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AN INVESTIGATION OF CONVENTIONAL AND NON-CONVENTIONAL OPTIMIZATION TECHNIQUES INCNC MACHINING

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Abstract: In recent times, there has been a dramatic shift in the manufacturing techniques. The levels of automation and digital interfacing, particularly in machining, have increased to higher planes. Constantly growing demand and machining complexity has led to incorporation of a variety of methods to improve the machining accuracy and productivity. This paper investigates various conventional methods such as Taguchi method, RSM, linear programming, etc. and non-conventional methods like genetic algorithm, PSO, simulated annealing, etc. in the optimization of machining parameters and toolpath. The paper also highlights the advantages and drawbacks of different methods to set future scope of optimization in machining.

Keywords - *CNC, Cutting Parameters, Toolpath, Conventional, Non-conventional, Optimization.*

application-- --

I INTRODUCTION

In most manufacturing industries, task of programming a CNC machine is carried out through manual programming practices. In any such environment, selection of optimal machining data depends upon the person responsible for programming task, either programmer or operator. Skills and knowledge of programmer have a huge impact on firm‟sproductivity which many researchers have argued to be replaced by more reliable automatic programming approach. E. Poutsma suggested that product variety and batch size are driving factors for integrative and autonomous characterization of programming task[9].

In conventional systems, where part programmers are assigned CNC programming, the machining data is obtained through experience or handbooks (or a guess) which may be conservative and uneconomic leading to production limitations. K. Park and S. Kim [2] studied that the above selected machining data can prove to be incapable of eliminating inordinate amount of matching errors from tool failures such as tool deflection, wear, breakage, etc. Consequently, these conservative and non-optimal machining parameters results in low metalremoval rate. In such cases, optimal data is needed to be described to consider economic, technological and geometric limitations for recommended machining conditions [4].

The selection of optimal machining data and cutting conditions under the given machining situation was not an easy task and a topic for debate from 1980s to mid-1990s. S.H. Yeo et al. considered the decision ofmachiningparametersasa„knowledgebottleneck‟. It was primarily due to expanding range of manufacturing processes and materials, including rapidly diminishing number of skilled machinists[10]. They mentioned cutting tool selection, machine tool selection, cutting fluid selection, tool usage/cut selection, cutting speed/feed selection and checking against process constraints as a machining problem in a productionfloor.

Furthermore, they developed an expert system named „computerized machinability data base systems (CMDBS) to automate the process of machining data selection. CMDBS was one of the early implementation of expert system/optimization technique in CNC machines with following aims [10]:-

- Reduce productiondown-time.

- Production of more consistent and accurate parts.
- Compensate for lack of skillshortage.
- Capture and permanently retain knowledge within the organization.
- Rationalizedexpertise.
- Provide quick and easy update of new materials.

After success of CMDBS, a number of attempts were made to optimize CNC machining, from offline adjustments to online adaptive controls which enabled the programmer to save more time spending on selecting optimal values. A process of optimization can be directed to obtain different objective functions such as minimum cost, maximum production, maximum, or a combination of these (multi-objective optimization). Such an optimization is governed by a number of factor which require more comprehensive algorithms[4].

II CLASSIFICATION OF OPTIMIZATION TECHNIQUES

Over the time a number of optimization techniques have been implemented in CNC systems for optimization of machining process. Several researchers brought out the advantages and disadvantages of various techniques. They tested the potential of every technique in order to find their capabilities in solving a variety of problems related to machining. The successful implementation of optimization techniques offer a number of constraints for a particular machining environment, viz. data availability, design of models, boundary constraints, etc. It implies that the selection of an appropriate optimization technique depends upon type of problem to be solved, problem domain, and problem constraints.

The process of optimization of a cutting process is carried out in two stages namely, modelling of parameters and determination of optimal or near-optimal conditions. In the first stage, a relationship is formed between various parameters involved in a machining process. These parameters can be input – output parameters on in-process parameters. Some important parameters in machining process are, cutting speed, feedrate and depth of cut [3], [6]. The relationship between these parameters was first depicted by Taylor‟stool life equation. Some researchers have used the same equation in their works whereas someof them modified Taylor‟sequation according to their assumptions and objectives. Some important modelling techniques as described by I. Mukherjee and P.K. Ray are, Statistical regression technique, Artificial neural network and Fuzzy set-theory based modelling techniques[11].

In the second stage, optimization techniques are applied to obtain optimal or near-optimal machining data. To obtain the optimal data for a given machining environment with a particular objective function constrained to a number of input – output and in-process parameters is a significant and challenging task [11]. For solving such optimization problems numerous techniques has been developed which can be classified as Conventional and Non-conventional techniques. Conventional techniques are based on formulation of a mathematical model for the given machining conditions and environment. On the other side, non-conventional techniques do not rely on model formulation for theirfunction.

