Optimization of Process Plans by considering Material Handling Cost for RMS

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To my exceptional parents, adored wife and daughter

Maryam Rafay 😊

Abstract

In global market, responsiveness is the way to be competitive for the enterprises which have the various part families. This can be achieved by the use of CAPP along with advanced optimization techniques. Process planning optimization can be performed on the basis of total production cost of a product. Total production cost consists of material handling cost (MHC), machines and tool usage costs & machine, tool and setup change costs. In literature it is found that MHC is not considered for optimization purposes. According to literature, MHC accounts for 20-50% of total manufacturing cost of a product and by optimization, total manufacturing cost can be reduced 15 to 30%. So, MHC must be considered while optimizing the process plan. In this thesis MHC, along with other costs from literature, has been considered for the process plan optimization. In literature, all the costs are in different ranges and multiplied by different indices to make comparable. In this thesis, the normalization of each cost is recommended for better results. Effect of each cost element is relatively controlled by their corresponding normalized weights, i.e. increasing the effect of any cost results in decreasing the effect of all other costs collectively. Genetic algorithm with edge selection encoding strategy is used to find optimal process plans in MATLAB. The effect of material handling cost vanished by switching off its weight function for benchmarking with previous work. Convergence is performed to select suitable population size, crossover probability, mutation probability and the stopping criteria for recent objective function. Effect of material handling cost is checked by increasing the value of its weight (w_6) gradually for first optimized process plan (generated at w_6=0). It is observed that material handling cost and total cost increase gradually and sum of all other costs decreases with the rise of w_6. A range for the value of w_6 is selected where it comprises of near about 20% of the total cost. At this range different process plans are generated and total cost of first optimized process plan is also re-calculated. In case of increasing in the importance of MHE, a new process plan is generated. A comparison of total costs of new process plans with first optimized process plan at the same value of w_6 shows that first optimized process plan becomes costly because it was not designed as MHC perspective. It is recommended to add MHC to get optimized result for the cases where the varieties of material handling equipment are available.

Key Words: *Genetic Algorithm, process planning, Reconfigurable manufacturing systems, optimization, precedence constraints, Mutation, Material handling cost.*

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Chapter 1: Introduction

1.1 Motivation

A large number of people are under poverty level in Pakistan, and this is the major concern of our country. They are suffering to meet their fundamental rights (needs) like healthy food, cloth, education and shelter etc. Standard of living people can be raised by increasing the goods production at lesser cost, and this can be achieved by increasing production efficiency which is also known as productivity. Now a days, the development and economic health of a country is dependent on its advancement of expertise in industries. The use of advanced manufacturing technologies is incredibly enhancing than ever (Kesavan et al., 2004).

A manufacturing environment always went on changing due to competition, fluctuations in demands, customer needs and new technologies. For large production, most profitable system was dedicated transfer lines till mid of 1990s (Koren and Shpitalni, 2010). In 1990s, quality, productivity and flexibility were the main goals of manufacturing enterprises. Due to market global competition FMS failed to provide flexibility to absorb unexpecting demand changes, and it revealed that FMS is not so good to provide the economic solutions in competitive situation and had a slow production rate as well. In 1995, University of Michigan proposed principle and characteristic of RMS by comparing it with traditional flexible lines, and mathematical model was described to facilitate the RMS design (Mehrabi et al., 2000). RMS are the best choice in case of unpredictable market and large quantities.

1.2 Optimization

The humans being always rush towards the better and best since the start of the world. The most effective use of available resources is called optimization. Optimization is defined as "the discipline of adjusting a process plan so as to optimize (most effective/best use of) some specified set of parameters without violating some constraint" (Venter, 2010). After the availability of computers, the theory of optimization developed in 1960s. The optimization is an integrated part of CAPP and it is about finding the best process plans which have minimum processing cost or time. In 1960 Rechenberg started the evolutionary computing in his research "Evolution strategies", later on this idea was improved by other researchers. Evolutionary algorithms are suitable to find the solution of the problems which have lack of human expertise. The process plan optimization is a type of NP-hard problems, and evolutionary algorithms are also suitable to find optimal solutions due to their stochastic nature. Figure 1-1 shows classification of search techniques used for optimization purposes. As, this thesis is related to process planning so evolutionary algorithms will be discussed in the coming chapter.

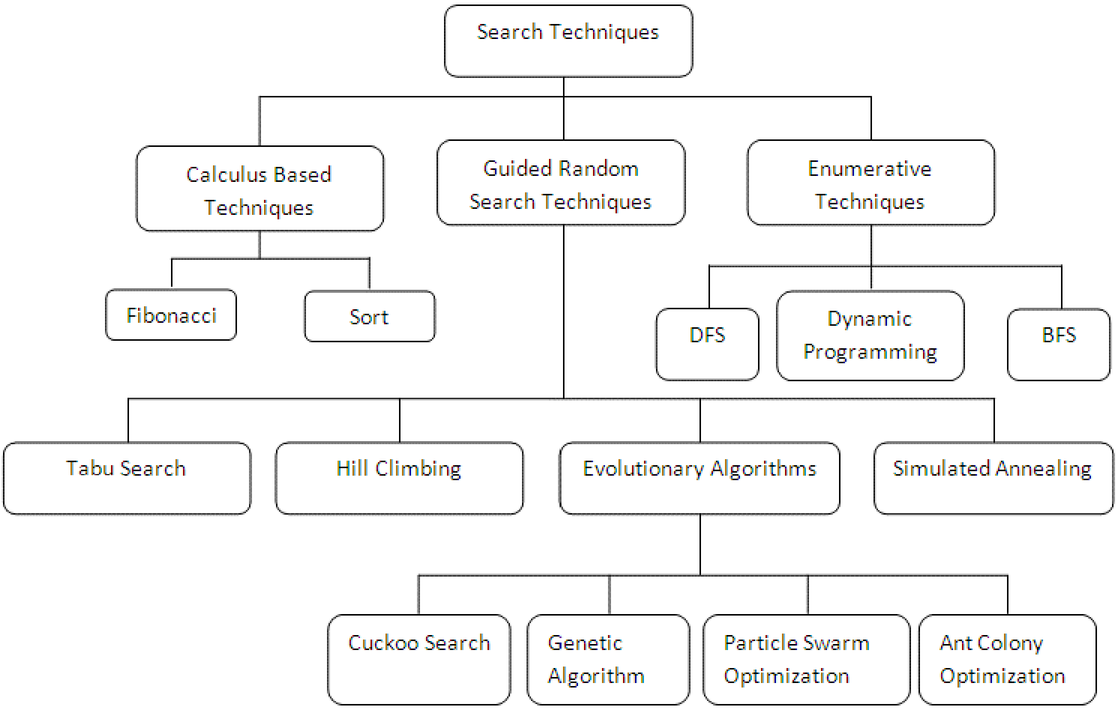


Figure 1-1 classifications of search techniques

In engineering or any other field of life, the optimization is the prime focus of any problem that deals with the decision making. Some applications of optimization are travelling salesman problems (TSP), medicines, expert system, time tabling and process planning.

1.3 Material handling importance

"MHC is the cost of the equipment that involved in short distance movement within the building (warehouse or plant) & between a building & transportation agency" (Kay, 2012). Different studies indicate that more than twenty percent of total manufacturing cost is consists of the cost of material handling Tompkins et. al. (1996). A responsive and competitive manufacturing system focused on all parameters that are responsible for adding a cost and hence, considered all available resources. The priority of an efficient system is to handle the product as less as possible. A good MH system can,

- Reduce the manufacturing cycle time
- Enhance productivity at lower manufacturing cost
- Minimize MH cost and increase capacity of storage
- Provide a better control of material flow

1.4 Problem description

In RMS due to the countless feasible combinations of substitute process plans, the objective is to find such a process plan that provide the optimal result for the concerned production scenario. These problem required a thorough analysis of activities involved in decision making, made them NP-hard problems (Oduguwa et al., 2005). Such problems cannot be expressed by finite search space. Thus, the use of classical techniques is difficult to solve such problems. These problems are easy to solve by using evolutionary approaches like GA, PSO, ACO etc. Based upon some predefined criteria (min cost or time), an optimal process plan can be obtained. The minimum cost criteria contain different cost factors and MHC is one of them as recently described in previous section.

Here, in this thesis, to find an optimal process plan, a minimum cost criterion has been set which include the effect of MHC. It was not considered in the previous researches. The problem is generally divided in two parts, mathematical modeling and application of GA to the proposed problem.

1.5 Thesis outline

This thesis is divided in 5 chapters. The 1^{st} chapter is the introduction of thesis; it provides an overview and application of optimization in different fields. The second chapter explain and compared different manufacturing systems and explore a manufacturing system well enough to compete the unpredictive market. Process planning along with its different approaches are discussed and literature review is presented in detail for process plans optimization using different techniques. A gap is highlighted and objective of thesis is explained. In chapter 3 an objective function is developed according to new strategy and implantation of genetic algorithm is provided in detail. In chapter 4 deal with validation, results & discussions. The 5^{th} chapter consists of the conclusion and future work in this stream.

1.6 Summary

This chapter provides an overview of manufacturing system, optimization and its applications, importance of material handling cost, problem description and outline of the chapters of this thesis. In the coming chapter, literature will be discussed in detail.

Chapter 2: Literature Review

This chapter deals with the brief introduction of manufacturing systems, process planning and the literature of process-plans optimization. The chapter begins with the traditional manufacturing systems and their comparison. The characteristics of a responsive and a market competitive system are discussed. The process planning, its approaches and the need of CAPP are discussed. Different optimization techniques, especially genetic algorithm is discussed in detail and by focusing on objective function, a gap is found and a proposal is made in the end of this chapter.

2.1 Manufacturing Systems

Manufacturing is a mainstay of industrialized nation, consists of 20-30% approximate value of all producing goods, & directly related to country economic health (Rao, 2011). In objective to get profit and the reputation, a raw material is transformed to the required product in a manufacturing environment (Beamon, 1998). The survival of a company is fully dependent on the successful achievement of predefined objective. The performance of manufacturing system is affected by manufacturing environment. A better understanding of the manufacturing leads towards the general strategies to meet requirements. There are three major manufacturing systems which are briefly described in the coming section.

2.1.1 Dedicated manufacturing lines (DML)

DML were designed in the start of 20th century and these are used to produced company's core products in a large quantity based upon a fixed automation. Due to high production rate, per unit cost in DML is low as compared to other manufacturing systems. DML are cost effective in case of stable market demand, and in case of competition they can't operate at full capacity and may cause the loss. As DML structure is fixed so up or down scaling is not possible and hence, the role of DML is limited in today's competitive environment.

2.1.2 Flexible manufacturing systems

In 1913, mass production paradigms started when Henry Ford discovered the moving assembly line. The FMS were developed in early 1980s after the invention of numerical-controlled machines (NC) and then CNC machines (1970). FMS are capable to produce different product verities by utilizing CNC machines and programable automation. FMS has following drawbacks,

- FMS are not cost effective like DMLs
- Machines are expensive than DML

- Single tool production resulted in low production rate

Stecke and Solberg (1981) provided the solutions for mathematical modeling of FMS. Cochran et al. (2001) pointed out that design of manufacturing system should have the ability to fulfill the strategic objectives of a company and these objectives vary with demand fluctuations. So, it is required to scale-up or scale-down a physical structure with respect to demand and this can't be met with traditional FMS.

2.1.3 Need of Reconfigurable manufacturing systems

For large production, most profitable system was dedicated transfer lines till the mid of 1990s (Koren and Shpitalni, 2010). The productivity, quality and flexibility were the primary focus of manufacturing enterprises in 1990s. Then after some time due to market global competition FMS failed to provide flexibility to absorb the unexpecting demand changes, and it revealed that FMS is not so good to provide the economic solutions in the competitive situation and had a slow production rate as well. In 1995, University of Michigan proposed principle and characteristic of RMS by comparing it with traditional flexible lines, and mathematical model was described to facilitate the RMS design (Mehrabi et al., 2000) .

2.1.4 Reconfigurable manufacturing systems

In RMS, a physical structure which is designed for the production of a specific part family, can be changed easily & cost effectively. i.e. rapidly add/remove CNC machines, axis of motion or tool magazines changes etc. These changings (machine level & system level) made RMS well suited to handle market fluctuations (R Landers et. al 2001). A RMS should have the following characteristics, (Koren, 2006).

I. Customization

This characteristic distinguishes RMS from other manufacturing systems. It provides ease to customize the system design to produce a part family rather than a single part.

II. Convertibility

In specific time limit, it is the ability to change the configuration of specific batches. i.e. changing in machines, tools, axes, software, and controls (da Silva et al., 2016)**.** It is an advanced mechanism to switch the production between two members in a part family, it should be quickly done to become more effective.

III. Scalability

It enables the system to alter the production capacity easily via adding/subtracting machines or spindle to increase productivity. It is designed for the capacity changes.

IV. Modularity

It enables the system to consider each component (i.e. axes, tooling, software, structural elements & controls) is ready to change as per requirement (Lameche et al., 2017)

V. Integrability

It is the ability to quickly integrate modules with a set of mechanical, control & informational interfaces which facilitate communication & integration (Koren and Shpitalni, 2010).

VI. Diagnosability

It is designed for machine failure detection and exploring the causes of final defective products which are then quickly corrected to produce quality parts.

Table 2-1 DMS, FMS, RMS Comparison Table (Koren, 2006)

	DML	**RMS**	**FMS**
Objective	Specific Product	Responsiveness	Variety
System Focus	Part	Part family	Machine
Scalability	No	Yes	Yes
Simultaneously Operating Tool	Yes	Yes	No
Producibility	High	High	Low
Machine structure	Fixed	Adjustable	Fixed
Market	Stable	Uncertain	Predictable
Flexibility	No	Customized	General
Lifetime Cost	Low	Medium	Reasonable

Table 2-1 provides the comparison of three manufacturing systems. The flexibility of RMS is "customized flexibility" so it can provide all flexibility required for a part family and this feature makes it less expensive than FMS. RMS has the ability of both DMS and FMS and that's why they are the prime choice of modern manufacturing industries.

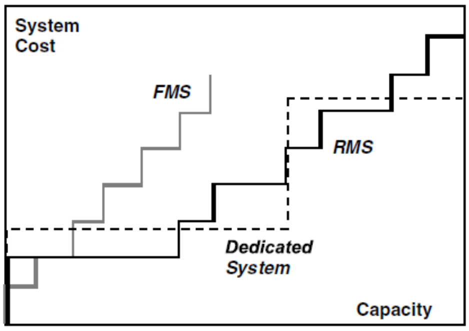


Figure 2-1 System cost vs production rate (capacity) (Koren, 2006)

In short if DML operates at 75% to its full capacity then these are the most economical. FMS are the best if small quantities are needed. In case of unpredictable market and large quantities are required then RMS are the best choice.

Kosanke et al. (1999) revealed the possibility to model a manufacturing system from different perspective. In order to meet the manufacturing system requirements Bi et al. (2008) generalized different strategies and used it to compare the different manufacturing paradigms and concluded that RMS is most effective paradigms.

2.2 Process planning (PP)

A subsystem of manufacturing system (Figure 2-2) which is responsible to convert the design data into work instructions is process planning (Kesavan et al., 2004). It is like a bridge b/w design & the final product. Process planning is determining of most suitable assembly and manufacturing processes and their acceptable sequence to result a desired part according to given product design specifications set's documentation. The planned processes are generally limited to available equipment and company's technological capabilities.

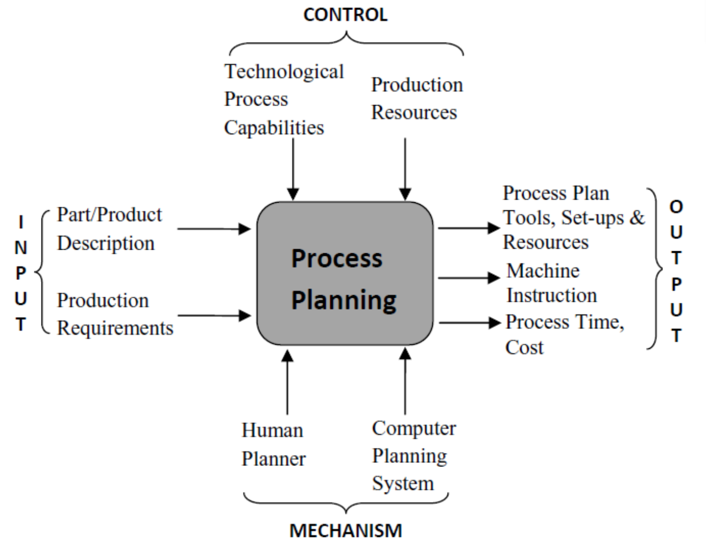


Figure 2-2 Process planning role in manufacturing system (Ma and Zhang, 2012)

Machining process planning is about machining of individual workpiece on each single machine, while assembly process planning is about the assembling order of various workpieces to form a machine part. Process planning used here is actually the short form of "machining process planning". Here is some steps that must be taken into consideration while the process planning carried out, (Kamrani et al., 1995, Groover, 1996)

- Analyze product drawing carefully (material, dimensions, tolerances, surface finish etc.)

- The required processes and their appropriate sequences (constraints) must be considered, select a suitable available equipment
- A decision should be taken about the required tooling for every processing step
- Define work place layout, tools used and hand or body motions wherever required
- Each operation must have a standard time and should be time measured
- The cutting tool and cutting conditions are specified for machining operations as per given handouts of machines

2.2.1 Process planning for a part

For the fabrication of a part, processing sequence shown in Figure 2-3 is required which is explained as,

Basic Process: It determined work part starting geometry. Basic process includes sheet metal rolling, metal casting etc.

Secondary Processes: In the result of basic processes, starting geometry is obtained & must be refined with the secondary processes to transform it to final geometry. These are the machining operations, i.e. milling, drilling, threading etc.

Property Enhancing Processes: These processes enhance the physical & mechanical properties of the part without altering its geometry. These processes are not always desired so Figure 2-3 has the alternative path.

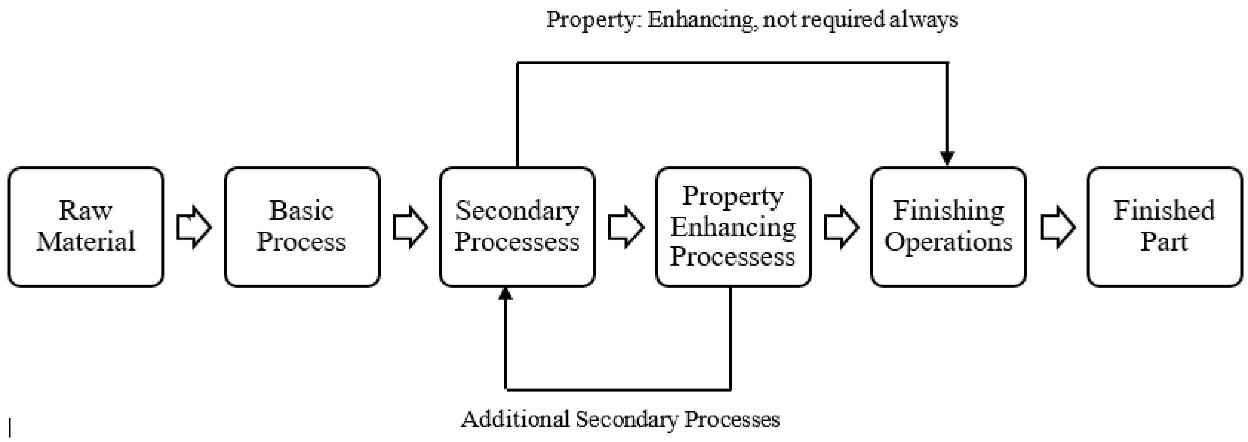


Figure 2-3 Processing Sequence for an individual part manufacturing

Finishing operations: Operations involved in coating on the surface of work part to change color, enhance appearance and prevent the metal from corrosion. e.g. thin film deposition techniques, electroplating etc.

