worst %B of the whole population) in the antibody population are eliminated and randomly created antibodies are replaced with them. This mechanism allows finding new schedules that correspond to new search regions in the total search space [5.10]. In this work, B is assumed as 30%, 50% and 80%.

Chapter 6

# Results and Discussions

In this chapter the performance of AIS is evaluated by comparing to the optimal solution of several problems mentioned in chapter 5. Here we have used two different type of methodology to optimize the component sequencing problem i.e minimization of total distance travelled by head of pick and place machine. First methodology based on the specific AIS algorithm developed only for the PCB problem and second one based on the Integer programming mathematical model. We have compared both of results obtained from the above technics and also described the effect of AIS parameter on the solution obtained by algorithm.

This part of the thesis is consist three part to evaluate the AIS algorithm's performance. The parts are as follows: First part consisting 10×6 PCB problem to evaluate the performance of AIS algorithm and shows its characteristics in form of decrement graph. In second part, for checking of homogeneity in solution we solved four different type of PCB assembly using AIS and compared with the IP model. In third part the effect of receptor editing percentage are shown during solving any problem from AIS algorithm.

## 6.1 Result of AIS performance

At first to check the performance of AIS algorithm using a PCB assembly model which is already discussed in chapter 5, it contains total 10 components on PCB assembly board consist of 6 different type of components in different feeders so that here 6 numbers of feeders are provided to pick the components and place it to their predefined position on the assembly board with the help of PAP machine. Before starting the solution we have to decide some AIS parameters like, population size (*pop*) = 20, number of iteration (*max_itre*) = 150, receptor editing percentages (%B) = 50%, and perform the AIS algorithm. As a result of AIS we obtained a global optimal point in the form of minimum travel distance by the PAP machine is 575.3 cm in 30 iterations, the decrement graph between fitness value and number of iteration is shown in fig 6.1.

## 6.2 Comparison with IP model

For the checking of homogeneity of AIS algorithm we have taken some more problems to solve them in AIS and integer programming methods. After iteration as we have received the results of AIS is providing a very effective and efficient solution for every problem compared to integer programming model. Here four types of problem are taken on which the AIS is

applied and the results are compared with the solution of integer programming mathematical model. The comparison results of different problem using AIS and integer programming is tabulated in Table 6.1. The problems are as follows:

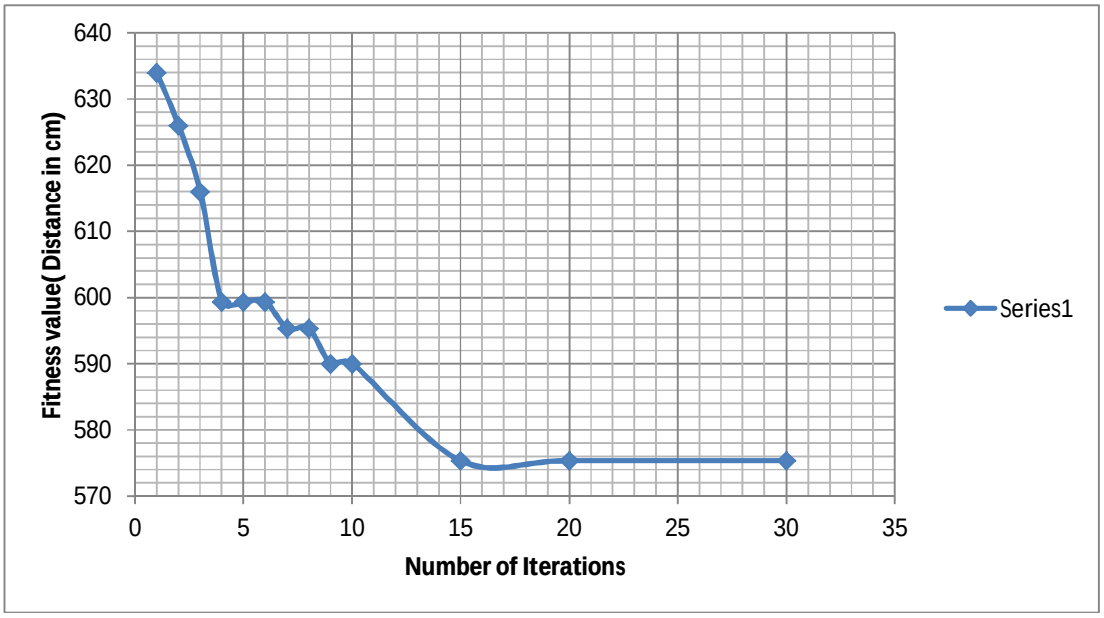



Fig.6.1 Decrement graph between fitness value and iteration number.