III CONVENTIONAL TECHNIQUES

The conventional techniques have been used for a long time in context of machining and computer numerical control. They can be implemented to a vast variety of problem domain and provide good results as compared to other techniques. The conventional techniques are *deterministic* approaches which doesn‟t predict the solutions but determine good solutions. These techniques are „model-based‟‟ which depend on modelling of a given system with given conditions and constraints. Suitable mathematical models, either mechanistic or empirical, are formed for a given machining condition and environment. Based on machining parameters such as cutting speed, feedrate and depth of cut, some models are generated which depict the relationship of these variables such as machining process models, cutting force models and tool wear models are common in literature [2].In machining and metal cutting, most of mathematical models are based on Taylor‟s tool life equation or some extended form of it. It provides a generic relationship between tool life and cutting speed as shown below:

$$V.T^n = C$$

where, V is the cutting speed (mm/min), T is tool life, n and C are Taylor‟s constant. The above equation in its general form is rarely used whereas extended Taylor‟s equation is used by a number of researchers and practitioners in their works, see [1], [6], [10], [12]–[15]. In the extended form, many factors are lumped together, such as workpiece hardness, rigidity of cutting system, chip thickness, and maximum or minimum allowable depth of cut.

Conventional techniques can be further categorized as experimental techniques and mathematical iterative techniques [11]. Experimental techniques include statistical design of experiment such as Taguchi method and Response Surface Design Methodology (RSM). The iterative techniques include Linear Programming (LP), Non-linear Programming (NLP) and Dynamic Programming (DP).Design of experiments have been extensively used in CNC machines for a long time. Many researchers have implemented and solved optimization problems with Taguchi method and RSM. These two techniques are also used in collaboration to solve multi-objective optimization problems. Taguchi method find applications in turning process very often in literature. Process parameters of machining, particularly turning, such as surface finish, tool wear and material removal rate (MRR), are selected as objective functions. Taguchi and RSM are applied to obtain set of optimal parameters satisfying objective functions in turning [16]–[20]. These methods are also implemented in milling and drilling processes [21], [22]. On the other hand, mathematical iterative techniques find limited scope and applications in CNC machines. M. Mendes et al. implemented LP for determination of part mix, tool allocation and process plan selection in CNC machining centers [23]. Linear programming is also implemented for velocity planning under confined feedrate, acceleration and jerk [24]. A. Sonomez et al. optimized cutting parameters for multi-pass milling operations maximizing production rate [25]. In their work, dynamic programming was used to determine optimum number of passes while a non-linear programming approach was used to obtain values of optimum cutting conditions. Dynamic programming has also been used to calculate optimizedtool-paths in 5-axis flank milling operations with good results [26], [27].

D. Goldberg emphasized that the solutions obtained through conventional methods are generally local optimum solutions, i.e. the solution they seek are the best in a neighborhood of the current point [7]. S. Yeo et al. have also considered that a system or procedure based on these methods generally compute pseudo-optimum solutions [10]. Other disadvantages are discussed in more details in following sections.

IV DRAWBACKS OFCONVENTIONAL TECHNIQUES

To find an optimal solution to an objective function formulated from models and constraints by using a suitable optimization technique is a difficult task for researchers. Conventional methods provided a good alternative to such tasks with ease of implementation. These methods have been found to be efficient to solving multi-attribute decision making problems, viz. multi-objective and process optimization [28]. Taguchi and RSM methods have been very successful in designing high quality products and processes of many different fields. Though they have been implemented in CNC machining for optimization of machining processes [19].

I. Mukherjee and P.K. Ray pointed out some shortcomings of these methods in their work [11]. They suggested following postulates related to drawbacks of experimental technique. According to the study, Taguchi method fails to deal with many important interactions in system design due to a limited number of arrays. Also, it can lead to sub-optimal results when number of experiments are not adequate enough. On the other side, Response Surface Design Methodology (RSM) is not cost effective to be implemented by manufacturers. Moreover, it has been found difficult to solve highly non-linear, multi-model objective functions. The mathematical iterative techniques are unable to handle overall cutting process complexities but specific aspects of cutting such as cutting force, tool wear, and temperature. This is because of inability to covert overall conditions in their respective domain. They are also found to be costly and unreasonable to adopt and implement in manufacturingunits.

The limitation of conventional methods, as above mentioned, point that the methods are not robust. With increasing complexity of problems, a combination of these techniques would be needed to optimize the process. The reasons for this can be summarized as mentioned by R. Saravanan[6]:

1. The convergence to an optimal solution depends on the chosen initialsolution.
2. Most algorithms tend to become stuck on a suboptimal solution.
3. An algorithm efficient in solving one machining optimization problem may not be efficient in solving a differentproblem.
4. Computational difficulties in solving multivariable problems, typically more than four.
5. Algorithms are not efficient in handling multiobjectivefunctions.

To overcome the above-mentioned setbacks of conventional methods, non-conventional methods are implemented for optimization of machining process.

V NON-CONVENTIONALTECHNIQUES

The non-conventional techniques are used in problem domain when adequate solutions cannot be obtained through conventional techniques. Conventional techniques as discussed above possess several disadvantages which makes them difficult to implement in certain machining problems. These problems usually arise due to a large solution search space with large number of local optima. In such cases it becomes difficult to direct a conventional method of optimization towards finding a good or near-optimal solution. On the other hand, non-conventional techniques provide a good option to solve multi-objective problems with varying machining conditions, environment and multiple process variables. These techniques are generally studied in two different yet co-related forms, namely ***heuristics*** and***metaheuristics***.

A heuristic technique or simply a heuristic, is a search method of problem solving that employs a rational method of finding a solution generally local in scope. The strategies for such methods are generally derived from past experiences. Though the solutions obtained are not guaranteed to be optimal, but sufficientfortheimmediategoals.Heuristicsconsist of set of rules and readily accessible information to control problem solving in machines. Such methods can be used to speed up the process of optimization and obtaining a satisfactory as well as acceptable solution at a reasonable computational cost [11],[29].