Generally, basic processes are already done when the parts (jobs) or materials arrived at factory, e.g. for machined parts the process plan starts with the machining operations in an enterprise workshop, because jobs (raw material) are purchased from venders and have completed the basic processes of casting or forging.

Many factors must be taken into consideration in order to obtain the optimal feasible process plan. i.e. datum selection, rough before finishing processes, major before minor processes and bright datum should be done before ordinary processes etc. Zhang (1994) mentioned some tasks of process planning which are given below,

- Determination of design data of product, constraints, tolerances, operational dimensions, sequence of operations, total time and total cost
- Selection of machining processes, tool approach directions (TADs), cutting tools and Material handling equipment

A part comprised of many features which may have mutual relationships, care must be taken while dealing with such kind of relationships to avoid unfeasible process plans, these mutual relationships are known as "constraints" for process planning. Some types of important constraints are (Su et al., 2018).

Datum Constraints: Whenever relative positional relationships (concentricity, perpendicularity, parallelism) are required between the surfaces, lines or points, the concept of datum constraints is meaningful. i.e. Figure 2-4 shows that the hole should be machined after surfaces A, B & C to reduce machining error.

Hole related precedence constraints: Figure 2-5, if we drill a hole after slot, then there is a greater chance of deformation is thin wall. Hence, hole will be drilled before the slot.

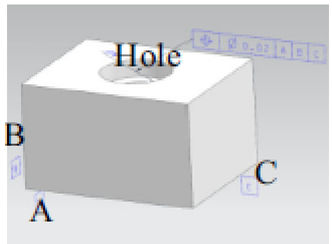


Figure 2-4, Datum Constraints

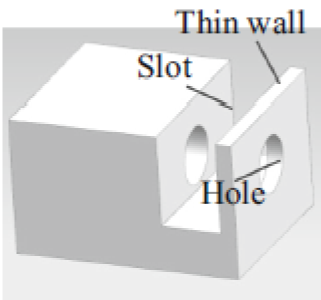
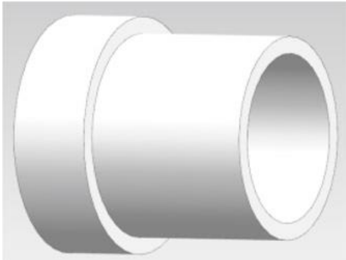


Figure 2-5, Hole related constraints

Fixed order constraints: Figure 2-6, External cylinder has three operations, rough turning, semi finish turning and finish turning respectively. These operations will be done in the same order as mentioned.

Geometric relationship constraints: Figure 2-7, in order to ensure the access of milling tool to pocket, the step should be machined first.



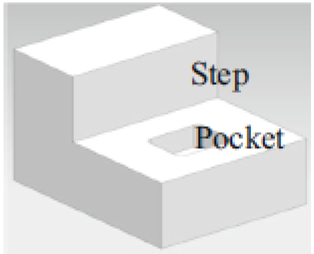


Figure 2-6, Fix order constraints *Figure 2-7, Geometric Constraints*

2.2.2 Process planning approaches

There are two main approaches for process planning, that are manual process planning and CAPP. MPP & CAPP approaches are further subdivided into different approaches which are given in Figure 2-8,

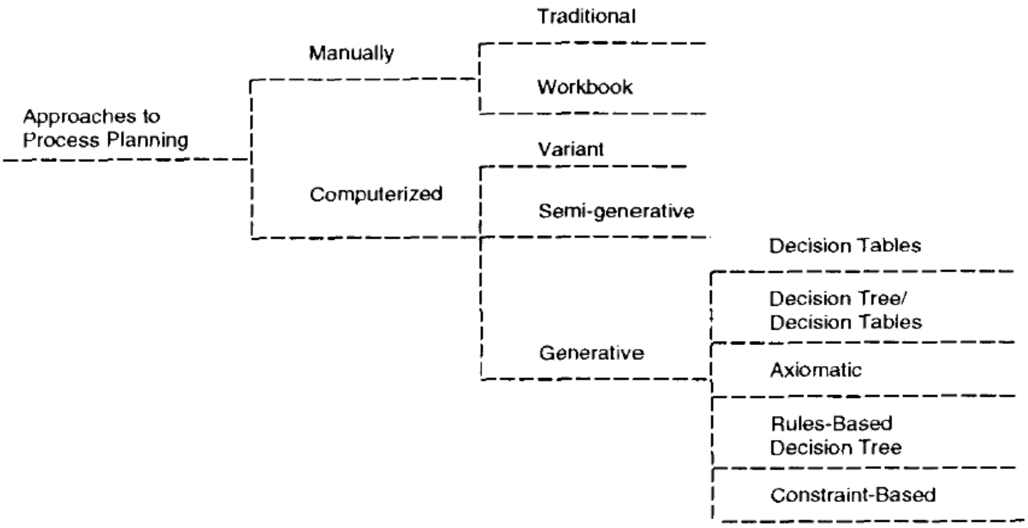


Figure 2-8 Process planning approaches classifications (Zhang, 1994)

1) **Manual Process planning**

"Based upon the knowledge of the materials, machine capabilities, tooling and shop practice, MPP developed process plans by examining engineering drawing of the product" (Steudel, 1984). Two approaches of manual process planning are traditional approach and workbook approach. MPP is best for the small companies and parts having a smaller number of process plans. An experienced process planner can generate accurate and cost-effective process plans. Limitations of MPP are given below,

- Tasks dimensions becomes too large to handle with the increase of features, number of parts and tooling etc.
- Manually generated process plans are actually a reflection of process planner personal preferences and experience

- MPP is time consuming and no one can compromise on time in a competitive environment

2) **Computer Aided Process Planning**

To speed up consistency and responsiveness, companies have given up the MPP and are looking forward for CAPP. Niebel (1965) was the first person to discuss the idea of CAPP. Later, Feasibility of the automated process plans was discussed by Berra and Barash (1968) of "Purdue University". The companies are solving their problems of automatic process planning by using CAPP and hence overcoming the skilled labor issues. There are four major goals of CAPP (Anon, 1987)

- Reduce load on process plan engineers
- Within companies, standardize best process plans for component families
- For particular components families, standardize production time & cost
- Optimize existing and new plans by using machines, tools etc. information

CAPP is further subdivided in three approaches.

Variant approach. It is computer-assisted extension to manual traditional process planning in which by recalling, retrieving and identifying the existing process plan of similar master part, new process plan is created for new parts with some modifications. The computer provide assistance in making an efficient system for editing, retrieval & management of process-plans (Steudel, 1984).

Generative approach. Generative approach has highest level of automation in CAPP. This approach is a programming for process plan production, it takes design specification and handover the complete information to the computer. Process plans are developed based upon the formulas, decision logics, geometry-based data and evolutionary algorithms to perform processing decisions. Equipment capabilities and manufacturing rules are stored in a computer memory. The most using input method of generative approach is graphic input, for which CAD module (interface input) is source of part data. In early stages, CAPP system was difficult to develop due to its complex nature. The advancement of artificial intelligence techniques and its successful implementation in different areas, encouraged the use of artificial intelligence techniques in process planning. Consistent process plans resulted by the use AI techniques are fully automated, consistent and integrated easily with CIM. For long term, the generative approach is desirable in large companies that have small lot sizes of large number of products.

Semi generative CAPP Approach. It is variant approach & generative approach combination. In semi-generative approach the preprocess plans are modified and used in real production.

Semi-generative CAPP approach provides interaction between human and computer. In systems the human built, formulas, decision logic, artificial intelligence algorithms and geometry-based encoding scheme (for the translation of physical features) etc. and then computer generates process plans according to provided (Steudel, 1984; Zhang, 1994). formulas and algorithms.

Constructive and artificial intelligence approaches can be also included in above mentioned three CAPP approaches (Steudel, 1984; Zhang, 1994).

2.2.3 CAPP Advantages over MPP

CAPP has following advantages over manual process planning (Ma and Zhang, 2012),

- Consistent and accurate process plans are generated
- Lead time for process plan reduced and cost as well
- Skilled process planner's demands are reduced
- Software interfacing for lead time, work standards and cost are easy
- Responsiveness increased which is the key factor of success of RMS
- Productivity increased

Different factors suggested that the demand of automated process planning will increase continuously. High capital equipment and labor costs, experienced process planner's shortage, & competition from large production enterprises are few common reasons. In addition, the less costs of the computer software & hardware are present to assist the feasibility of automated planning. Hence, CAPP has now become a compulsory and key objective of computer integrated manufacturing (CIM) system.

2.2.4 Integration areas of CAPP

Integration must have multidimensional perspective and is required in following planning areas of CAPP.

Knowledge planning. The science-based principle with combination experience-based knowledge should be integrated. Heuristic methods are good for physics integrations.

Activities planning. Integrated CAPP should have operation planning (with physics of planned manufacturing process) as downward, and production planning as upward integration.

Constraints planning. during the stage of planning, the planning constraints (i.e. local/global, technical/non-technical, user-provided/expert-provided) should be integrated.

Feedback planning. For the improvement of future planning decisions, some mechanism should be integrated for automatic feedback from planning.

Techniques planning. The modeling & simulations, GT, knowledge-based approaches and optimization techniques must be integrated for true robust planning system. This is further explained in the coming sections.

2.3 Process plan optimization

Optimization is defined as "the discipline of adjusting a process plan so as to optimize (most effective/best use of) some specified set of parameters without violating some constraint" (Venter, 2010). The optimization is a part of CAPP and it is about finding the best process plans which have minimum processing cost or time. In 1960 Rechenberg started the evolutionary computing in his research "Evolution strategies", later on this idea was improved by other researchers. Evolutionary algorithms are suitable to find the solution of the problems which have lack of human expertise. The process planning is a type of NP-complete problems, and evolutionary algorithms are also suitable to find optimal solutions due to their stochastic nature. There are many optimization algorithms used in literature but in the coming section, the techniques are discussed which are using in process planning literature.

2.3.1 Ant Colony optimization

Ants are the social insects, living in colonies and worked for the survival of colony as whole. Ants while moving, spreads a substance (Pheromone) in their path for the guidance of posterior ants and the quantity of this pheromone is proportional to the number of ants travelling through that path. The pheromone vanishes in a short time due to evaporation, and hence shorter path has more substance and chances to follow by posterior ants (Solimanpur et al., 2010). Colorni et al. (1992) mimics the behavior of real ants and became the first person to proposed the ant colony algorithm. Advanced version of ACO reported by Dorigo and Stützle (2004).

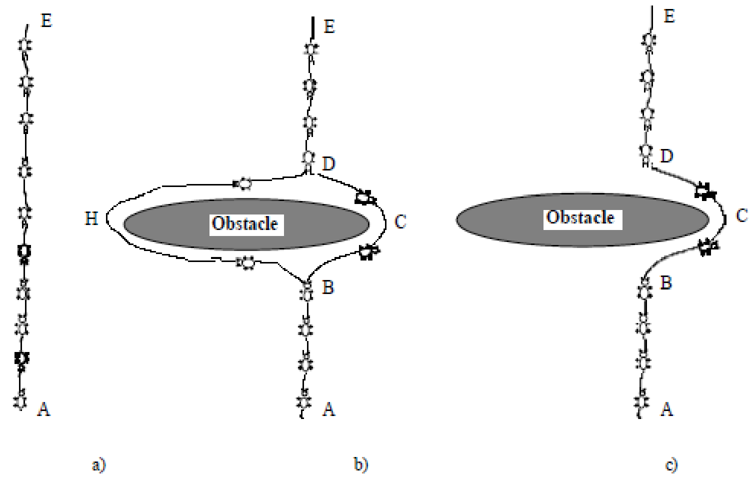


Figure 2-9 (a) Ants walking on path A-E (b) Obstacle suddenly appeared but ants gets around it (c) Ants choose shorter path (Colorni et al., 1992)

“ACO is a general search, stochastic, population-based and meta-heuristic technique used for solving the complex combinatorial problems” (Zhou et al., 2009). In order to use ACO, the optimization problem is transformed to the problem of finding the best path on a weighted graph. The ants (artificial) by moving on a graph, build a solution which is biased by pheromone model. Pheromone model is a set of parameters that is associated with graph components and modified by the ants. Ant system and ant colony system are used to update pheromone.

ACO basic operational flow is given in following steps (Sivanandam and Deepa, 2007),

Step 1: Represent the solution space

Step 2: ACO parameter initialization

Step 3: From each ant’s walk, generate random solutions

Step 4: Update the pheromone intensities

Step 5: repeat step 3 and 4 till convergence or pre-specified number generations

Jain and Gupta (2005) adopted ACO to solve the operation sequencing problem using precedence graph with the aim of “minimize total changeover cost”. Zhou et al. (2009) proposed ACO in Job shop scheduling problem & found that ACO performs well in case of less machine utilization (utilization<90%) and small variation time. Srinivas et al. (2012) find optimal process plan using ACO (coded in Micro-soft Visual C++) based upon two objective functions (total cost, number of machine changes). For the processing cost optimization of a process planning problem, the code developed by Liu et al., (2013) can only work for one part one time and hence, not suited for multiple parts. For the process planning of prismatic part (based on minimum cost), Wang et al. (2016) used ACO with “weighted graph for the representation of process plan” and “pheromone updating strategy”. The repetition in process plans is controlled by a new simple method to avoid local convergence. Despite process planning and scheduling problems, ACO is used to solve other problem like, (Dorigo and Stützle, 2004)

- Traveling salesman problem
- Disassembly line balancing problem
- Vehicle routing problem
- Quadratic assignment problem

2.3.2 Particle swarm optimization (PSO)

PSO is a stochastic, population-based and metaheuristic optimization technique first proposed in 1995 by “Dr. Eberhart and Dr. Kennedy”. Sources of inspiration for PSO are fish schooling, birds flocking and swarms of insects. PSO has a lot of similarities with GA. In PSO population is generated randomly and then by updating generation the optimal solution is searched out. PSO has an inherited ability of being ‘crazy (random)’ in its movement due to absence of crossover and mutation operators. Consider a swarm is searching for optimum solution by flying in parameter space. Then every particle is ranked by its velocity & position vectors. Each particle has its pbest and gbest during the process which can be define as, Pbest is own best position so far (individual knowledge) and gbest is pbest of its best neighbor (social knowledge). PSO basic steps are,

Step#1: Initialization of swarm

Step#2: Evaluate fitness function for each particle

Step#3: Update pbest, gbest & velocity

Step#4: Rearrange each particle

Step#5: Move to step 2 and stop if stopping criteria fulfill

Application of PSO are, NP-Hard problems, mobile networking, multi objective optimization, power system operation and control and Image processing. Guo et al., (2006, 2009), Ma and Zhang (2012) used PSO to solve process planning and scheduling problems.

2.3.3 Tabu search Algorithm

Tabu search created by Glover (1986) and formalized in 1990, is a metaheuristic algorithm and it can guide the search space in order to overcome the local optimum solutions. Some concepts of GA and SA are used in TS algorithm (Li et al., 2004). Just like other techniques TS starts with random initial-solutions. A solution is considered as optimum and its immediate neighbors are checked for improvement. It usually done with the help of memory structure (short, intermediate or long-term memory structure) that describes the visited solution. Basic procedure of TS algorithm is given in Figure 2-10

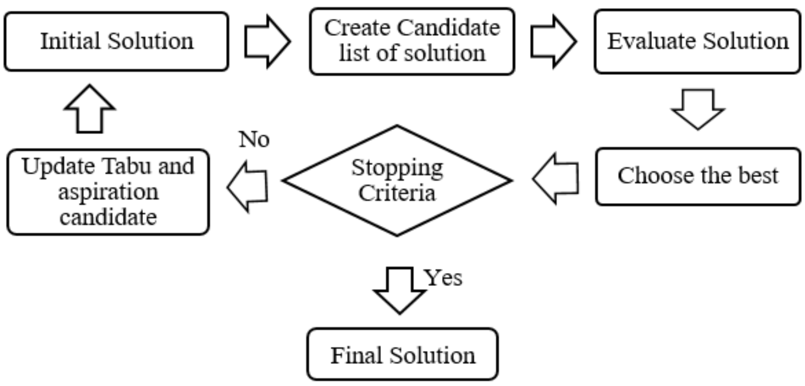


Figure 2-10 Basic TS algorithm flowchart (Schoen, 2005)

W D Li et al. (2003) used TS algorithm for solving constraint base process planning optimization problems. A penalty value is added to the cost whenever violation in constraints found, and hence, infeasible process plans are neglected during the algorithm due to low fitness. Number of violating constraints define penalty cost (PC) and this cost is added to weighted fitness function. The results are generated and compared with SA and GA.

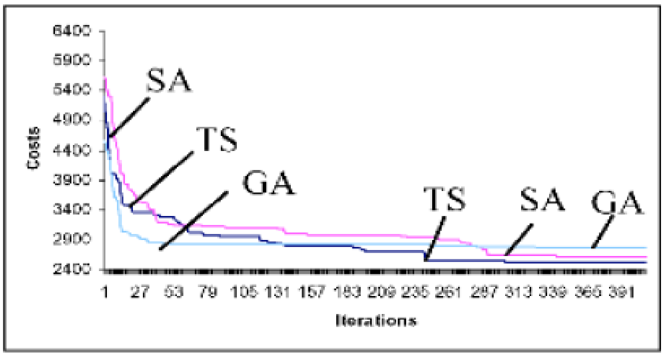


Figure 2-11 Comparison of TS, SA and GA (W D Li et al., 2003)

TS used has three main strategies, freeing strategy, forbidden strategy and aspiration strategy. Forbidden strategy controls the solution entering in a search memory (Tabu list). Freeing strategy is used to manage the solution that exit the Tabu list. For the selection of trial solution, 'aspiration strategy' is the interplay between the forbidding & freeing strategies.

Limitations: TS have tendency to stuck in local optima and to reach the final solution TS uses the exclusive memory function.

2.3.4 Simulated Annealing (SA)

To deal highly non-linear problems, SA was developed in 1983. SA find optimal solution just like bouncing ball that bounce on mountain from valley to valley. SA starts with high temperature (high bounce) and on decreasing the temperature the bounce reduced and can be trapped into a valley (Busetti, 2003). SA is stochastic search technique that is used in a large search space for finding optimum solution. It is inspired by the annealing process of metallurgy. The annealing is a crystal formation in solids during physical cooling phenomenon. Slow cooling rate forms more perfect crystal as compared to fast cooling rate. On cooling the structure converges naturally to minimum state of energy. Ma et al. (2000) used an effective SA algorithm in process planning problem to get optimal solution (Minimum total production cost that consists of MUC, MCC, TUC, TCC, SCC) based upon the customizable environment, provide an ease of database modification for the user, hence, it makes the system more realistic. Li and McMahon, (2007) combine the scheduling and sequencing problem and developed a SA approach to find the optimal solution (based upon makespan, machine utilization, total cost and job tardiness) from complex search space. To test the algorithm, case studies under different working conditions are used. Figure 2-12 shows a comparison between PSO, GA and SA for 8 different parts that are used to test and compare the algorithm with the objective of minimum makespan.

