MODELING AND OPTIMIZATION OF TURN-MILLING PROCESSES FOR CUTTING PARAMETER SELECTION

by

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To my family

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Abstract

Turn-milling is a relatively new machining process technology offering important advantages such as increased productivity, reduced tool wear and better surface finish. Because two conventional cutting processes turning and milling are combined in turn-milling, there are many parameters that affect the process making their optimal selection challenging. Optimization studies performed on turn-milling processes are very limited and consider one objective at a time. In this work, orthogonal turn-milling is considered where spindle and work rotational speeds, cutter (tool-work axes) offset, depth of cut and feed per revolution are selected as process parameters. The effects of each parameter on tool wear, surface roughness, circularity, cusp height, material removal rate (MRR) and cutting forces were investigated through process model based simulations and experiments carried out on a multi-tasking CNC machine tool. Tool life and surface roughness are formulated including cutter offset for the first time in this present work. Also, for the first time, turn-milling process is defined as a multi-objective problem and an effective method is proposed to handle this optimization problem. Minimum surface error, minimum production cost and minimum production time are aimed at the same time, and results are generated for selection of optimal cutting process parameters. After optimal parameter sets are found, they are compared with the parameters proposed by tool suppliers in machining tests. In addition, orthogonal turn-milling process is compared with conventional turning process comprehensively in order to demonstrate the process advantages.

Keywords: Turn-milling, Multi-objective optimization, Cutting parameter selection, Cutter offset, Circularity, Material removal rate (MRR)

FREZEYLE TORNALAMA SÜREÇLERİNİN KESME PARAMETRELERİ SEÇİMİ İÇİN MODELLENMESİ VE ENİYİLENMESİ

Mehmet Emre Kara

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Tez Danışmanı: Prof Dr. Erhan Budak

Özet

Frezeyle tornalama teknolojisi, takım aşınmasını önemli ölçüde azaltan dolayısıyla yüksek takım ömrü sağlayan, iyi bir son yüzey sunan ve yüksek üretkenliğin mümkün olduğu görece yeni bir talaşlı imalat sürecidir. Frezeyle tornalama, iki geleneksel yöntemin bir araya getirilmesi ile oluştuğu için süreci etkileyen parametre sayısı da geleneksel yöntemlere göre fazladır. Bu yüzden, süreci eniyileyen kesme parametreleri seçimi zorlu bir hale gelmektedir. Frezeyle tornalama süreçleri üzerinde yapılan eniyileme çalışmaları çok kısıtlı olmakla birlikte, yapılan çalışmalarda sadece tek bir amaç göz önünde bulundurulmaktadır. Bu çalışmada dik frezeyle tornalama süreci ele alınarak iş mili ve iş parçası dönme hızları, takım-iş parçası eksen farkı, kesme derinliği ve eksenel yöndeki ilerleme sürecin kesme parametreleri olarak seçilmiştir. Her bir parametrenin takım aşınması, yüzey pürüzlülüğü, yuvarlaklık, pürüz yüksekliği, malzeme kaldırma hızı ve kesme kuvvetleri üzerine olan etkileri, benzetime ve çok amaçlı CNC tezgahında yapılan deneylere dayalı modellere göre incelenmiştir. Takım-iş parçası eksen farkı göz önünde bulundurularak takım aşınması ve yüzey pürüzlülüğü ilk kez bu çalışmada matematiksel olarak formüle edilmiştir. Ayrıca ilk defa frezeyle tornalama süreci çok kriterli eniyileme problemi olarak modellenmiş ve bu problemin çözümünde kullanılabilecek yöntemler araştırılmıştır. Minimum yüzey hatası, minimum maliyet ve minimum üretim zamanı aynı anda hedeflenmiş ve süreci eniyileyen kesme parametreleri setleri elde edilmiştir. Eniyileme sonucu elde edilen kesme parametreleri ve takım tedarikçisinin önerdiği kesme parametreleri kullanılarak iki farklı deney yürütülmüş ve bir karşılaştırma yapılmıştır. Ayrıca süreç avantajlarını görmek adına, frezeyle tornalama süreci, geleneksel tornalama süreciyle kıyaslanmıştır.

Anahtar kelimeler: Frezeyle tornalama, Çok kriterli eniyileme, Kesme parametreleri seçimi, Takım-iş parçası eksen farkı, Yuvarlaklık, Malzeme kaldırma hızı

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CHAPTER 1 INTRODUCTION

Manufacturing is the process of transforming raw materials into finished goods to use them functionally. Basically it is a value-adding activity, where the conversion of materials into products adds value to the original material. Thus, the objective of the a company engaged in manufacturing is to add value and do so in the most efficient manner, using the least amount of time, material, money, space, and labor.

Manufacturing processes are often grouped into four basic “families”, as casting, deformation, consolidation and material removal processes. Casting processes exploit the properties of a liquid as it flows into and assumes the shape of a prepared container, and then solidifies upon cooling. Deformation processes exploit the ductility or plasticity of certain materials, mostly metals, and produce the desired shape by mechanically moving or rearranging the solid. Consolidation processes build a desired shape by putting smaller pieces together. Included here are welding, brazing, soldering, adhesive bonding, and mechanical fasteners. The material removal processes remove selected segments from an initially oversized piece. Traditionally, these processes have often been referred to as machining, a term used to describe the mechanical cutting of materials. The more general term, material removal, includes a wide variety of techniques, including those based on chemical, thermal, and physical processes.

Machining (e.g. turning, milling, drilling) is the most widespread metal shaping process in mechanical manufacturing industry. It is the process of removing unwanted material from a work piece in the form of chips to obtain desired geometry where tight tolerances and finishes are required. To perform the operation, relative motion is required between the tool and work. This relative motion is achieved in most machining operations by means of a primary motion, called the cutting speed, and a secondary motion, called the feed. The shape of the tool and its penetration into the work surface, combined with these motions, produces the desired geometry of the resulting work surface. The predominant cutting action in machining involves shear deformation of the work material to form a chip; as the chip is removed by using cutting tool that is harder and stronger than work piece material, a new surface is exposed. Conventional operations, turning, milling, broaching, drilling, grinding and non-traditional operations, EDM, LBM, EBM are the basic metal cutting operations.

Turning is a machining process in which a cutting tool, typically a non-rotary tool bit, describes a helical toolpath by moving linearly while the work piece rotates. When turning, a piece of relatively rigid material (such as metal, plastic or wood) is rotated and a cutting tool is traversed along 1, 2, or 3 axes of motion to produce precise diameters and depths. In Figure 1.1 simple external turning operation can be seen. Turning can be either on the outside of the cylinder or on the inside (also known as boring) to produce tubular components to various geometries. The turning processes are typically carried out on a lathe, considered to be the oldest machine tools, and can be of four different types such as longitudinal turning, profile turning, face turning and external grooving. In general, turning uses simple single-point cutting tools. Turning processes can produce cylindrically symmetric materials such as straight, conical, curved, or grooved work piece.

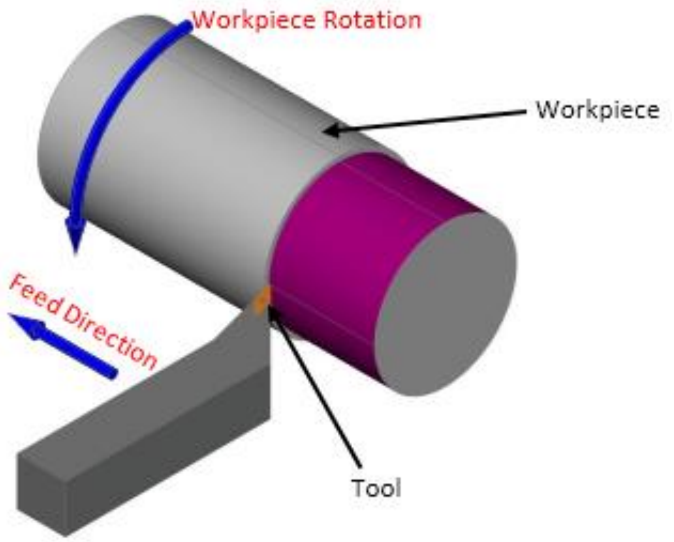


Figure 1.1: Longitudinal turning process.

Several cutting processes and machine tools are capable of producing complex shapes typically with the use of multitooth cutting tools. Milling is one of the most versatile machining processes, in which a multitooth cutter rotates along various axes with respect to the work piece. Milling includes a number of versatile machining operations that use a milling cutter, a multitooth tool that produces chips. The type of milling operations such as slab milling, face milling, end milling are some of the examples for milling operations. Face milling operation can be seen in Figure 1.2.

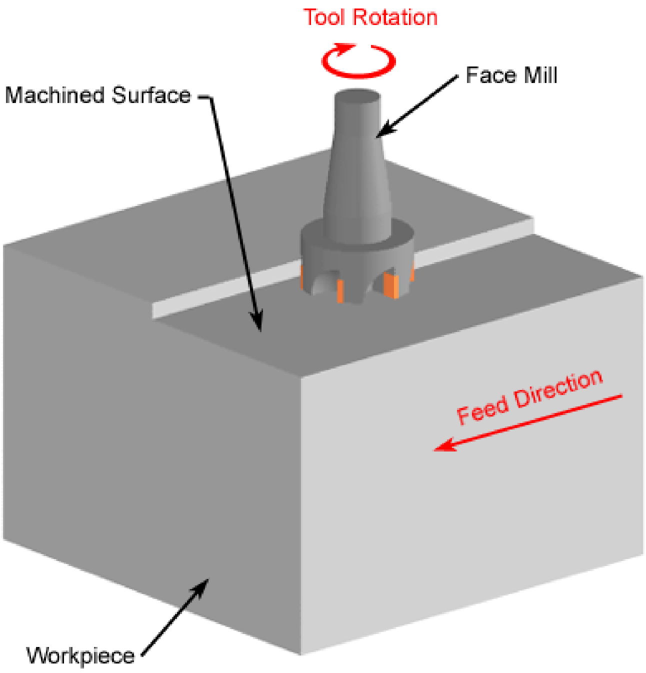


Figure 1.2: Face milling process.

1.1 Problem Definition

Turn-milling is a promising method for machining of cylindrical and non-coaxial (eccentric) parts with improved productivity. This method consists of turning and milling operations. Essentially it is a turning operation carried out using a milling cutter. In turn-milling cutting tool and work piece rotate around their own axes simultaneously. Owing to these special aspects, turn-milling offers several advantages. First of all, due to rotational movements of both tool and work piece, high cutting speed can be achieved in turn-milling operations. This is an important advantage particularly for parts with large diameter which cannot be rotated at high speeds. Furthermore, because of the interrupted cutting in turn milling, chips are broken and cutting temperature reduces which in turn decreases tool wear and increases tool life. Lower cutting temperatures make also higher cutting speeds possible. Additionally high surface quality and low cutting forces can be obtained in turn-milling [1,2].

Turn-milling is a relatively new concept in manufacturing technology, where in both, the work piece and the tool, are given rotary movements simultaneously. After 1980's, as products become increasingly complex and ever-increasing demands of production efficiency, shapes have become more intricate, and precision, efficiency and other requirements have become more sophisticated. In many cases, conventional processes may not meet these requirements. Conventional manufacturing processes, e. g. turning or milling, often approach their limits with regard to technology and economy especially in manufacturing of difficult parts either due to their shape, size, material or quality requirements. For example, in turning the rotational speed is limited by the centrifugal forces particularly for parts with large diameter. Turn-milling which is a combination of these two processes opens new ranges of application in the manufacturing. The productivity could be much greater in comparison to the conventional turning.

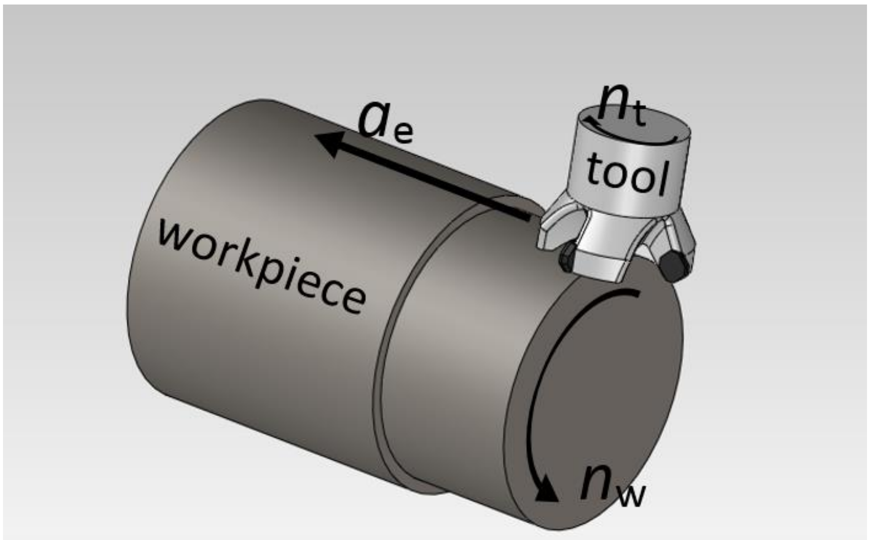


Figure 1.3: Orthogonal turn-milling operation.

Even though turn-milling offers many advantages, its use is not widespread. This is primarily caused by implementation of turn-milling operation is complicated and relatively difficult than other methods. In addition, the process consist more cutting parameters but there is no proposed method for the selection of these parameters. In order to overcome this lack of knowledge, process must be described comprehensively and an appropriate cutting parameter selection method should be provided for turn-milling processes. Moreover, to obtain all the benefits of this new machining approach, optimization studies must be carried out within parameter selection process.

1.2 Literature Survey

At the end of the 1800s Tilghman [3] used milling cutter instead of turning tool to reduce temperature at the contact zone. Academic studies on turn-milling, on the other hand, started in 1990s. Schulz et al. [4] stated that by integrating conventional turning and milling machine tools with each other in the creation of new machine tools, in particular setup time is reduced and it is possible to shorten production time and reduce costs. Schulz [5] divided turn-milling operations into two groups: orthogonal and co-axial. In the study, plain bearing half liners are machined and it is showed that better surface roughness is achieved in comparison to turning operation. In another study of Schulz [6] kinematic conditions and its influence on the tool wear and surface roughness are handled.

Recent studies on turn-milling have mostly focused on experimental investigation of the surface quality. Kopac and Pogacnik [7] investigated effects of tool position according to the work piece and vibrations on the surface quality. In same study, they indicated eccentricity (tool-work axes offset) effect on surface roughness in orthogonal turn-milling. Choudhury et al. [8] studied effects of spindle speed and feed rate for different work piece materials for orthogonal turn-milling and compared the surface roughness with those obtained by conventional turning. They claim that 10 times better surface quality can be achieved by turn-milling compared to turning. In a later study, Choudhury et al. [9] continued their work on the surface roughness in orthogonal turn-milling this time including effects of work piece rotational speed, cutter diameter and depth of cut. They indicated that the surface roughness in turn-milling is also better than the conventional milling. Neagu et al. [10] researched the kinematics of orthogonal turn-milling based on circularity, cutting speed and tool geometry. As a conclusion they claimed that turn-milling can achieve up to 20 times higher productivity than turning. Savas and Ozay [11] investigated effects of cutting parameters on the surface roughness in tangential turn-milling which is a new method developed by them. As a result of their studies, they observed that the obtained surface roughness is close to the grinding quality. Filho [12] studied orthogonal turn-milling by using a five axis machining center to measure cutting forces and compared them with the analytical model predictions. Cai et al. [13] carried out orthogonal turn-milling experiments with different machining parameters and obtained conclusions about cutter wear and work piece roughness. Zhu et al. [14] described surface topography in orthogonal turn-milling, and proposed mathematical models to describe theoretical surface roughness and topography of rotationally symmetrical work piece.

Previous researches [15] in machining process optimization have focused on mathematical modeling approaches to determine optimal cutting parameters with regard to various objective functions. Also the latest techniques for optimization include ant colony technique, particle swarm optimization (PSO), genetic algorithm (GA), Taguchi technique and response surface methodology (RSM) are being applied successfully in industrial applications for optimal selection of process variables in the area of machining. Three main objectives have been recognized mostly as part of the single-objective optimization problems: 1) minimizing surface roughness [16-27]; 2) minimizing production or machining cost [28-47]; and 3) maximizing production rate or minimizing cycle time [48-55]; or a combined criterion based on a weighted sum of these [56-63].

Beside these ones, researchers have begun to include more than one objective into their studies to make the problem more realistic by using multi-objective optimization approaches for cutting parameter optimization. Multi-objective optimization (MOO) addresses the issue of competing objectives using concepts first introduced by Edgeworth [64], then expanded and developed by Pareto [65], the French-Italian economist who established an optimality concept in the field of economics based on multiple objectives. A Pareto front [66] is generated that allows designers to trade-off one or more objectives against another. The first application of evolutionary algorithms in finding multiple trade-off solutions in one single simulation run was suggested and worked out in 1984 by David Schaffer [67]. That first method was developed on selection, crossover and mutation operations. But the field was not attracted researchers until 1989 when David Goldberg [68] suggested a non-dominated sorting method in his book about genetic algorithms in 1989. Further developments on multi-objective evolutionary algorithms were happened starting from 1993 and still continues to develop today.

In the area of machining, Karpat and Ozel [69] studied three objective optimization problem based on surface roughness, machining time and material removal rate and they introduced a procedure to formulate and solve optimization problems by particle swarm optimization technique. Abburi and Dixit [70] used GA and sequential quadratic programming (SQP) methods to minimize total production time with constraints of tool life, surface finish, cutting force and machine power. Yang and Natarajan [71] achieved to obtain optimal set of machining parameters for minimum tool wear and maximum material removal rate in turning process using elitist non-dominated sorting genetic algorithm (NSGA-II) approach. Another studies about application of multi-objective optimization methods on machining processes can also be found in the literature [72-78].

Optimization studies on turn-milling started with Pogacnik and Kopac [79]. This experimental study presents guidelines on how to avoid dynamic instability by using optimum entry-exit conditions which can be achieved through a proper set-up of the process parameters. As a result, they proposed a decision diagram. Savas and Ozay [80] performed a study of cutting parameter optimization to minimize surface roughness in tangential turn-milling process using genetic algorithm based on experimental results.

1.3 Organization of the Thesis

This thesis is divided into 7 chapters.

After this introductory Chapter 1, fundamentals, configurations and parameters of turn-milling processes are presented in Chapter 2.

In Chapter 3, objectives of the optimization process are presented. In order to define tool life and surface roughness objectives completely some experiments are needed which are also given in this chapter.

Chapter 4 is dedicated to multi-objective optimization methods which are discussed extensively in this chapter.

In Chapter 5, the proposed optimization methods are applied into our problem and results are presented. Optimization procedure and results are discussed.

In Chapter 6, conventional turning process is compared with orthogonal turn-milling process in all aspects. Some experimental results are also given.

In Chapter 7, conclusions obtained from this study are presented. Results are summarized and future work is outlined in this area.

1.4 Summary

In introduction chapter, information is given about machining processes and turn-milling. Problems encountered in turn-milling processes are also defined. Due to rotation of the work piece and tool at the same time, turn-milling has relatively complex geometry and as a result there are more cutting parameters to be selected. An overview of previous studies on turn-milling processes is given in here. Detailed literature survey is also provided on optimization of machining processes and solution methods. In addition, optimization studies in turn-milling are also mentioned. Finally layout of the thesis is given at the end of this chapter.