On the other side, metaheuristics are special purpose heuristics designed for a particular problem domain. These methods are typically higher-level heuristics that may provide a sufficiently good solution to an optimization problem, especially with incomplete or imperfect information or limited computation capacity. In metaheuristics, a sample of set of solutions is generated which is too large to be completely sampled. Also, some assumptions may be made about the optimization problem being solved which enables them to be used for a variety of problems.As compared to conventional optimization techniques, metaheuristics do not guarantee a global optimal solution to be obtained on some class of problems [30]. Many metaheuristics implement some form of stochastic optimization [31], which means they work by using probabilistic methods to solve problems [32]. Sometimes, a problem itself may be stochastic as well. In combinatorial optimization, by searching over a large set of feasible solutions, they can often find good solutions with less computation efforts than conventional optimization methods such as experimental techniques, iterative techniques or simple heuristics[30].

There are a wide variety of metaheuristics which can be classified along a number of properties. One approach is to categorize the type of search strategies such as local search and global search [30]. A popular example of local search metaheuristic is Hill Climbing used to find local optima. Other methods such as Simulated Annealing, Tabu Search, Iterated Local Search, etc. are general referred as both local and global search metaheuristics.Another classification dimension is single solution and population-based searches [30], [33]. The single solution approaches focus on improving a single candidate solution, whereas population-based search approaches maintain and improve multiple candidate solutions. Population characteristics affects the solution search and often used to guide the search. Single solution approaches include Simulated Annealing, Iterated Local Search, andVariable

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Neighborhood Search. Population-based approaches are Evolutionary Algorithms such as Genetic Algorithm, Genetic Programming, Evolutionary Programming, Differential Evolution and Evolution Strategy, Particle Swarm Optimization, Ant Colony Optimization, etc. [33].

A very active area of research is to design nature-inspired search and optimization metaheuristics which mimic the natural occurring phenomenon. Many recent metaheuristics, especially evolution- based algorithms are based on natural systems and principles. Other metaheuristics include Simulated Annealing, Evolutionary Algorithms, Ant Colony Optimization, Bee Colony Optimization and Particle Swarm Optimization. One practical issue in applying many natural computing algorithms, as mentionedby A. Brabazon et al., is the number of parameters which must be set in order to apply the algorithm to a particular problem [5].The optimization techniques mentioned hereof, have different advantages and disadvantages related to them. Although, there is a clearer distinction in their capabilities and characteristics. No single guideline or criterion exists in literature to choose the best optimization method for a particular problem space. Also, it is difficult to judge their performance any metal cutting process optimization problem. Hybrid methods and variants of existing methods possess different areas of application in CNC machining. Some methods are productive for parameters optimization in particular whereas some other methods are used in process planning and tool-path planning exercises. I. Mukherjee and P. Ray provided a list of typical applications and areas of different optimization methods, see[11].

VI GENETIC ALGORITHMS ANDCNC STANDPOINT

Genetic algorithm is one of the most explored form of meta-heuristics and particularly evolutionary algorithms. It was introduced by John Holland and his colleagues in 1975. Genetic algorithms operate on a population of candidate solutions. Initial population is selected randomly consisting of a fixed number of individuals. Genetic operators such as crossover and mutation are applied to the individuals on a random probabilistic basis. Application of operators result in a new population of offspring from previous population. The fitness values of the offspring are calculated using a fitness function which serves as a performance measure of the individuals. The individuals with higher fitness score have higher chances of survival and mating through upcoming generations. In other words, highly fit individuals are assigned a higher probability of being selected for reproduction than others. The process continues for a particular number of generations. The average fitness of individuals is likely to increase with evolution as fitter individuals are more likely to be selected and less fit individuals are discarded. The process of evolutions continues and reproduction is repeated unless a termination criterion is reached. The termination criteria may be reached when a particular number of generations is achieved, or specific average/maximum fitness value is obtained or a mean deviation of fitness of individuals [34]. A typical pseudo-code of genetic algorithms is presented below in Figure 1.

```
Encode parameter set and define fitness function;
Initialize population;
Calculate fitness of each individual of population;

repeat
  repeat
    Select parents from population based on fitness scores;
    Perform crossover on selected parents with probability, p_cross, to produce
    offspring;
    Perform mutation with probability, p_mut on offspring;
  until  n offspring have been created;
  Replace old population with newly created population of offspring;
  Calculate fitness of each individual of population;
until  termination condition;
```

Figure 1. A typical genetic algorithm pseudo-code. [5]

VII MERITS OF GENETICALGORITHMS

Unlike other conventional methods, genetic algorithms require parameter set of an optimization problem to be coded as a string of finite length. Initially, binary encoding was initially used as primary encoding scheme [5]. Overtime, as this scheme proved to be a limiting factor, other schemes such as tree, value and permutation encoding were used [35]. Genetic algorithms, therefore, are largely

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unconstrained by the limitations of other methods working directly with the parameter set. Also, GAs work with a rich database of points (solutions) simultaneously, climbing many peaks in parallel. In many of the conventional methods, a solution is determined from search space by moving from a single point to the next point. This involves using a set of transition rules (usually deterministic in nature) for determination of subsequent points and hence locates local peaks or optimum values in multimodal search spaces [7]. Whereas, the probability of finding a local peak in GAs is reduced with evolution.