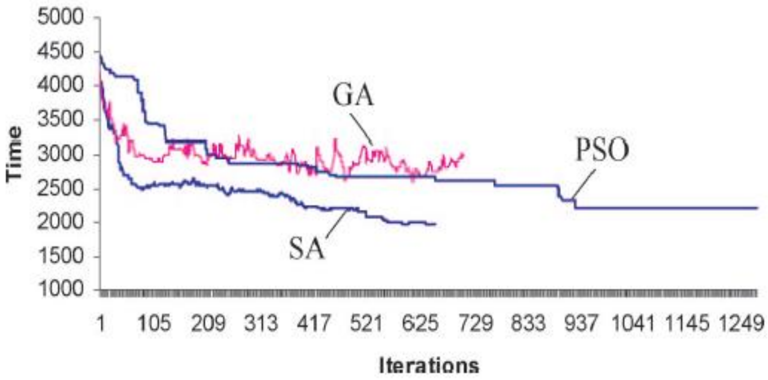


Figure 2-12 comparison of SA, GA and PSO (Li and McMahon, 2007)

SA competed very well as shown in Figure 2-12 but still lack in quite a many characteristic. SA well performed in traveling salesman and printed circuit board problems (Sivanandam and Deepa, 2007). Infinite time is required to control the rate of cooling in simulated annealing to get optimal solutions (Busetti, 2003).

2.3.5 Hybrid Algorithms

Li et al. (2002) developed a hybrid approach to solve the process planning optimization problem in which he simultaneously considered the machining resources assignments, set-up plan selections & machining operation sequencing for a prismatic part. The output of GA is used as input for the simulated annealing algorithm. A constrained adjustment algorithm was run to repair the infeasible process plans. Result computation was based on different condition and criteria, i.e. all machines available, some machine or tools subtracted etc.

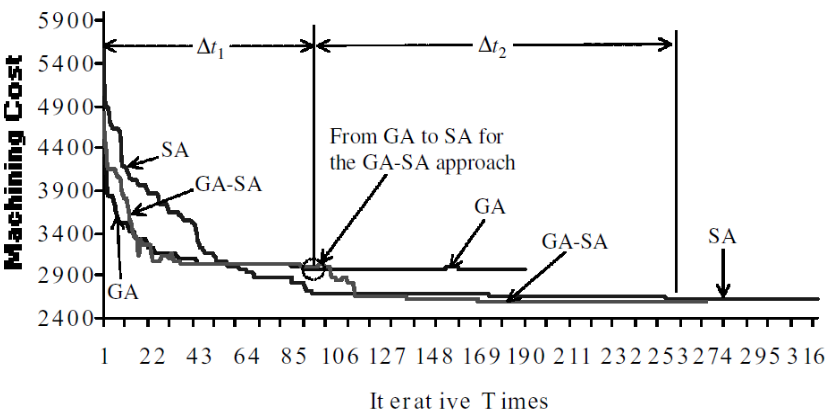


Figure 2-13 comparison of hybrid approach with SA & GA

Result of hybrid GA-SA approach (Figure 2-13) shows that hybrid approach is more effective than single GA or SA approach.

Ma et al. (2002) describes the development of GA-SA based integrated process planning system to get global optimal solution. Machine, tools and TADs selections for each operation type & operation sequencing, is done simultaneously together with precedence constraints. The process plan resulting in this procedure retains the entire solution space and hence, the global solution is possible. In dynamic manufacturing environment Ong et al. (2002) developed a setup planning optimization system using hybrid GA-SA algorithm. added 4 and 5 axis machines to the available resources, heuristic included for tool accessibility analysis and for the dynamic changes in workshops re-planning strategy proposed. Optimized process plan consists of the minimum cost including 5 costs. He also explains that cost indices with all costs are nothing but are constant numbers.

Jia et al. (2007) combined genetic algorithm with Gantt chart for a scheduling problem in distributed manufacturing systems (Multiple factories can be selected in distributed manufacturing system). GC are effectively applied to transform chromosome in feasible schedules. Gantt chart are used for scheduling problems and are responsible to improve the computational performance of GA by providing the ease in fitness function evaluation. Lian et al. (2009) proposed a hybrid GASA approach for cost based optimal solution findings. A comparison with single approaches also performed and concluded that hybrid algorithm outperforms the single approaches Figure 2-14.

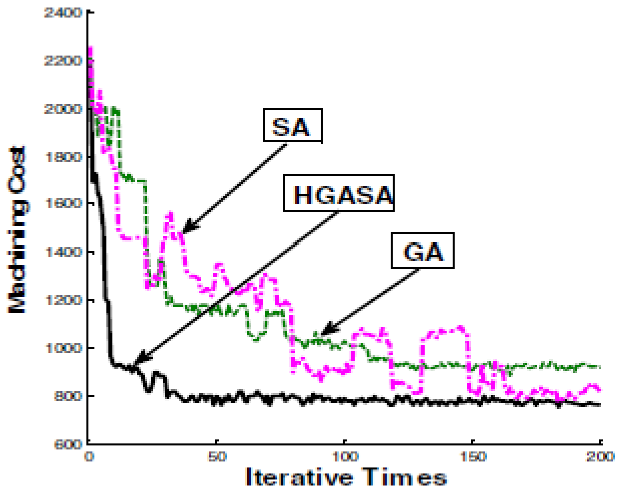


Figure 2-14 Comparison of hybrid approach with single GA & SA approaches (Lian et al., 2009)

Huang et al. (2012) adopted hybrid graph genetic algorithm (HGGA) approach for process plan optimization by concurrently considering machine resources assignment, sequence plan determination and setup plans. By operation precedence graph, operation sequencing conducted in a feasible domain, Hence, search space reduced and efficiency of the algorithm can be improved. By this approach he generated multiple optimal process plans, which provides the flexibility of selection among these and implementation of algorithm is done under relaxed set of constraints. Objective function includes 5 basic costs as used by others.

For the same objective function Wang et al. (2012) proposed a novel solution representation by encoding process plans in continuous position value and then an algorithm is developed for decoding it to discrete solutions for the evaluation of the objective function. By doing this the problem of PSO implantation with continuous characteristics in a solution domain of discrete problem, is solved. To avoid premature convergence and trapping in local optimal, a local search strategy is incorporated with PSO. Hybrid approach is compared with individual PSO and SA approaches on set of examples, and revealed that hybrid approach outperform the individual approaches in robustness and solution quality. Dhingra et al. (2014) checked the performance of GASA over GA and SA algorithms with the objective of minimizing the weighted sum of total completion time and makespan in a scheduling problem Figure 2-15. In these problems, GA performing better than SA and close to hybrid algorithm.

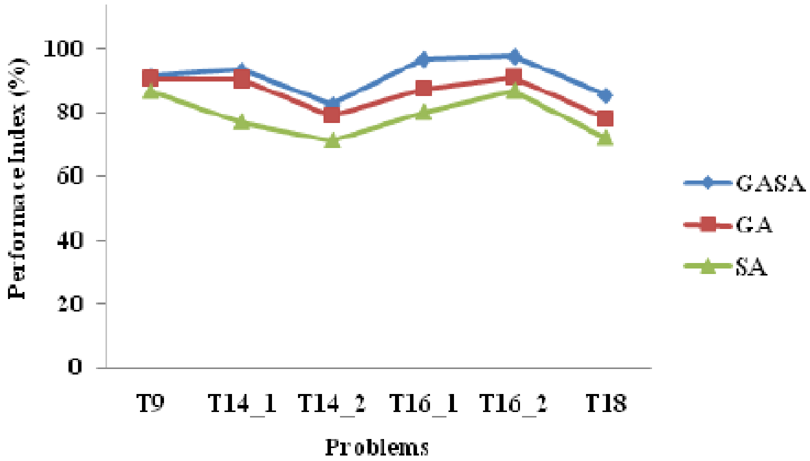


Figure 2-15 Performance of GASA, GA and SA for different scheduling problems (Dhingra et al., 2014)

2.3.6 Genetic Algorithm

Genetic algorithm is one of the evolutionary algorithms that are designed to tackle the real-world complicated problems. It was first proposed by Holland in 1975 and Darwin theory was the source of inspiration. Holland explain the implementation of nature evolution principles to the optimization problems and now this approach is available in developed form and acting as powerful tool for solving search and optimization problems, i.e. timetabling, job-shop scheduling, process plan sequencing, games playing etc.

I. Problem type

Jia et al. (2003), MORAD and ZALZALA, (1999) and Shao et al. (2009) used GA for sequencing and scheduling problems, Li et al. (2005) used GA for sequencing of process plans in distributed environment while all other researcher (Table 2-2) adopted GA for process plans sequencing problems.

II. Encoding Strategy

Encoding is the representation of individual genes. This can be done using arrays, bits, real number and trees etc. The majority of the researchers (Table 2-2) used the knowledge-based integer string (natural number) chromosomes to represent the operations, machines, tools and tool approach directions. (Ahmad et al., 2010) used binary encoding. Shabaka and ElMaraghy, (2008), Youssef and ElMaraghy (2006) used continuous variables for mapping of the optimization problems and (Jia et al., 2003) used mix integer coding.

III. Initialization of first generation

Usher and Bowden, (1996) used look up table as a reference for decoding to generate feasible process plans. A string represents the process plan, each element in the string represents feature, a coded string generated which contain digits 1-6, available branches are noted from feature precedence graph and selected one branch by looking inside the "look up table". He tried to avoid infeasible process plans but, in the end, he left with 10% infeasible process plans due to constraints violation. Yip-Hoi and Dutta (1996) used a encoding strategy that involves in feature precedence tree construction. Jain and Elmaraghy (1997) said that initial population can be generated in two ways, well adapted (seeded) or randomly. Wang et al. (2011) randomly initialize the population and then a checking algorithm applied to traversed the genes indulge in constraints violation.

IV. Evaluation of fitness function

Fitness function guide the search space and key parameter of genetic algorithm, in Table 2-2 , objective functions used in process planning problems are given. Minimum total processing cost and minimum production time are widely used objective functions. The elements of minimum total cost are further shown in Table 2-5 .

V. Selection methods

The chance of fittest individuals is high in nature and GA used this basic concept of nature for reproduction (Mirjalili, 2019). Selection is basically done to select the parent chromosome for the production of new population. Some selection methods are roulette wheel selection, tournament selection, elitism method, linear ranking method, stochastic universal sampling, random selection and Boltzmann selection etc. The Table 2-3 provides information about the selection methods used in literature for process plans optimization.

Table 2-2 Inialization strategies, objective functionn and population size adopted by different researchers

Name	Objective function	Initialization	Pop. Size
Usher and Bowden (1996)	Min setup, precedence and continuity score	Random, Lookup table	100
Yip-Hoi and Dutta (1996)	Machining time	Random Precedence Tree branches (10)	25
Jain and Elmaraghy (1997)	Mean flow time, make-span	recursive procedure, all possible permutation randomly	100
Zhang et al. (1997)	Optimize total cost, setup change, tool change and machine change	Random, PR	50
Candido (1998)	Mean completion time plus make-span	MASGA	100
Dereli and Filiz (1999)	Optimal cutting parameter based upon unit cost	Random Branch & Bound Method	400
MORAD and ZALZALA (1999)	Min total processing time, total cost, make-span	Random	1000
Reddy (1999)	Total production cost	Random, PCM	40
Rocha et al. (1999)	Production cost in terms of time	Random, PCM	constant
Lee et al. (2001)	Overall machining time (OMT)	Random	70
Jia et al. (2003)	Production Cost, make-span, Weighted PC & M	Random	200
Li et al. (2005)	Production time, Production Cost	Random, PCM (select operation having no precedence)	50

Shabaka and ElMaraghy (2008)	Min cost	Continuous variable, permutation	200
Shao et al. (2009)	Production time	Random, PC	40, 50
Salehi and Tavakkoli-Moghaddam (2009)	Production cost	Random, PC	50
Ahmad et al. (2010)	Total machining time	Random	N/A
Wang et al. (2011)	Minimize fixture, tool and machine changes	Random, checking algorithm	20
Yun and Moon (2011)	Min traveling time	Random (topological sort)	20
Salehi and Bahreininejad (2011)	Processing time, processing cost	Int. search strategy	50
Ma and Zhang (2012)	Min cost	Random, penalty function for invalid strings	50-200
Su et al. (2018)	Min cost	Random, edge selection (PCM)	150

VI. Crossover

The crossover is main GA parameter and is used for the production of next generation. In absence of this operator, the next generation will be exact copy of parents and in 100% crossover the whole population will be replaced with offspring. Some examples of crossover are, One-point crossover (OPX), two-point crossover (TPX), order crossover (OX), position crossover (PX), partially mapped crossover (PMX), cyclic crossover (CX), heuristic crossover (HX), edge Recombination crossover (ERX) (Umbarkar and Sheth, 2015). Ma and Zhang (2012) suggested that the crossover rate should be in 0.5-1.0 range. PMX, OX & CX are mostly used for precedence constraints-based problems. “OX is 11% better than PMX & 15% better than CX” (Oliver et al., 1987). The Table 2-3 shows the rate and type of crossover used in literature.

VII. Mutation

Mutation is a background operator and performed after crossover to prevent the GA from being trapped in local optimum solution. It helps the crossover in exploration of the whole search space by randomly disturbing the genetic information. It can be done by flipping, interchanging or reversing the genes in a chromosome, examples are given below (Dag, 2016),

Flip Mutation: A randomly selected gene is flipped out (0 to 1 or 1 to 0). This is applicable in binary encoding problems.

Insertion Mutation: A randomly selected gene is removed from the current position and placed at a new position. In the given example the 3rd gene is removed from its current position and placed at new 5th position.

Reversed Mutation: The gene next to randomly selected gene is reversed (Sivanandam and Deepa, 2007).

Swap Mutation: Two randomly selected genes are swapped in a chromosome. A majority of researcher listed in coming tables used this type of mutation.

Mutation rate is very important for performing mutation, 100% mutation will change the whole population and 0% will do nothing. It usually kept low, near about 10%, because it tries to divert the searching. For high mutation rate, an algorithm will not be able to converge to the global optimal solution due to high disturbance (scattering). Mutation rate used by different researchers is given in Table 2-3.

Jia et al. (2003) and Li et al. (2005) applied mutation two times, mutation 1, taken as local GA operator and used for swapping of two randomly selected genes within the chromosome, mutation 2 is taken as global GA operator and used to change the randomly selected gene with factory ID randomly from feasible factory list of that gene (job). (Shao et al., 2009) used two mutation operators, randomly selected two-point swapping in a randomly selected chromosome, and changing the value of randomly selected point in process plan string with alternative in selection range. Similarly Zhang et al. (1997) used mutation operator for machine, tool and TAD alternatives and Ma and Zhang (2012) applied it on operation sequence as well.

VIII. Stopping criteria

Stopping criteria is used to stop the algorithm. two types of stopping criteria is used in literature,

(**1) Maximum generations:** The algorithm will be stopped if predefined number of generation/iterations occurred.

(2) Stall Generations: Algorithm stops if there is no improvement in objective function up to a specific number of generations. The time can also be specified in both cases, after consuming that time, algorithm will be stopped. Table 2-3 shows that criteria 1 is adopted by majority of researchers.

Table 2-3 Breeding cycle and stopping criteria

Name	Selection Method	Crossover Rate	Type of crossover	Mutation	Stopping criteria (Gen.)
Usher and Bowden (1996)	Elitist Method	Pc=1	OPX	0.001	100
Yip-Hoi and Dutta (1996)	N/A	5,6,7,8 /gen.	OPX TPX	1 per generation	100
Jain and Elmaraghy (1997)	Bias selection (1-2)	1	ESX	N/A	10,000
Zhang et al. (1997)	Elitist, RWM	0.7	CX	0.6	8000
Candido (1998)	Elitist	0.8, 0.6	UX	0.05, 0.1	100
MORAD and ZALZALA (1999)	Elitist, 10%	0.5	OX, PX, (TPX)	0.5	100
Reddy (1999)	N/A	0.9	PMX (TPX)	0.1	100
Rocha et al. (1999)	RWM, Elitism	N/A	PMX (TPX)	N/A	Fix
Lee et al. (2001)	Elitist, SUS	0.7	PMX (TPX)	0.6	4000
Jia et al. (2003)	Elitist, LRM	0.005	TPX	Two times	(1) 25 (2)10
Li et al. (2005)	Random	0.7	PMX	0.6	8000
Shabaka and ElMaraghy (2008)	N/A	6 time each	LX, AX, HX, SX	12 times/gen	150
Salehi and Tavakkoli-Moghaddam (2009)	TS	0.7	OX	0.6	8000
Shao et al. (2009)	TS, b=2, Pr=0.10	PP-0.60, S-0.80	PX	PP-0.10, S-0.10	PP-30, S-100

Ahmad et al. (2010)	Elitist, RWM	1	OPX	0.1-0.5	15
Wang et al. (2011)	Elitism	0.8	TPX	0.05	100
Yun and Moon (2011)	Elitist	0.5	New (OPX, TPX)	0.05	2000
Salehi and Bahreininejad (2011)	TSM, Elitist	0.7	OX	0.6	8000
Ma and Zhang (2012)	RWS	0.7	CX	0.7	8000
Su et al. (2018)	TSM	0.8	OX	---	---

"The process planning is a NP hard problem, global search techniques are required to solve such problems" (Kusiak, 1990). Usher and Bowden (1996) taken square weighted sum of "number of setups, loose precedence and continuity of motion" as objective function. These three terms individually normalized between 0 and 1. Different techniques are adopted for each individual, i.e. max-min for number of setups, divide individual maximum in loose precedence case.

Yip-Hoi and Dutta (1996) used GA for sequencing the process plan operations with parallel machining by using the combination of interacting tool-holding & work-holding devices. New coding method allow only feasible string of operations. Operation features with multiple parents were not considered. In an instructive paper, Davis (1985) first introduced genetic algorithm in simple job shop scheduling problems by a simpler example, while the realistic problems are much complex.

Zhang et al. (1997) selected a job shop environment, user can easily change database according to need. Applied genetic algorithm and compared the results with state-space graph result and found GA provide better results. GA performed well in reliable and efficient manner for complex part, containing 23 operations. Jain and Elmaraghy (1997) developed GA model for scheduling problem (NP-Complete problem) with the objective of minimizing makespan and mean flow time, in job shop environment & concluded that GA save computation time up to 50%. Difficulty increases with increasing number of machines. He uses high selection bias (>1.5) & medium population size (100) but suggested that, for fine tuning different combination must be run. Edge recombination operator (developed by Whitley 1989) is better than all other crossovers (partially matched crossover, order crossover, cyclic crossover). Reddy (1999) presented a heuristic search technique based upon a genetic algorithm, optimal solution found in 10-40 seconds depending upon the number of operations. Several runs of algorithm suggested for the help of process planner as the computation is low.

Dereli et al. (2001) used genetic algorithm for the optimization of cutting parameter in process plan sequencing. Jia et al. (2003) applied a modified GA for new emerged scheduling multi objective optimization problem. Production cost, makespan and weighted makespan & cost were three objective functions. Initial population generated by encoding the both candidate factories and jobs along with their operations. One crossover and two types of mutation applied. To evaluate GA performance, case studies are carried out for both traditional and distributed scheduling problems. CPU time to get optimal result was low as compared to complexity and GA handle the both traditional and scheduling problem with high efficiency.