CHAPTER 2 TURN-MILLING PROCESSES

2.1 Fundamentals of Turn-Milling Process

Conventional manufacturing processes, e.g., turning or milling, often approach their limits with regard to technology and economy. In turning operations, high cutting speeds are limited due to the centrifugal stress of the clamping chuck. In milling, the limitation is due to the centrifugal forces acting upon the tool. These limitations can be overcome if the rotation of the work piece is combined with the motion of the rotating tool.

Turn-milling is a relatively new concept in manufacturing technology, where in both, the work piece and the tool, are given a rotary movement simultaneously. In order to understand this new process, turning and milling must be known thoroughly. On multi-tasking machines many operations such as turning, milling and drilling can be performed, although limited operations can be carried on turning or milling machines.

In general, as an advanced technology turn-milling is widely used in machining of crankshafts, cams and other complex parts. With the help of multi-teeth tools, it has the ability to obtain high surface-quality with high production rate. It offers an ability to get flat and also cylindrical shapes. It has several advantages compared to conventional turning and milling however, it has more complex geometry than these other methods.

2.2 Mill-Turn Machine Tools

Despite all advantages, turn-milling requires integrated mill-turn machining centers. That is an obstacle in spreading this technology over areas with lower economic power. Yet, there is also possible approach to make this technology closer to metal cutting industry by combining turning centers with live tooling. This combination might be done in an acceptable manner and can be effectively performed on universal lathes.

Mill-turn centers are machines that are capable of both rotating-work piece operations (turning) and rotating-tool operations (namely milling and drilling). Generally these machines are based on lathes. The machine is typically recognizable as a horizontal or vertical lathe, with spindles for milling and drilling simply available at some or all of the tool positions. The function of mill-turn machines is similar to the combination of the 3-axis NC lathe, the 4-axis NC mill and the drill machine [82]. The turrets on mill-turn machines are equipped with common turning cutters and live tools. Live tools provide milling, drilling, counterboring, slotting, rolling, sawing, deburring, broaching, and even thread cutting within the same setup. With a machine such as this, a part requiring a variety of operations can be machined in one setup, particularly if a sub-spindle allows the part to be passed from one spindle to another during machining [82,83].

More recently, introduced mill-turn machines depart from the lathe design into something much more like a hybrid machine. Many shops have discovered that, even though these machines developed from lathes, they are not necessarily limited to round parts. Various non-round parts can be machined on the same platform as efficiently.

Advantages of using mill-turn machines include significantly higher tolerances and lower machining cycle times since a work piece can be completely machined from raw stock to finished part on the same machine in a single setup [81].

2.3 Configurations of Turn-Milling

Basically there are three types of turn-milling operation depending on the rotation axes of cutting tool, work piece and contact area between them. First, orthogonal and co-axial turn-milling processes were introduced in 1990 by Schulz [5], after, in 2007 Savas and Ozay [11] developed a new method which they called tangential turn-milling. Movement systems and contact conditions of these methods are shown in Figure 2.1.

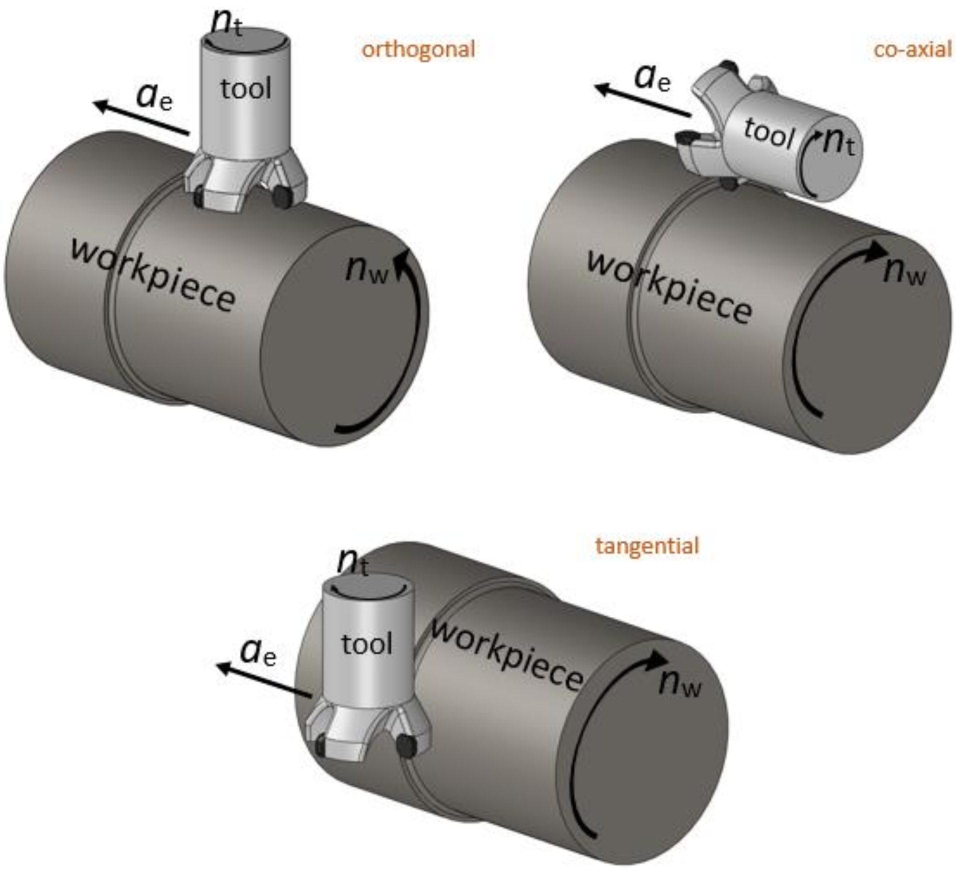


Figure 2.1: Turn-milling types and motion systems.

The position of the tool determines whether it is orthogonal, co-axial or tangential. Depending on the type, the chip formation differs but as common in all three types the chip is formed by combination of two motions: work piece rotation and feed in axial direction. As a result of this we have two different feed rates, circumferential and axial feed rates. Circumferential feed includes relative motion of tool and work piece rotations where degree of penetration is related to the ratio of tool and work piece rotational speeds. For the axial feed, the mechanism is similar to conventional milling where tool radius and feed are important for the engagement limits.

2.3.1 Orthogonal Turn-Milling

Orthogonal turn-milling operation can be seen in Figure 2.2 schematically. In orthogonal turn-milling the cutting tool is perpendicular to the work piece rotation axis. That's why in orthogonal turn-milling the chip is formed by the action of side and bottom part of the cutting tool. In orthogonal turn-milling, cutting motion comes from tool rotation and feed motion comes from work piece rotation with tool movement which is parallel to axis of the work piece.

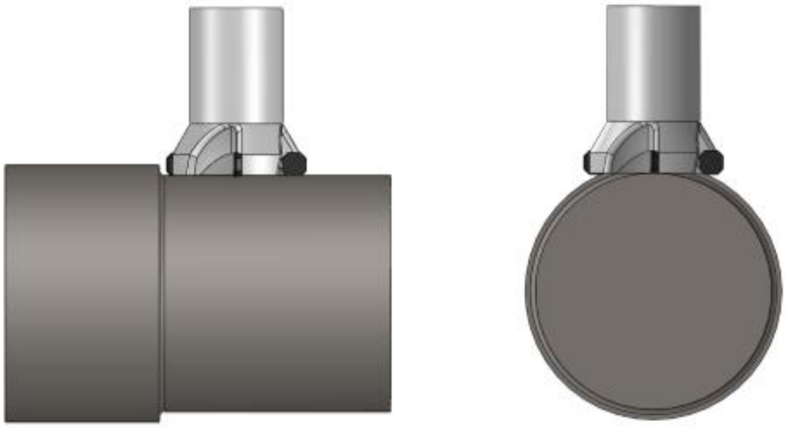


Figure 2.2: Orthogonal turn-milling.

In this type of turn-milling, it is possible to offset the tool in *Y*-axis however as result of this chip thickness changes. Parameter that defines this arrangements between work piece and tool is called tool *Y*-axis compensation or shortly eccentricity or cutter offset. When cutting tool rotation axis and work piece rotation axis intersect, operation is called concentric orthogonal turn-milling, otherwise if there is no intersection, operation is called eccentric orthogonal turn-milling. These two cases are shown in Figure 2.3.

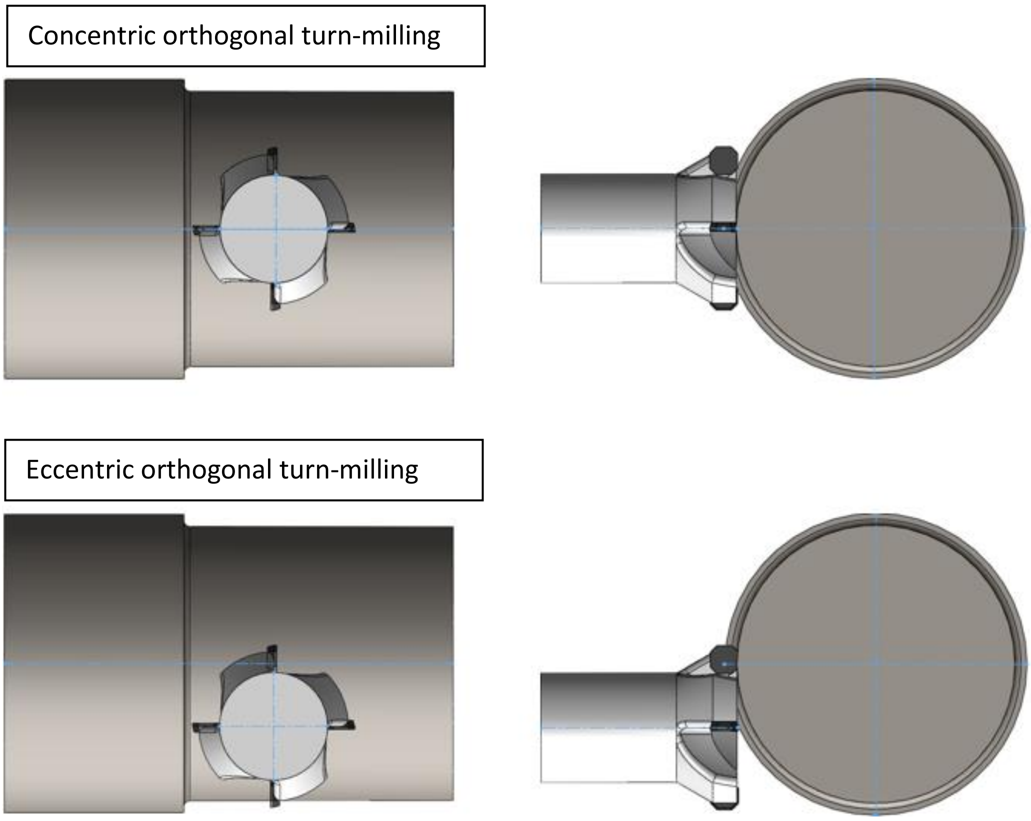


Figure 2.3: Cutter offset in orthogonal turn-milling.

Cutter offset is a peculiar parameter in orthogonal turn-milling. This compensation in orthogonal turn-milling causes change in chip formation whereas offset value increases only side of the cutting tool is involved in the chip formation.

Figure 2.4 shows the procedure to obtain the uncut chip geometry. The uncut chip geometry is a basic information needed in process modeling, and can be obtained by considering the initial and the final positions of the tool within one tool revolution.

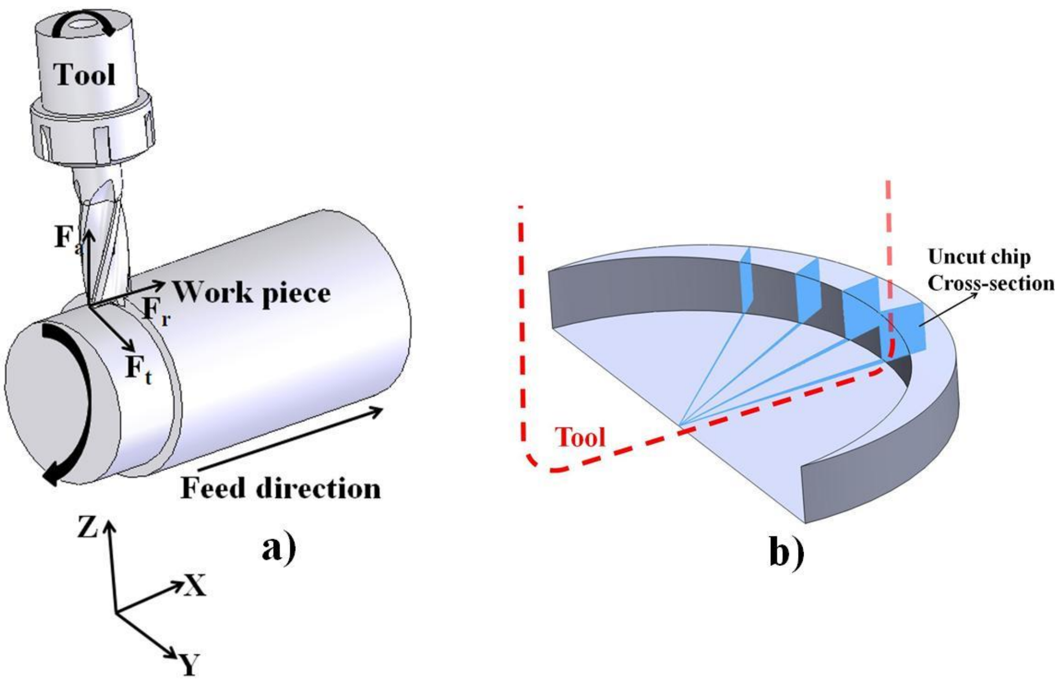


Figure 2.4: a) Orthogonal turn-milling operation b) Uncut chip geometry in orthogonal turn-milling [84].

2.3.2 Co-Axial Turn-Milling

Co-axial turn-milling is operation that axis of cutting tool and work piece are in the same direction. It enables to machining of inner and outer surface of the work piece. However in this type of turn-milling, total machining length is limited by the cutter length. Configuration of this type of turn-milling process is shown in Figure 2.5.

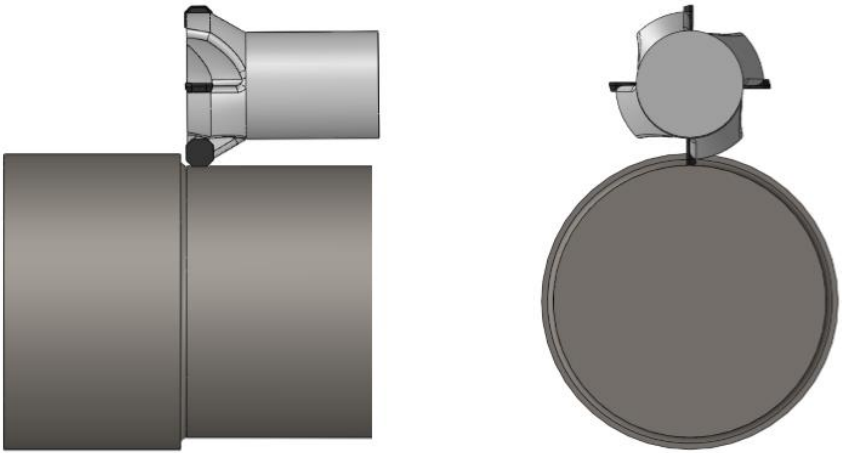


Figure 2.5: Co-axial turn-milling.

Figure 2.6 describes the procedure for determining the uncut chip geometry for co-axial turn-milling. Unlikely the orthogonal turn-milling there are no line boundaries in co-axial turn-milling, the chip geometry in this case is formed by arcs.

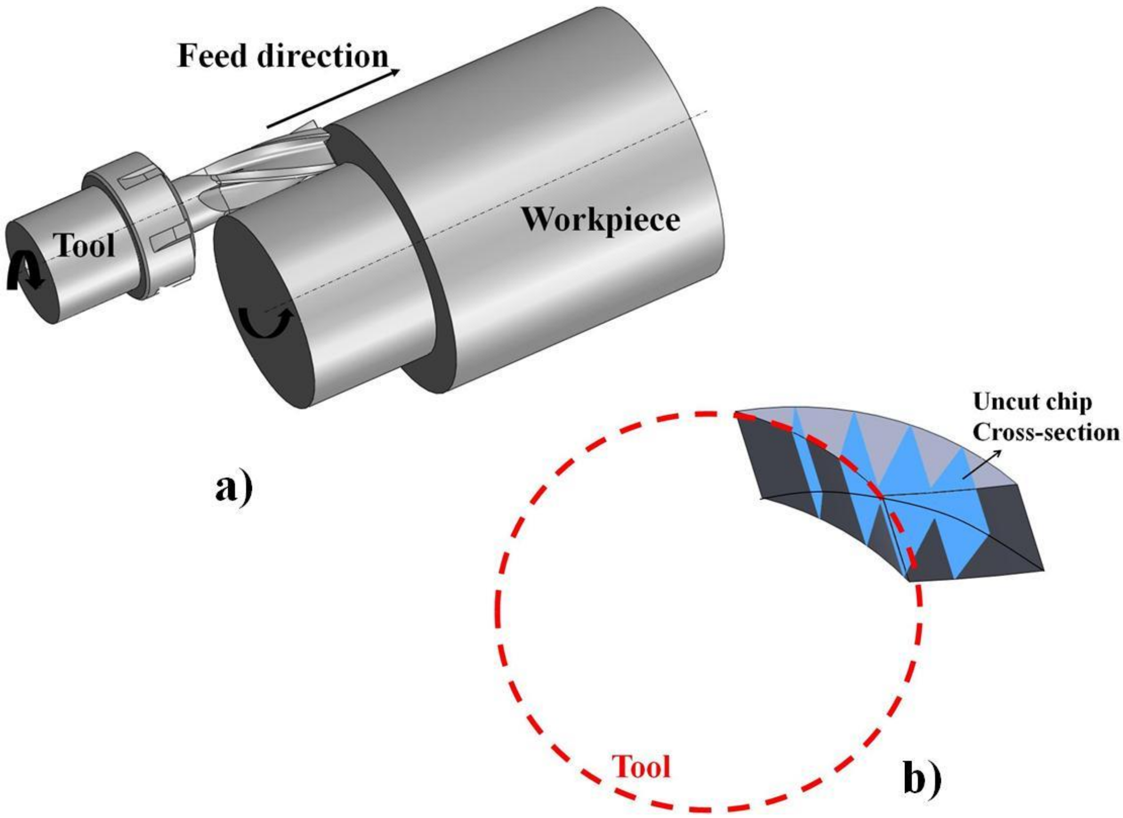


Figure 2.6: a) Co-axial turn-milling operation b) Uncut chip geometry in co-axial turn-milling [84].

2.3.3 Tangential Turn-Milling

Tangential turn-milling is another type of turn-milling operation in which cutting tool is tangent to the work piece. This process is more suitable for using end milling cutters. In this type of turn-milling the chip formation mechanism is different from orthogonal turn-milling.

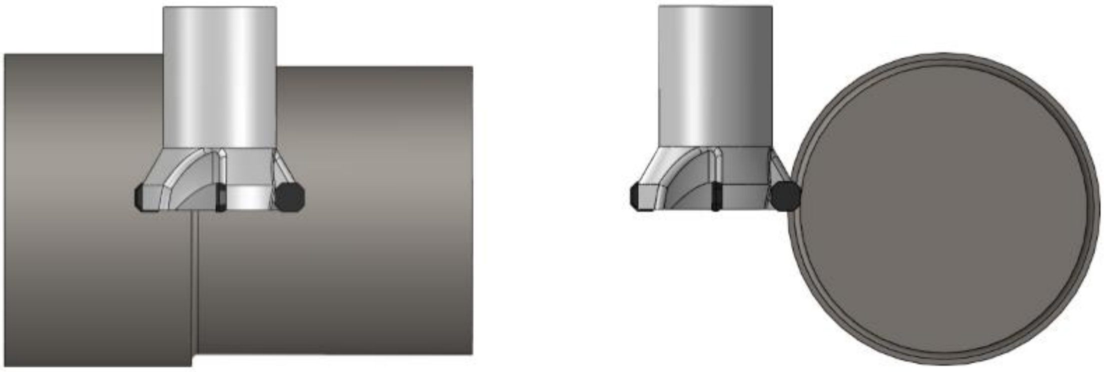


Figure 2.7: Tangential turn-milling.