Genetic algorithms tend to be more canonical than many search and optimization techniques. This is primarily due to the fact that GAs do not require any auxiliary information relating to an optimization problem. Some optimization techniques require much auxiliary information such as derivatives and process parameters in order to work properly. In case of GAs, only require payoff values such as fitness score of an individual string. One of the major distinctions of GAs from conventional methods is that genetic algorithms use probabilistic transition rules to guide their search. This may prove to be a huge confinement, but D. Goldberg points out the method to be more of a simple random search[7].

VIII OPTIMIZATION OFCUTTING PARAMETERS

Selection of parameters for enhanced surface finish, production rate, productivity and reduced machining time is desirable in every manufacturing industry. For this purpose, conventional methods such as design of experiments and iterative techniques have been applied with success. Most of the times such methods become imprecise to be implemented due to complexity of the machining problem. As discussed earlier, a machining optimization problem becomes complicated with intricate machining conditions involved. In such environment, it becomes obligatory to assign optimization problem to non-conventional techniques. Evolutionary algorithms and in particular, genetic algorithms have been successfully implemented in CNC machining for a longtime.

Y. Tarng et al. purposed such an implementation of genetic algorithms in CNC turning machines [36]. They used GA for controlling the contour error and setting of optimal controller parameters. Contour error is the shortest distance between the desired and actual contours obtained by a control system in CNC. This execution is sometimes regarded as one of the earliest implementations of genetic algorithms in CNC machines. L. Lin and G. Lee proposed a hierarchical fuzzy control system for low speed control of C-axis in CNC turning centers [37]. An evolutionary learning technique based on genetic algorithms was used to search for the best hierarchical structure of the controller along with the parameters. Later that year, Y. Liu and C. Wang presented a modified genetic algorithm for parameter optimization in CNC milling [34]. Modified GA, in which operating domain of optimizing variables could be changed, was claimed to increase convergence speed. F. Cus and J. Balic proposed a genetic algorithm optimization approach for cutting process. They considered a number of cutting constraints affecting the economics of machining; such as tool-life constraint, cutting force constraint, power, stable cutting region, chip-tool interface temperature, surface finish, roughening and finishing constraints. Experiments showed that accuracy and precision of results was reliable and GA approach provided a sufficient approximation to the true optimal solution in comparison with other optimization techniques[13].

IX OPTIMIZATION OFTOOL-PATHS

The distance travelled by a tool is a key component in machining to look upon. It contributes predominantly to machining time of any product. A vague toolpath in which tool has to travel distance more than required, claims increased machining time lowered productivity of a plant. Therefore, a particular attention is given to optimization of toolpaths in machining by a number of researchers. Optimization of a toolpath is directed to reduce the distance travelled by a tool to a cut a particular part or contour. Another parameter which is optimized is material removal rate. An optimal toolpath involving optimization of both these parameters increases the productivity of a plant, lowers machining time, and reduces tool travel thus toolwear.

In literature, optimum toolpath planning is traditionally regarded as a "travelling salesman problem" (TSP) [38]. Main objective of this problem lies is finding a suitable for tool such that required material is removed. But this classical problem have huge complexities associated with it. Also, TSP is found to have large search spaces which are very difficult to solve. Researchers have tried a number of methods to solve TSP, such as nearest neighbor, cutting planes, branch and bound, to name a few [38]. Due to complexity of problem, a new strategy to obtain good results is using evolutionary approach. Mainly, genetic algorithms have been extensively used in literature to solve such toolpath optimization problems.

One such strategy was presented by A. Krimpenis and G.C. Vosniakos. They proposed an optimization technique based on GA to optimize toolpaths for roughing operations on sculptured surfaces. Machining time was considered to be minimized for the goal of optimization [39]. They opted for a "machining cylinder slice" strategy for cutting hemispheres on 3-axis machining centers. Results obtained were optimum enough to find a good sequence of available tools and the scallop height distribution which produced minimum cutting time among the possible combinations. J.C Chen and T.X. Zhong proposed a hybrid genetic algorithm for the solution of such travelling salesman problem [38]. The so-called hybrid-coded genetic algorithm (HCGA) was used to optimize non-productive paths in CNC contour machining such as laser engraving and flame cutting. They represented the problem consisting of contours formed of productive and non-productive contours connected through nodes. One chromosome called master chromosome, used a real-number encoding scheme, represented the sequence of productive contours. Another chromosome called slave chromosome, used binary encoding scheme and represented the entry or exit node in the productive contours.Results showed effective performance of HCGA as compared to traditional GA. Initial non-productive paths were reduced from 24028.9 mm to 5964.7 mm after evolution to 200 generations [38]. This is a huge reduction in toolpath length, about 24.8%, and is evident from Figure 2.