1. **4x2 Problem:** In this problem, a total of 4 components consisting of 2 different types are considered. For these components *two* feeders are provided and each feeder containing different type of component.
2. **4x4 Problem:** In this problem, a total of 4 components consisting of 4 different types are considered. For these components *four* feeders are provided and each feeder containing different type of component.
3. **6x4 Problem:** In this problem, a total of 6 components consisting of 4 different types are considered. For these components *four* feeders are provided and each feeder containing different type of component.
4. **10x6 Problem:** In this problem, a total of 10 components consisting of 6 different types are considered. For these components *six* feeders are provided and each feeder containing different type of component.

Table 6.1 Comparison table for different PCB problem

| | IP Model Result | No. of Iteration(IP Model) | AIS Result | No. of Iteration (AIS) | Percentages of effectiveness |
|---|---|---|---|---|---|
| **4x2 Problem** | 267.69 | 16 | 236 | 12 | **11.8%** |
| **4x4 Problem** | 327.77 | 10 | 310 | 11 | **5.4%** |
| **6x4 Problem** | 320.17 | 18 | 312 | 14 | **2.5%** |
| **10x6 Problem** | 592.34 | 19 | 575.6 | 15 | **2.85%** |

## 6.3 Effect of receptor editing percentages

In third part of result section we have been gone through the various effect on the total distance travelled by the PAP head due to change in percentages of receptor editing. For this part we have solved a 10×6 PCB assembly's sequencing problem using AIS algorithm by varying the receptor editing percentages in to three values i.e. 30%, 50% and 80%. The effect on fitness value is plotted on graph. Shown in fig.6.2:

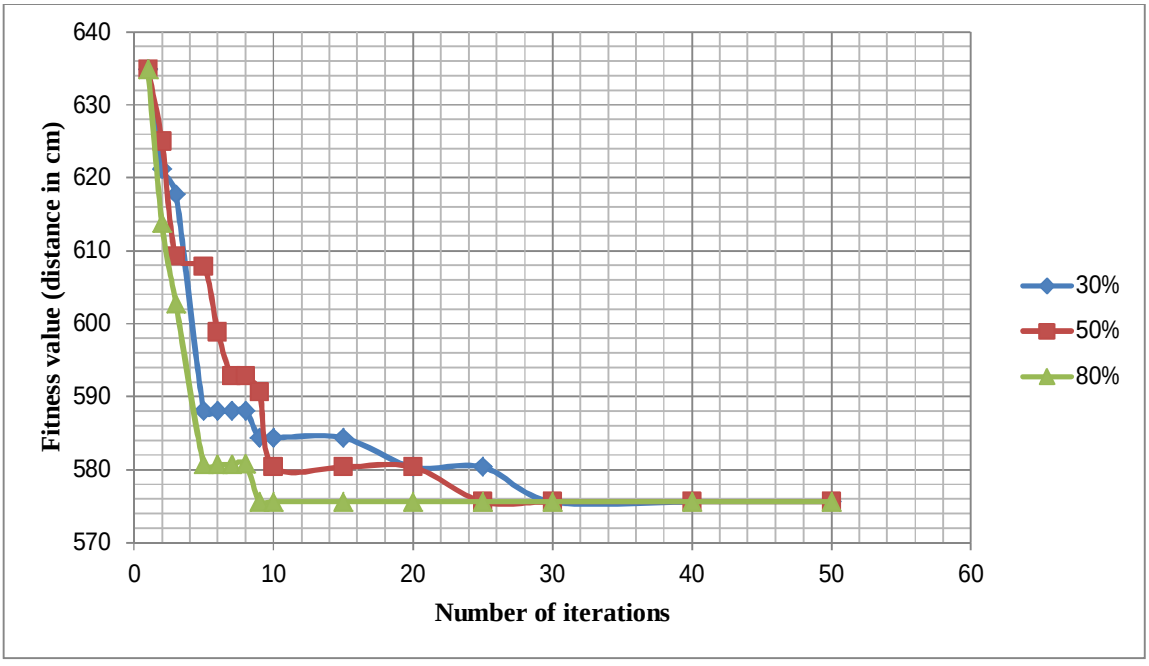



Fig.6.2 The effect of receptor editing percentage on fitness value.