Unlike in the case of orthogonal turn-milling, in this case the chip is formed by only periphery of the cutting tool as shown in Figure 2.8a. The procedure for determining the uncut chip geometry in Figure 2.8b is similar to the case of orthogonal turn-milling.

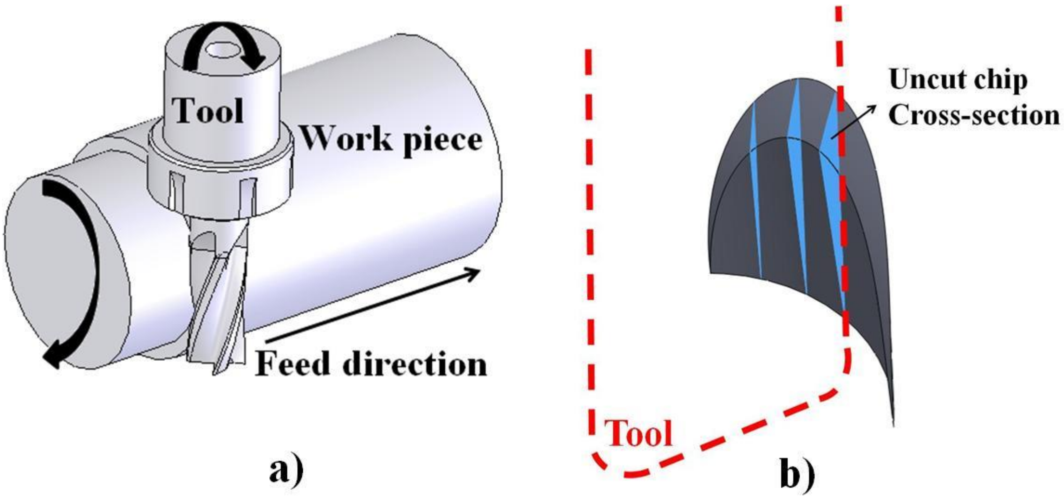


Figure 2.8: a) Tangential turn-milling operation b) Uncut chip geometry in tangential turn-milling [84].

2.4 Process Geometry and Parameters

Turn-milling has a complex geometry due to rotational motions of both cutting tool and work piece. Figure 2.9 illustrates the geometry of orthogonal turn-milling and the parameters in the process.

The cylindrical surface of work piece results from the interaction of two rotational motions. First motion is made by the work piece, with the number of revolutions n_w, and the second is made by the tool, with the number of revolutions n_t, respectively. Speed ratio is defined as r_n where ratio of n_t/n_w. In addition, there are two different feeds in turn-milling; axial and circumferential feeds. Axial feed is the translation motion of the cutting tool along the work piece similar to conventional milling; on the other hand, circumferential feed is defined as the tool rotational motion around the work piece which is a result of the work piece rotation and axial feed. Here, a_e is the feed per revolution in the axial direction. The combined motions of two feed rates result in a helical tool path and feed per tooth in this path is indicated as f_z. Moreover a_p, R_w, R_t represents depth of cut, radius of tool and radius of work piece respectively.

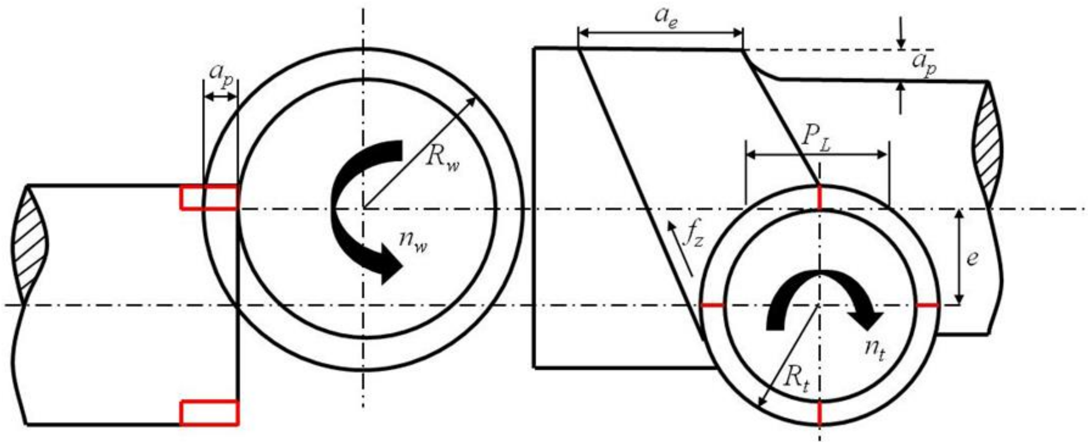


Figure 2.9: Process geometry and parameters in orthogonal turn-milling [17].

Figure 2.9 also tells us that turn-milling can be defined by an analogy to conventional milling operation. If one assumes that the work piece is stationary and the tool moves around it, the circumferential feed corresponds to the feed rate in conventional milling where axial feed (a_e) defines the radial depth of cut.

2.5 Summary

In this chapter, basics of turn-milling and machine tools which are suitable to carry out turn-milling are given. Then, types of turn-milling are introduced and their configurations demonstrated visually. Because of uncut chip geometry is important to analyze cutting force, temperature and stability, the tool-work piece contact area is shown and chip geometries are introduced for orthogonal, tangential and co-axial turn milling. Process parameters of turn-milling are also handled within this chapter.

CHAPTER 3 FACTORS THAT AFFECT PARAMETER SELECTION STRATEGY IN TURN-MILLING

Intelligent manufacturing achieves substantial savings in terms of money and time if it integrates an efficient automated process-planning module. Process planning involves determination of appropriate machines, tools for machining parts, cutting fluid to reduce the average temperature within the cutting zone and machining parameters under certain cutting conditions for each operation of a given machined part.

Turn-milling is a relatively new concept in manufacturing technology. It's an advanced cutting approach that can meet the demand of dimensional accuracy, surface roughness and residual stress of the work piece. Turn-milling is not bound by the limitations of both turning and milling. However, parameter selection is quite important for process efficiency.

The machining economics problem consists in determining the process parameter. In orthogonal turn-milling process; cutting speed, work piece rotational speed, tool Y-axis compensation, axial feed and depth of cut are desired to find optimally. A number of objective functions by which to measure the optimality of machining conditions include: minimum surface errors, minimum unit production cost and minimum production time. These are actually defined with tool life, surface roughness, circularity and material removal rate. Several cutting constraints that should be considered in turn-milling process include: cutting force constraint, power, stable cutting region constraint, chip-tool interface temperature constraint and roughing and finishing parameter relations.

In this section these criteria for turn-milling are handled one by one. These factors or criteria are especially important because they form the basis of optimization study in turn-milling.

3.1 Tool Wear and Tool Life

Tool life improvement is crucial to reduce the cost of production. Cutting tools have a limited life due to inevitable wear and consequent failure, and ways must be found to increase tool life. Cutting tools fail either by gradual or progressive wear on cutting edges or due to chipping or plastic deformation [85]. The change of shape of the tool from its original shape, during cutting, resulting from the gradual loss of tool material is called tool wear [86]. Generally a tool wear criteria is defined as a threshold value of the tool life.

Tool wear is a process which depends on time. As cutting proceeds, the amount of tool wear increases gradually. But tool wear must not be allowed to go beyond a certain limit in order to avoid tool failure. The most important wear type from the process point of view is the flank wear as can be seen in Figure 3.1, therefore the parameter which has to be controlled is the width of flank wear land, *VB*. This parameter must not exceed an initially set safe limit. The safe limit is referred to as allowable wear land (wear criterion), *VB* as shown in Figure 3.2. The cutting time required for the cutting tool to develop a flank wear land of width *VB* is called tool life, *T* (min), a fundamental parameter in machining.

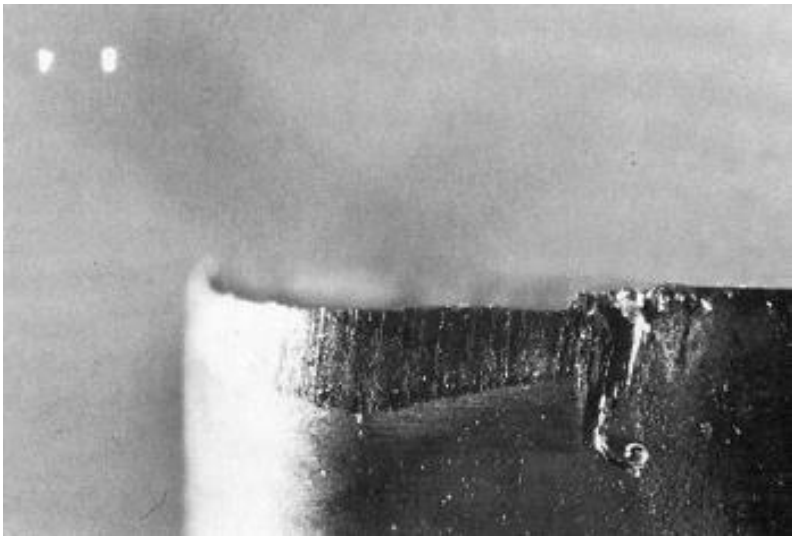


Figure 3.1: Wear on flank face of the tool.

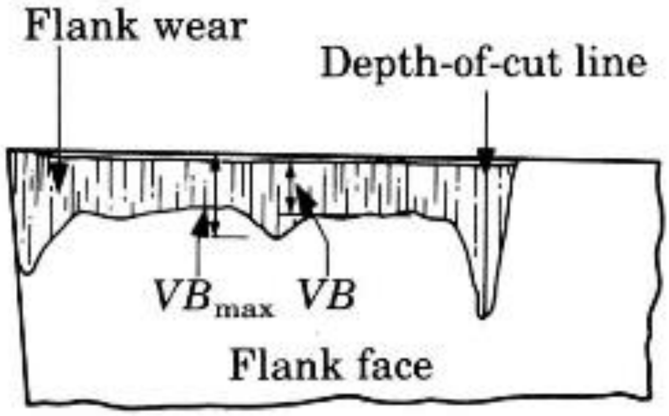


Figure 3.2: Flank face of the tool.

Parameters, which affect the rate of tool wear in turn-milling are as follows [2];

- cutting conditions (cutting speed V, cutter offset e, and depth of cut a_p)
- cutting tool geometry
- work material
- cooling conditions (dry, with fluid or MQL)

It is well known that from these parameters, cutting speed is the most important one for tool life [85]. As cutting speed is increased, wear rate also increases, so the same wear criterion is reached in less time. Taylor [87] approximated this by the following well-known equation:

$$VT^n = C \tag{3.1}$$

where n and C are constants whose values depend on cutting conditions, work and tool materials and tool geometry. In order to construct tool life equation for turn-milling process, these case dependent constants should be determined first by conducting some experiments.

As can be seen from the above equation there is no cutter offset effect for tool life, to investigate and include this effect, some experiments also are carried on. Effect of the offset is expressed and included to tool life formula as a function as follows:

$$T = \left(\frac{C}{V}\right)^{1/n} \cdot f(e) \tag{3.2}$$

3.2 Surface Roughness

The quality of machined surface is characterized by the accuracy of its manufacture with respect to the dimensions specified by the designer. Every machining operation leaves some characteristic marks on the machined surface. This pattern is known as surface finish or surface roughness.

Surface roughness is a widely used index of product quality and in most cases there is a technical requirement for products. Achieving the desired surface quality is of great importance for the functional behavior of a part. Surface roughness value can be measured by analyzing roughness profile.

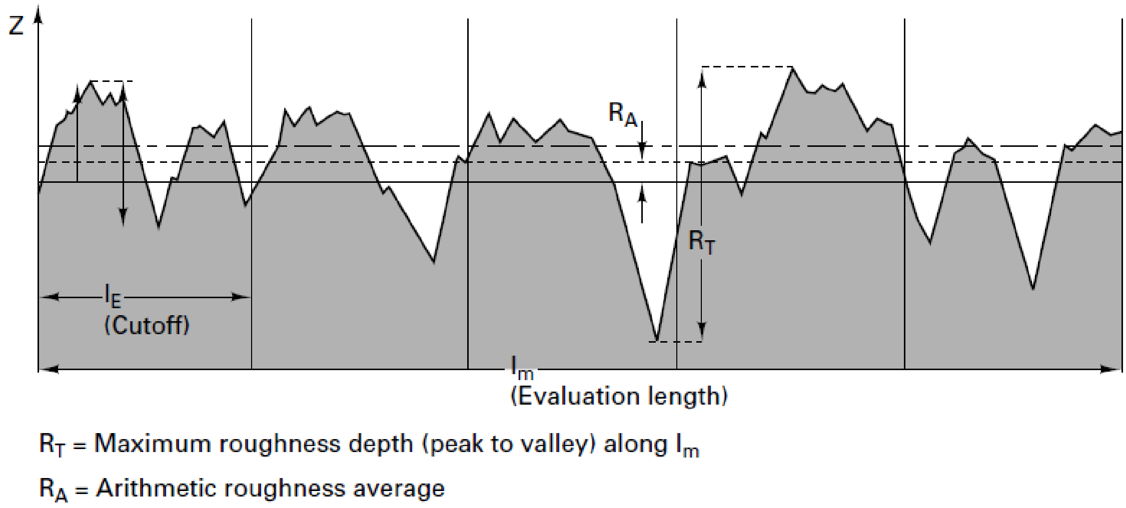


Figure 3.3: Roughness profile.

For orthogonal turn-milling operation theoretical surface roughness, R_a (μm) is defined as follows [14]:

$$R_a = \left\{ R_t - \sqrt{R_t^{\,2} - \left\{ \frac{n_w^{\,2} \cdot \left[a_e^{\,2} + (2\pi(Rw - a_p))^2 \right]}{2 \cdot z \cdot n_t^{\,2}} \right\}} \right\} \cdot f(e) \tag{3.3}$$

where R_t = radius of tool (mm); n_w = work piece rotational speed (rpm); a_e = axial feed (mm/rev); R_w = radius of work piece (mm); a_p = depth of cut (mm); z = number of teeth; n_t = spindle speed (rpm) and $f(e)$ = function of cutter offset (mm). Effect of cutter offset on the surface roughness is also investigated experimentally and results are presented within this chapter.

3.3 Circularity

In turn-milling process, since cutting tool and work piece rotate simultaneously, it is not possible to produce an ideal circle and the resulting machined part cross section is a polygon as shown in Figure 3.4. Polygon vertices create deviation from ideal circle causing circularity error.

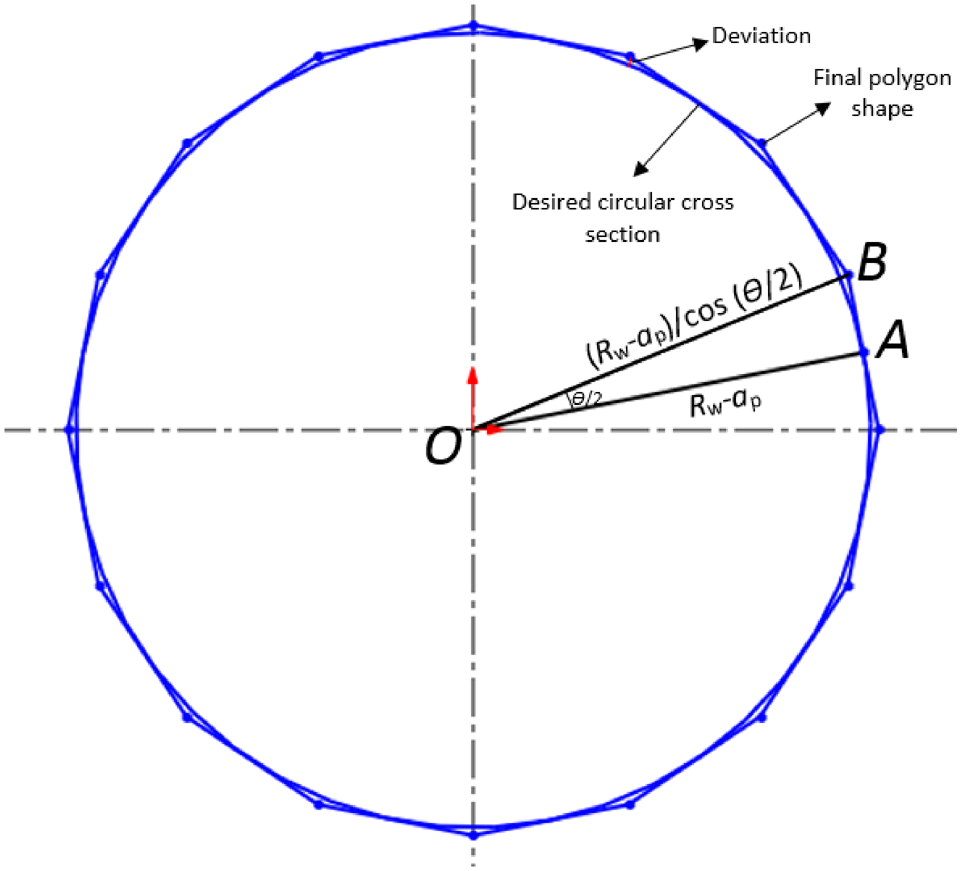


Figure 3.4: Partial cross section of work piece produced in turn-milling.

The difference between the desired and the machined shapes can be denoted as *OB-OA*. The definition of circularity error, C_e (μm) for orthogonal and tangential cases can be derived from the geometry as follows [1]:

$$C_e = OB - OA = (R_w - a_p) \cdot \left(\frac{1}{\cos((\pi \cdot n_w)/(z \cdot n_t))} - 1 \right) \tag{3.4}$$

This expression represents the relation between the cutting parameters and the circularity error. Hence, one can optimize the circumferential surface roughness through selection of cutting parameters. In addition, it is obvious that r_n has a significant effect on circularity where the depth of cut has a slight effect. As a result, it can be suggested that the ratio of rotational speeds should be increased in order to improve circularity.

3.4 Cusp Height

Cusp which is another form error in turn-milling and shown in Figure 3.5, is the height of remaining material during tool motion and directly associated with the tool, work piece diameter and step over. Step over can be defined as the size of the cutter's diameter that is engaged in a cut. In conventional milling process, feed rate and cutting tool radius have direct effects on the cusp height. a_e in turn-milling process is equivalent to radial depth of cut in conventional milling process. Increasing a_e in order to achieve higher MRR, results in high cusp height.

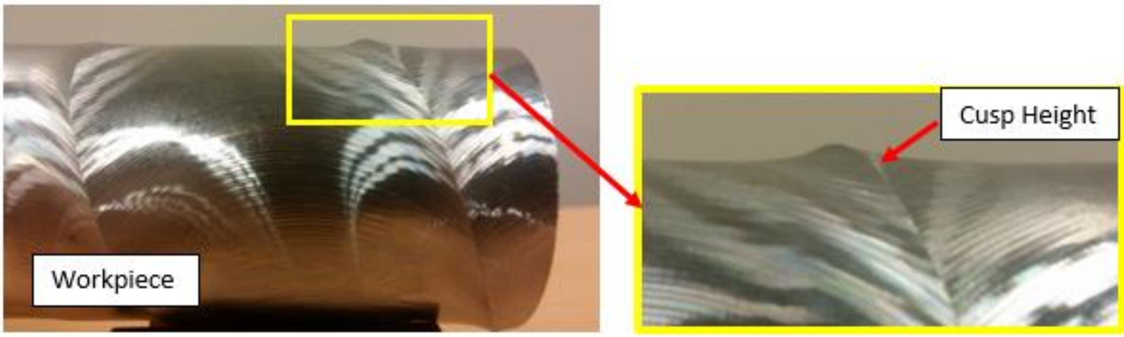


Figure 3.5: Cusp height form error in turn-milling.