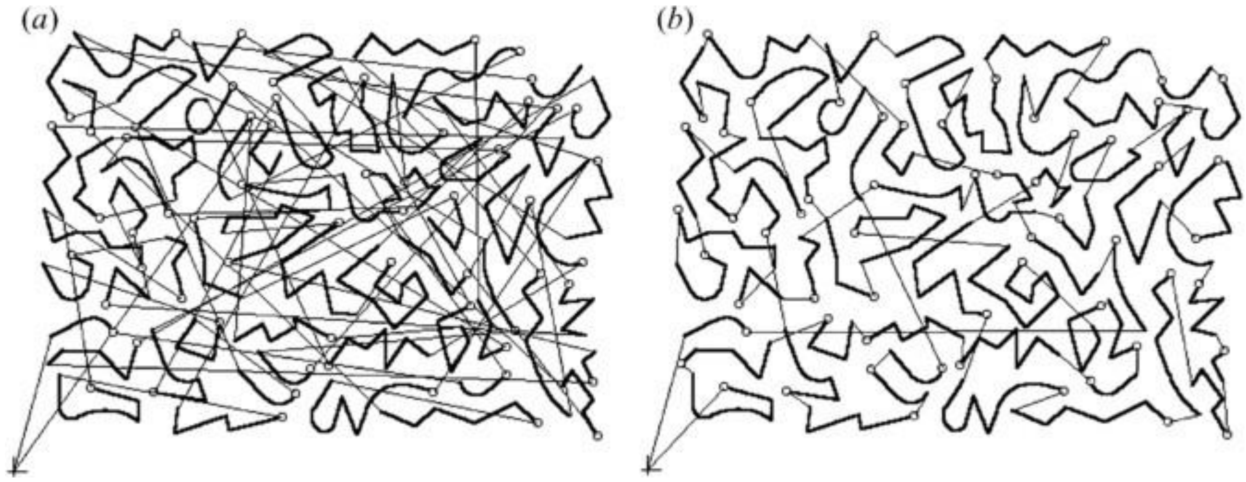

Figure 2. Comparison of initial and final non-productive paths [38].

M. Kovacic and J. Balic, proposed a concept to automate a manufacturing process and hence find an optimal cuttingtoolpath (or „strategy", as used by authors) in laser cutting [8]. The objective of presented concept was to develop an intelligent manufacturing system capable of intelligent decision making and programming based on evolutionary approach. The comparison of results obtained by them with a random toolpath showed a reduction of 31.81% in tool travel. Also, the programming costs were reduced by nearly 30% and production costs by 10%. Similar results were reported by B. Vaupotic, M. Kovacic et al [40].M. Lee and K. Kwon measured the performance of a proposed toolpath optimization based on genetic algorithms by relative effectiveness. The proposed method was similar to methods discussed above. Relative effectiveness was the percentage deviation from optimal values. Results showed 0.04%, 0.42% and 1.09% relative effectiveness in threedifferent cases. It showed the high accuracy of such algorithms [41].

The above presented literature is mainly focused on non-conventional CNC cutting machines such as laser, plasma, flame and water-jet machining. But still, optimization of toolpaths in CNC turning and machining centers is less emphasized. These two machining systems contribute to a large part of manufacturing industries, so it is important to consider optimization of toolpaths in these machines. This, in turn, can considerably affect the overall production costs of a manufacturing plant as compared to above discussed non-conventional manufacturing systems.

X TOOLPATH OPTIMIZATIONUSING DISCRETIZATIONFRAMEWORK

M. Kovacic et al. proposed an evolutionary concept of CNC toolpath optimization and programming for both machining and turning operations. Their concept was based on discretization of machinable area. A machinable area is considered to comprise of tool motions, which are discretized into squares in case of turning and boxes in case ofmilling,

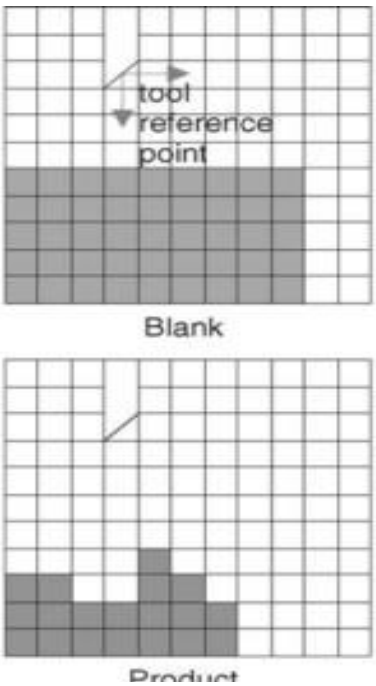

Figure 3. Discretization of machinable area. [42]

as shown inFigure 3. A tool, generally of one square thickness, can move in either direction and cut the material. Therefore, a toolpath can be considered as a sequence of squares. First, data input related to workpiece and product is processed, then machining area is divided into adequate number of squares. After discretization, definition of starting and final points of tool are given. In the end, an evolutionary approach based on genetic algorithms is applied to autonomously generate and optimize toolpaths (comprising of squares) through generations. Experimental results showed that conventional machining differed from genetic-assisted machining by 24.24% with respect to path length and for 85.71% with respect to tool wear. Another experiment suggested a 47.90% increase in productivity through path lengths as compared to conventional machining [42].

Discretization approach presented by M. Kovacic et al. is a fresh and innovative technique. This universal technique can yield valid results by reducing the complexity of toolpath generation and optimization. The size of search space is considerably reduced in this approach. The authors suggest that above technique is efficient and universal. Universality of the approach makes it usable for other NC machines also such as CMM, laser, plasma cutting machines, robots,etc.