Performance of GA can never be accessed on single run, Li et al. (2005) run the GA code for 10 times. Different end results obtained, make a graph and selection is done on the base of frequency. 1739-1745 is the cost range of obtained results. Frequency of 1742 is 6 higher than the other, so process plan with 1742 end result is selected. Youssef and ElMaraghy (2006) presented a general GA model to optimize capital cost that can be applied to complex parts as well with features in large numbers. It is also applicable for configuration selection problems of any manufacturing system. Number of parallel machines and stages, machine configuration and operation operations in the form of clusters were considered in objective function. Decision variables was mapped in continuous domain instead of discrete domain and get rid of constraints issues.

Salehi and Tavakkoli-Moghaddam (2009) divided the process planning in two stages, preliminary process planning and secondary (detailed) process planning. In preliminary process planning feasible sequences of operation are generated by constraints analysis and using GA. In secondary process planning he used GA again to obtain the optimized sequence of operation, optimized selection of machines, cutting tools and TADs. Ahmad et al. (2010) observed that in genetic algorithm, elitist method converges faster than roulette wheel selection method. Chaudhry (2012) used spreadsheet-based GA method for process planning and scheduling in a job shop environment. For multicriteria process plan optimization, Zahid and Baqai (2013) used GA for finding optimal process based upon minimum setup and tool changes. A penalty function is added whenever constraints violation observed after mutation. Reconfigurability of the algorithm is checked by adding a feature in test part.

Kumar and Pandey (2015) implemented genetic algorithm to optimize the mean flow time, makespan and resources utilization for job shop scheduling problem. Jiang et al. (2016) worked on remanufacturing process planning with dual objective. (1) minimize the process cost that include machine cost and tool cost. (2) maximize the reliability. Reliability depends upon the process failure rate and decay of machines & tools.

Su et al. (2018) adopted a novel encoding approach (ES) and compared it with the hybrid approaches and concluded that ES approach makes the GA most effective. A comparison is shown in Figure 2-16.

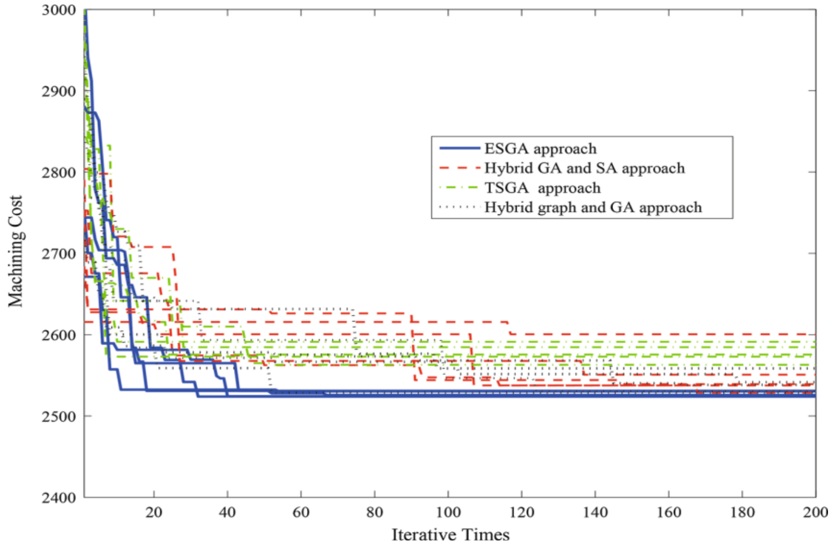


Figure 2-16 Edge selection GA comparison with other approaches (Su et al., 2018)

Some advantages of genetic algorithms are given below (Sivanandam and Deepa, 2007),

- When everything failed and there is no knowledge of search space then GA are something worth trying
- Modified easily for different problems (large scale also) and provide excellent results
- Have resistance to trapped in local optima
- Gradient information not required about response surface
- GA does not guarantee the global solution but find acceptably good solution. This can be removed by increasing the number of iteration or by running the algorithm many times and adopting the best suitable solutions

2.4 Total processing cost

Total processing cost used in literature is given below,

$$TC = MUC + MCC + TUC + TCC + SCC$$

In a process plan, MUS is cost of using machines, MCC is machine change cost and occurred when two operations used two different machines, TUC is the cost of using tools, TCC is tool change cost and occurred when two operations required two different tools and SCC is setup change cost and occurred when two operations required two different tool approach direction under the same machine. Equations 1,3 and second forms of equation 2,4 and 5 are widely used in literature. Shabaka and Elmaraghy (2007) grouped (cluster) all the operations having datum and logical constraints in order to save the cost of machining. The first form of equation 2,4 and 5 is used by Shabaka and ElMaraghy (2008), which shows that machine configuration change will be considered as machine change & number of setup change and tool changes are counted in the clusters and among the clusters.

$$MUC = \sum_{i=1}^{NOC} MC_{mi} * MCI \tag{1}$$

$$MCC = MCCI * \sum_{x=1}^{NOC-1} [1-(1-\Omega(MS(i), MS(i+1)))] * (1-\Omega(MCS(i), MCS(i+1)))$$

<u>or</u> (2)

$$MCC = MCCI * \sum_{x=1}^{NOP-1} [1-(1-\Omega(MS(i), MS(i+1)))]$$

$$TUC = \sum_{x=1}^{NOP} CT(t_x) * TCI \tag{3}$$

$$TCC = \begin{aligned} & TCCI * \sum_{i=1}^{NOC-1} \sum_{x=1}^{NOPCS_i-1} \Omega[T_S((\sum_{z=1}^{i} NOPCS_z) - NOPCS_i + x), \\ & T_S((\sum_{z=1}^{i} NOPCS_z) - NOPCS_i + x + 1)] \\ & + TCCI * \sum_{i=1}^{NOC-1} [(1-\Omega(M_S(i), M_S(i+1))) * (1-\Omega(MC_S(i), MC_S(i+1))) \\ & * \Omega(T_S(\sum_{z=1}^{i} NOPCS_z), T_S(\sum_{z=1}^{i} NOPCS_z + 1))] \end{aligned} \tag{4}$$

<u>or</u>

$$TCC = TCCI * \sum_{i=1}^{NOP-1} [(1-\Omega(MS(i), MS(i+1))) * \Omega(TS(i) + TS(i+1))]$$

Cost Indices: MCI, MCCI, TCI, TCCI, TDCCI are machine cost index, machine change cost index, tool cost index, tool change cost index and tool direction change cost index resp. All these indices are constant and are used to reflect the real cost. The real cost depends upon many factors so for simplification these constant amounts are multiplied (Ong et al., 2002).

$$SCC = \begin{array}{l} TDCCI * \sum_{i=1}^{NOC-1} \sum_{x=1}^{NOPCS_i -1} \Omega[TADS((\sum_{z=1}^{i} NOPCS_z) - NOPCS_i + x), \\ TADS((\sum_{z=1}^{i} NOPCS_z) - NOPCS_i + x + 1)] \\ +TDCCI * \sum_{i=1}^{NOC-1} [(1-\Omega(MS(i), MS(i+1)))*(1-\Omega(MCS(i), MCS(i+1))) \\ *\Omega(TADS(\sum_{z=1}^{i} NOPCS_z), TADS(\sum_{z=1}^{i} NOPCS_z + 1))] \end{array} \quad (5)$$

<u>or</u>

$$SCC = TDCCI * \sum_{i=1}^{NOP-1} [(1-\Omega(MS(i), MS(i+1)))*\Omega(TAD(i) + TAD(i+1))]$$

2.4.1 Material Handling cost

"MHC is the cost of the equipment that involved in short distance movement within the building (warehouse or plant) and b/w a building & transportation agency. It increases the cost of a product rather than product value " (Kay, 2012). Different MHE and their function are given in *Table 2-4.*

Paulo et al. (2002) developed a mathematical model to minimize the operation allocation model cost (that is sum of operation cost, machine setup cost and transportation cost) and provide its output as input to solve MHS model and select a piece of equipment capable to perform all material handling operations. Sujono and Lashkari (2007) extended the Paulo et. al. (2002) work. He used ε-constraints method to solve the multi objective model. Generated model demonstrate that ε-constraints model is feasible & it can be applied to demonstrate the viability of developed model. The equation of material handling cost used by both researchers is geven below,

$$MHC = \sum_{i=1}^{n} di \sum_{p=1}^{P(i)} \sum_{s=1}^{S(ip)} \sum_{j \in J_{ips}} \sum_{h=1}^{H} \sum_{h'=1}^{H'} \sum_{e \in E_{jhh'}} T_{ijhh'} X_{sjhh'} \quad (6)$$

The MH system is an important part of a manufacturing system and should be taken into consideration while dealing with manufacturing system design as it composes of about 20-50% of the total operating costs. If optimized, might be responsible to lower the total cost 15-30%. Selection of costly MH system can lead towards large lead time and low productivity (Paulo, et al., 2002).

Table 2-4 Material handling equipment and functions (Kay, 2012)

MHE	Function	Example
Positioning Equipment	handle material at a single location	Small Robot, Hoist, Rotary Index table, Human
Transportation equipment	Move material from one location to another	conveyors, cranes, and industrial trucks
Unit Load Formation Equipment	Restricting material when transported or stored as a unit/single load	Pallets, Slip-sheets, Baskets, carton, bags
Storage Equipment	used for holding materials over a period of time	Frames & Racks

Table 2-5 Different costs taking by the authors in objective function

Authors	Algorithm	MUC	TUC	MCC	TCC	SCC	MHC
Zhang et al. (1997)	GA	Y	Y	Y	Y	Y	***N***
Rocha et al. (1999)	GA	Y	Y	Y	Y	Y	***N***
Reddy (1999)	GA	***N***	***N***	Y	Y	Y	***N***
Li et al. (2002)	GA, SA	Y	Y	Y	Y	Y	***N***
Paulo et al. (2002)	---	Y	***N***	***N***	N	Y	Y
Ong et al. (2002)	GA-SA	Y	Y	Y	Y	Y	***N***
W. D. Li et al. (2003)	TS	Y	Y	Y	Y	Y	***N***
Li et al. (2005)	GA	Y	Y	Y	Y	Y	***N***
Sujono and Lashkari (2007)	---	Y	***N***	***N***	***N***	Y	Y
Shabaka and ElMaraghy (2008)	GA	Y	Y	Y	Y	Y	***N***
Salehi and Tavakkoli-Moghaddam (2009)	GA	Y	Y	Y	Y	Y	***N***
Lian et al. (2009)	GASA	Y	Y	Y	Y	Y	***N***
Wang et al. (2011)	GA	***N***	***N***	Y	Y	***N***	***N***
Salehi and Bahreininejad (2011)	GA	Y	Y	Y	Y	Y	***N***
Srinivas et al. (2012)	ACO	Y	Y	Y	Y	Y	***N***
Ma and Zhang, (2012)	GA	Y	Y	Y	Y	Y	***N***

Zahid and Baqai (2013)	GA	***N***	***N***	***N***	Y	Y	***N***
Jiang et al. (2016)	GA	Y	Y	***N***	***N***	***N***	***N***
Su et al. (2018)	GA	Y	Y	Y	Y	Y	***N***
Proposed	**GA**	**Y**	**Y**	**Y**	**Y**	**Y**	***Y***

2.5 Objective of the thesis

A study of optimization algorithms reveals that GA after some modification is efficient for the process plan optimization problems (Su et al., 2018). From Table 2-5 it is observed that MHC is not considered in the F.F of process plans optimization. As material handling cost is major part of total processing cost so it should not be neglected at process planning stage. An optimized process obtained by neglecting MHC might be responsible of major capital loss of enterprises. So, there is a need to include the MHC as a part of F.F. The objective of this thesis is to add the material handling cost to the cost model proposed by Shabaka and ElMaraghy (2008) and find optimal process plan using ESGA proposed by Su et al. (2018) by normalizing all costs.

2.6 Summary

In this chapter the manufacturing systems types and comparison discussed. Process planning and the advantages of CAPP are highlighted. Then stochastic algorithms adopted by researchers in process plans optimization problems are discussed and compared. Implementation of Genetic algorithm by different authors is summarized in the table form along with objective function and parameters. Different costs considered in different researches are also summarized in the table. By observing the gap objective of the thesis is presented. In the next chapter development of objective function for the proposed model and genetic algorithm implantation is explained.

Chapter 3: Proposed Model

In this chapter the steps involving in the development of objective function are explained and then genetic algorithm is implemented to the recently developed objective function.

3.1 Development of objective function

The proposed objective function is comprised of six costs element, the equation of first five costs are taken with minor modification from the cost model of Shabaka and ElMaraghy (2008) and material handling cost equation is taken from Sujono and Lashkari (2007) and modified according to our requirements.

3.1.1 Machine usage cost

This is the total cost of using machines for p^{th} process plan to machine all operation clusters. 'MC' is the cost of machine at position 'M_i' that is from the matrix of candidate machines and used to machine the operation cluster at position 'i'. MCI is machine cost index and used to reflect real cost.

$$MUC_p = \sum_{i=1}^{NOC} MC(M_i) * MCI \tag{7}$$

3.1.2 Tool usage cost

TUC_p is total cost of using tools in p^{th} process plan to machine all operations and calculated as,

$$TUC_p = \sum_{x=1}^{NOP} CT(T_x) * TCI \tag{8}$$

Where 'T_x' will provide information about the tool number being used at position 'x' & 'CT' is the cost of that individual tool. TCI is tool cost index.

3.1.3 Machine change cost

MCC_p is total number of machine changes in p^{th} process plan. If two consecutive operation clusters in process plan sequence required two different for machining then machine change will be occurred and counted as 1 and multiplied by a constant (MCCI).

$$MCC_p = \sum_{x=1}^{NOC-1} \Omega(M_i, M_{(i+1)}) * MCCI \tag{9}$$

For equation (1) (10) (11) and (13) the value of $\Omega(x, y)$ will be found as

$\Omega(x, y) = 1$ if $x \neq y$ & $\Omega(x, y) = 0$ if $x = y$

Hence machine change will only be considered when $x \neq y$.

3.1.4 Tool change cost

TCC_P is total number of tool changes within the process plan. First term of equation (10) count the number of tool changes between two operation clusters and second term count the number of tool changes within the operation cluster. A tool change is takes place when two operation under same machine or under same operation cluster required different tool for machining operation.

When machines of two consecutive OC will different then $\Omega(x,y)=1$ and 1-1=0, hence the effect of first term of given equation will turn OFF, similarly it will effect in equation (11).

$$TCC_p = \begin{matrix} TCCI * \sum_{i=1}^{NOC-1} [(1-\Omega(M_i, M_{(i+1)})) * \Omega(T_{x'}, T_{(x'+1)})] \\ +TCCI * \sum_{i=1}^{NOC-1} \sum_{x=1}^{NOPCS_i-1} \Omega(T_{(x'-NOPCS_i+x)}, T_{(x'-NOPCS_i+x+1)}) \end{matrix} \quad (10)$$

3.1.5 Setup change cost

SCC_p is total number of setup changes within the process plan. Setup change takes place when required tool approach direction of two consecutive operation of same operation cluster is different or two consecutive OC having same machine required different TAD. First term of following equation count number of setup changes between OC and second term count change within the OC.

$$SCC_p = \begin{matrix} TDCCI * \sum_{i=1}^{NOC-1} [(1-\Omega(M_i, M_{(i+1)})) * \Omega(TAD_{x'}, TAD_{(x'+1)})] \\ +TDCCI * \sum_{i=1}^{NOC-1} \sum_{x=1}^{NOPCS_i-1} \Omega(TAD_{(x'-NOPCS_i+x)}, TAD_{(x'-NOPCS_i+x+1)}) \end{matrix} \quad (11)$$

Term x' counts the total number of operations up-to current position 'i' and help out to compare the two consecutive OC for setup or tool change. For example, if value of 'i' is 4 then x' will be equal to the total number of operations of first four OC.

$$x' = \sum_{z=1}^{i} NOPOC_z \quad (12)$$

3.1.6 Material handling cost

MHC_p is total material handling cost of p^th process plan. MHEC is material handling equipment cost matrix that is accessible by (M, MHE) order matrix MHEC, where 'M' represents the row of concerned matrix and equals to the number of machines and 'MHE' represents column and contained positioning or transportation equipment value.

$$MHC_p = \begin{array}{l} MHEC(M_1, PE_1) + MHEC(M_{NOC}, PE_{NOC}) \\ + \sum_{i=1}^{NOC-1} [\Omega(M_i, M_{(i+1)}) * [MHEC(M_i, TE_i) + MHEC(M_i, PE_i) + MHEC(M_{(i+1)}, PE_{(i+1)})]] \end{array} \quad (13)$$

3.1.7 Normalization

As all six costs are at different scale, so there is a need to normalize them in order to compare. Hence, each cost element is divided by its maximum value (cost indices are neglected), it is shown in Table 3-1.

Table 3-1: Normalized values of all cost elements

Costs	Maximum Value	Normalized value	Sample (value)	Sample of Normalized Value
MUC_p	$MUC_{\max}$	$muc = \frac{MUC_p}{MUC_{\max}}$	8900	0.87
MCC_p	$MCC_{\max}$	$mcc = \frac{MCC_p}{MCC_{\max}}$	960	0.80
TUC_p	$TUC_{\max}$	$tuc = \frac{TUC_p}{TUC_{\max}}$	250	0.73
TCC_p	$TCC_{\max}$	$tcc = \frac{TCC_p}{TCC_{\max}}$	260	0.86
SCC_p	$SCC_{\max}$	$scc = \frac{SCC_p}{SCC_{\max}}$	700	0.70
MHC_p	$MHC_{\max}$	$mhc = \frac{MHC_p}{MHC_{\max}}$	26	0.87

3.1.8 Objective function

The costs are normalized, now the objective function of proposed methodology can be defined which is to minimize the total weighted normalized cost. The objective function is given in the following equation.

$$Minimize\ \left(T.W.C\right) = \frac{w_1}{w} muc + \frac{w_2}{w} mcc + \frac{w_3}{w} tuc + \frac{w_4}{w} tcc + \frac{w_5}{w} scc + \frac{w_6}{w} mhc \quad (14)$$

Where muc, mcc, tuc, tccc, scc and mhc are normalized costs and $w_1 - w_6$ are their corresponding weights, ‘w’ is the sum of all these weights.

$$w = \sum_{a=1}^{6} w_a \quad (15)$$

Weightages has two important benefits

- Switch functions
- Customized flexibility

Switch function: Weights provide the ease for the users to decide either to select or neglect the cost factors, and hence act as the switch functions. For example, in the workshop environment where total tool usage and tool change cost have a less impact on the total cost & total machine usage, machine and setup change costs have a greater impact, the user has autonomy to vanish the effect of costs which have the low impact by simply assigning the relevant weights a zero value and 1 to the rest ones. i.e. ($w_3=w_4=0$, $w_1=w_2=w_5=w_6=1$).

Customized flexibility: Another useful function of weights is to provide customized optimization problem flexibility whenever needed. For example, as material handling equipment cost has a greater impact on overall cost so its weight can get a higher value with respect to other weights.