The geometrical representation of cusp height is;

$$ch = \sqrt{(R_w - a_p)^2 + \left(\left[e + \left[(R_w - a_p) * \tan\left(\frac{180^\circ}{z * r_n}\right)\right]\right] - \left[\sqrt{(R_t)^2 - \left(\frac{a_e}{2}\right)^2}\right]\right)^2} - (R_w - a_p) \quad (3.5)$$

As it can be seen from Eq. 3.5, the cusp height, ch (μm) depends on many parameters. The formulation of cusp height geometry is first derived by Uysal [88], while previous studies considered circularity as the only form error in turn-milling. The analytical formulation predicts that unlike the circularity form error, cusp height is an avoidable case.

a_e can be increased up to the critical value, which is represented in following equation, without producing any cusp. By this way, MRR can be increased without sacrificing surface quality. a_{ecrit} represents the projected length (P_L) of tool onto work piece as shown in Figure 2.9. If a_e is defined higher than this value, tool leaves uncut surface on the work piece. The peak of that uncut surface is the cusp height.

$$a_{e\ crital} = 2 \cdot \sqrt{(R_t)^2 - \left(e + \left[(R_w - a_p) \cdot tan\left(\frac{180°}{z \cdot r_n}\right)\right]\right)^2} \tag{3.6}$$

3.5 Material Removal Rate (MRR)

Manufacturing time, cost and quality of machined work pieces are affected by productivity. Material removal rate (MRR) is an indicator of the productivity as it represents the removed material volume in unit time. Although higher MRR is possible in turn-milling it may cause increase circularity error and cusp height formation in finished surface.

The equation below represents the MRR (mm^3/min) for turn-milling process [89]:

$$MRR = V_f \cdot a_p \cdot a_e \tag{3.7}$$

where V_f is feed speed;

$$V_f = f_t \cdot n_t \cdot z \tag{3.8}$$

3.6 Cutting Forces

In orthogonal turn-milling, using the chip thickness expression cutting forces are calculated including cutter offset by Karaguzel [1, 84] according to mechanistic modeling described in [90, 91]. Karaguzel developed and simulated cutting forces by oblique transformation of orthogonal cutting data and the chip thickness expressions. Turn-milling forces can be determined by dividing the uncut chip into elements within the cutting zone. Tangential ($dF_{t,j}$), radial ($dF_{r,j}$), and axial ($dF_{a,j}$) forces acting on a differential flute element with height dz are expressed as follows [90, 91]:

$$\begin{aligned} dF_{t,j}(\phi,z) &= \lfloor K_{tc}h_j(\phi_j(z)) + K_{te} \rfloor dz \\ dF_{r,j}(\phi,z) &= \lfloor K_{rc}h_j(\phi_j(z)) + K_{re} \rfloor dz \\ dF_{a,j}(\phi,z) &= \lfloor K_{ac}h_j(\phi_j(z)) + K_{ae} \rfloor dz \end{aligned} \tag{3.9}$$

In this study, a simulation program is developed based on proposed cutting force model and it is used when calculating resultant cutting force.

3.7 Experiments

There is no general formulation for tool life as it strongly depends on work piece and tool materials. In order to formulate tool life for selected work piece and tool in this case, some experiments must be conducted to determine related constants before starting optimization study. Additionally, a survey has to be carried out to find how cutter offset effects tool life and surface roughness.

3.7.1 Experimental Setup

Experiments on orthogonal turn-milling are carried out on Mori Seiki NTX 2000 multi-tasking machine tool shown in Figure 3.6a in Sabancı University, Manufacturing Research Laboratory (MRL). Primary axes and milling spindle are shown in Figure 3.6b. Tool spindle can rotate around only *Y*-axes but can move linearly along the *X*, *Y* and *Z* axes. As a result of this configuration; turning, milling and turn-milling operations can be performed easily on this machine.

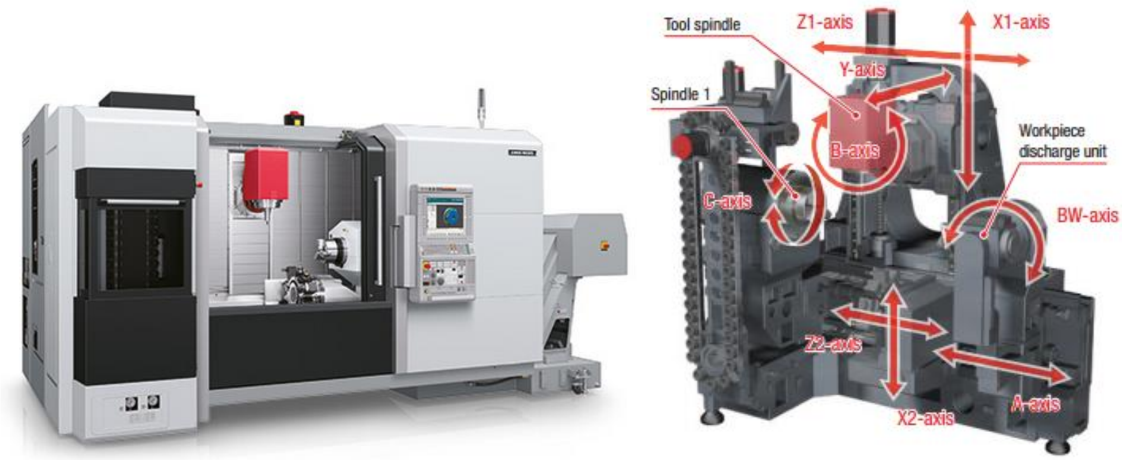


Figure 3.6: (a) Mori Seiki NTX 2000 multi-tasking machine; (b) Possible axes on the machine tool.

Cylindrical work piece of AISI 1050 steel of Ø100 mm diameter and 150 mm length were fixed between three jaws universal chuck as in the Figure 3.7.

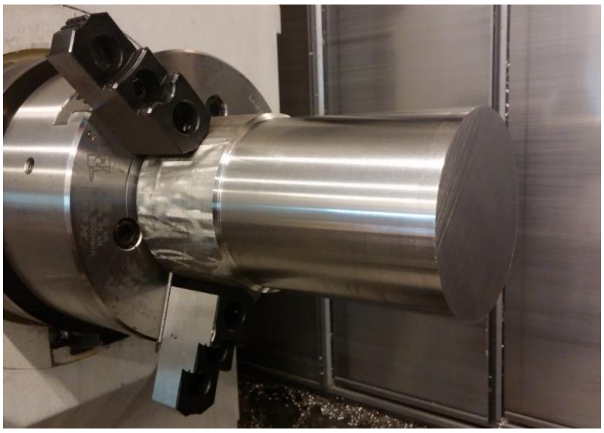


Figure 3.7: AISI 1050 steel bar, Ø100 mm x 150 mm.

AISI 1050 is a high quality structural plain carbon steel and it is very commonly used in manufacturing. This carbon steel is used in parts of ships, automobiles, aircrafts, weapons, railways, pressure vessels. The metallurgical properties of AISI 1050 are seen in Table 3.1.

Table 3.1: Metallurgical properties of AISI 1050 steel.

Element	C	Mn	P	S	Fe
Content (%)	0.47 - 0.55	0.6 - 0.9	≤ 0.04	≤ 0.05	Balance

Density of AISI 1050 alloy is 7850 kg/m^3. The mechanical properties and thermal properties are found in Table 3.2 and Table 3.3, respectively.

Table 3.2: Mechanical properties of AISI 1050 steel.

Property	Metric Unit
Tensile Strength	635 MPa
Yield Strength	515 MPa
Shear Modulus	80 GPa
Bulk Modulus	140 GPa
Elastic Modulus	190 - 210 GPa
Poisson’s Ratio	0.27 - 0.3
Elongation at Break	10 - 15 %
Reduction of Area	30 - 40 %
Hardness, Brinell	187 - 197 HB
Impact Strength	16.9 J

Table 3.3: Thermal properties of AISI 1050 steel.

Property	Metric Unit
Specific Heat Capacity	0.486 J/kg*°C
Thermal Conductivity	49.8 W/m*K
Coefficient of Thermal Expansion	$11.3*10^{-6}$/°C

Plain carbon steels have the best machinability properties compared to other steel types. Carbon content is the main affecting parameter of machinability. High carbon steels are difficult to cut since they are strong and they may contain carbide particles. On the other hand, low carbon steels are very soft such that these alloys are gummy and stick to cutting tool causing BUE at the tool tip with shortened tool life.

In turn-milling experiments a Ø50 mm Seco QuattroMill® 220.53-0050-12-4A milling tool with four cutting teeth was used with CVD coated MP2500 grade inserts which are recommended for high speed machining of steel. Minor cutting edge length of the tool insert is 4 mm. Cutting tool and insert used in the experiments can be seen in Figure 3.8.

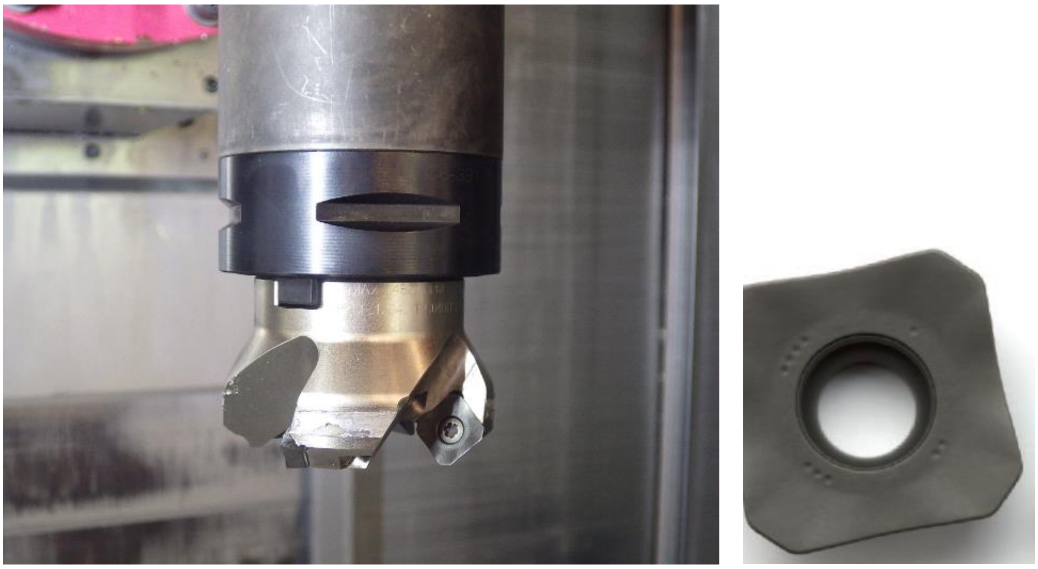


Figure 3.8: (a) Cutting tool; (b) Cutting insert.

Experimental setup is given in Figure 3.9. Experiments were performed under dry cutting condition.

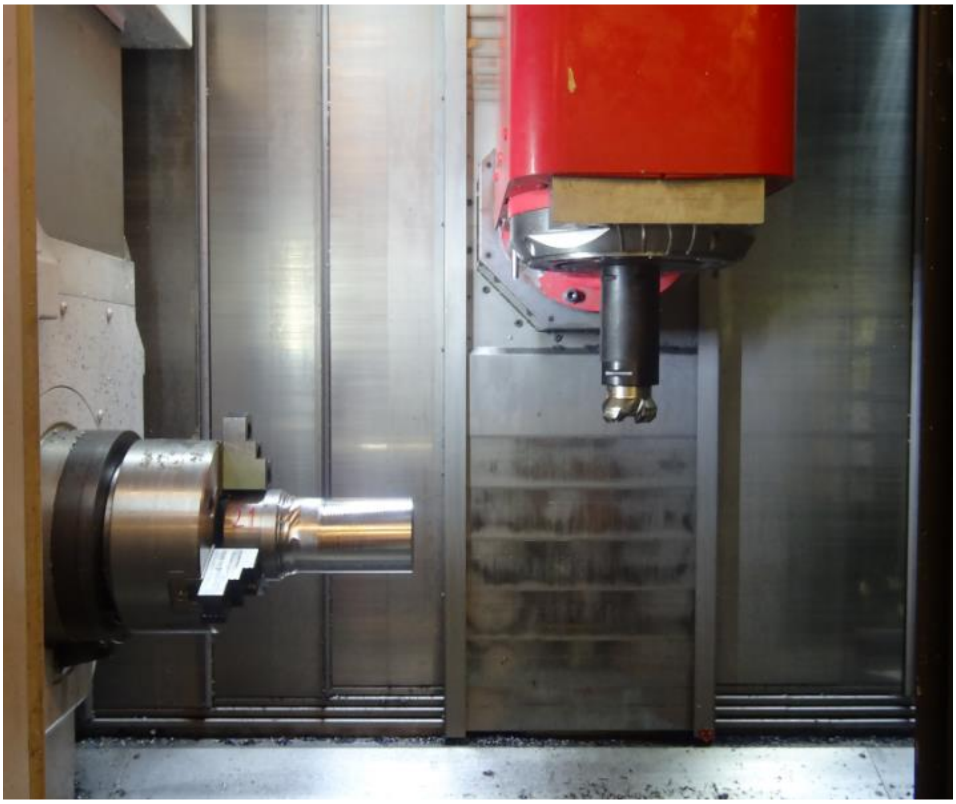
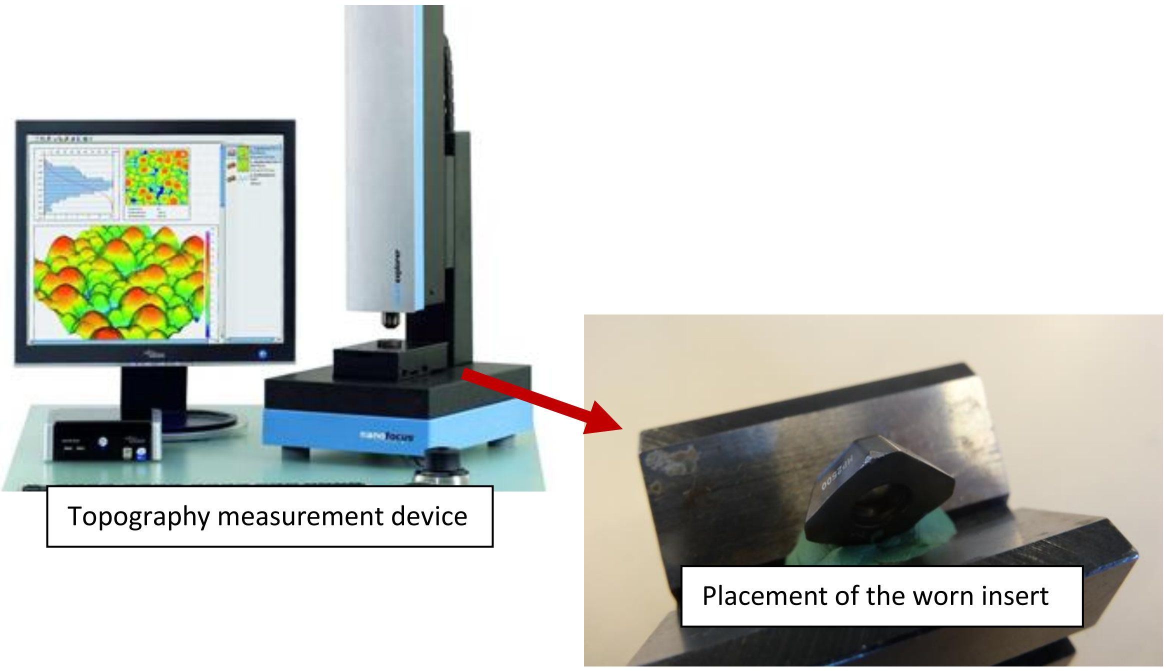


Figure 3.9: Experimental setup.

3.7.2 Measurements

Tool flank wear was measured by NanoFocus µsurf surface metrology system. Measurement procedure can be seen below in



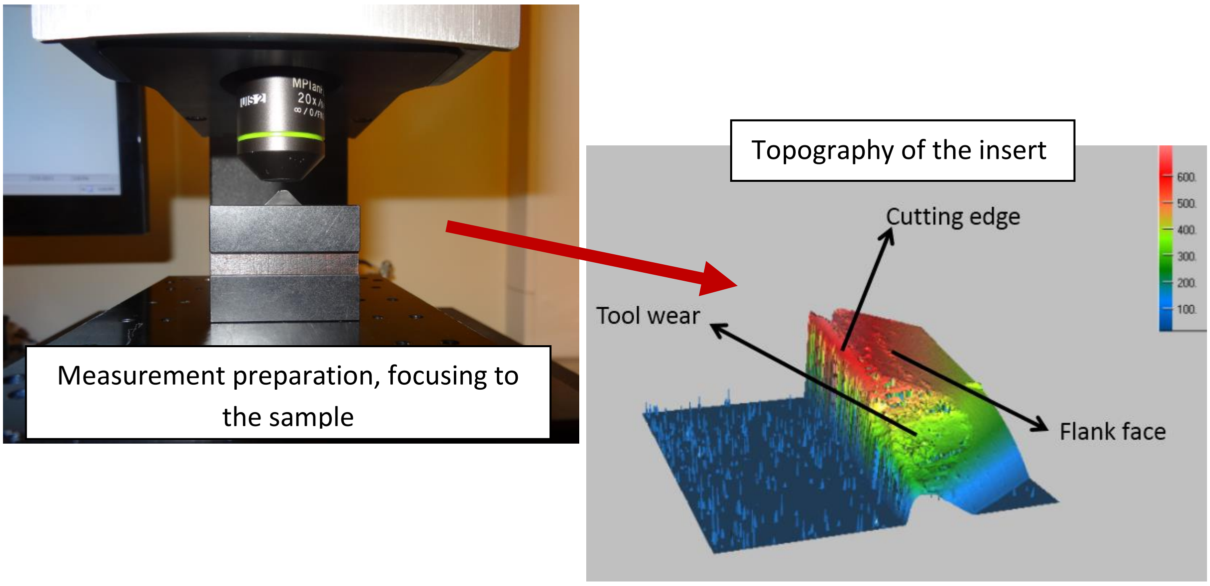


Figure 3.10: Tool wear measurement procedure.

Surface finish was determined using MITUTOYO SJ 301 surf test instrument as shown in the Figure 3.11.

Figure 3.11: Surface roughness measurement equipment.

Setup that is shown in Figure 3.12 was designed after the machining process to determine surface roughness of the cylindrical work pieces. To precise measurement, detector of the instrument was attached to the spindle head of the machine tool to be able to gain sensitive positioning.