## 6.4 Discussion points

As mentioned earlier, the fixed setup strategy is when part of the component types on a PCB have already been assigned to the feeder carriage and the placement sequence are to be determined. It means the component carrying by feeder is fixed or predefined; only sequencing problem has been solved. When constructing a feederassignment for the component types used on a PCB, the total number of component types alreadyassigned to the feeder carriage consists of the component types of the PCBs whose feederassignment has already been determined. The component types already assigned to the feedercarriage may or may not include some of the component types used on the PCB whose feederassignment and placement sequence is being constructed. So that in every type of PCBs problem used here to solver using AIS have fixed feeders arrangement, they only used for optimize the minimum travelled distance covered by PAP head to complete the whole assembly of PCB. After evaluation of above results there are some points come in the picture for discussion. They are listed below:

- From fig. 6.1, AIS provide the global optimal value 575.3 in very small range of iterations i.e. 30 only. Above AIS algorithm is only developed for the optimization of sequencing problem.
- The research carried out in this field reveals that very few researchers considered sequencing problem in their work. Results are available for same type of PCB assembly used above considering both problem feeder arrangement and component sequencing. Due to this the result obtained by the researchers are quit less and effective then the AIS results.
- From Table 6.1, it shows that the AIS is providing an effective and efficient results in very less number of iteration as compare to IP model which is solved by a commercial IP solver “LINGO”.
- From Fig. 6.2, it shows the effect of one of the parameter of AIS algorithm i.e. Receptor editing percentages. Receptor editing is a kind of editing of worst antibodies carryout within the algorithm after completing all type of mutation process during transferring population size from current iteration to next iteration.
- Variation in percentage of receptor editing shows that more % percentage receptor editing provide more search space for optimization and take less number of iteration to finding out the global optimal point.

Chapter 7

# Conclusions and Future works

## 7.1 Conclusions

This research has addressed one of the decision problems associated with process optimization in printed circuit board assembly systems for a specific assembly machine. Specifically, a solution approach was developed for determining the component placement sequence for a PAP style Chip Shooter type machine.An AIS algorithm has been proposed for the pick and place sequence problem inPCB assembly, with the objective of minimizing the PCBtotal assembly time. Results from this algorithm were subject to three segments:

- **Evolution of performance:**For evolution of effectiveness, we assign a 10 component problem for checking the performance of AIS algorithm. We found that it gives an optimal value which is very close to the result of researchers who found out by considering feeder arrangement and component placement problem together.
- **Comparison with IP model:** the four different type of PCB assembly which contains different number of component on the assembly board have used to compare result of AIS with the mathematical tool i.e. IP model.The result shows that AIS is providing a better global optimal solution in less number of iteration as compare to the IP models results.
- **Effect of receptor editing percentage:**To evaluate the effect of receptor editing percentage, we have ranged the percentage in to three values i.e. 30%, 50% and 80%. We have found that the increase in receptor editing percentages also increase the search space for optimization and decreases the number of iteration to obtain the optimal point.

For a small problem, such as our 10 component example, the benefit of a better solution may be small unless a very large number of components are assembles. However for large problems with more than hundred components, the assembly distance can be decreased significantly and the solution can be obtained more rapidly than by other methods. In addition our algorithms allows placement of a component type to more than one feeder, which can provide additional flexibility and reduce total travelled distance by PAP head.

## 7.2 Future work

As mention earlier the cost function desires a lot of research. Is it attainable to describe an effective cost function while out solving the sequencing problem or is it attainable to describe the placement order within the same method as solving the feeder assignment problem? One interested plan to unravel the sequencing problem carried out with the feeder arrangement problem. So that the extension of this work will going to be solve the path optimization considering the both problem i.e. component sequencing and feeder arrangement together to achieve best throughput.Several areas for further research have been identified while conducting this research, where we need to do work to improvement of this technique and make more effective to utilise it for a large level.

- ✓ The placement order affects the ultimate production time and it omission can never provide an effective result. Therefore this half needs to be understood and researched a lot.
- ✓ As we know here we are performing only sequencing problem by fixing the feeder arrangement AIS stuck at a point after reaching an optimal value so that the incorporation of feeder arrangement is important to get more significant path optimization.
- ✓ Future work with heuristic algorithms will ameliorate a performing some more pre-calculations on where the components should be within the feeder racks.

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