A similar approach to above presented work is proposed by J. Barclay, V. Dhokia and A. Nassehi. In their study [43], they used a simplified model to reduce the search space of optimization problem. They divided the workpiece into layers, and each layer was discretized into squares as shown in Figure 4. Furthermore, a cutting tool can be considered as occupying a certain square or a number of squares at any time. The initial priority of the approach was to find a valid tool-path (i.e. sequence of squares) to cut desired area, then it was shifted to optimize those solutions to make them more efficient using genetic approach.They concluded that above method was able to perform an active search and respond to changes in product shape with ease. The method wasalso compared to a random search algorithm, and results showed that it found better solutions by chance. Resolution of a grid affects the approximation of a product shape. Increasing resolution of grid (i.e. small-sized squares) will result in better approximation of tool-paths but it would increase expense of complexity.

In the same year, A. Nassehi, W. Essink and J. Barclay proposed a discretization framework for generation and optimization of milling tool-paths [44]. The framework was based on evolutionary approach that allows various properties to be optimized without changing the algorithm. In order to generate a discretized model, a grid of equidistant points was superimposed over the geometry of a part being machined. Similar to above presented works, a toolpath represents a set of all points visited on the grid. Procedure for the same is shown in Figure 5.

After defining the boundary of a part, all the polylines and curves are offset by tool radius to determine the boundaries of desired tool-path. A grid is then superimposed on the part and all points falling outside the boundaries are deleted. If a tool is positioned at each individual point in a sequence without crossing the boundary, the part is machined and such a sequence of points contributes a feasible millingtool-path.

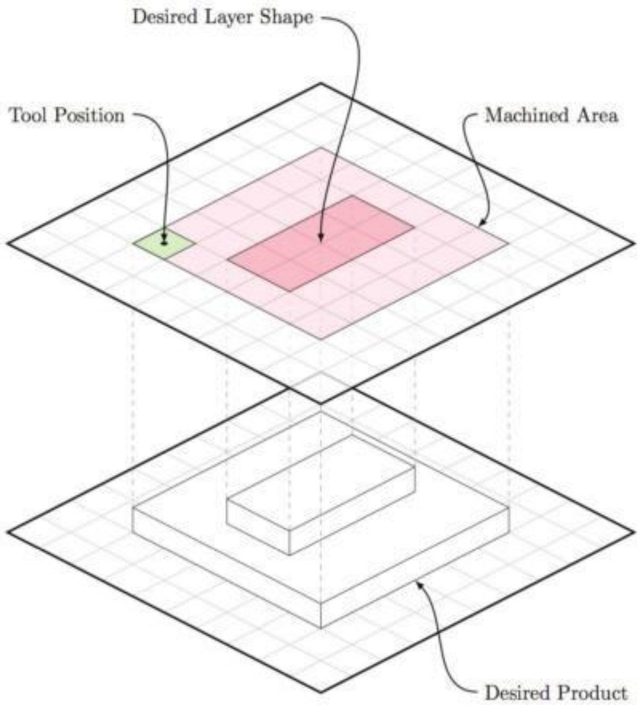

Figure 4. Discretization of a part into using square grid. [43]

Three objectives were selected to demonstrate the versatility of specified approach. These objectives were, minimization of cutting time, minimization of jerk and keeping constant cutter engagement. Results showed the effectiveness of proposed framework in optimizing these three objectives. The authors were able to generate different tool-paths for various objectives by only modifying the primary optimization objective.

Using such discretization approaches, CNC machining tool-paths can be easily generated and optimized. Discretization of a problem provides structure to the solutions and allow the well-established computationally efficient optimization methods such as evolution-based techniques.

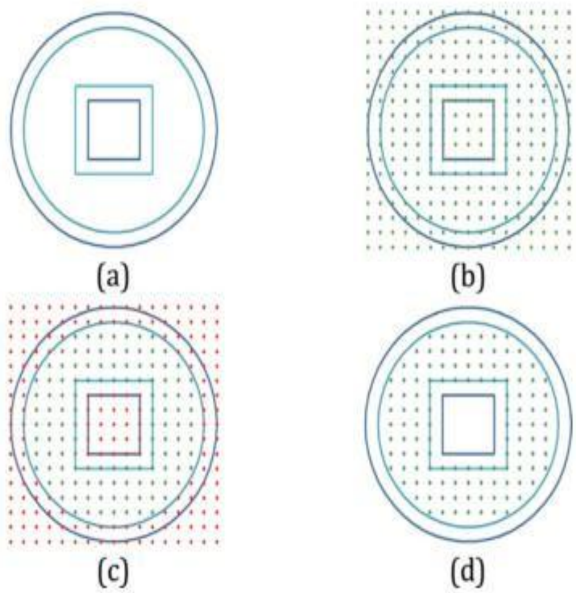

Figure 5. Steps in discretization algorithm. [44]

XI CONCLUSION

In recent times, conventional techniques have been replaced by evolutionary approach for toolpath optimization. This is evident from literature that most emphasis is kept on using genetic algorithms for this. The paradigm shift occurred because of complexity of toolpath problem. The complicacies in finding an optimal toolpath makes conventional methods unable to handle such problems. On the other hand, genetic algorithms can be easily implemented in a variety of problems. They are robust and efficient as compared to conventional methods. However, these are probabilistic approaches in which there are chances of non-optimal or pseudo-optimal solutions.