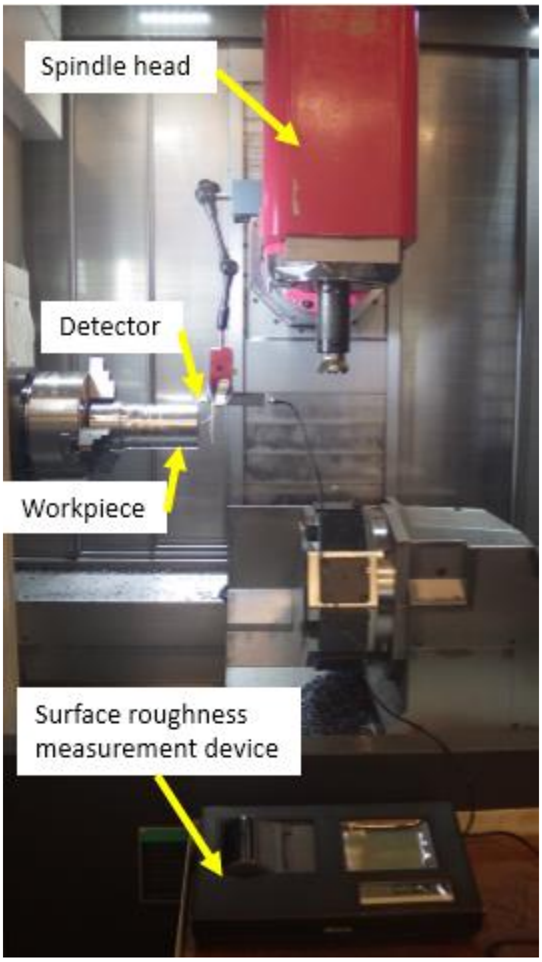


Figure 3.12: Surface roughness measurement setup.

Surface roughness measurements were taken in the direction of axial feed which is parallel to work piece rotation axis.

3.7.3 Tool Life Experiments

Firstly, for the selected work-tool materials and the tool geometry, *C* and *n* constants were identified. In order to do this orthogonal turn-milling experiment were carried out at two different cutting speeds. Result can be seen in Figure 3.13.

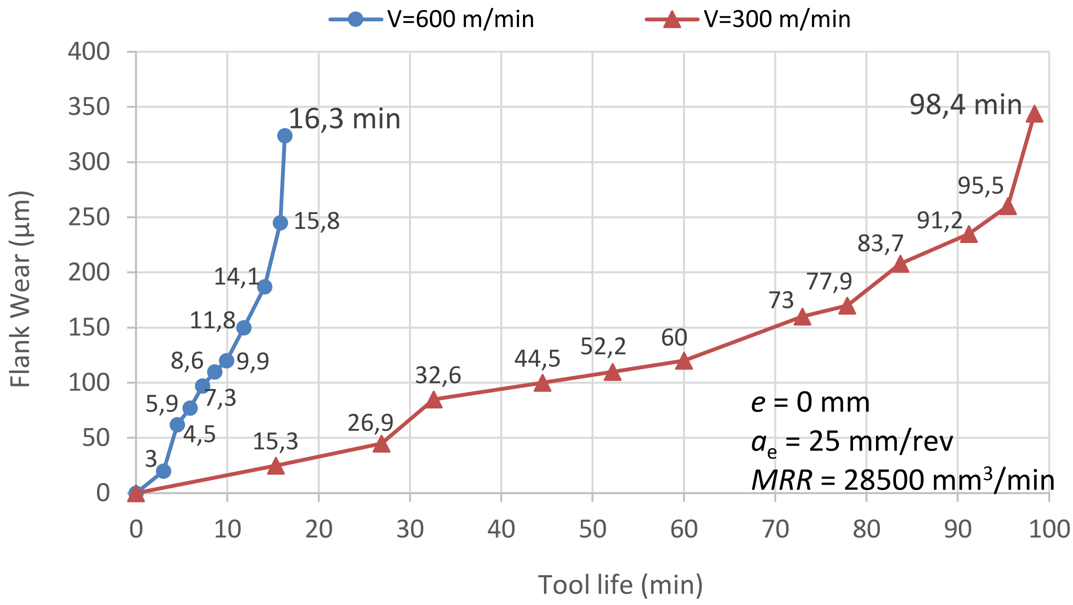


Figure 3.13: Effect of cutting speed on tool life in orthogonal turn-milling.

C and *n* values were identified as 1756 and 0.38, respectively. After this, effect of cutter offset on tool life is searched for four different offset values (0 mm, 10 mm, 21 mm, 25 mm) and experimental data shown in Figure 3.14 were obtained. Curve fitting process is applied by constructing a curve that has the best fit to a series of data points, with mathematical function.

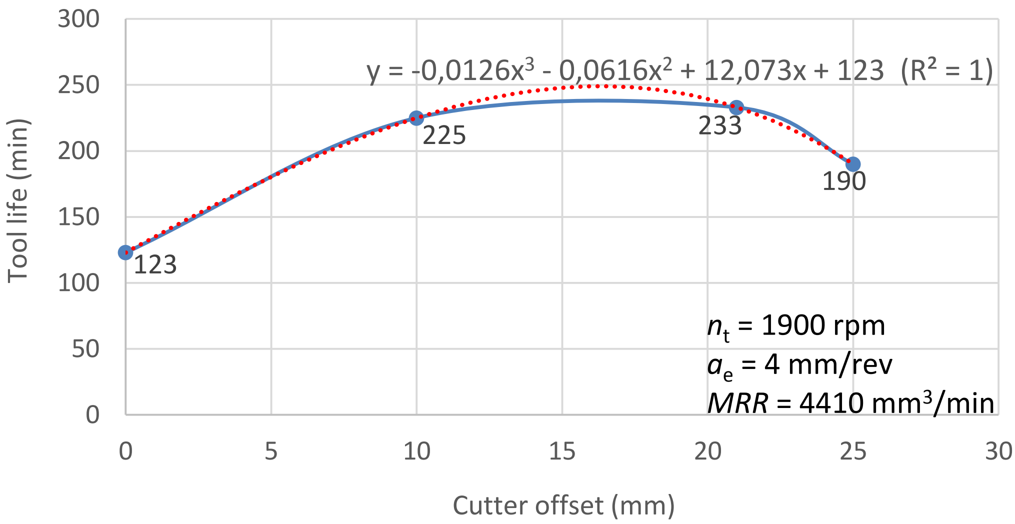


Figure 3.14: Effect of cutter offset on tool life in orthogonal turn-milling.

As shown in the Figure 3.14, after curve fitting, the effect of offset can be incorporated into the Taylor's formula as follows:

$$T = \left(\frac{1756}{\pi \cdot D_t \cdot n_t / 1000} \right)^{2.6} \cdot \left(\frac{-0.012e^3 - 0.06e^2 + 12e + 123}{233} \right) \tag{3.10}$$

As it can be seen from Figure 3.14, the tool life increases with the cutter offset up a certain point and after this value tool life starts to decrease. This critical value is defined as optimal cutter offset for tool life and it can be found by using the equation below [5]:

$$e_{opt} = R_t - l_n \tag{3.11}$$

where R_t and l_n are the tool radius and the cutting edge length of the tool insert, respectively. By using Eq. 3.11 the optimal cutter offset is selected (e=21mm), the engagement length of tool and work piece becomes maximum, and the cutting pressure is well-distributed. As a result of this, maximum tool life is obtained for this case. It can be obviously observed from the Figure 3.14 that increasing cutter offset up to optimal value results with increasing tool life. When cutter offset equals to cutting tool radius, the engagement length between cutting tool and work piece reduces substantially. Since only the side edges of the cutting tool involves in cutting, excessive cutting pressures are exerted on a relatively small part of cutting tool. As a result, for e=25mm case tool life decreases dramatically.

3.7.4 Surface Roughness Experiments

As mentioned before for orthogonal turn-milling process the theoretical surface roughness expression that is defined by Zhu et al. [14] does not include effect of cutter offset. However, our experiments have shown that surface roughness changes with that offset as expected. In Figure 3.15 variation of the surface roughness, R_a with four different offset (0 mm, 10 mm, 21 mm, 25 mm) can be seen.

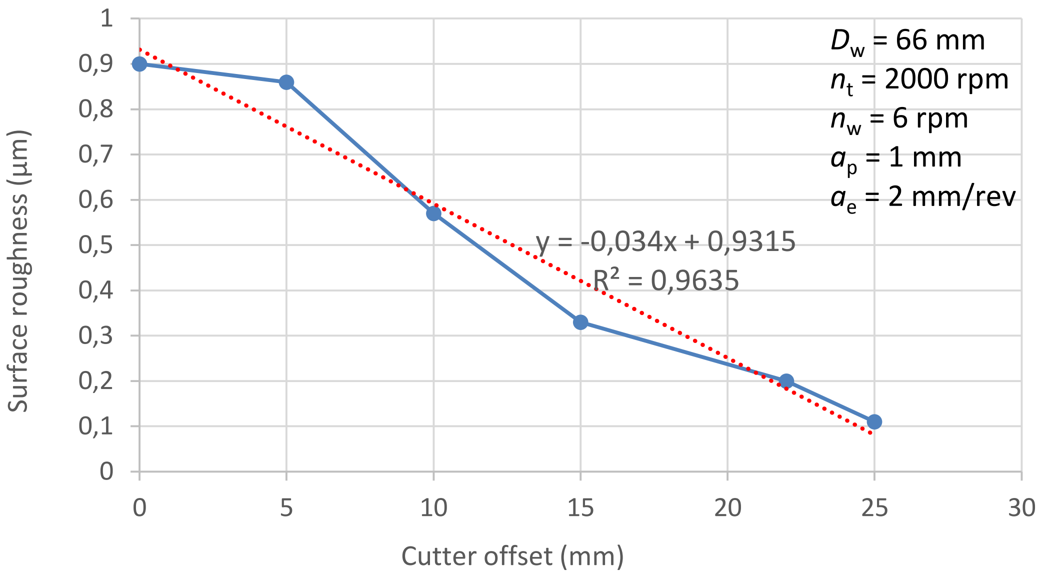


Figure 3.15: Effect of cutter offset over the surface roughness in orthogonal turn-milling.

As it can be seen from the graph in order to reduce surface roughness, offset should be increase as much as possible. In order to express this mathematically with curve fitting another term can be added to existing surface roughness relation that is given by Equation 3.3. In our case ultimate surface roughness equation for orthogonal turn-milling becomes:

$$R_a = \left\{ R_t - \sqrt{R_t^2 - \left\{ \frac{n_w^2 \cdot \left[a_e^2 + (2\pi(Rw - a_p))^2 \right]}{2 \cdot z \cdot n_t^2} \right\}} \right\} \cdot \left(\frac{-0.03e + 0.9}{0.9} \right) \tag{3.11}$$

3.8 Summary

In this chapter turn-milling process is addressed with all aspects. Some experiments are conducted to examine effects of cutter offset on tool life and surface roughness. It is observed that relatively high offset value is desired for better tool life and surface roughness but it should be remembered when offset is increased critical axial feed rate become smaller, therefore, formation of cusp height become more likely. Mathematical equations are derived for the calculation of the objectives of turn-milling operations.

CHAPTER 4 MULTI-OBJECTIVE OPTIMIZATION METHODS

In this chapter, optimization methods that can be applied for turn-milling process are searched. Problems consist more than one objective are called multi-objective optimization problems (MOOPs). Most real-world search and optimization problems are naturally posed as multi-objective optimization problems. Indeed selection of turn-milling parameters is also a multi-objective optimization problem. Therefore this chapter is assigned discussing multi-objective optimization (MOO) concepts and techniques.

Optimization is finding one or more feasible solutions where these solutions are the extreme points of the related objective or objectives [66]. There are two types of optimization in terms of number of objective functions. First one is single objective optimization in which the aim is to find the best solution under given constraints. Second one is multi-objective optimization which aims to find a set of solutions where one solution is not dominating another solution in all objective function values. In other words, the type of optimization which aims to optimize several objective functions at the same time in a systematical way is named MOO [93]. When multi-objective problems are reviewed it can be derived that the objectives are usually conflicting, and these conflicts prevent optimization of each objective at the same time and generally real life optimization problems have multi- objective structures [94]. Cost minimization, performance maximization, and environmental effect minimization can be listed as example to multi-objectives. This multi-objective structure of the problems makes them hard to solve but more realistic. When one of the objectives is improved other objectives may be negatively affected. Because of this characteristic of MOOP a set of better solutions are being tried to be reached. Within this set of solutions, one can be selected according to the properties of the studied problem by a decision maker (DM). When decision making is emphasized, the objective of solving a multi-objective optimization problem is referred to supporting a decision maker in finding the most preferred Pareto-optimal solution according to his/her subjective preferences [95,96]. The underlying assumption is that one solution to the problem must be identified to be implemented in practice. Here, a human decision maker plays an important role. The term of preference is used to define the comparative significance of different objective functions [93].

A multi-objective optimization problem has a number of objective functions which are to be minimized or maximized. For a nontrivial multi-objective optimization problem, there does not exist a single solution that simultaneously optimizes each objective. In that case, the objective functions are said to be conflicting, and there exists a (possibly infinite number of) Pareto-optimal solutions. A solution is called non-dominated, Pareto-optimal, Pareto efficient or non-inferior, if none of the objective functions can be improved in value without degrading some of the other objective values [65]. In the following, multi-objective optimization problem is defined in its general form [66]:

$$\begin{array}{llll} \text{Minimize/Maximize} & f_m(x), & m = 1,2,\ldots,M; & \\ \text{subject to} & g_j(x) \leq 0, & j = 1,2,\ldots,J; & \\ & h_k(x) = 0, & k = 1,2,\ldots,K; & (4.1) \\ & x_i^{(L)} \leq x_i \leq x_i^{(U)}, & i = 1,2,\ldots,n. & \end{array}$$

A solution x is a vector of n decision variables: $x = (x_1,x_2,\ldots,x_n)^T$. $g_j(x)$ and $h_k(x)$ are constraints which any feasible solution must satisfy. The last set of constraints are called variable bounds, restricting each decision variable x_i to take a value within a lower $x_i^{(L)}$ and an upper $x_i^{(U)}$ bound.

There are M objective functions $f'(x) = (f_1(x), f_2(x),\ldots,f_M(x))^T$ considered in the above formulation. Each objective function can be either minimized or maximized. The duality principle [97-99] in the context of optimization, suggests that we can convert a maximization problem into a minimization one by multiplying the objective function by -1. The duality principle has made the task of handling mixed type of objectives much easier. Many optimization algorithms are developed to solve only one type of optimization problems, such as e.g. minimization problems. When an objective is required to be maximized by using such an algorithm, the duality principle can be used to transform the original objective for maximization into an objective for minimization.

Figure 4.1 demonstrates the basic steps of the MOO procedure. First a MOOP is solved with an appropriate optimization method and tool. Then multiple trade-off solutions are reached. Final step is to select a solution from the set of solutions with higher level information. Wide range of Pareto-optimal solutions provides alternative solutions related to the higher level information.

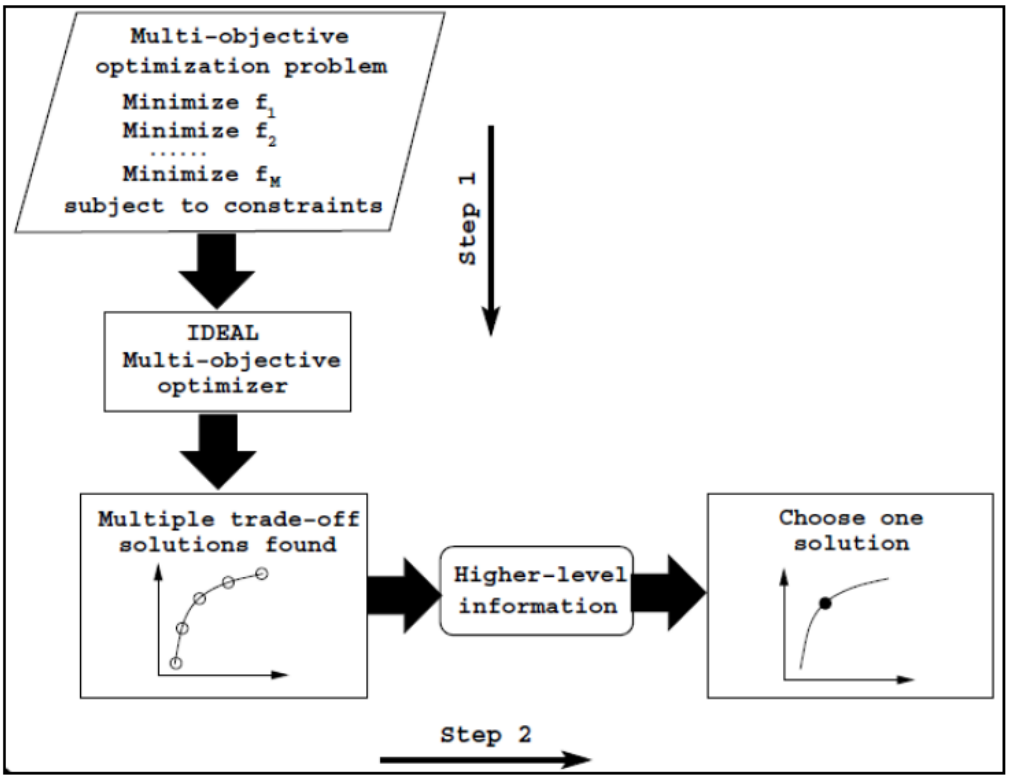


Figure 4.1: Steps of multi-objective optimization (MOO) procedure [66].

Researchers study multi-objective optimization problems from different viewpoints and, thus, there exist different solution philosophies and goals when setting and solving them. MOO methods are fundamentally classified as no preference, a priori, a posteriori and interactive methods [100].

The no preference methods do not assume any information about the importance of objectives in other words DM does not define preferences, but a heuristic is used to find a single optimal solution. In a priori methods, preference information is first asked from the DM and then a solution best satisfying these preferences is found. In a posteriori methods, a representative set of Pareto-optimal solutions is first found and then the DM must choose one of them. In interactive methods, the decision maker is allowed to iteratively search for the most preferred solution. In each iteration of the interactive method, the DM is shown Pareto-optimal solution(s) and describes how the solution(s) could be improved. The information given by the decision maker is then taken into account while generating new Pareto-optimal solution(s) for the DM to study in the next iteration. In this way, the DM learns about the feasibility of his/her wishes and can concentrate on solutions that are interesting to him/her. The DM may stop the search whenever he/she wants to. Among these methods a priori and a posteriori methods are introduced in this study. Before that, concept of Pareto optimality should be explained.

4.1 Pareto Optimality

Different from single objective optimization the solution of MOOPs is a set of solutions. Here the term called domination should be explained. Let's consider a bi-objective (minimization type) problem with equal importance of these functions. A pair of solutions is said to be non-dominated if none of them can be marked as a better one comparing both of the objective function values. For example points A and B in Figure 4.2 are called Pareto-optimal solutions. If a solution is worse in terms of both objective function values than any member of Pareto-optimal solutions is said to be non-Pareto-optimal (point D when compared to point B). Also the curve crossing all Pareto-optimal points is named as Pareto-optimal front (Figure 4.2). Simply all feasible solution space can be divided into two; Pareto-optimal solutions and non-Pareto-optimal solutions. Suppose that there are two sets of solutions and the first set includes Pareto-optimal points and called P_1 and other set is called P_2, where all solutions in the set of P_1 do not dominate each other, and at least one solution in P_1 dominates any solution in P_2. Set P_1 is called the non-dominated set and P_2 is called the dominated set [66]. When the solutions of a MOOP is being considered, suppose that first set of solutions which includes Pareto-optimal points is called P_1 and other set is called P_2, where all solutions in the set of P_1 do not dominate each other, and at least one solution in P_1 dominates any solution in P_2. Set P_1 is called the non-dominated set and P_2 is called the dominated set [66]. For instance in Figure 4.2 set of P_1 contains points {A, B, C} and set P_2 includes point {D}.