Constraints

The following constraints should be strictly followed in order to get the feasible process plan,

Clusters should only be assigned once

$$OC_i \neq OC_j \, , \; \forall i \neq j \tag{16}$$

Operation should only be assigned once

$$OP_x \neq OP_y \, , \; \forall x \neq y \tag{17}$$

All OC must not violate the precedence constraints

$$PM_c(OC_i, OC_j) \neq -1 \, , \; \forall i \neq j \tag{18}$$

All operation must not violate precedence constraints

$$PM_{op}(OP_x, OP_y) \neq -1 \, , \; \forall x \neq y \tag{19}$$

Operation with tolerance or logical constraints are assigned to same OC

$$\begin{gathered} OC(OP_i, OP_x) = OC(OP_i, OP_y) \, , \; \forall PM_x(OP_x, OP_y) = 2 \, , \forall i, x, y \\ OC(OP_i, OP_x) = OC(OP_i, OP_y) \, , \; \forall PM_x(OP_x, OP_y) = 3 \, , \forall i, x, y \end{gathered} \tag{20}$$

In equations (16) to (20)

$x, y = 1, 2, 3, \ldots, NOP$

$i, j = 1, 2, 3, \ldots, NOC$

Constraints for decision variables

All OC, selected machines, MHE, operations, TAD & tools must from respective candidate matrices.

OC Sequence:

$$oc_i \in \{1,2,...,NOC\}, \forall i = 1,2,...,NOC \tag{21}$$

Assigned machines,

$$M_i \in candM_i(c,m), \forall i = 1,2,...,NOC, \forall c \in \{1,2,3,4\}, \forall m \in \{1,2,...,NM\} \tag{22}$$

Assigned positioning equipment:

$$PE_i \in MHEC_{m,h} \forall i = 1,2,...,NOC, \forall m \in \{1,2,...,NM\}, \forall h \in \{1,2,3\} \tag{23}$$

Assigned transportation equipment:

$$TE_i \in MHEC_{m,h} \forall i = 1,2,...,NOC, \forall m \in \{1,2,...,NM\}, \forall h \in \{4,5,6\} \tag{24}$$

Operation sequence:

$$OP_x \in \{1,2,...,NOP\} \forall x = 1,2,...,NOP \tag{25}$$

Assigned Tool approach directions:

$$TAD_x \in \{1,2,...,NTAD(x)\} \forall x = 1,2,...,NOP \tag{26}$$

Assigned Tools:

$$T_x \in candT(x,a) \forall x = 1,2,...,NOP, \forall a = 1,2,3 \tag{27}$$

3.2 Decision variables

Sequence of operation clusters.

$OC_S = \{OC_1, OC_2, OC_3, ..., OC_{NOC}\}$, where OC_i is operation that occupied i^{th} position.

Sequence of Machines:

$M_S = \{M_1, M_2, M_3, ..., M_{NOC}\}$, where M_i is machine assigned to OC at i^{th} position.

Sequence of positioning equipment:

$PE_s = \{PE_1, PE_2, PE_3, ..., PE_{NOC}\}$, where PE_i is the positioning equipment used for (un) load for corresponding machine at i^{th} position.

Sequence of transportation equipment:

$TE_S = \{TE_1, TE_2, TE_3, ..., TE_{NOC}\}$, where TE_i is the transportation equipment for corresponding machine at i^{th} position.

Sequence of operations:

$OP_S = \{OP_1, OP_2, OP_3, ..., OP_{NOP}\}$, where OP_x is the operation at x^{th} position.

Sequence of TAD:

$TAD_S = \{TAD_1, TAD_2, TAD_3, ..., TAD_{NOP}\}$, where TAD_x is the tool approach direction assigned at x^{th} position.

Sequence of Tool:

$T_S = \{T_1, T_2, T_3, ..., T_{NOP}\}$, where T_x represents the assigned tool at x^{th} position.

Table 3-2 Proposed process plan expressing decision variables

Machine	M_1	M_2		-	-	-	M_{NOC}	
OC	OC_1	OC_2		-	-	-	OC_{NOC}	
TE	TE_1	TE_2		-	-	-	TE_{NOC}	
PE	PE_1	PE_2		-	-	-	PE_{NOC}	
OP	OP_1	OP_2	-	-	-	-	OP_{NOC-1}	OP_{NOC}
TAD	TAD_1	TAD_2	-	-	-	-	TAD_{NOC-1}	TAD_{NOC}
Tool	T_1	T_2	T_3	-	-	-	T_{NOC-1}	T_{NOC}

Table 3-2 is a sample of proposed model in which transportation equipment and position equipment rows are added. These were not present in the previous models.

3.3 Genetic Algorithm

GA is population based, stochastic, metaheuristic and intelligent search method that required a domain specific knowledge for problem solving and finding of approximate solutions. The objective function is sufficient to guide GA search and hence, for complex systems, mathematical equation formulations and any prior knowledge is not required, hence, GA application range is very broad. Figure 3-1 represent the flowchart of genetic algorithm where stopping criteria is added after ranking of population based on objective function. In this way, an extra crossover and mutation can be avoided.

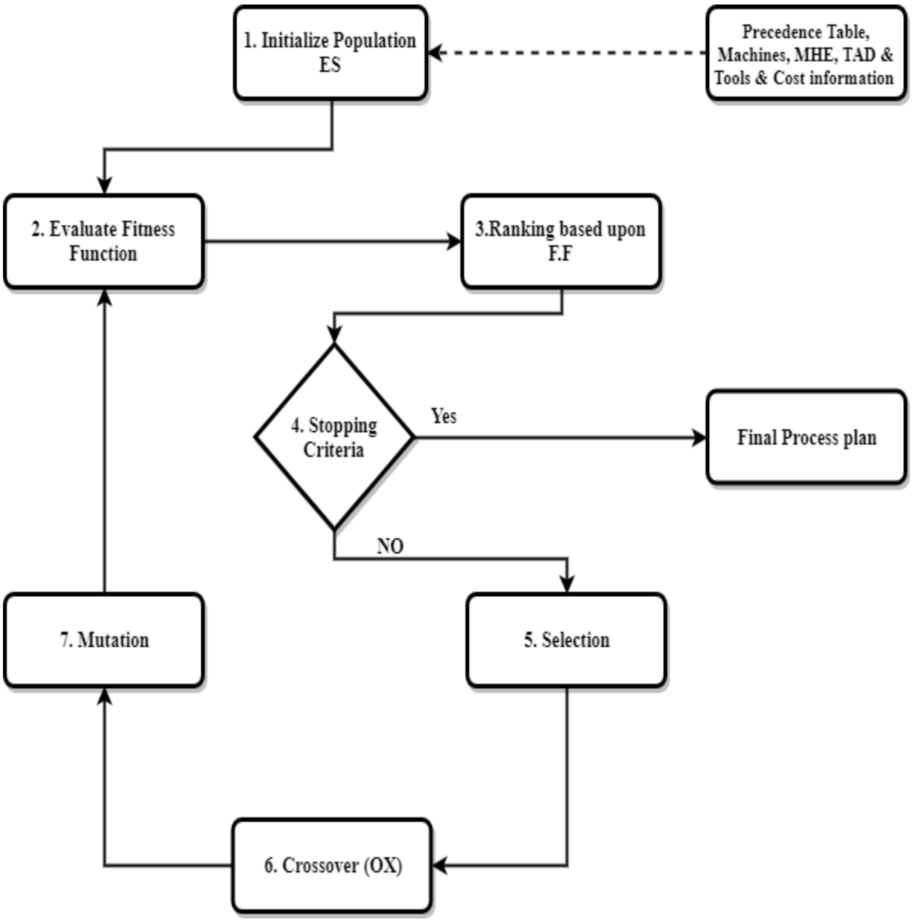


Figure 3-1 GA Algorithm used

3.3.1 Generate Initial Population

(Grefenstette,1987) for the effective use of genetic algorithm, system that need to be optimized, should be represented with a chromosome as much as possible. Initial population can be generated in two ways, well adapted (seeded) or randomly (Jain and Elmaraghy, 1997). First and initial step to formulate a genetic algorithm for process planning is mapping of process plan (problem solution) to string representation. A knowledge-based string is used to represent a process plan. For 'N' operation clusters and 'n' operations the string consists of four chromosome of 'N' genes and three chromosome of 'n' genes. This initial step further consists of following steps,

I. Generate feasible operation cluster sequence

Encoding approaches are responsible of GA performance. As discussed in previous section that edge selection encoding is best suited for GA optimization problems so this technique is adopted for initialization. The procedure to fill up first chromosome is given as

- From PM_c find and store all edges, i.e. $a_{i,j} = 1$, this is shown in Figure 3-3.

1	1	1	1	1	2	5	5	4	4	7	7
2	4	5	7	8	5	6	11	3	9	3	10

Figure 3-2 Table of all OC edges

- Randomly select one column from the table and save it to infant chromosome. For example, 7th column is selected, delete it from the edge table and assign its values to operation cluster sequence chromosome. First row gene will always predecessor of 2nd row gene.

1	1	1	1	1	2	5	5	4	4	7	7
2	4	5	7	8	5	6	11	3	9	3	10

Figure 3-3 updated edge table

5	**6**

Figure 3-4 OC_S chromosome

- Select edge randomly, i.e. 3rd of Figure 3-5, that has genes ‘1 & 5’, neglect already present gene ‘5’, and ‘1’ has only one position, behind the ‘5’ in this case

1	1	1	1	1	2	5	4	4	7	7
2	4	5	7	8	5	11	3	9	3	10

1	**5**	6

Figure 3-5 OC_s chromosome and updated edge table

- Select edge randomly, i.e. 8th of Figure 3-6, that has genes ‘4 & 9’, randomly assign ‘4’ to any candidate, can be placed before and after 5 & 6 gene both, assign a position to ‘9’ after the position of ‘4’.

1	1	1	1	2	5	4	4	7	7
2	4	7	8	5	11	3	9	3	10

1	**4**	5	6	**9**

Figure 3-6 OC_s chromosome and updated edge table

- Similarly repeat previous procedure until length of OC_S chromosome reach to total number of operation cluster.

1	1	1	1	2	5	4	7	7
2	4	7	8	5	11	3	3	10

1	1	1	1	2	4	7	7
2	4	7	8	5	3	3	10

1	4	**5**	6	**11**	9

1	4	**8**	5	6	11	9

Figure 3-7(a), (b) OC_s chromosome and updated edge table

1	1	1	2	4	7	7
2	4	7	5	3	3	10

1	1	1	2	7	7
2	4	7	5	3	10

1	**4**	8	5	**3**	6	11	9

1	4	8	5	**7**	**3**	6	11	9

Figure 3-8(c), (d) OC_s chromosome and updated edge table

1 & 4 were present, so delete and repeat the procedure.

1	1	1	2	7
2	4	7	5	10

1	1	7
2	7	10

1	4	**2**	8	**5**	7	3	6	11	9

1	4	2	8	5	7	3	10	6	11	9

Figure 3-9 (e), (f) OC_s chromosome and updated edge table

- As (f) has reached the number of operation cluster and remaining gene 1 & 2 are present in the chromosome, hence the final OC_S chromosome is

OC	1	4	2	8	5	7	3	10	6	11	9

Figure 3-10 Final OC_s

Now, machines and operations are assigned according to OC, positioning and transportation equipment are assigned corresponding M_S, tools and tool approach directions are assigned according to the corresponding operations. This is shown in Figure 3-11.

<table>
<tr><th>Machines</th><td>1</td><td>4</td><td>2</td><td>5</td><td colspan="5">5</td><td>6</td><td>6</td><td>5</td><td colspan="2">5</td><td colspan="2">4</td><td colspan="4">5</td></tr>
<tr><th>OC</th><td>1</td><td>4</td><td>2</td><td>8</td><td colspan="5">5</td><td>7</td><td>3</td><td>10</td><td colspan="2">6</td><td colspan="2">11</td><td colspan="4">9</td></tr>
<tr><th>TE</th><td>4</td><td>5</td><td>5</td><td>5</td><td colspan="5">4</td><td>4</td><td>4</td><td>6</td><td colspan="2">5</td><td colspan="2">5</td><td colspan="4">5</td></tr>
<tr><th>PE</th><td>3</td><td>3</td><td>2</td><td>3</td><td colspan="5">1</td><td>2</td><td>3</td><td>2</td><td colspan="2">2</td><td colspan="2">1</td><td colspan="4">3</td></tr>
<tr><th>OP</th><td>1</td><td>4</td><td>2</td><td>13</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>12</td><td>3</td><td>18</td><td>10</td><td>11</td><td>19</td><td>20</td><td>14</td><td>15</td><td>16</td><td>17</td></tr>
<tr><th>TAD</th><td>3</td><td>4</td><td>4</td><td>1</td><td>4</td><td>4</td><td>4</td><td>4</td><td>4</td><td>4</td><td>4</td><td>2</td><td>4</td><td>4</td><td>3</td><td>3</td><td>7</td><td>7</td><td>7</td><td>7</td></tr>
<tr><th>Tool</th><td>7</td><td>7</td><td>7</td><td>2</td><td></td><td>7</td><td>3</td><td>9</td><td>10</td><td>7</td><td>2</td><td>6</td><td>1</td><td>5</td><td>9</td><td>10</td><td>3</td><td>9</td><td>10</td><td>7</td></tr>
</table>

Figure 3-11 1st generated Process Plan

Now the first process plan is finalized. Similarly process plans equal to population size are generated and stored as generation 1.

II. Evaluate total weighted cost

After creating the first generation, the objective function (TWC) is computed for all process plans and stored. Table 3-3 contains a sample of computed objective functions of first 10 process plans, it can be seen that sum off all costs is less than 1, it is because of normalized costs values.

Table 3-3 Sample of calculated F.F for first 8 process plans

PP. No	MUC	MCC	TUC	TCC	SC	MHC	TWC
1	0.114	0.138	0.096	0.080	0.032	0.198	0.660
2	0.119	0.138	0.117	0.080	0.032	0.217	0.705
3	0.109	0.1386	0.126	0.080	0.032	0.181	0.667
4	0.110	0.156	0.118	0.071	0.016	0.246	0.718
5	0.114	0.156	0.093	0.071	0.016	0.184	0.635
6	0.094	0.138	0.107	0.071	0.016	0.192	0.628
7	0.115	0.121	0.119	0.088	0.032	0.170	0.647
8	0.117	0.138	0.115	0.080	0.032	0.174	0.657

III. Sorting (Ranking)

In this stage the whole population is ranked out based upon total cost, and a sample of some chromosomes is given in the following table,

Table 3-4 A sample of sorted table of first generation

PP. No	MUC	MCC	TUC	TCC	SC	MHC	TWC
161	0.108	0.069	0.106	0.097	0.064	0.093	0.540
59	0.115	0.086	0.126	0.088	0.032	0.106	0.555
180	0.112	0.104	0.103	0.097	0.032	0.130	0.579
111	0.111	0.138	0.092	0.080	0	0.158	0.581
167	0.112	0.138	0.092	0.080	0.016	0.143	0.583
117	0.116	0.104	0.124	0.088	0.032	0.117	0.583
48	0.117	0.104	0.1087	0.106	0.016	0.134	0.587
76	0.098	0.138	0.095	0.071	0.016	0.170	0.589

IV. Stopping Criteria

In literature there are used two types of stopping criteria,

- Predefined maximum number of generations
- If convergence not found up to specific iterations

A very few researchers used the second criteria so initially we will use predefined maximum number of generations to stop the algorithm.

V. Selection: Elitist Method

Selection has a key role in genetic algorithm by improving the population quality. Elitism concept is about to save the fittest process plan to next generation in order to avoid the loss of global optimal process plan.

From the Table 3-4, we can see that the process plan '161' is the fittest in first generation. In it easy to select fittest individuals from the sorted population. In this step a portion of current population is saved for the next generation. i.e. 10 percent.

VI. Crossover (OX)

The crossover is the main process of genetic algorithm and has significant impact on performance of a genetic algorithm. Appropriate selection of crossover operator helps to avoid the premature convergence. As stated in chapter 2, ordered crossover is best suited for the process plan optimization problem, hence, OX is selected to use in the proposed strategy. Order crossover guarantees that no constraint will be violated in the next generation during the reproduction. The steps involved in order crossover are,

1. Randomly select the start and end points for crossover in parent 1.
2. Copy left and right portion of end points of parent 1 genes to offspring 1.
3. Search out the sequence of parent 1 uncopied genes in parent 2 and enlist them in offspring 1 in the same order. Offspring 1 is completed, and it has the combined properties of the parent.
4. Repeat step 1-3 to generate offspring 2.

This procedure is further explained with the help of following Figure 3-12.

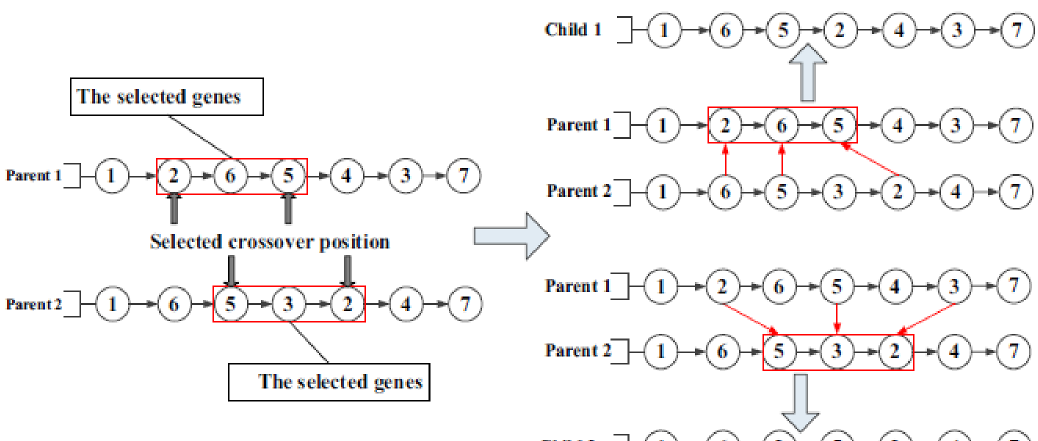


Figure 3-12 Order crossover (su et. al., 2018)

VII. Mutation

Mutation is used to avoid from the local optimal solutions. In the absence of this operator the local solution can seems as optimum solution. As there are many decision variables in our case so mutation is required at machine, TAD and tool selection level as well. After mutation move to step 4.3.

The procedure of mutation is,

- Randomly select a gene in OC_s
- Remove it from the current position
- Randomly placed it to the new possible position
- Randomly select a gene from M_s, TAD_s and T_s each
- Exchanged it with alternate from the respective candidate list

This procedure of OC mutation ensures that there will be no violation of precedence constraints. In all previous approaches, the constraints violation was occurred (infeasible PP) while performing mutation. It was overcome either by adding a penalty cost to decrease such PP chances to select in the next generation or by performing mutation only in case of fulfilment of precedence constraints.

3.4 Summary

In this chapter, each cost element is explained and then objective function is developed by adding material handling cost. Objective function consists of 6 normalized cost elements having corresponding weights to control their effect according to the requirements. After development of objective function, a procedure of implementing genetic algorithm to proposed objective function is explained. In the next chapter this algorithm will be tested on a test part and final results will be obtained.

Chapter 4: Application of proposed algorithm

This chapter deals with the results obtained by the implementation of genetic algorithm to a test part for achieving the proposed objective. Some required inputs for the case study of test part are provided in the starting portion, validation is performed and then to achieve goal different graphs are generated and discussed.

4.1 Case study

A test part ANC-101 (Figure 4-1) is taken for validation and implementation of proposed model. This test part consists of 14 features and 20 operations that include milling, drilling, reaming, boring and tapping.

A test part ANC-101 (Figure 4-1) is taken for validation and implementation of proposed model. This test part consists of 14 features and 20 operations that include milling, drilling, reaming, boring and tapping.