An exclusive drawback of evolutionary approaches, more specifically genetic algorithms is the execution time. Convergence to an optimal solution can take significant time in comparison to other methods. Sometimes, premature convergence can affect the quality of results. For better results, it is always advisable to perform higher number of evaluations. In other words, evolution of individuals should continue for longer periods of time to get fitter individuals. This would increase the computational complexity and costs associated withcomputation.

The criterion for a toolpath generation strategy that a toolpath must cover the entire machinable area without damaging any part of the finished surface. The material removal rate (MRR) should be maximized in respect of the surface quality and normal usage conditions of tool and machine (i.e. no breakage, no chatter, no overheating, etc.). A number of researchers have presented different algorithms and frameworks for toolpath generation based on above criterion, as discussed earlier. They have showed good results in obtaining cost and time effective toolpaths with less efforts. Automatic toolpath generation and programming can improve the productivity of a machining process by providing shorter programming time, optimum toolpaths, convenient cutting parameters, and error-free machining code. It can also relieve the part programmer of long and tedious part programmingefforts.

The generation of an optimal toolpath is a less explored area of CNC machining. Optimization of toolpaths is most often overlooked while emphasizing other aspects such as machining parameters. After selection optimal set of parameters, the tests are conducted with part programs (toolpaths) generated by CAM software which are not optimized. If an optimal toolpath is used with optimal parameters, gains would be much higher. The discretization framework used by a few researchers has shown a lot of potential in solving sequencing problems. The framework is efficiently applied to the machining process for generating optimal toolpaths. The combination of discretization with genetic algorithms has opened up new possibilities of toolpath optimization.

REFERENCES

1. 1.S. Gurel and M. S. Akturk, “Considering manufacturing cost and scheduling performance on a CNC turning machine,” Eur. J. Oper. Res., vol. 177, no. 1, pp. 325–343, 2007.

2.K. S. Park and S. H. Kim, “Artificial intelligence approaches to determination of CNC machining parameters in manufacturing:a review,” Artif.Intell. Eng., vol. 12, pp. 127–134,1998.

3.B. Malakooti and J. Deviprasad, “An Interactive Multiple Criteria Approach for Parameter Selection in Metal Cutting,” Oper. Res., vol. 37, no. 5, pp. 805–818, 1989.

4.E. H. T. Wee, A. Y. C. Nee, and T. N. Goh, “Off-line adaptive optimization of CNC lathe turning.,” Int. J. Prod. Res., vol. 28, no. 12, p. 2157,1990.

5.A. Brabazon, M. O"Neill, and S. McGarraghy, Natural Computing Algorithms. Springer,2015.

6.R. Saravanan, P. Asokan, and M. Sachithanandam, “Comparative analysis of conventional and non-conventional optimisation techniques for CNC turning process,” Int. J. Adv. Manuf. Technol., vol. 17, no. 7, pp. 471–476, 2001.

7.D. E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, Seventeent. Pearson Education, Inc., 2015.

8.M. Kovacic and J. Balic, “Evolutionary programming of a CNC cutting machine,” Int. J. Adv. Manuf. Technol., vol. 22, no. 1–2, pp. 118–124, 2003.

9.E. Poutsma and A. Zwaard, “Programming CNC Equipment - The Effects of Automation in Small Scale Industrial Enterprises,” Int. Small Bus. J., vol. 56, no. 3, pp. 460–474,1996.

10.S. H. Yeo, M. Rahman, and V. C. Venkatesh, “Development of an expert system for machinability data selection,” J. Mech. Work. Technol., vol. 17, no. C, pp. 51–60, 1988.

11.I. Mukherjee and P. K. Ray, “A review of optimization techniques in metal cutting processes,”Comput.Ind.Eng.,vol.50,pp.15–34, 2006.