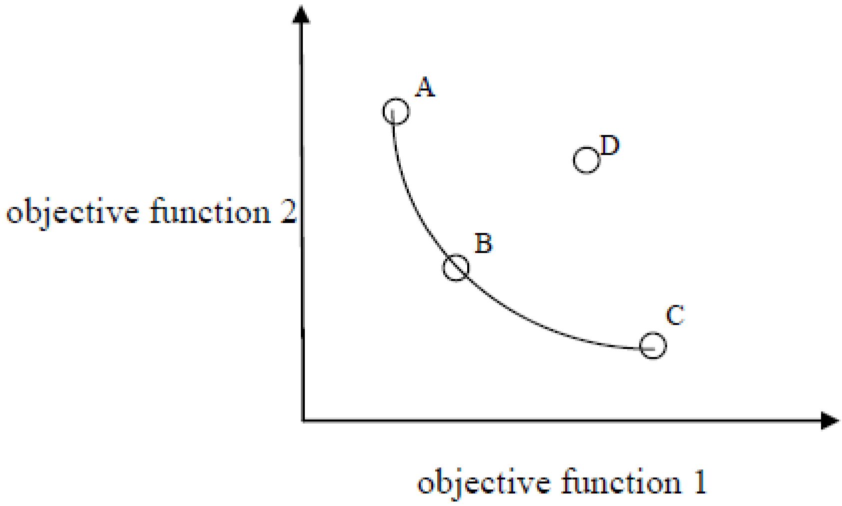


Figure 4.2: Pareto-optimal and non-Pareto-optimal solutions.

There is a point to be explained about set of solutions; if we compare solutions C and D we can observe that one cannot dominate each other in values of both objective functions. Also if we do not include solutions A and B, solution D becomes a non-dominated solution. But since we have solution B which dominates solution D but cannot dominate solution C in both objective function values solution D becomes a dominated solution. So it is essential to compare the non-dominated set collectively with any other solution to decide which set should include this solution.

4.2 A Priori Methods

The part of this section includes some of the most known a priori methods used to handle MOOPs. A priori methods require that sufficient preference information is expressed before the solution process [100]. Well-known examples of a priori methods include the weighted sum method, epsilon ($\mathcal{E}$) – constraint method, weighted metric method and goal programming.

4.2.1 Weighted Sum Method

This method is the simplest approach and is probably the most widely used priori approach. Faced with multiple objectives, this method is the most convenient one that comes to mind. Weighted sum method requires weighting the objectives to produce a single objective function. These weights are determined according to the importance of objectives by the user. By using this function, optimal solution may be found. If there is a lack of information about the relative importance of the objectives it may be hard to determine the weights [33]. General formulation of weighted objective methods is as follows:

$$
\begin{aligned}
&\text{Minimize} && F(x) = \textstyle\sum_i^N w_i f_i(x) \\
&\text{subject to} && g_j(\mathrm{x}) \geq 0 \;,\; j = 1,2,\ldots,\mathrm{m}\,, \\
& && h_l(\mathrm{x}) = 0 \;,\; l = 1,2,\ldots,\mathrm{e}\,,
\end{aligned}
\tag{4.2}
$$

where N is the number of objectives, m represents the quantity of inequality constraints and e represents the quantity of equality constraints. In most of the studies total weight (w) is equal to 1. If the problem is convex and weights are all positive then Pareto-optimal is reached and in other cases, such as the problem is non-convex or negative weights exists, this method is not suggested to be used [95].

4.2.2 Epsilon ($\mathcal{E}$) - Constraint Method

This method is used when the problem is not convex and weighted methods fail to solve [95]. One of the objective functions is used as the objective of the global problem and other objectives are turned into constraints with $\mathcal{E}_i$ upper bound [101]. General formulation of $\mathcal{E}$-constraint methods is as follows:

$$
\begin{aligned}
&\text{Minimize} && f_N(x) \\
&\text{subject to} && f_i(x) \leq \mathcal{E}_i \;,\; i = 1,2,\ldots,N\text{-}1\,, \\
& && g_j(\mathrm{x}) \geq 0 \;,\; j = 1,2,\ldots,\mathrm{m}\,, \\
& && h_l(\mathrm{x}) = 0 \;,\; l = 1,2,\ldots,\mathrm{e}\,,
\end{aligned}
\tag{4.3}
$$

where Nth objective function remains as the objective to be minimized and other N-1 objectives are defined as constraints with an upper bound of $\mathcal{E}_i$, m represents the quantity of inequality constraints and e represents the quantity of equality constraints. Determining the upper bounds is the key issue in this type of problems. Since the solution is Pareto-optimal with given set of $\mathcal{E}_i$, the closer upper bounds to the ideal are given, the better solutions are reached [95]. So this method requires high level of knowledge about the objectives to correctly define $\mathcal{E}$ values. Also there is a chance to omit the global optimum from solution space with $\mathcal{E}$-constraints in non-convex problems [101].

4.2.3 Weighted Metric Method

Like weighted sum method, this method also produces a single objective from all objective functions [101]. General formulation of weighted metric method is as follows:

$$
\begin{aligned}
&\text{Minimize} && I_p(x) = \left(\sum_{i=1}^{N} w_i \left|f_i(x) - f_i^{ideal}\right|^p\right)^{1/p} \\
&\text{subject to} && g_j(x) \geq 0,\ j = 1,2,\ldots,m, \\
& && h_l(x) = 0\ ,\ l = 1,2,\ldots,e\ ,
\end{aligned}
\tag{4.4}
$$

where N is the number of objectives, m represents the quantity of inequality constraints and e represents the quantity of equality constraints. In this formulation the value of p is between $1 \leq p \leq \infty$. It can easily be seen that this is a generalized form of weighted objective method. If $p = 1$ then the formulation turns into weighted objectives method. If $p = \infty$ then it can be seen that the problem turns into the minimization of maximum $\left|f_i - f_i^{ideal}\right|$ value and this type of method is called weighted Tchebycheff method [101]. Each ideal solution is produced by considering each objective function as single objective and solving the problem for each objective function.

4.2.4 Goal Programming

The main idea in goal programming is to find solutions which attain a predefined target for one or more objective functions. If there exists no solution which achieves pre-specified targets in all objective functions (the user is being optimistic), the task is to find solutions which minimize deviations from the targets. On the other hand, if a solution with the desired target exists, the task of goal programming is to identify that particular solution. In some sense, this task is similar to that in satisficing decision making and the obtained solution is a satisficing solution, which can be different from an optimal solution.

There are four different types of goal criteria as follows:

1. Less than equal to ($f(x) \leq t$),
2. Greater than equal to ($f(x) \geq t$),
3. Equal to ($f(x) = t$),
4. Within a range ($t^l \leq f(x) \leq t^u$).

The variations from these goals are defined as variables. These variables are notated as

d^+ and d^- where they indicate how much we overachieved or underachieved the goal respectively. Objective function of the problem is formulated as the minimization of the sum of these variables. There are several types of goal programming methods according to the formulation of objective function. Formulation of weighted goal programming is as follows:

$$\begin{aligned}
&\text{Minimize} && \textstyle\sum_{i=1}^{N}(w_i d_i^+ + v_i d_i^-) \\
&\text{subject to} && f_i(\mathrm{x}) - d_i^+ + d_i^- = t_i \qquad (4.5)\\
& && d_i^+,\ d_i^- \geq 0\ ,\ i = 1,2,\ \ldots\ldots\ N,
\end{aligned}$$

where N is the number of objectives. d_i^+ represents positive variations, and d_i^- represents negative variations. w_i and v_i represents the weights of these variables [101].

There is another method for solving goal programming problems. In this method there is a precedence order among the objectives and the problem is solved according to these relations in each step. This is called sequential goal programming.

Finally min-max goal programming is explained here. This approach is similar to the weighted goal programming approach, but instead of minimizing the weighted sum of the deviations from the targets, the maximum deviation in any goal from the target is minimized.

Formulation of min-max goal programming method is as follows:

$$\begin{aligned}
&\text{Minimize} && d \\
&\text{subject to} && w_i d_i^+ + v_i d_i^- \leq d \\
& && f_i(\mathrm{x}) - d_i^+ + d_i^- = t_i, \qquad i = 1,2\ldots\ldots\ldots N, \qquad (4.6)\\
& && d_i^+\ ,\ d_i^- \geq 0
\end{aligned}$$

where N is the number of objectives. d represents maximum variation between goals and t represents goal values.

The user must define goals to reach the objectives, and these goals must be represented mathematically. In most of the problems it is hard to define the goals. If goals are defined exactly goal programming is an efficient method, but for non-convex problems or problems with non-linear objectives this method may not be sufficient to find optimal solution or solutions.

4.3 A Posteriori Methods

So far a priori methods are explained, different from a priori methods, a posteriori methods allows DM to choose from a set of solutions without defining preferences in the first place. Since it is sometimes difficult to define preferences of each objective function, these kinds of methods are more effective for MOOPs [93].

Most a posteriori methods fall into either one of the following two classes: mathematical programming based a posteriori methods, where an algorithm is repeated and each run of the algorithm produces one Pareto-optimal solution, and evolutionary algorithms where one run of the algorithm produces a set of Pareto-optimal solutions.

4.3.1 Mathematical Programming

Well-known examples of mathematical programming based a posteriori methods are the normal boundary intersection (NBI), modified normal boundary intersection (NBIm), normal constraint (NC), successive Pareto optimization (SPO) and directed search domain (DSD) methods that solve the multi-objective optimization problem by constructing several scalarizations. The solution to each scalarization yields a Pareto-optimal solution, whether locally or globally. The scalarizations of the NBI, NBIm, NC and DSD methods are constructed with the target of obtaining evenly distributed Pareto points that give a good evenly distributed approximation of the real set of Pareto points.

4.3.1.1 Normal Boundary Intersection (NBI)

This method is presented as a response to weighted methods in terms of representing Pareto-optimal set accurately. The formulation of the method is as follows [102]:

$$\begin{aligned} &\text{Minimize} && \tau \\ &\text{subject to} && \Phi\beta + \tau v = F(\chi) \qquad (4.7) \\ & && h(\chi) = 0,\ g(\chi) \le 0,\ a \le \chi \le b \end{aligned}$$

The payoff matrix Φ is a n x n matrix whose jth column is $F_j^* - F^*$. $\Phi\beta$ then denotes the reference points H. $Fj^* = F(\chi_j^*) = [f_1(\chi_j^*), \ldots, f_n(\chi_j^*)]^T$ represents the objectives and this vector is evaluated at the jth objective function's minimum. The diagonal of Φ are composed of all zeros, β is a vector of scalars where $\sum_{j=1}^{n} \beta_i = 1$ and $\beta \ge 0$, and $v = -\Phi e$. e is a column vector composed of ones. v is called quasi-normal vector. Since all components of Φ positive the negative of it in the formula makes sure that v points towards the origin of the criterion space. v gives this method the preference that for any β, a point of solution is not dependent to the scaling of the objective functions. As β is changed in a systematical manner, the solution gives a distributed set of Pareto-optimal points representing the Pareto-optimal front [93].

4.3.1.2 Normal Constraint (NC)

This method is an improved alternative of NBI method. This method always yields to Pareto-optimal points where NBI method sometimes yields non Pareto-optimal points [93]. The procedure of this method is explained step by step:

First utopia point which is the ideal solution is found and it is used to make normalization on the objectives. The mimima of this normalized objective function is called utopia hyper-plane [93]. Some evenly distributed points are determined in the solution space by varying the weights. Then points are plotted on the Pareto-optimal surface. This is done by finding the solution of a single objective problem separately. This separate problem aims to minimize one of the objectives including additional inequality constraints. Also a Pareto filtering mechanism is used to eliminate dominated solutions. This filter works by comparing each solution with other solutions.

4.3.2 Evolutionary Algorithms

Since multi-objective problems are usually NP-hard, most of the time, it is impossible to find Pareto-optimal set for these methods. Also when integer programming (IP) problems are considered, it can also be impossible to reach Pareto-optimal set for these kinds of discrete problems. Also IP problems usually have a non-convex solution space. And NP-hard problems usually solved using heuristic approaches [101]. Evolutionary algorithm (EA) defines a class of non-deterministic optimization methodologies simulating the process of evolution. In real world most of the problems are multi-objective instead of single. Evolutionary multi-objective optimization (EMOO), which uses forms of genetic algorithms called multi-objective evolutionary algorithms (MOEA), can be used for solving multi-objective optimization problems.

All of the MOEA make a search for a set of solutions from which a selection will be made as a final decision. This solution set is diversified by two operations, which are called selection and variation. According to Deb, evolutionary optimization procedure is a perfect match for MOOPs [66].

Evolutionary optimization starts with a population of solutions and usually these individuals are randomly created according to bounds [66]. There are four main operations of EAs to create new populations; selection, crossover, mutation and elitism. Another property of EA is terminating criteria. This can be total number of generations to be produced or a condition can be defined to stop the algorithm such as after a number of un-improved generations produced.

If some solutions are known to be good among others, using these for creating initial solutions may be useful to reach better final solutions faster [96]. This procedure can be seen in Table 4.1.

Table 4.1: General algorithm of an evolutionary optimization procedure.

Evolutionary Optimization Procedure:
$t = 0$;
Initialization(P_t);
do
Evaluation(P_t);
P_t' = Selection(P_t);
P_t''= Variation(P_t');
P_{t+1} = Elitism(P_t,P_t'');
*$t = t + 1$; **od**;*
while
*(Termination(P_t,P_{t+1})); **od***

Table 4.1 represents the general form of evolutionary optimization procedure. First step is to create initial solution, P_0 (a set of individual solutions). Once the initial solution is created, the next step is to evaluate this solution, which means calculating this solutions objective function values and checking if the solution is feasible by calculating constraint values. Each solution is ranked or all solutions are sorted according to the applied method. Evaluation procedure differs between methods, which are explained in following parts of this section.

After evaluation step, better solutions are selected. The simplest form of selection is tournament selection [66]. Two solutions are selected from the evaluated population and they are compared, the one with the better order (rank) is selected.

The next step is variation which is provided by crossover and mutation operations. Crossover means exchanging information between individuals (members of solutions set) randomly. A predefined probability represents the proportion of individuals which are subject to crossover operation. Rest of the individuals is directly moved to the next population (usually called as child).

Another operator of variation is mutation. Individuals which are subject to mutation operation are again defined with a predefined probability. Difference of mutation operation from crossover is independency. Mutation operator allows making a local search around a randomly selected individual solution, independent from rest of the population [96].

Elitism is another important step of evolutionary optimization procedure. Elitism means keeping some elite solutions among new (child) and old (parent) generations. This assures a non-degrading progress. Different methods are being used to select elite solutions and some of them are explained in following parts.

All definitions of EAs can be found at the end of this dissertation (Appendix A: Evolutionary Optimization Terminologies).

So far operations of evolutionary optimization procedure is explained in a generalized manner; initialization, evaluation, selection, crossover, mutation, and elitism. These operations provide variation and carrying better solutions from generation to generation, which is essential to decrease the probability of sticking a local optimum and reaching a better solution faster.

Finally another thing to be decided is terminating condition, which is usually a number of total iterations or an objective function value. It means to stop the search for a solution after a predefined goal or a number of iteration is reached.

A brief explanation of evolutionary optimization procedure is made by Kalyanmoy Deb [96] and is as follows; "an EO procedure is a population-based stochastic search procedure which iteratively emphasizes its better population members, uses them to recombine and perturb locally in the hope of creating new and better populations until a predefined termination criterion is met".

EAs are popular approaches to generating Pareto-optimal solutions to a multi-objective optimization problem. Evolutionary algorithms such as the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Strength Pareto Evolutionary Algorithm 2 (SPEA-2) have become standard approaches, although some schemes based on particle swarm optimization and simulated annealing are significant. The main advantage of evolutionary algorithms, when applied to solve multi-objective optimization problems, is the fact that they typically generate sets of solutions, allowing computation of an approximation of the entire Pareto front. The main disadvantage of evolutionary algorithms is their lower speed and the Pareto optimality of the solutions cannot be guaranteed. It is only known that none of the generated solutions dominates the others.

4.3.2.1 Elitist NSGA (NSGA-II)

The NSGA-II procedure is one of the most popular EMOO procedures, which searches for the Pareto-optimal solutions in a MOOP. This method has the following three features [66]:

1. it is an elitist procedure,
2. it has an explicit diversity preserving mechanism, and
3. it emphasizes non-dominated solutions.

As in traditional genetic algorithms, offspring and parent populations (Q_t, P_t) are generated at each generation t. Then these populations are combined in a set and this new population is called R_t. Because offspring and parent populations are combined this new population's size is $2N$, where N is the number of individuals in initial population. After that the R_t is separated into classes of non-domination sets. The individuals in these sets are used to fill the set of R_t. Firstly the frontier non-dominated set members are placed in new population and these are followed by remaining classes' members respectively. There can be only N members in next population so the first N members of R_t are selected to form the new population. The individuals which cannot be placed in the new population are removed. When selecting N individuals any class may needed to be divided into selected and unselected members. When selecting the members for new population from the last frontier class, the members which provide the highest diversity are selected and others are removed as illustrated in Figure 4.3. To achieve this highest diversity crowding distance method is used. Crowding distance for any solution i, is the perimeter of the cuboid formed between solutions $i+1$ and $i-1$. After computing crowding distances the individuals in the last frontier set is sorted in a descending order according to their crowding distance values as shown in Figure 4.4. The individuals are selected from this sorted list to complete the selection of N individuals as new population. Shortly for any solution the crowding distance is the perimeter of a cuboid, where the two corners of this cuboid is the nearest solutions.

Genetic Algorithms are one of the best resulting search methods for the solution of large and complex mathematical models. Evolved from GA, NSGA-II is a robust elitist evolutionary multi-objective optimization algorithm [96, 103]. Also most of the multi-objective evolutionary algorithms, more or less, have the same framework with NSGA-II [104].

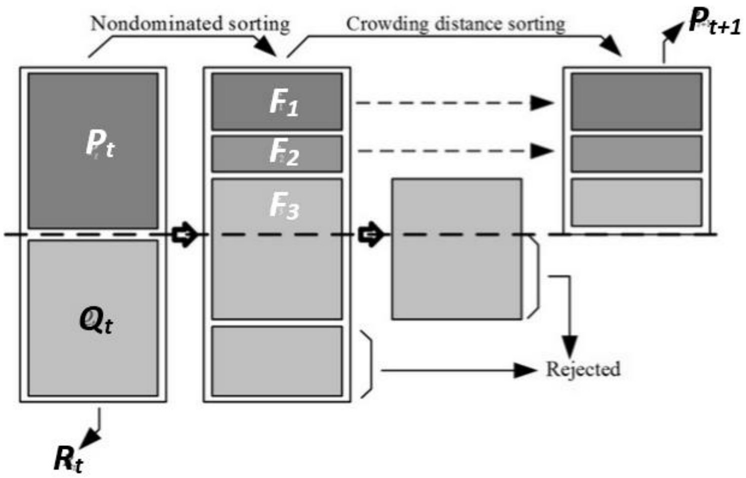


Figure 4.3: NSGA-II Procedure [66].

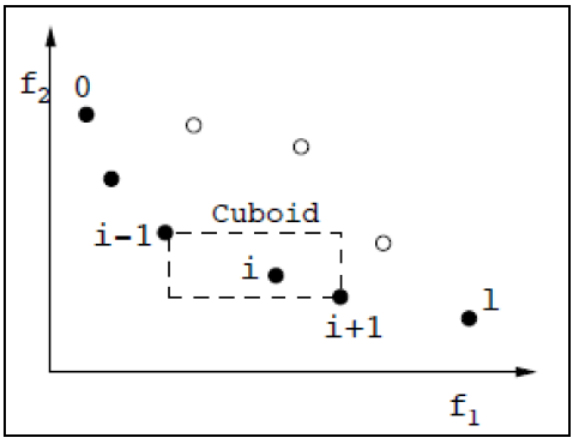


Figure 4.4: Crowding Distance [66].