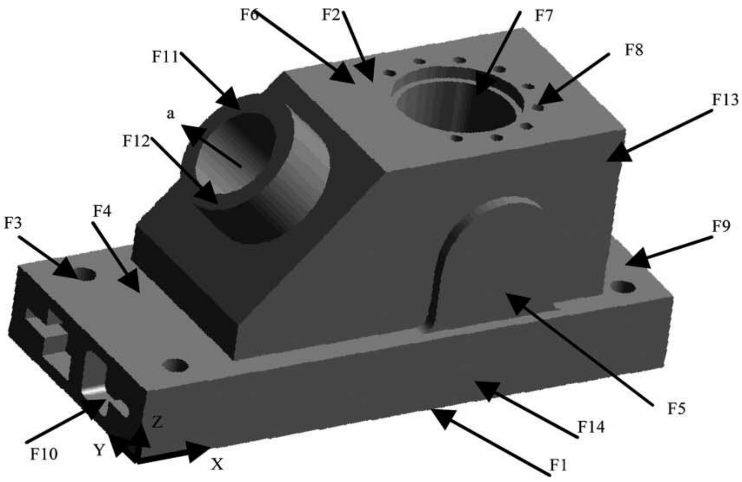


Figure 4-1 ANC-101 Test part

A feature can be obtained in one or more operations, so number of operations should be greater than the number of features for completeness and perfectness of the feature. A hole feature required reaming after drilling operation for having the better surface finish, so reaming can’t be performed before drilling and this is the logical constraint for the two operations, similarly datum constraints are also taken into consideration. Shabaka and Elmaraghy (2007) made a cluster of the operation having datum or logical constraints and this cluster is performed on same machine. Figure 4-2 is the graphical representation of precedence constraints for the 20 operations and Table 4-2 have all operation clusters, containing different operations.

Precedence relationship between clusters is provided in Table 4-3 which is called upon while generating random population, performing crossover and mutation.

Table 4-1 Features, operations, candidate TAD & tools for ANC-101 (Shabaka and Elmaraghy, 2007)

Feature	Description	Operation	Operation ID	TAD Candidate	Tool Candidate
1	Planar Surface	M	1	+z	6,7,8
2	Planar Surface	M	2	-z	6,7,8
3	Four holes arranged as replicated features	D	3	+z, -z	2
4	A step	M	4	+x, -z	6,7
5	Rib	M	5	+y, -z	7,8
6	Rib	M	6	-y, -z	7,8
7	A Compound hole	D	7	-z	2,3,4
		R	8		9
		B	9		10
8	Nine holes arranged as replicated features	D	10	-z	1
		T	11		5
9	A step	M	12	-x, -z	6,7
10	Two pockets arranged as replicated features	M	13	+x	1,2
11	A boss	M	14	A	2,3,4
12	A compound hole	D R B	15 16 17	A	9 10 7,8
13	A pocket	M	18	-x	6,7
14	A compound hole	R B	19 20	-z	9 10

Table 4-1 contains the description of each operation, possible tool approach directions to perform operation and tools available for that operation. Based upon the tool approach directions (Shabaka and Elmaraghy, 2007) find minimum axis of rotation required to perform the specific operation for each combination of TAD. He generated a list of capable machines to obtain a feature for all possible combination of TAD after comparing the required and available machine's capabilities. Table 4-4 contains the list of candidate machines for the machining of OC for different TAD combinations.

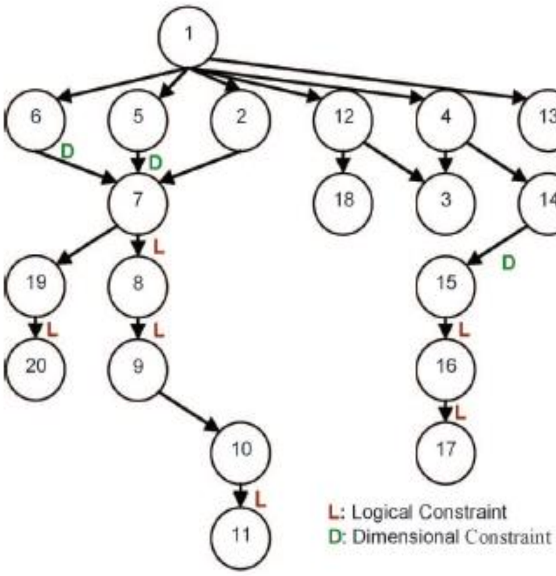


Figure 4-2 Precedence operation graph for part ANC-101 (Shabaka and Elmaraghy, 2007)

Table 4-2 Operations in OC (Shabaka and Elmaraghy, 2007)

OC#	1	2	3	4	5	6	7	8	9	10	11
OP#	1	2	3	4	5, 6, 7, 8, 9	10,11	12	13	14,15,16,17	18	19,20

Table 4-3 Precedence constraints matrix for ANC-101

OC	1	2	3	4	5	6	7	8	9	10	11
1	0	1	0	1	1	0	1	1	0	0	0
2	-1	0	0	0	1	0	0	0	0	0	0
3	0	0	0	-1	0	0	-1	0	0	0	0
4	-1	0	1	0	0	0	0	0	1	0	0
5	-1	-1	0	0	0	1	0	0	0	0	1
6	0	0	0	0	-1	0	0	0	0	0	0
7	-1	0	1	0	0	0	0	0	0	1	0
8	-1	0	0	0	0	0	0	0	0	0	0
9	0	0	0	-1	0	0	0	0	0	0	0
10	0	0	0	0	0	0	-1	0	0	0	0
11	0	0	0	0	-1	0	0	0	0	0	0

Table 4-4 candidate machiens and cases (Shabaka and ElMaraghy, 2008)

Operation Cluster No.	Cases (Different combination of TAD for machining of OC)			
	1	2	3	4
1	1,2,3,4,5			
2	1,2,3,4,5,6			
3	1,2,3,4,5,6	1,2,3,4,5,6		
4	4,5	1,2,3,4,5		
5	3,5	3,5	3,5	1,2,3,4,5
6	1,2,3,4,5,6			
7	4,5	1,2,3,4,5		
8	4,5	1,2,3,4,5,6		
9	3,5			
10	4,5			
11	1,2,3,4,5,6			

Table 4-5 cost information (Li et al., 2002)

Machine ID	Type	Cost	Tool ID	Type	Cost
1	1 Spindle 3 axis	760	1	Drill 1	7
2	1 Spindle 3 axis RMT	860	2	Drill 2	5
3	1 Spindle 4 axis RMT	1010	3	Drill 3	3
4	1 Spindle 4 axis RMT	1010	4	Drill 4	8
5	1 Spindle 5 axis RMT	1110	5	Tapping Tool	7
6	Drill Press	385	6	Mill 1	10
MCCI =160 TDCCI= 100 TCCI=20			7	Mill 2	15
			8	Mill 3	30
			9	Ream	15
			10	Boring Tool	20

Table 4-5 contains the cost information for using machine and tools. Different cost indices are also listed in this table which are constants. The “Table 4-6” contains the cost information of using of positioning and transportation equipment during the machining process, it is assumed that available machines has thr same values as the value of first six machines used by Sujono and Lashkari (2007).

Table 4-6 MHEC information (Sujono and Lashkari, 2007)

Machines	(un) Load Equipment			Transportation Equipment		
	Light Load Robot	Heavy Load Robot	Human	Forklift truck	Roller belt conveyor	Light belt conveyor
1	0.6	0.8	0.4	4	5	3
2	0.5	0.5	0.4	4	1	3
3	0.8	0.7	0.6	5	6	1
4	0.8	0.5	0.4	5	5	5
5	0.5	0.6	0.4	5	1	3
6	0.7	0.5	0.6	4	5	3

4.2 Validation of proposed algorithm

A MATLAB GA code is generated and run to find the maximum individual costs using the information provided in the Table 4-5" , theses maximum costs are taken as weights, results are given below after dividing with 1000,

Table 4-7 Maximum individual costs

MUC (w_1)	MCC (w_2)	TUC (w_3)	TCC (w_4)	SCC (w_5)	w_6
1.210	1.600	0.342	0.300	0.100	0

After finding the maximum values and taken them as weights for individual costs, genetic algorithm is run by taking w_6=0 (as at this stage we have no idea about this weight) and optimal solution is found (process plan) for the same parameter as used by Shabaka and ElMaraghy, (2008).

M	1	1	1	1	1					4	3				6		6	6	6	
OC	1	7	2	4	5					10	9				11		3	8	6	
TE	6	6	6	4	4					4	4				5		5	5	6	
PE	3	2	2	1	2					4	3				3		3	3	3	
OP	1	12	2	4	6	5	7	8	9	18	14	15	16	17	19	20	3	13	10	11
TAD	5	6	6	6	6	6	6	6	6	2	7	7	7	7	5	5	5	1	6	6
Tool	7	7	7	7	7	7	3	9	10	6	3	9	10	7	9	10	2	2	1	5

Figure 4-3 process plan at w_6 =0

Table 4-8 Benchmark process plan

M	4	4	4	4	4					4	4	6		3				6	6	
OC	1	4	7	2	5					8	10	6		9				3	11	
OP	1	4	12	2	6	5	7	8	9	13	18	10	11	14	15	16	17	3	19	20
TAD	5	6	6	6	6	6	6	6	6	1	2	6	6	7	7	7	7	5	5	5
Tool	6	6	6	6	7	7	3	9	10	2	6	1	5	3	9	10	7	2	9	10

Table 4-9 Comparison of result with benchmarked process plan cost

Costs	**Optimized process plan at w6=0 (Proposed)**		**Benchmarked process plan (Shabaka and ElMaraghy, 2008)**
	Normalized	**Decoded**	
MUC	0.165	736	923.5
MCC	0.108	480	480
TUC	0.056	250	230
TCC	0.045	200	240
SCC	0.067	300	300
MHC	0.5720	28.6	---
Total cost	0.4416	1966	2173.5

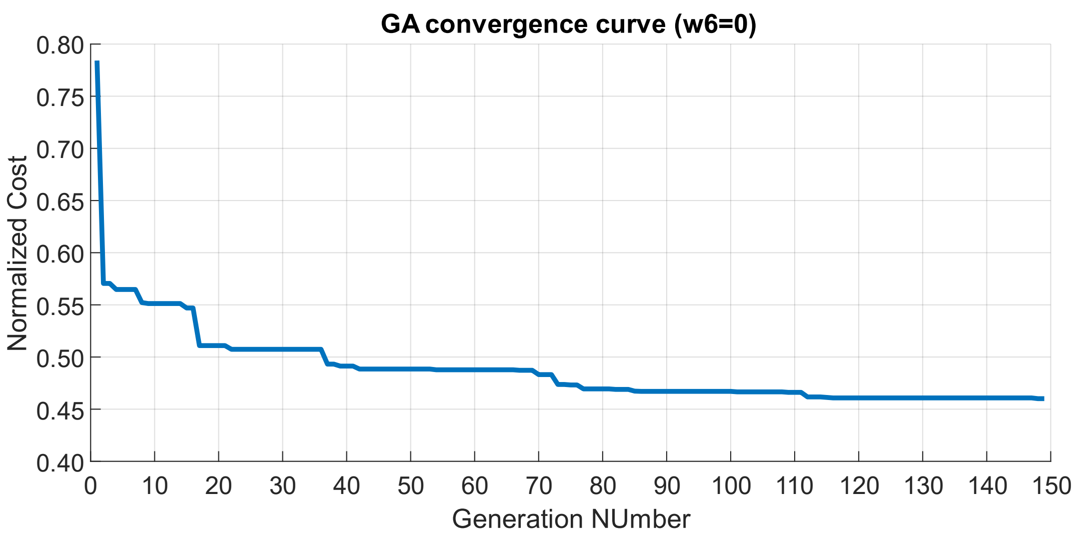


Figure 4-4 Convergence curve

4.3 Results and discussion

Table 4-9 shows the comparison between obtained and benchmarked result. As mentioned in chapter 3 that the objective function is consists of normalized cost elements so, GA provided the normalized values, which are decoded and compared with the benchmarked costs and it can be seen that new strategy is performing well. As w_6 is zero, its mean that MHC exists but the effect is eliminated. This value can be seen in a light color and it will be hidden cost that might be the cause of economic loss. When we eliminate the effect of w_6, the case becomes similar to the case of previous researches in which MHC was not considered in process plan optimization problems (of RMS), and process plan is only regenerated when some machines are added or deleted.

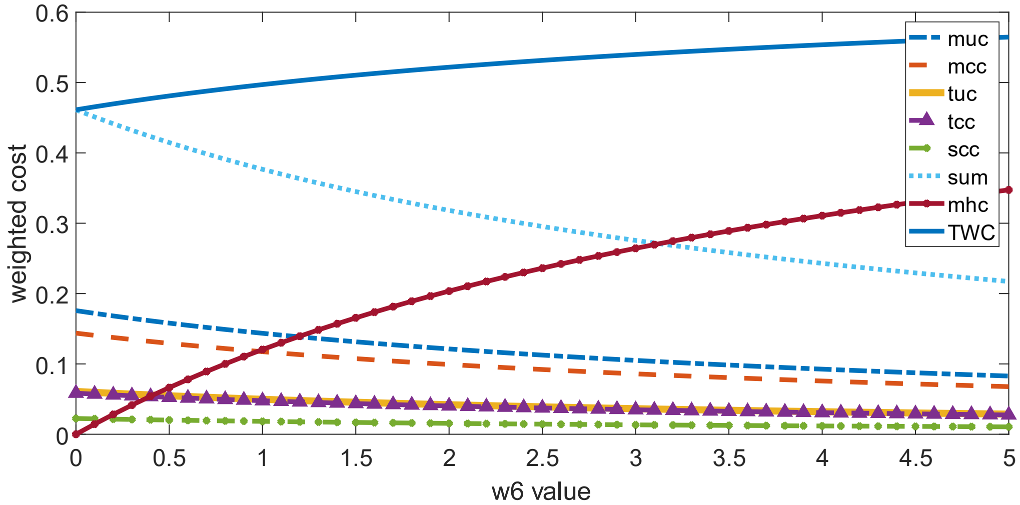


Figure 4-5 Total cost of a process plan of "Figure 4-3"

Figure 4-5 shows that for process plan showing in "Figure 4-3", if we will not consider the effect of material cost then total cost will go on increasing with the increase in material handling equipment importance or adding the costly equipment or eliminating the cheaper one.

Now for our case, the different computational experiments are performed to select suitable parameters for genetic algorithm. Search space increases with the increase in population size which results in increasing of computation time. Too small population size slows down the optimization rate. For the test part ANC-101, different researchers show that population size of 100-250 range is suitable so in Figure 4-6 three graphs are generated at population size of 100, 150 and 200. It can be seen that GA at population size of 200 is performing well.

Figure 4-7 and Figure 4-8 are representing the convergence curves for the different crossover and mutation rates respectively. The range of the crossover rate should be from 50 to 100 percent and mutation rate from 1 to 10 percent, as mentioned in the literature. In our case algorithm is giving better performance at 70 percent crossover & 6 percent mutation rates.

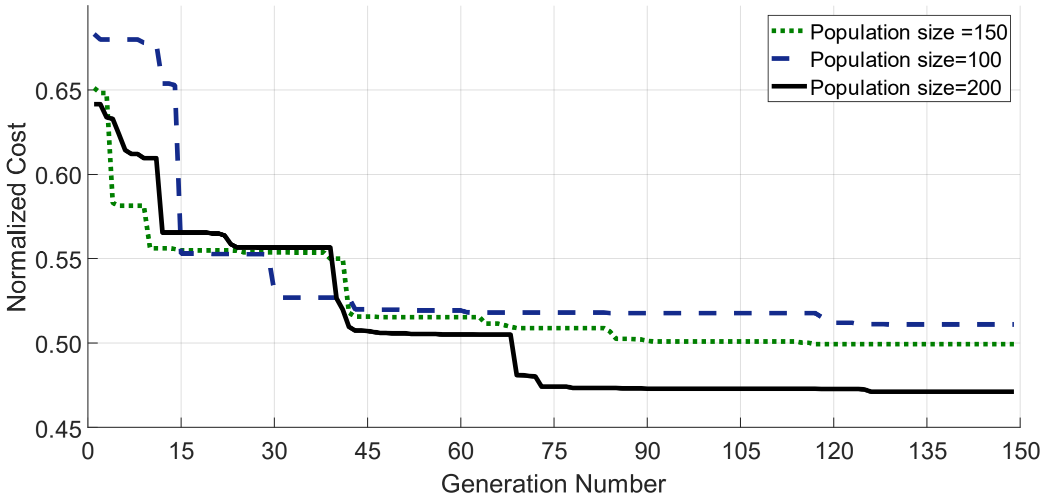


Figure 4-6 Different population size graphs

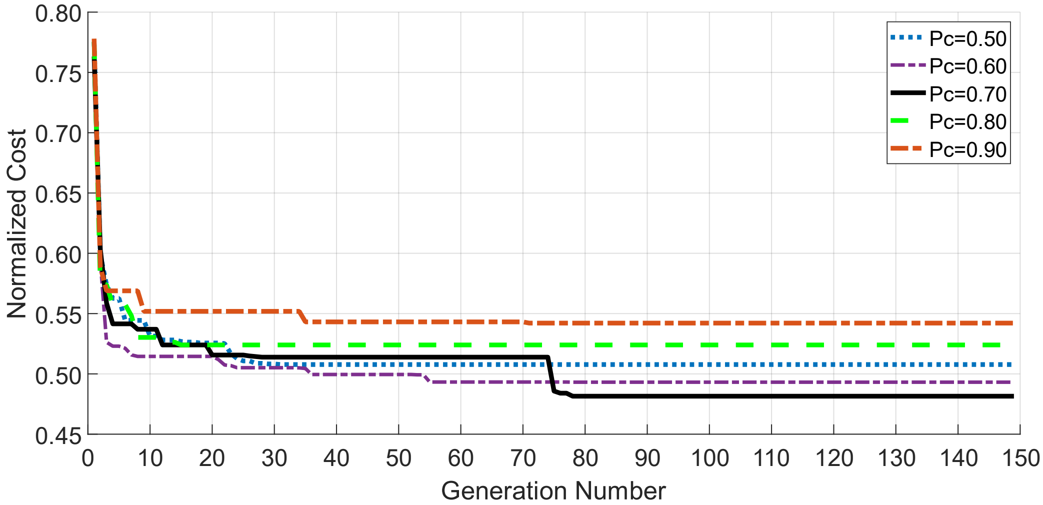


Figure 4-7 Graphs at different crossover rates

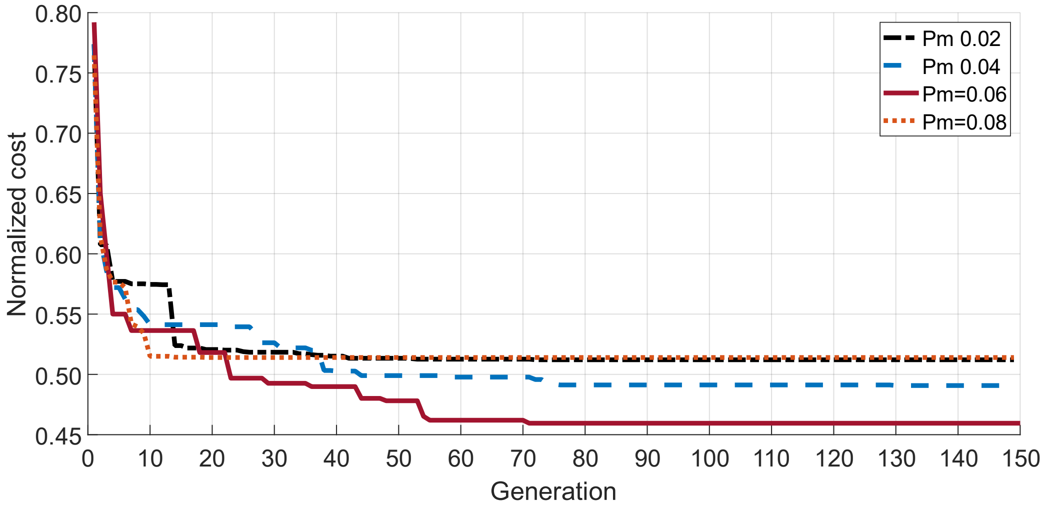


Figure 4-8 Graphs at different mutation rates

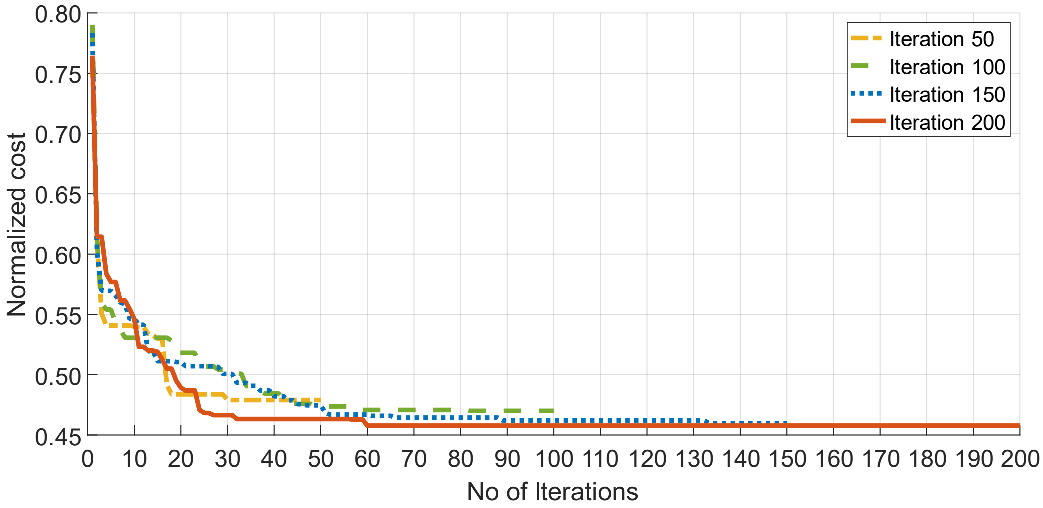


Figure 4-9 Graphs at different iterations

Figure 4-9 contains the different iteration curves, shows that 100 or 150 is suitable number of generations for the concern case.