12. A. Hatna, R. J. Grieve, and P. Broomhead, "Automatic CNC milling of pockets: geometric and technological issues," Comput. Integr. Manuf. Syst., vol. 11, no. 4, pp. 309–330,1998.
13. F. Cus and J. Balic, "Optimization of cutting process by GA approach," Robot. Comput. Integr. Manuf., vol. 19, no. 1–2, pp. 113–121, 2003.
14. S. Bharathi Raja and N. Baskar, "Optimization techniques for machining operations: A retrospective research based on various mathematical models," Int. J. Adv. Manuf. Technol., vol. 48, no. 9–12, pp. 1075–1090, 2010.
15. A. Turkcan and M. S. Akturk, "A problem space genetic algorithm in multiobjective optimization," J. Intell. Manuf., no. 14, pp. 363–378,2003.
16. M. Sarikaya and A. Güllü, "Taguchi design and response surface methodology based analysis of machining parameters in CNC turning under MQL," J. Clean. Prod., no. 65, pp. 604–616,2014.
17. I. Asiltürk and S. Neşeli, "Multi response optimisation of CNC turning parameters via Taguchi method-based response surface analysis," Meas. J. Int. Meas. Confed., vol. 45, no. 4, pp. 785–794, 2012.
18. I. Asiltürk and H. Akkuş, "Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method," Meas. J. Int. Meas. Confed., vol. 44, no. 9, pp. 1697–1704, 2011.
19. V. K. Sharma, Q. Murtaza, and S. K. Garg, "Response Surface Methodology & Taguchi Techquines To Optimization of C.N.C. Turning Process," Int. J. Prod. Technol., vol. 1, no. 1, pp. 13–31, 2010.
20. M. Nalbant, H. Gökkaya, and G. Sur, "Application of Taguchi method in the optimization of cutting parameters for surface roughness in turning," Mater. Des., vol. 28, no. 4, pp. 1379–1385,2007.
21. E. Bagci and Ş. Aykut, "A study of Taguchi optimization method for identifying optimum surface roughness in CNC face milling of cobalt-based alloy (stellite 6)," Int. J. Adv. Manuf. Technol., vol. 29, no. 9–10, pp. 940–947, 2006.
22. G. C. Onwubolu and S. Kumar, "Response surface methodology-based approach to CNC drilling operations," Journal of Materials Processing Technology, vol. 171, no. 1. pp. 41–47,2006.
23. M. Mendes, M. D. Mikhailov, and R. Y. Qassim, "A mixed-integer linear programming model for part mix, tool allocation, and process plan selection in CNC machining centres," Int. J. Mach. Tools Manuf., vol. 43, no. 11, pp. 1179–1184,2003.
24. W. Fan, X. S. Gao, C. H. Lee, K. Zhang, and Q. Zhang, "Time-optimal interpolation for five-axis CNC machining along parametric tool path based on linear programming," Int. J. Adv. Manuf. Technol., vol. 69, no. 5–8, pp. 1373–1388, 2013.
25. A. I. Sonomez, A. Baykasoglu, T. Dereli, and I. H. Filiz, "Dynamic optimization of multipass milling operations via geometric programming," Int. J. Mach. Tools Manuf., vol. 39, pp. 297–320, 1999.
26. P. H. Wu, Y. W. Li, and C. H. Chu, "Optimized tool path generation based on dynamic programming for five-axis flank milling of rule surface," Int. J. Mach. Tools Manuf., vol. 48, no. 11, pp. 1224–1233, 2008.
27. C. H. Chu, P. H. Wu, and W. T. Lei, "Tool path planning for 5-Axis flank milling of ruled surfaces considering CNC linear interpolation," J. Intell. Manuf., vol. 23, no. 3, pp. 471–480, 2012.
28. S. Moshat, S. Datta, A. Bandyopadhyay, and P. Pal, "Optimization of CNC end milling process parameters using PCA-based Taguchi method," Int. J. Eng. Sci. Technol., vol. 2, no. 1, pp. 95–102, 2010.
29. Wikipedia, "Heuristic." 2017.
30. C. Blum and A. Roli, "Metaheuristics in combinatorial optimization: Overview and conceptual comparison," vol. 35, no. 3, pp. 268–308, 2003.
31. L. Bianchi, M. Dorigo, L. M. Gambardella, and W. J. Gutjahr, "A survey on metaheuristics for stochastic combinatorial optimization," Nat. Comput., vol. 8, no. 2, pp. 239–287, Jun. 2009.
32. Wikipedia, "Stochastic." 2017.
33. E.-G. Talbi,Metaheuristics: from design to implementation. John Wiley & Sons,2009.

34. Y. Liu and C. Wang, "A Modified Genetic Algorithm Based Optimisation of Milling Parameters," Int. J. Adv. Manuf. Technol., no. 15, pp. 796–799, 1999.

35. N. Sadawi, "An Introduction to Genetic Algorithms." .

36. Y. S. Tarng, H. Y. Chuang, and W. T. Hsu, "An Optimisation Approach to the Contour Error Control of CNC Machine Tools Using Genetic Algorithms," Int. J. Adv. Manuf. Technol., no. 13, pp. 359–366, 1997.

37. L. C. Lin and G. W. Lee, "Hierarchical fuzzy control for C-axis of CNC turning centers using genetic algorithms," J. Intell. Robot. Syst., vol. 211938, no. 25, pp. 255–275, 1999.

38. J. C. Chen and T. X. Zhong, "A Hybrid-Coded Genetic Algorithm Based Optimisation of Non-Productive Paths in CNC Machining," Int. J. Adv. Manuf. Technol., pp. 163–168, 2002.

39. A. Krimpenis and G. C. Vosniakos, "Optimisation of multiple tool CNC rough machining of a hemisphere as a genetic algorithm paradigm application," Int. J. Adv. Manuf. Technol., vol. 20, no. 10, pp. 727–734, 2002.

40. B. Vaupotic, M. Kovacic, M. Ficko, and J. Balic, "Concept of automatic programming of NC machine for metal plate cutting by genetic algorithm method," J. Achiev. Mater. Manuf. Eng., vol. 14, no. 1–2, pp. 131–139,2006.

41. M. Lee and K. Kwon, "Cutting path optimization in CNC cutting processes using a two-step genetic algorithm," Int. J. Prod. Res., no. October 2014, pp. 37–41, 2007.

42. M. Kovacic, M. Brezocnik, I. Pahole, J. Balic, and B. Kecelj, "Evolutionary programming of CNC machines," J. Mater. Process. Technol., vol. 165, pp. 1379–1387, 2005.

43. J. Barclay, V. Dhokia, and A. Nassehi, "Generating Milling Tool Paths for Prismatic Parts Using Genetic Programming," Procedia CIRP, vol. 33, pp. 491–496, 2015.

44. A. Nassehi, W. Essink, and J. Barclay, "Evolutionary algorithms for generation and optimization of tool paths," CIRP Ann. - Manuf. Technol., vol. 64, no. 1, pp. 455–458, 2015.