4.3.2.2 Strength Pareto Evolutionary Algorithm 1-2 (SPEA and SPEA-2)

SPEA is proposed as an elitist multi-objective EA, which is based on non-domination of solutions [66]. This method is called Strength Pareto Evolutionary Algorithm (SPEA). The concept of this method is based on preserving all non-dominated solutions in a separate set, starting from the first generation and this set of solutions are used for genetic operations. This set forms another set by the addition of last population generated so far. The construction of this new set is the first step of this method. The second step is assigning fitness values to dominated and non-dominated solutions. This achieved by assigning a fitness to non-dominated solutions equal to the number of solutions they are dominating and to dominated solutions equal to the number of solutions dominating them plus one. This operation has two effects on the method's performance; first the search is being directed through the non-dominated solutions and also diversification is provided. For providing diversity, clustering is performed then the number of members in each cell is calculated to form a fixed sized archive. It is reported by the authors that, this method performs better in knapsack type problems.

SPEA-2 is an improved version of SPEA. Clustering, fitness assignment, and archive size keeping methods are slightly changed for better performance. Especially clustering method is modified in order to achieve diversity better. To calculate the distance between individuals, k^{th} nearest neighbor method is used. And to resolve a tie between two solutions with equal fitness values, density information is used [105,106].

4.3.2.3 Pareto Archived Evolution Strategy (PAES) and Pareto Envelope based Selection Algorithm 1-2 (PESA and PESA-2)

Knowles and Corne first proposed the method as Pareto Archived Evolution Strategy (PAES) [107]. PAES methodology has one parent and one child solution and these are compared to each other if one dominates the other. If the old solution is dominated by the new solution, child is selected to be the new parent and iterations proceed. When the opposite situation is occurred, the child is rejected and mutated to find a new solution. On the other hand, if there is no domination between solutions, a crowding procedure is used for solving the tie. So far found non-dominated solutions are kept to provide diversity. These kept solutions are compared to the child to see if any non-dominated archive solution is now being dominated by a new solution. If it is dominated, this new solution is selected and the solution dominated by this solution is deleted from archive. If there is no domination occurs when compared to archive, parent and child's Euclidean distances to the solutions in the archive is calculated, and if the child is placed in the least crowded area compared to archived solutions, it is selected as parent and added to the archive.

Another improved version of PAES is proposed and this method is called Pareto Envelope based Selection Algorithm (PESA). PESA is a multi-parent, PAES based method. In this version of method, SPEA and PAES are integrated. PESA has two populations like SPEA. These populations are the evolutionary algorithm population and archive population. Non-dominated solutions are found and crowding method, as used in PAES, is used for updating the archive in all iterations. Another version of PESA uses the concept of hyperboxes. The number of individuals positioned in a hyperbox is used to make selections. First hyperboxes are selected according to the number of solutions they contain and then a solution from selected boxes is randomly selected. Selecting the solution with this method performs better compared to individual solution selection of PESA.

4.4 Introducing Objectives of the Turn-Milling Process for the Optimization Study

The entire development of planning of the machine processes is based on the optimization of the economic and quality criteria by taking the technical and organizational limitations into account. In the cutting operations the economic criteria are the costs and the manufacturing time, whereas quality is defined with surface roughness and circularity of the work piece. The objectives of the turn-milling process are defined as minimization of surface errors, minimization of the costs and minimization of the production time.

In this section, based on the mathematical equations, surface quality, production cost and production time are expressed. Limitations are described for the study of optimization.

4.4.1 Minimizing Surface Errors

The most important criterion for the assessment of the surface quality is surface roughness but in turn-milling also circularity error must be taken into consideration.

To simplify optimization study, surface errors can be stated in one objective function that comprises surface roughness and circularity error together. However, due to Ra and Ce have different magnitudes, the normalization of objectives is required to get a Pareto-optimal solution. This method is called normalization in optimization studies [92]. Normalization procedure can be seen below:

$$Q = \frac{Ra - Ra_{min}}{Ra_{max} - Ra_{min}} + \frac{Ce - Ce_{min}}{Ce_{max} - Ce_{min}} \tag{4.8}$$

Note that, although cusp height formation is also directly affect the surface quality, it is not taking into consideration here because it is an evitable form error, hence with limiting axial feed, it is possible to produce parts without any cusp height formation.

4.4.2 Minimizing Production Cost

The operation cost can be expressed as the cost per product, C_p and it is calculated with the following equation:

$$C_p = C_t/T + C_l + C_o \tag{4.9}$$

where C_t = tool cost; C_l = labor cost and C_o = overhead cost. In some operations the C_t, C_l and C_o are independent of the cutting parameters.

4.4.3 Minimizing Production Time

Basically, maximizing the production rate is equivalent to minimizing the cutting time per part. Therefore, the aim is to complete the production order as quickly as possible. The total production cycle time for one part is composed of three items, i.e., set-up time, machining time, and tool change time. In turn-milling, the total production cycle time T_p for one part can be expressed as [61]:

$$T_p = T_s + V \times (1 + T_c/T)/MRR + T_i \tag{4.10}$$

where T_s = tool set-up time; T_c = tool change time; T_i = time during which the tool does not cut and V = volume of the removed material. In some operations, the T_s, T_c, T_i and V are constants so that T_p is the function of MRR and T.

4.4.4 Constraints

There are several factors limiting the cutting parameters. Those factors originate usually from technical specifications and organizational considerations. The following limitations are taken into account.

Due to the limitations on the machine and cutting tool and due to the safety of machining the cutting parameters are limited with the lower and upper bounds. Permissible range of cutting parameters:

$\upsilon_{min} \leq \upsilon \leq \upsilon_{max}$

$n_{w\ min} \leq n_w \leq n_{w\ max}$

$e_{min} \leq e \leq e_{max}$

$a_{e\ min} \leq a_e \leq a_{e\ max}$

$a_{p\ min} \leq a_p \leq a_{p\ max}$

Cusp height also can be count as a constraint because unlike the other form errors it can be avoidable if axial feed kept under critical level.

$a_e \leq a_{e\ critical}$

where $a_{e\ critical}$ can be calculated with the Eq. 3.6.

For the selected tool, the tool maker specifies the limitations of the cutting conditions. The limitation on the machine is the cutting power and the cutting force. Similarly, the machining characteristics of the work piece material are determined by physical properties.

The limitations of the cutting force and power:

$$F_c \leq F_{c\ max}$$
$$P \leq P_{max}$$

The problem of the optimization of cutting parameters can be formulated as the following multi-objective optimization problem:

$$min\ Q(\upsilon, n_w, e, a_e, a_p),$$

$$min\ C_p(\upsilon, n_w, e, a_e, a_p),$$
$$min\ T_p(\upsilon, n_w, e, a_e, a_p),$$

4.5 Summary

Multi-objective optimization has been applied in many fields of science, engineering, economics and logistics where optimal decisions need to be taken in the presence of trade-offs. Due to the parameter selection of turn-milling process is a multi-objective optimization problem, solution methods of MOOPs were searched and detailed literature review were made in chapter 4. Formulation of multi-objective optimization problem was established and Pareto-optimality term was explained here. Multi-objective optimization methods were handled as classifying in to two groups; priori methods and posteriori methods. Commonly used solutions methods were searched and their specifications were given in detail. Also objective functions and constraints of the turn-milling process are introduced here.

CHAPTER 5 OPTIMIZATION OF ORTHOGONAL TURN-MILLING PROCESS

In this chapter, multi-objective optimization; minimization of surface errors, production cost and production time on the turn-milling process is performed by applying different algorithms. Firstly one of priori algorithm; weighted sum method is applied to the problem. Then a posteriori algorithm; NSGA-II are performed. Also sensitivity analysis is conducted to test robustness of the results.

Next two figures show flowcharts of cutting parameters selection approaches in turn-milling for priori and posteriori algorithms respectively. These are also given in order to summarize this chapter.

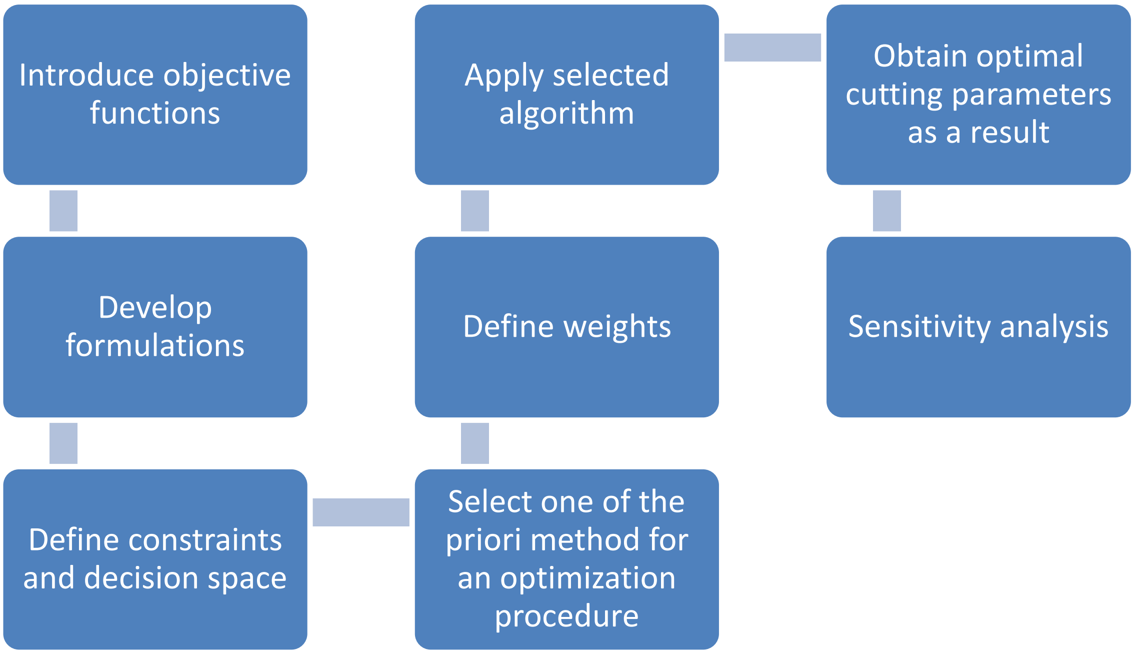


Figure 5.1: Steps of turn-milling process optimization by a priori methods.

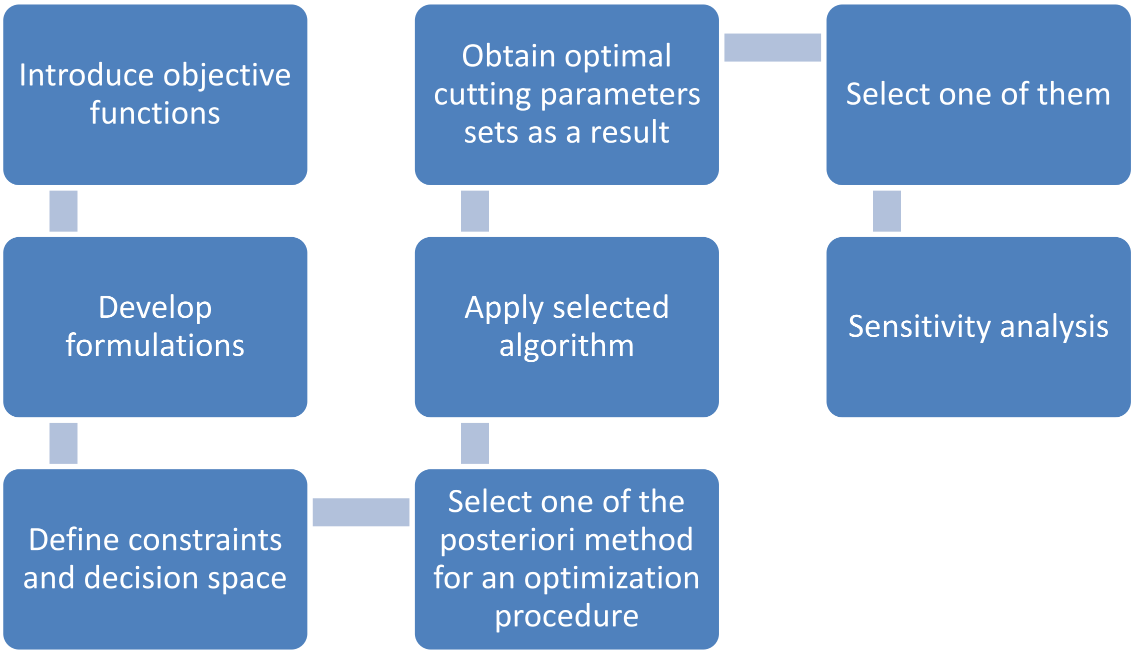


Figure 5.2: Steps of turn-milling process optimization by a posteriori methods.

5.1 Decision Variables of the Optimization Study

In order to be able to apply turn-milling process effectively process parameters should be selected properly. Spindle speed (n_t), work piece rotational speed (n_w), cutter offset (e), depth of cut (a_p) and axial feed (a_e) are defined as main process parameters of the orthogonal turn-milling process, which can effect tool life, surface roughness, circularity error, cusp height, MRR and cutting forces. Therefore, these five independent parameters can be selected as decision variables of the optimization problem. Preliminary tests were carried out to determine suitable parameter ranges. In Table 5.1 decision variables, their boundaries and system parameters are given for orthogonal turn-milling of 1050 steel under dry condition.

Cutting speed range is selected as 250 m/min to 360 m/min which are recommended values in face milling of 1050 steel. Axial feed was varied between 2 and 30 mm/rev but it should be remembered that due to process geometry the maximum value that can be selected depends on the cutter offset. If the offset is increased, axial feed rate value that you should select decreases because of the prevent cusp height form error. On the other hand, if you decrease the offset in order to select high axial feed, surface roughness of the work piece starts to increase. For instance when offset is zero, axial feed rate should not be more than 4 mm/rev (minor cutting edge length of the tool insert) in order to not to leave uncut material on the part as surface roughness. Maximum selectable axial feed values can be computed according to Equation 3.6.

Table 5.1: Decision variables and parameters.

Decision variables					
	Symbol	Description	Lower bound	Upper bound	Unit of measure
x_1	n_t	spindle speed	1600	2300	rpm
x_2	n_w	work rot. speed	2	10	rpm
x_3	e	cutter offset	0	25	mm
x_4	a_e	axial feed	2	30	mm/rev
x_5	a_p	depth of cut	0.4	1.2	mm

Parameters				
	Symbol	Description	Value	Unit of measure
p_1	D_w	work piece diameter (avg.)	70	mm
p_2	D_t	tool diameter	50	mm
p_3	z	number of teeth	4	
p_4		cutting condition	Dry	
p_5		work piece material	1050 steel	
p_6		tool material	TiN coated carbide	

The diameter of work piece and tool, number of teeth, cooling condition, work piece and tool materials are taken as invariable parameters. Work piece diameter changes in every pass, but to simplify it was assumed to remain constant as equal to the average work piece diameter.

In addition, according to decision variables, lower and upper bound of the objectives can be calculated. Table 5.2 shows boundary values of the important criteria.

Table 5.2: Lower and upper bounds of tool life, surface roughness, circularity error and material removal rate.

	T (min)	R_a (µm)	C_e (µm)	MRR (mm^3/min)
Lower	98,2	0,0127	0,0078	351
Upper	302,5	1,3	0,416	79168

In the calculation of production cost; tool, labor and overhead costs must be known. Besides, to calculate total production time; tool set-up time, tool change time, time during which the tool does not cut and volume of the removed material have to be obtained. For our case these values are given in Table 5.3.

Table 5.3: Some coefficients for cost and time calculations.

For the cost calculation			For the time calculation			
C_t (\$)	C_l (\$/min)	C_o (\$/min)	T_s (min)	T_c (min)	T_i (min)	V (mm^3)
13,55	0,31	0,08	1	2	1	197920

Including these coefficients, Equations 4.8, 4.9 and 4.10 can be used to find their minimum and maximum values. Table 5.4 shows results.

Table 5.4: Lower and upper bounds of the objective functions.

	Q, factor of surface error	C_p (\$/min)	T_p (min)
Lower	0	0,4348	4,51
Upper	2	0,528	575,95

5.2 Gradient Based Optimization

Pareto fronts can be obtained by weighted sum approach using gradient based optimization algorithm. Therefore one of the gradient based algorithm; sequential quadratic programming (SQP) is applied to our problem.

5.2.1 Sequential Quadratic Programming Method

The SQP method based on the iterative formulation and solution of quadratic programming sub-problems, obtains sub-problems by using a quadratic approximation of the Lagrangian and by linearizing the constraints.

SQP algorithm:

$$\text{Min } \frac{1}{2} p^T B_K p + \nabla J(x_K)^T p \,, \tag{5.1}$$

$$x_L - x_K \le p \le x_U - x_K$$

B_K: Positive-definite approximation of the Hessian

x_K: Current iterate

p_K: Solution for the sub-problem

Line search is used to find the new point x_{K+1}.

$x_{K+1} = x_K + \alpha_K p_K, \quad \alpha \in (0,1]$

Merit function *(Augmented Lagrange function)* will have lower function value at the new point. If optimality is not achieved, B_K is updated according to modified BFGS formula.

The MATLAB is used to employ the SQP optimization. The MATLAB code requires objective function information and the gradient information of the objective function. After normalization and duality principle are applied, objective function can be defined as;

$$\min J = w_1 \cdot \frac{Q - Q_{\min}}{Q_{\max} - Q_{\min}} + w_2 \cdot \frac{C_p - C_{p\min}}{C_{p\max} - C_{p\min}} + w_3 \cdot \frac{T_p - T_{p\min}}{T_{p\max} - T_{p\min}} \tag{5.2}$$

subject to $x_L \le x \le x_U$

$a_e \le a_{e\ \mathrm{critical}}$

$\mathrm{F} \le \mathrm{F}_{\mathrm{critical}}$

Gradient of the objective function:

$$\nabla J = w_1 \cdot \frac{\nabla Q - Q_{\min}}{Q_{\max} - Q_{\min}} + w_2 \cdot \frac{\nabla C_p - C_{p\min}}{C_{p\max} - C_{p\min}} + w_3 \cdot \frac{\nabla T_p - T_{p\min}}{T_{p\max} - T_{p\min}} \tag{5.3}$$

where,

$$\nabla Q = \begin{bmatrix} \dfrac{\partial Q}{\partial n_t} & \dfrac{\partial Q}{\partial Qn_w} & \dfrac{\partial Q}{\partial e} & \dfrac{\partial Q}{\partial Qa_e} & \dfrac{\partial Q}{\partial Qa_p} \end{bmatrix}$$

$$\nabla C_p = \begin{bmatrix} \dfrac{\partial C_p}{\partial n_t} & \dfrac{\partial C_p}{\partial Qn_w} & \dfrac{\partial C_p}{\partial e} & \dfrac{\partial C_p}{\partial Qa_e} & \dfrac{\partial C_p}{\partial Qa_p} \end{bmatrix}$$

$$\nabla T_p = \begin{bmatrix} \dfrac{\partial T_p}{\partial n_t} & \dfrac{\partial T_p}{\partial Qn_w} & \dfrac{\partial T_p}{\partial e} & \dfrac{\partial T_p}{\partial Qa_e} & \dfrac{\partial T_p}{\partial Qa_p} \end{bmatrix}$$

As shown in above equations w_1, w_2 and w_3 are weights of the objectives and these are very important in this approach. As mentioned before in priori methods, decision maker should define the weights before optimization process. Therefore, in this stage to implement optimization procedure for turn-milling, decision maker must get involved in order to define the weights. There is not an exact procedure for these weight selection, but one can use AHP (Analytic Hierarchy Process) or it can be selected as follows for finishing and roughing operations respectively:

Table 5.5: Weights of the objectives.