4.4 Finding suitable range for w_6 and final results

The different GA parameters are finalized in the previous section, now there is a need to find a suitable value for w_6. The Effect of w_6 increases by increasing its value while the individual values (Figure 4-10) and combined effect percentage (Figure 4-11) of all other weights decreases. This will go on increasing until w_6 controls the whole algorithm.

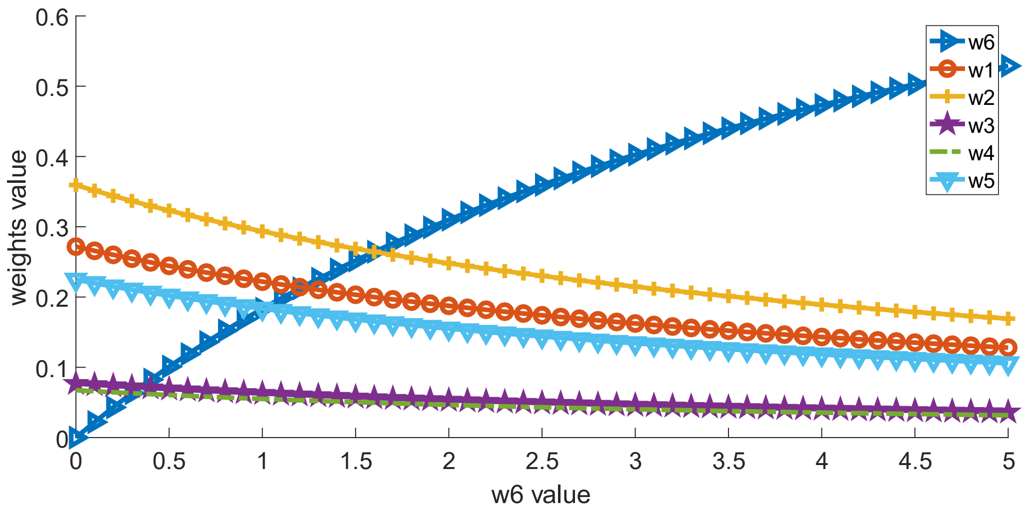


Figure 4-10 comparison of all weights value by increasing w_6 effect

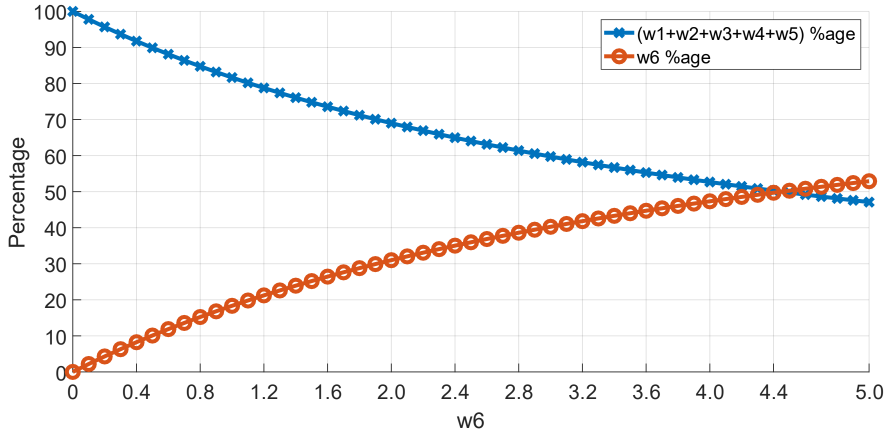


Figure 4-11 Effect on percentage of sum of 5 weightages by increasing w_6 effect

Table 4-10 weights percentage table for different w_6

w_6 value	w_1%	w_2%	w_3%	w_4%	w_5%	(w_1-w_5) %	w_6 %
0	27.17	35.93	7.68	6.73	22.46	100	0
0.1	26.58	35.14	7.51	6.59	21.96	97.80	2.19
0.2	26.01	34.39	7.35	6.44	21.49	95.70	4.29
0.3	25.46	33.67	7.19	6.31	21.04	93.68	6.31
0.4	24.93	32.97	7.04	6.18	20.61	91.75	8.24
0.5	24.43	32.31	6.90	6.05	20.19	89.90	10.10
0.6	23.95	31.67	6.76	5.93	19.79	88.12	11.87
0.7	23.48	31.05	6.63	5.82	19.40	86.41	13.58
0.8	**23.03**	**30.46**	**6.51**	**5.71**	**19.04**	**84.76**	**15.23**
0.9	**22.60**	**29.89**	**6.39**	**5.60**	**18.68**	**83.18**	**16.81**
1.0	**22.19**	**29.34**	**6.27**	**5.50**	**18.34**	**81.658**	**18.34**
1.1	**21.79**	**28.81**	**6.15**	**5.403**	**18.01**	**80.18**	**19.81**
1.2	**21.40**	**28.30**	**6.05**	**5.30**	**17.69**	**78.76**	**21.23**
1.3	21.03	27.81	5.94	5.21	17.38	77.39	22.60
1.4	20.67	27.34	5.84	5.12	17.08	76.07	23.92
1.5	20.32	26.88	5.74	5.04	16.80	74.79	25.20
1.6	19.99	26.43	5.65	4.95	16.52	73.56	26.43
1.7	19.66	26.00	5.55	4.87	16.25	72.366	27.63
1.8	19.35	25.59	5.47	4.79	15.99	71.20	28.79
1.9	19.04	25.18	5.38	4.72	15.74	70.08	29.91
2.0	18.75	24.79	5.30	4.64	15.49	69.00	30.99

In Figure 4-11 it can be seen that percentage of w_6 increases gradually while the percentage of all other weights decreases and combined effect also decreases. The literature says that material handling cost consists of 20 to 50 percent of the total cost, and as it is not considered in the optimization problems, so 0.8-1.2 range is suitable where w_6 effect is near about 20 percent. By increasing a specific weight, the search space is biased to the particular objective and above 1.2, w_6 effect starts to dominate all other effects which is not desirable.

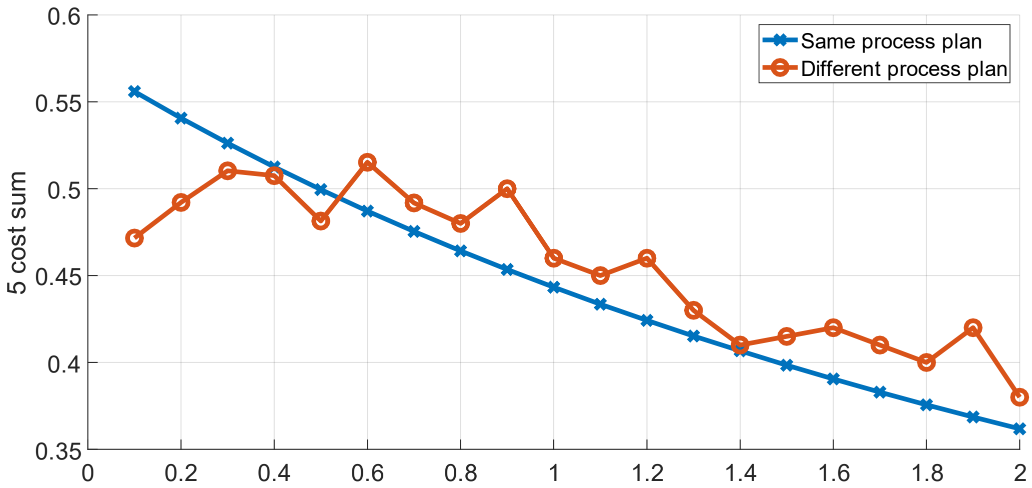


Figure 4-12 Comparison of sum of 5 costs of new process plan and same process plan

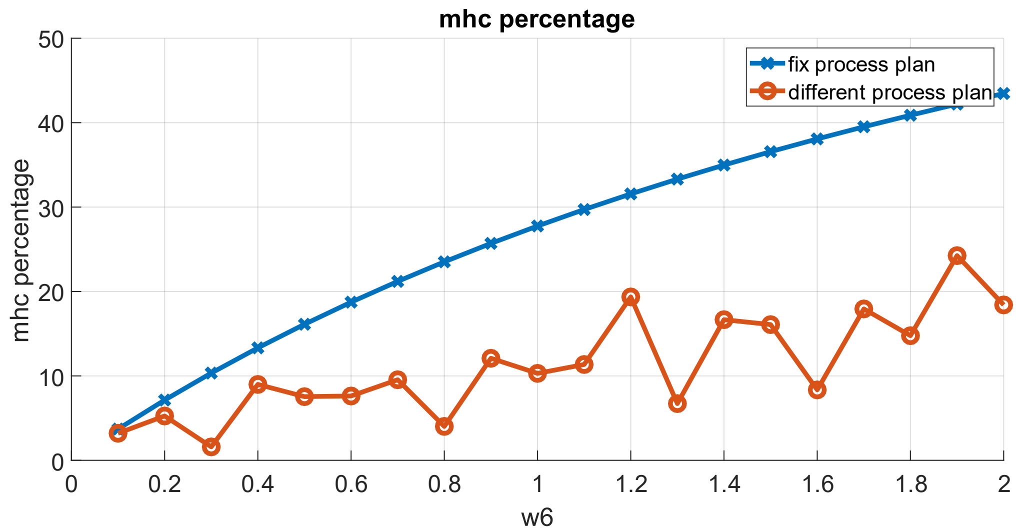


Figure 4-13 MHC in same and changing process plan

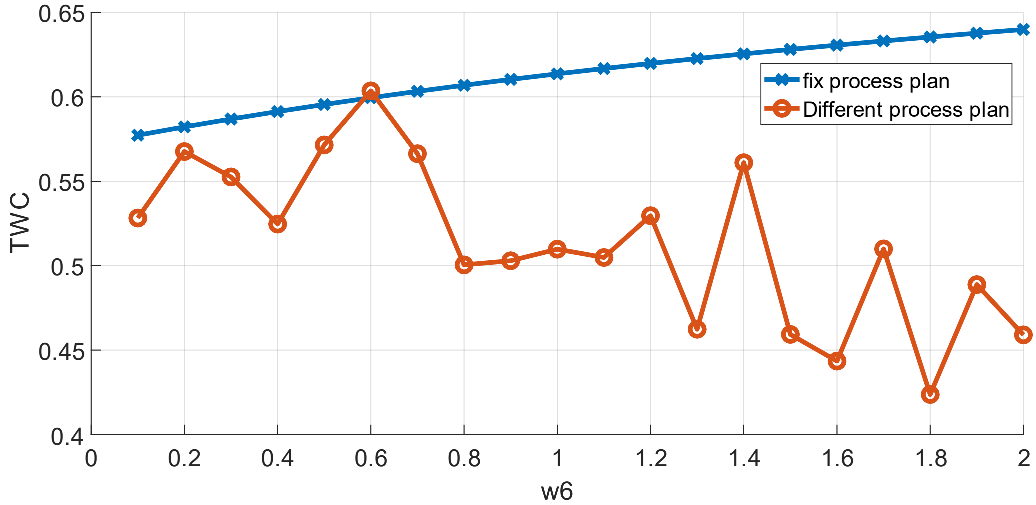


Figure 4-14 Effect of w_6 on total cost of same and different process plan

Figure 4-12, comparison of total cost without MHC is carried out for the same and different process plan with the increase in w_6. It can be seen that the sum of 5 cost decreases for the same process plan linearly (constant actually if divide by its weighted percentage) and for different process plan is greater than fix process plan and decreases non-linearly due to randomness (almost constant). Here, material handling cost is the only important variable which has to be controlled. Form *Figure 4-13 and Figure 4-14*, the algorithm has a check on MHC as it is included in the objective function for the new process plan. The process plans on the selected range of w_6 are generated and given in Table 4-11, which shows that almost 15 % cost is optimized by including material handling cost. In the previous strategies the process plan was only regenerated in case of adding or removal of machines and was independent of MHC but now in present strategy process plan is regenerated upon increasing material handling importance. Hence, In the circumstances where the material handling equipment is the major concern, the user can assign a higher value to w_6 and can get acceptable results.

Table 4-11 Process plans generated at selected range of w_6

w_6	muc	mcc	Tuc	tcc	scc	mhc	TWC	Reduction in TWC
0	0.165	0.107	0.056	0.044	0.067	0.572	0.442	---
0.8	0.179	0.091	0.044	0.041	0.038	0.045	0.440	5.68
0.9	0.207	0.029	0.047	0.044	0.074	0.025	0.429	7.368
1.0	0.167	0.058	0.045	0.040	0.055	0.033	0.400	16.42
1.1	0.166	0.057	0.042	0.043	0.072	0.077	0.412	14.09
1.2	0.216	0.001	0.041	0.042	0.088	0.004	0.393	16.22

The Table 4-4 shows that 5-axis machine is capable to performs all operation clusters. Its cost is high with respect to all other machines and it is not selected in optimal process plan. Now by increasing its cost and running the code, obtained PP have no 5-axis machine and by decreasing its cost, the final PP has 5-axis machine for all OC (Table 4-12). Similarly, the same procedure is used for MHE as well. The optimal process plan is regenerated on adding, removing machines and material handling equipment.

Table 4-12 Effect of machine cost

5 axis machine cost = 2020	**M**	4	4	4	4	4	4	3	3	3	3	3
	OC	1	7	10	2	4	5	11	3	9	8	6
5 axis machine cost = 585	**M**	5	5	5	5	5	5	5	5	5	5	5
	OC	1	2	4	7	5	6	11	3	8	9	10

4.5 Summary

A MATLAB code generated for the proposed algorithm is tested and accepted by validating after eliminating the MHC effect. Different computational experiments are performed in order to obtain the GA parameters suitable to our objective. The weights in the objective function are helpful to achieve priorities, so an effective range of w_6 is selected based upon the different graphs and final results are obtained in this chapter.

Chapter 5: Conclusion and future work

An efficient, stochastic and metaheuristic algorithm is required to solve the CAPP optimization problem. In this thesis, we applied a genetic algorithm on a test part ANC-101 using MATLAB to find the optimal process plan based upon minimum total cost criteria for a proposed fitness function. The material handling cost (MHC) that consists of 20-50% of total cost (Sujono and Lashkari, 2007) was not considered by previous researchers in the cost model, is added as sixth cost. The costs of machine and tool usages (MUC, TUC), costs of changing machine, setup and tool (MCC, SCC, TCC), which was considered in literature are also used here. For the development of objective function, all these costs are normalized and then added in fitness function by assigning different weights. A suitable population size, stopping criteria, Pc, Pm and a range for the weight of material handling cost are adopted by performing different iterations.

The manufacturing database can be modified according to the user needs, this makes the system more realistic and advantageous as compared to the other approaches. Effect of any cost can be eliminated easily by assigning a zero value or their effect can be controlled according to the requirements. On assigning a suitable value to w_6 we found a process plan having more optimized (near about 15%) total cost. Literature (Sujono and Lashkari, 2007) also mentioned that total cost can be further reduced 15 to 30 percent by including MHC effect. Hence, the manufacturing environments where the material handling cost playing a major role, its weight should have a higher value and must be taken into consideration.

To check the reconfigurability we assigned a large cost value to 5 axis machine and our algorithm did not select this machine in the final optimal process plan, similarly on assigning a low-cost value to same machine, the final process plan shifted to this machine. The same procedure is repeated for the available material handling equipment and observed that costly equipment and machine having costly MHE both are not selected in the final process plan.

Future work may include experimental work of the same strategy. The data of a real part can be taken from industry and this strategy can be applied by changing inputs. This work can also be implemented in industry using GA or other evolution algorithm like firefly, butterfly and honey bee algorithms, and results can be compared to choose the best.

Appendix

Following input parameters are used in this thesis,
NOC=11: Total number of clusters
NOP=20: Total number of operations

$PM_c(i,j) = \begin{pmatrix} a_{1,1} & \cdots & a_{1,j} \\ \vdots & \ddots & \vdots \\ a_{j,1} & \cdots & a_{i,j} \end{pmatrix}$: A matrix containing precedence constraints between OC

- $i, j = 1,2,3,...,NOC$
- $a_{i,j} = 1$ if constraint fulfill (cluster 'i' will be performed before cluster 'j')
- $a_{i,j} = -1$ if constraint violate (cluster 'j' will be performed before cluster 'i')
- $a_{i,j} = 0$ in case of no relation between the OC

$PM_{op}(x,y) = \begin{pmatrix} a'_{1,1} & \cdots & a'_{1,y} \\ \vdots & \ddots & \vdots \\ a'_{y,1} & \cdots & a'_{x,y} \end{pmatrix}$ A matrix containing operation precedence constraints

- $x, y = 1,2,3,...,NOP$
- $a'_{x,y} = 1$ if operation constraint fulfills
- $a'_{x,y} = -1$ if operation constraint violates
- $a'_{x,y} = 2$ for datum constraints
- $a'_{x,y} = 3$ for logical constraints
- $a'_{x,y} = 0$ if operation have no precedence

NOPOCS(i): A matrix include number of operations in operation cluster 'i'
$candT(x,a)$: Matrix containing list of candidate tools for each operation. $a = 1,2,3$
$CT(t_x)$: array having cost information of tool t_x
$candM(i,b)$ is matrix of candidate machines, while 'b' is maximum number of any cluster candidate machine
$MC(M_i)$: array with machine cost information
$TAD(op,d)$: Matrix of candidate tool approach directions 'd' for operation 'op'
$MHEC(M_i, h_i)$: Matrix having cost information of material handling equipment 'h' for machine 'm'
$TWC(i)$: Matrix having all weighted calculated costs for process plan 'i'

References

Ahmad, Z., Rahmani, K., D'Souza, R.M., 2010. Applications of genetic algorithms in process planning: tool sequence selection for 2.5-axis pocket machining. J Intell Manuf 21, 461–470. https://doi.org/10.1007/s10845-008-0201-6

Anon, 1987. SOFTWARE ENHANCES ACCURACY AND CONSISTENCY. American machinist and automated manufacturing.

Beamon, B.M., 1998. Supply Chain Design and Analysis: Models and Methods. International Journal of Production Economics 55, 281–294.

Bi, Z.M., Lang, S.Y.T., Shen, W., Wang, L., 2008. Reconfigurable manufacturing systems: the state of the art. International Journal of Production Research 46, 967–992. https://doi.org/10.1080/00207540600905646

Busetti, F., 2003. Simulated annealing overview 10.

Candido, M.A.B., 1998. A genetic algorithm based procedure for more realistic job shop scheduling problems. International Journal of Production Research 36, 3437–3457. https://doi.org/10.1080/002075498192148

Chaudhry, I.A., 2012. A Genetic Algorithm Approach for Process Planning and Scheduling in Job Shop Environment 5.

Cochran, D.S., Arinez, J.F., Duda, J.W., Linck, J., 2001. A Decomposition Approach for Manufacturing System Design 36.

Colorni, A., Dorigo, M., Maniezzo, V., 1992. Distributed Optimization by Ant Colonies, in: PROCEEDINGS OF ECAL91. Presented at the EUROPEAN CONFERENCE ON ARTIFICIAL LIFE, ELSEVIER PUBLISHING, Paris, France.

da Silva, R.M., Junqueira, F., Filho, D.J.S., Miyagi, P.E., 2016. Control architecture and design method of reconfigurable manufacturing systems. Control Engineering Practice 49, 87–100. https://doi.org/10.1016/j.conengprac.2016.01.009

Dag, H., 2016. The Impact of Crossover and Mutation Operators on a GA Solution for the Capacitated Vehicle Routing Problem. Universal Journal of Engineering Science 6.

Dereli, T., Filiz, İ.H., 1999. Optimisation of process planning functions by genetic algorithms. Computers & Industrial Engineering 36, 281–308. https://doi.org/10.1016/S0360-8352(99)00133-3

Dereli, T., Filiz, I.H., Baykasoglu, A., 2001. Optimizing cutting parameters in process planning of prismatic parts by using genetic algorithms. International Journal of Production Research 39, 3303–3328. https://doi.org/10.1080/00207540110057891

Dhingra, S., Gupta, S.B., Biswas, R., 2014. HYBRID GASA FOR BI-CRITERIA MULTIPROCESSOR TASK SCHEDULING WITH PRECEDENCE CONSTRAINTS 11.

Dorigo, M., Stützle, T., 2004. Ant colony optimization. MIT Press, Cambridge, Mass.

Glover, F., 1986. Future paths for integer programming and links to artificial intelligence. Computers & Operations Research 13, 533–549. https://doi.org/10.1016/0305-0548(86)90048-1

Groover, M.P., 1996. Fundamental of modern manufacturing, 4th ed. JOHN WILEY & SONS, INC.

Guo, Y.W., Li, W.D., Mileham, A.R., Owen, G.W., 2009. Applications of particle swarm optimisation in integrated process planning and scheduling. Robotics and Computer-Integrated Manufacturing 25, 280–288. https://doi.org/10.1016/j.rcim.2007.12.002

Guo, Y.W., Mileham, A.R., Owen, G.W., Li, W.D., 2006. Operation sequencing optimization using a particle swarm optimization approach. Proceedings of the Institution of

Mechanical Engineers, Part B: Journal of Engineering Manufacture 220, 1945–1958. https://doi.org/10.1243/09544054JEM647
Huang, W., Hu, Y., Cai, L., 2012. An effective hybrid graph and genetic algorithm approach to process planning optimization for prismatic parts. Int J Adv Manuf Technol 62, 1219–1232. https://doi.org/10.1007/s00170-011-3870-9
Jain, A.K., Elmaraghy, H.A., 1997. Single process plan scheduling with genetic algorithms. Production Planning & Control 8, 363–376. https://doi.org/10.1080/095372897235172
Jain, P.K., Gupta, V.K., 2005. Operation Sequencing Using Ant Colony Optimization Technique, in: 2005 IEEE International Conference on Systems, Man and Cybernetics. Presented at the 2005 IEEE International Conference on Systems, Man and Cybernetics, IEEE, Waikoloa, HI, USA, pp. 270–275. https://doi.org/10.1109/ICSMC.2005.1571157
Jia, H.Z., Fuh, J.Y.H., Nee, A.Y.C., Zhang, Y.F., 2007. Integration of genetic algorithm and Gantt chart for job shop scheduling in distributed manufacturing systems. Computers & Industrial Engineering 53, 313–320. https://doi.org/10.1016/j.cie.2007.06.024
Jia, H.Z., Nee, A.Y.C., Zhang, Y.F., 2003. A modified genetic algorithm for distributed scheduling problem. Journal of Intelligent Manufacturing.
Jiang, Z., Zhou, T., Zhang, H., Wang, Y., Cao, H., Tian, G., 2016. Reliability and cost optimization for remanufacturing process planning. Journal of Cleaner Production 135, 1602–1610. https://doi.org/10.1016/j.jclepro.2015.11.037
Kamrani, A.K., Sferro, P., Handelman, J., 1995. Critical issues in design and evaluation of computer aided process planing systems. Computers & Industrial Engineering 29, 619–623. https://doi.org/10.1016/0360-8352(95)00144-P
Kay, M.G., 2012. Material Handling Equipment.
Kesavan, R., C. Elanchezhian, Ramnath, B.V., 2004. Process Planning and Cost Estimation, Second Edition. New Age International Publishers 248.
Koren, Y., 2006. General RMS Characteristics. Comparison with Dedicated and Flexible Systems, in: Dashchenko, A.I. (Ed.), Reconfigurable Manufacturing Systems and Transformable Factories. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 27–45. https://doi.org/10.1007/3-540-29397-3_3
Koren, Y., Shpitalni, M., 2010. Design of reconfigurable manufacturing systems. Journal of Manufacturing Systems 29, 130–141. https://doi.org/10.1016/j.jmsy.2011.01.001
Kumar, R., Pandey, V., 2015. Job Shop Scheduling With Alternate Process Plan by Using Genetic Algorithm 8.
Kusiak, A., 1990. Intelligent Manufacturing Systems, Prentice-Hall international Series. Industrial and Systems Engineering.
Lameche, K., Najid, N.M., Castagna, P., Kouiss, K., 2017. Modularity in the design of reconfigurable manufacturing systems. IFAC-PapersOnLine, 20th IFAC World Congress 50, 3511–3516. https://doi.org/10.1016/j.ifacol.2017.08.939
Lee, K.S., Rahmand, M., Zhang, Y.F., Low, C.Y., 2001. A genetic algorithm based process planning system for mould base. IJCAT 14, 190. https://doi.org/10.1504/IJCAT.2001.000273
Li, L., Fuh, J.Y.H., Zhang, Y.F., Nee, A.Y.C., 2005. Application of genetic algorithm to computer-aided process planning in distributed manufacturing environments. Robotics and Computer-Integrated Manufacturing 21, 568–578. https://doi.org/10.1016/j.rcim.2004.12.003
Li, W.D., McMahon, C.A., 2007. A simulated annealing-based optimization approach for integrated process planning and scheduling. International Journal of Computer Integrated Manufacturing 20, 80–95. https://doi.org/10.1080/09511920600667366

Li, W D, Ong, S.K., Lu, Y.Q., Nee, A.Y.C., 2003. A Tabu Search-Based Optimization Approach for Process Planning, in: Palade, V., Howlett, R.J., Jain, L. (Eds.), Knowledge-Based Intelligent Information and Engineering Systems. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 1000–1007. https://doi.org/10.1007/978-3-540-45226-3_137

Li, W.D., Ong, S.K., Nee, A.Y.C., 2004. Optimization of process plans using a constraint-based tabu search approach. International Journal of Production Research 42, 1955–1985. https://doi.org/10.1080/00207540310001652897

Li, W. D., Ong, S.K., Nee, A.Y.C., 2003. A hybrid method for recognizing interacting machining features. International Journal of Production Research 41, 1887–1908. https://doi.org/10.1080/0020754031000123868

Li, W.D., Ong, S.K., Nee, A.Y.C., 2002. Hybrid genetic algorithm and simulated annealing approach for the optimization of process plans for prismatic parts. International Journal of Production Research 40, 1899–1922. https://doi.org/10.1080/00207540110119991

Lian, K., Zhang, C., Li, X., Gao, L., 2009. An Effective Hybrid Genetic Simulated Annealing Algorithm for Process Planning Problem, in: 2009 Fifth International Conference on Natural Computation. Presented at the 2009 Fifth International Conference on Natural Computation, IEEE, Tianjian, China, pp. 367–373. https://doi.org/10.1109/ICNC.2009.689

Liu, X., Yi, H., Ni, Z., 2013. Application of ant colony optimization algorithm in process planning optimization. J Intell Manuf 24, 1–13. https://doi.org/10.1007/s10845-010-0407-2

Ma, G., Zhang, F., 2012. Genetic Algorithms for Manufacturing Process Planning, in: Chiong, R., Weise, T., Michalewicz, Z. (Eds.), Variants of Evolutionary Algorithms for Real-World Applications. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 205–244. https://doi.org/10.1007/978-3-642-23424-8_7

Ma, G.H., Zhang, F., Zhang, Y.F., Nee, A.Y.C., 2002. An Automated Process Planning System Based on Genetic Algorithm and Simulated Annealing, in: Volume 3: 7th Design for Manufacturing Conference. Presented at the ASME 2002 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, ASMEDC, Montreal, Quebec, Canada, pp. 57–63. https://doi.org/10.1115/DETC2002/DFM-34159

Ma, G.H., Zhang, Y.F., Nee, A.Y.C., 2000. A simulated annealing-based optimization algorithm for process planning. International Journal of Production Research 38, 2671–2687. https://doi.org/10.1080/002075400411420

Mehrabi, M.G., Ulsoy, A.G., Koren, Y., 2000. Recongurable manufacturing systems: Key to future manufacturing. Journal of Intelligent Manufacturing 11, 403–419. https://doi.org/10.1023/A:1008930403506

Mirjalili, S., 2019. Genetic Algorithm, in: Evolutionary Algorithms and Neural Networks. Springer International Publishing, Cham, pp. 43–55. https://doi.org/10.1007/978-3-319-93025-1_4

MORAD, N., ZALZALA, A., 1999. Genetic algorithms in integrated process planning and scheduling. Journal of Intelligent Manufacturing 11.

Oduguwa, V., Tiwari, A., Roy, R., 2005. Evolutionary computing in manufacturing industry: an overview of recent applications. Applied Soft Computing 5.

Oliver, I.M., Smith, D.J., Holland, J.R.C., 1987. A Study of Permutation Crossover Operators on the Traveling Salesman Problem, in: Proceedings of the Second International Conference on Genetic Algorithms on Genetic Algorithms and Their Application. L. Erlbaum Associates Inc., Hillsdale, NJ, USA, pp. 224–230.

Ong, S.K., Ding, J., Nee, A.Y.C., 2002. Hybrid GA and SA dynamic set-up planning optimization. International Journal of Production Research 40, 4697–4719. https://doi.org/10.1080/00207540210155864

Paulo, J., Lashkari, R.S., Dutta, S.P., 2002. Operation allocation and materials-handling system selection in a flexible manufacturing system: A sequential modelling approach. International Journal of Production Research 40, 7–35. https://doi.org/10.1080/00207540110073028

Rao, R.V., 2011. Advanced modeling and optimization of manufacturing processes: international research and development, Springer series in advanced manufacturing. Springer, London ; New York.

Reddy, S.V.B., 1999. Operation sequencing in CAPP using genetic algorithms. International Journal of Production Research 37, 1063–1074. https://doi.org/10.1080/002075499191409

Rocha, J., Ramos, C., Vale, Z., 1999. Process planning using a genetic algorithm approach, in: Proceedings of the 1999 IEEE International Symposium on Assembly and Task Planning (ISATP'99) (Cat. No.99TH8470). Presented at the 1999 IEEE International Symposium on Assembly and Task Planning (ISATP'99), IEEE, Porto, Portugal, pp. 338–343. https://doi.org/10.1109/ISATP.1999.782981

Salehi, M., Bahreininejad, A., 2011. Optimization process planning using hybrid genetic algorithm and intelligent search for job shop machining. J Intell Manuf 22, 643–652. https://doi.org/10.1007/s10845-010-0382-7

Salehi, M., Tavakkoli-Moghaddam, R., 2009. Application of genetic algorithm to computer-aided process planning in preliminary and detailed planning. Engineering Applications of Artificial Intelligence 22, 1179–1187. https://doi.org/10.1016/j.engappai.2009.04.005

Schoen, M.P., 2005. Intelligent optimization techniques, genetic algorithms, tabu search, simulated annealing, and neural networks, D. T. Pham and D. Karaboga, Springer: Berlin, Heidelberg, New York; Springer London: London, 2000, 302pp, ISBN 1-85233-028-7. https://doi.org/10.1002/rnc.986

Shabaka, A.I., ElMaraghy, H.A., 2008. A model for generating optimal process plans in RMS. International Journal of Computer Integrated Manufacturing 21, 180–194. https://doi.org/10.1080/09511920701607741

Shabaka, A.I., Elmaraghy, H.A., 2007. Generation of machine configurations based on product features. International Journal of Computer Integrated Manufacturing 20, 355–369. https://doi.org/10.1080/09511920600740627

Shao, X., Li, X., Gao, L., Zhang, C., 2009. Integration of process planning and scheduling—A modified genetic algorithm-based approach. Computers & Operations Research 36, 2082–2096. https://doi.org/10.1016/j.cor.2008.07.006

Sivanandam, S.N., Deepa, S.N., 2007. Introduction to genetic algorithms. Springer, Berlin ; New York.

Solimanpur, M., Saeedi, S., Mahdavi, I., 2010. Solving cell formation problem in cellular manufacturing using ant-colony-based optimization. Int J Adv Manuf Technol 50, 1135–1144. https://doi.org/10.1007/s00170-010-2587-5

Srinivas, P.S., Raju, V.R., Rao, C.S.P., 2012. AN ANT COLONY OPTIMIZATION ALGORITHM FOR OPTIMIZATION OF PROCESS PLANS 12.

Stecke, K.E., Solberg, J.J., 1981. Loading and control policies for a flexible manufacturing system: International Journal of Production Research: Vol 19, No 5 [WWW Document]. URL (accessed 10.1.19).

Steudel, H.J., 1984. Computer-aided process planning: past, present and future. International Journal of Production Research 22, 253–266. https://doi.org/10.1080/00207548408942452
Su, Y., Chu, X., Chen, D., Sun, X., 2018. A genetic algorithm for operation sequencing in CAPP using edge selection based encoding strategy. J Intell Manuf 29, 313–332. https://doi.org/10.1007/s10845-015-1109-6
Sujono, S., Lashkari, R.S., 2007. A multi-objective model of operation allocation and material handling system selection in FMS design. International Journal of Production Economics 105, 116–133. https://doi.org/10.1016/j.ijpe.2005.07.007
Umbarkar, A.J., Sheth, P.D., 2015. CROSSOVER OPERATORS IN GENETIC ALGORITHMS: A REVIEW. ICTACT JOURNAL ON SOFT COMPUTING 06, 10.
Usher, J.M., Bowden, R.O., 1996. The application of genetic algorithms to operation sequencing for use in computer-aided process planning. Computers & Industrial Engineering 30, 999–1013. https://doi.org/10.1016/0360-8352(96)00048-4
Venter, G., 2010. Review of Optimization Techniques, in: Blockley, R., Shyy, W. (Eds.), Encyclopedia of Aerospace Engineering. John Wiley & Sons, Ltd, Chichester, UK, p. eae495. https://doi.org/10.1002/9780470686652.eae495
Wang, J., Du, B., Ding, H., 2011. A Modified Genetic Algorithm(GA) for Optimization of Process Planning - Google Search [WWW Document]. URL https://www.google.com/search?q=A+Modified+Genetic+Algorithm(GA)+for+Optimization+of+Process+Planning&oq=A+Modified+Genetic+Algorithm(GA)+for+Optimization+of+Process+Planning&aqs=chrome..69i57.279j0j4&sourceid=chrome&ie=UTF-8 (accessed 9.27.19).
Wang, J., Fang, X., Ding, H., 2016. An Improved Ant Colony Optimization Approach for Optimization of Process Planning. The Scientific World Journal 2016, 1–1. https://doi.org/10.1155/2016/5960614
Wang, Y.F., Zhang, Y.F., Fuh, J.Y.H., 2012. A hybrid particle swarm based method for process planning optimisation. International Journal of Production Research 50, 277–292. https://doi.org/10.1080/00207543.2011.571459
Yip-Hoi, D., Dutta, D., 1996. A genetic algorithm application for sequencing operations in process planning for parallel machining. IIE Transactions 28, 55–68. https://doi.org/10.1080/07408179608966252
Youssef, A.M.A., ElMaraghy, H.A., 2006. Modelling and optimization of multiple-aspect RMS configurations. International Journal of Production Research 44, 4929–4958. https://doi.org/10.1080/00207540600620955
Yun, Y., Moon, C., 2011. Genetic algorithm approach for precedence-constrained sequencing problems. J Intell Manuf 22, 379–388. https://doi.org/10.1007/s10845-009-0296-4
Zahid, T., Baqai, A.A., 2013. Multi-Criteria Optimization of Process Plans for Reconfigirable Manufacturing Systems: An Evolutionary Approach, in: Volume 2B: Advanced Manufacturing. Presented at the ASME 2013 International Mechanical Engineering Congress and Exposition, American Society of Mechanical Engineers, San Diego, California, USA, p. V02BT02A045. https://doi.org/10.1115/IMECE2013-64560
Zhang, F., Zhang, Y.F., Nee, A.Y.C., 1997. Using genetic algorithms in process planning for job shop machining. IEEE Trans. Evol. Computat. 1, 278–289. https://doi.org/10.1109/4235.687888
Zhang, H.C., 1994. Manufacturing Process Planning.
Zhou, R., Nee, A.Y.C., Lee, H.P., 2009. Performance of an ant colony optimisation algorithm in dynamic job shop scheduling problems. International Journal of Production Research 47, 2903–2920. https://doi.org/10.1080/00207540701644219

CERTIFICATE OF COMPLETENESS

It is hereby certified that the dissertation submitted by **NS Abdul Rafay Farooqi**, Reg. No. **00000172134**, Titled: ***Optimization of Process Plans by considering Material Handling Cost for RMS*** has been checked/reviewed and its contents are complete in all respects.

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