	Surface Errors	Production cost	Production time
Finishing	0,5	0,3	0,2
Roughing	0	0,35	0,65

The MATLAB code for the optimization is given in Appendix B. Design variables, objective function and its gradients are defined in *"Turn_milling_ObjFun.m"*, and constraints are defined in *"Turn_milling_ContsFun.m"*. The *"Turn_milling_SQP.m"* file calls the *"Turn_milling_ObjFun.m"* and *"Turn_milling_ContsFun.m"* and employ optimization algortihm.

The simulation is started 15 times with random initial conditions for finishing operation. It starts to search optimal cutting parameters with these random (cutting parameters) values. After number of iterations, it reaches optimal solution. The simulation is repeated again for the roughing operation. Initial cutting parameters, optimum objective function values, optimal values of the surface errors, production cost and time, optimal values of the cutting parameters and the convergence history for each generation are given in the next tables.

Table 5.6: Initial cutting parameters and optimum objective values for finishing operation.

X_0 (initial cond.)					J_{opt}	Q_{opt}	$C_{p\ opt}$	$T_{p\ opt}$	CPUtime
n_t	n_w	e	a_e	a_p					
2285	5,51	21,75	3,12	0,42	0,2410	0,0451	0,4361	14,5884	3,12
2016	4,09	22,44	13,41	1,17	0,2410	0,0451	0,4361	14,5884	1,45
1682	4,37	14,91	23,47	0,60	0,2410	0,0451	0,4361	14,5884	1,52
1659	4,09	8,11	21,10	0,84	0,2410	0,0451	0,4361	14,5884	2,37
2111	5,90	24,51	18,36	0,86	0,2410	0,0451	0,4361	14,5884	1,73
2274	6,37	19,39	22,18	1,19	0,2410	0,0451	0,4361	14,5884	1,84
2036	7,43	15,37	26,88	0,79	0,2410	0,0451	0,4361	14,5884	1,63
1626	9,08	21,57	10,69	0,97	0,2410	0,0451	0,4361	14,5884	1,27
1783	4,68	4,21	25,62	1,17	0,2410	0,0451	0,4361	14,5884	2,02
1674	7,23	18,58	21,71	0,97	0,2410	0,0451	0,4361	14,5884	1,26
2232	9,12	9,60	15,36	0,86	0,2410	0,0451	0,4361	14,5884	2,16
1621	7,95	24,38	23,43	1,12	0,2410	0,0451	0,4361	14,5884	1,56
2026	6,94	16,37	15,75	0,56	0,2410	0,0451	0,4361	14,5884	1,38
1728	3,91	21,14	17,60	1,90	0,2410	0,0451	0,4361	14,5884	1,79
1717	9,82	10,39	7,81	0,87	0,2410	0,0451	0,4361	14,5884	1,77

Table 5.7: Initial cutting parameters and optimum objective values for roughing operation.

X_0 (initial cond.)					J_{opt}	Q_{opt}	$C_{p\ opt}$	$T_{p\ opt}$	CPUtime
n_t	n_w	e	a_e	a_p					
1664	6,91	11,04	18,05	1,03	0.2592	0.5115	0.4352	6.7911	2,52
1764	5,58	3,27	3,71	0,79	0.2592	0.5115	0.4352	6.7911	1,12
2049	3,77	24,34	29,19	1,07	0.2592	0.5115	0.4352	6.7911	1,26
1954	4,23	18,98	8,63	1,16	0.2592	0.5115	0.4352	6.7911	1,02
2034	6,80	14,69	4,52	0,60	0.2592	0.5115	0.4352	6.7911	1,07
2200	9,28	23,79	22,30	0,58	0.2592	0.5115	0.4352	6.7911	1,01
2003	8,48	11,61	29,67	0,47	0.2592	0.5115	0.4352	6.7911	1,09
1824	6,09	13,24	22,31	0,84	0.2592	0.5115	0.4352	6.7911	0,99
1970	8,63	7,43	24,09	0,65	0.2592	0.5115	0.4352	6.7911	1,07
1916	8,01	21,43	5,07	0,61	0.2592	0.5115	0.4352	6.7911	0,92
1967	9,78	16,84	10,73	0,63	0.2592	0.5115	0.4352	6.7911	1,09
2195	9,29	9,55	9,15	0,47	0.2592	0.5115	0.4352	6.7911	1,21
2186	6,67	18,79	3,70	0,86	0.2592	0.5115	0.4352	6.7911	0,96
1799	8,62	21,76	14,39	0,71	0.2592	0.5115	0.4352	6.7911	1,15
2178	7,41	21,83	10,90	0,50	0.2592	0.5115	0.4352	6.7911	1,1

Optimization results which are proposed by the algorithm can be found in Table 5.8.

Table 5.8: SQP optimization results for 15 generations.

	$X_{optimal}$				
	n_t	n_w	e	a_e	a_p
Finishing	1600	2	21,92	23,92	1,199
Roughing	1600	5,2531	21	26,85	1,199

Table 5.9: Convergence history for SQP for 15 random iterations.

Generation	Iterations	funcCount	stepsize	Iterations	funcCount	stepsize
1	70	463	1,9635813	49	301	0,0143651
2	57	379	1,6099017	52	319	0,0071329
3	70	439	0,0001624	59	364	0,0932506
4	97	648	3,4933107	45	283	0,0199190
5	71	463	6,1654005	50	310	0,0184849
6	75	513	1,5221381	47	293	0,0038984
7	72	479	0,0001234	51	313	0,0192816
8	58	364	0,0001642	45	284	0,0029058
9	85	572	3,3966689	50	310	0,0029777
10	59	366	5,4580011	42	259	0,0185138
11	90	616	1,6711026	50	310	0,0005081
12	63	405	5,2689521	54	339	0,0164194
13	58	383	7,0265210	44	274	0,0202109
14	76	501	5,6226381	53	325	0,0237264
15	80	513	0,0001228	52	321	0,0933760

As it can be seen from the tables, the SQP algorithm converges to same minimum for 15 random initialization. However, it is known that SQP is a local extremum search technique, which means that it can be trapped to local minima in the feasible region. The global minimality of the SQP minimum can be satisfied in convex design spaces. If the Hessian of the objective function is positive definite at every point of closed and bounded design space, than the design space can be said to be convex. However, it is very difficult to observe the positive definiteness of the Hessian over the domain. In our optimization problem, the SQP minimum is most probably the global minimum for the objective function in the given design space because SQP algorithm goes to same minimum for 15 random generations. Note that SQP algorithm finds feasible minimums although it starts from infeasible region.

5.2.2 Sensitivity Analysis for SQP

Sensitivity analysis are performed in order to observe the effect of design variable variation on the optimal solution. The sensitivity of the objective function to the design variables can be measured with this analysis. The method depends on the evaluation of the objective function gradient at the optimal point, x_{opt}. For this purpose, the gradient of the objective function, which was derived in the previous section, is used for MATLAB code.

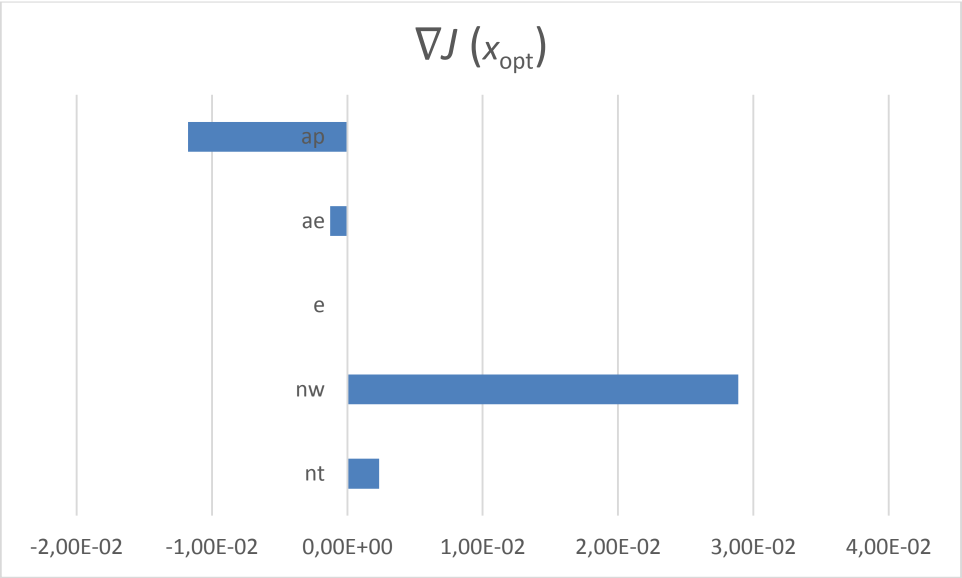


Figure 5.3: Sensitivities of J in finishing operation.

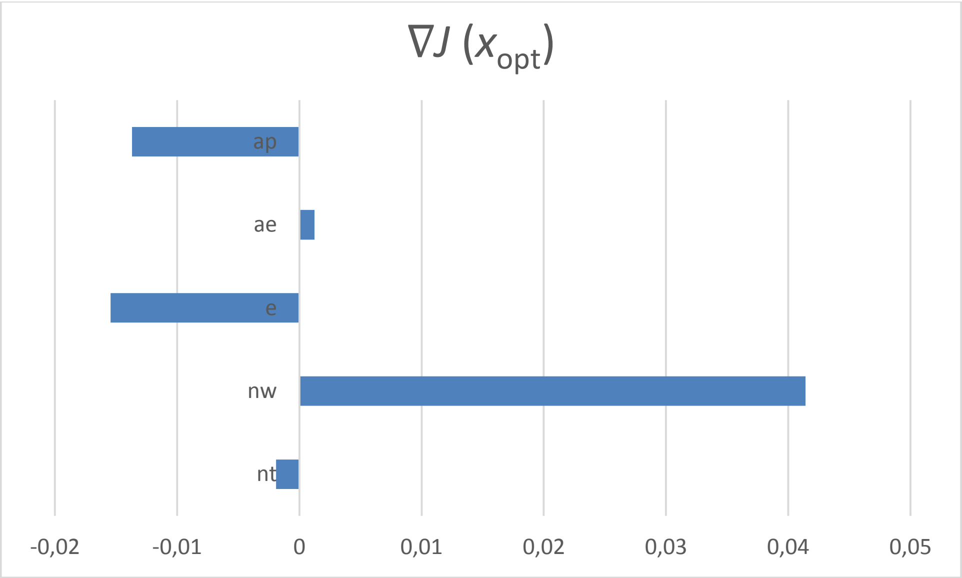


Figure 5.4: Sensitivities of J in roughing operation.

Results of sensitivity analysis shows that the objective function is more sensitive to cutter offset and depth of cut in the case of finishing. In roughing case, work rotational speed, cutter offset and depth of cut seem to be drivers for the system.

5.3 Heuristic Optimization

Heuristic optimization (HO) methods is that they start off with a more or less arbitrary initial solution, iteratively produce new solutions by some generation rule and evaluate these new solutions, and eventually report the best solution found during the search process.

5.3.1 NSGA-II Method

In this study, Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) [108] had been used to solve this multi-objective optimization problem by identifying the Pareto-optimal front (Pareto surface). Because NSGA-II is a GA based algorithm, it is commonly used to construct search algorithms that are robust and require minimal problem information. So, application of NSGA-II to optimization problems is rather easy compared to classical methods and other evolutionary algorithms. NSGA-II work with a population of solution instead of a single solution and they do not require any auxiliary information except the objective functions [66].

NSGA-II is an extension of the Genetic Algorithm for multiple objective function optimization and it is applied to our problem to improve the adaptive fit of a population of candidate solutions to a Pareto front constrained by surface topography errors, production cost and time. The Pareto-optimal front is defined as the point cloud of all optimal solutions obtained after putting different weights on objectives artificially. The population is sorted into a hierarchy of sub-populations based on the ordering of Pareto dominance. The best non-dominated solutions are called non-dominated solutions of level 1. In order to find solutions for the next level of non-domination, there is a simple procedure which is followed. Once the best non-dominated set is identified they are temporarily disregarded from the population. The non-dominated solutions of the remaining populations are then found and are called non-dominated solutions of level 2. In order to find the non-dominated solutions of level 3, all non-dominated solutions of levels 1 and 2 are disregarded and new non-dominated solutions are found. This procedure is continued until all populations members are classified into a non-dominated level. The working cycle of NSGA-II is explained through a few steps given below [109]:

1. The initial population is generated randomly based on the ranges of variables of the problem.

2. The initialized population is then sorted based on non-domination into a few fronts.
3. Each individual of every front is assigned a rank (fitness) and a crowding distance value. Individuals in the first front are given a fitness value of 1 and individuals in second front are assigned fitness value of 2, and so on. Crowding distance is calculated for each individual as a measure of how close an individual is to its neighbors.
4. Parents are selected from the population using binary tournament selection based on rank and crowding distance.
5. The selected population generates offspring through crossover and mutation operations.
6. The solutions in current population and current offspring are sorted again based on non-domination and only the best individuals are selected. The selection is based on the rank and crowding distance on the last front.

MATLAB Optimization Toolbox [110] is one of the important commercial program toolbox which can be used to solve the design and optimization problems. The multi-objective GA function, *gamultiobj* which developed based on NSGA-II in MATLAB is used to perform turn-milling optimization problem. An elitist GA (NSGA-II) always favors individuals with better fitness value. To maintain the diversity of population for convergence to an optimal Pareto front is very significant. This step is achieved by controlling the elite members of the population when the algorithm progresses. The options '*ParetoFraction*' and '*DistanceFcn*' are utilized in order to control the elitism in MATLAB. The first option Pareto fraction limits the number of individuals on the Pareto front. The distance function helps to maintain diversity on a front by favoring individuals that are relatively far away on the front.

5.3.2 Gamultiobj Solver

The *gamultiobj* solver tries to create a set of Pareto optima for a multi-objective minimization. It can be set bounds and constraints on variables. To be able to find local Pareto optima, *gamultiobj* solver utilizes the genetic algorithm. It can be specified an initial population, or the solver itself can generate one automatically. The fitness function should return a vector of type double. The population type consists of double, bit string vector, and custom-typed vector. If a custom population type is utilized, the user must write his/her creation, mutation, and crossover functions that accept inputs of that population type. After that, it must be specified the following functions: '*CreationFcn*' (creation function), '*MutationFcn*' (mutation function), and '*CrossoverFcn*' (crossover function).

5.3.3 Solution Steps, Optimization Results and Parameter Selection Procedure

There are three objective functions $f(x) = (f_1(x), f_2(x), f_3(x))^T$ considered in the given multi-objective optimization formulation. Each objective function wants to be minimized in this case. The objective functions can be defined as:

Minimize $f_1(x) = Q$,

Minimize $f_2(x) = Cp$,

Minimize $f_3(x) = Tp$,

subject to $1600 \le n_t \le 2300$, (5.4)

$2 \le n_w \le 10$,

$0 \le e \le 25$,

$0.5 \le a_p \le 1$,

$2 \le a_e \le 30$

$a_e \le a_{ecrit}$

$F_c \le F_{c\,max}$

When multiple conflicting objectives are important, similar to this problem, there cannot be a single optimum solution which simultaneously optimizes all objectives. The resulting outcome is a set of optimal solutions with a varying degree of objective values [66]. In turn-milling process optimization, same situation emerges. Changing spindle speed effects tool wear and circularity error in different way or changing depth of cut effects MRR and cutting forces differently. As bottom line there is no one solution that enhance all the objectives, so there must be a large number of optimal cutting parameters set.

Figure 5.5 represents the problem setup for the multi-objective genetic algorithm analysis of *gamultiobj* solver user interface. In Table 5.10 genetic algorithm parameters for multi-objective approach used in the model problems have been listed.

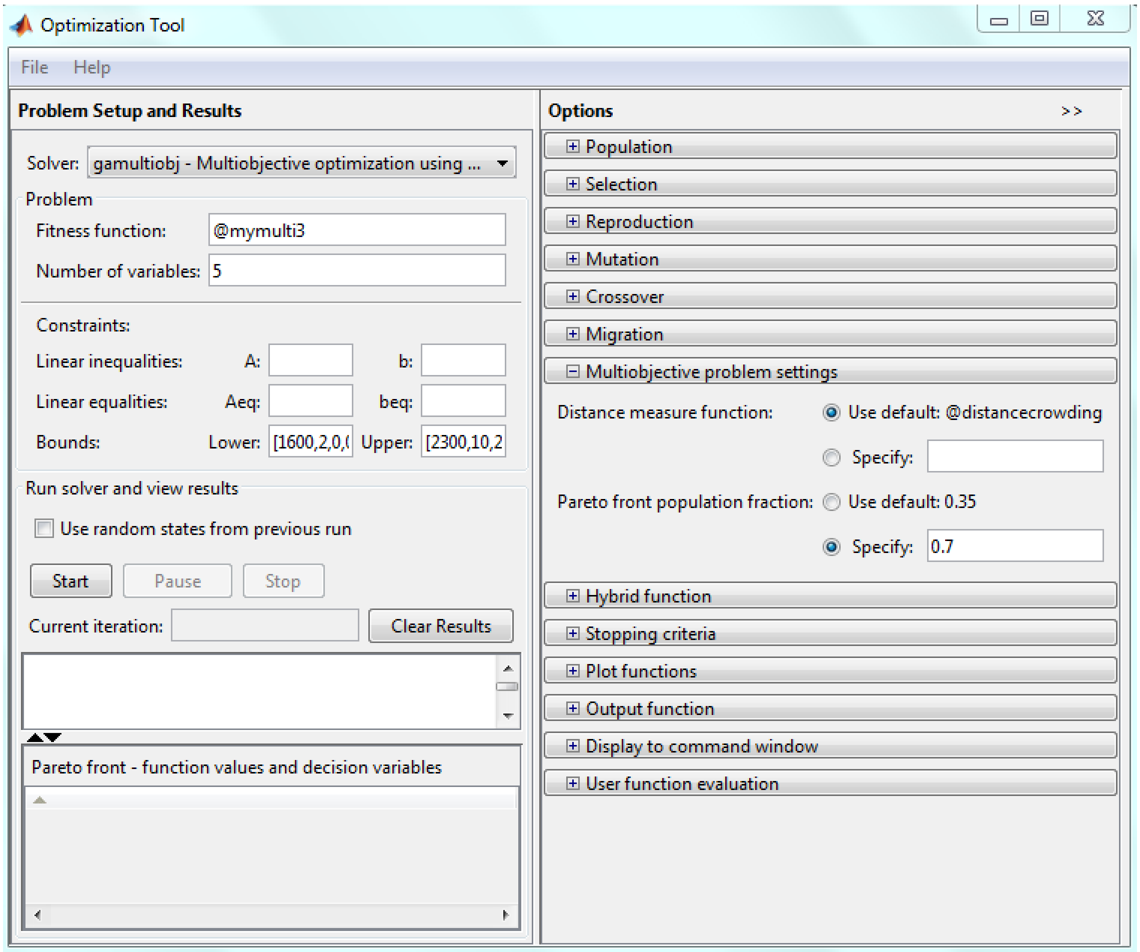


Figure 5.5: MATLAB optimization toolbox gamultiobj solver user interface.

Table 5.10: Genetic algorithm parameters for multi-objective optimization problem of turn-milling model.

Population Type	Double vector
Population size	300
Selection	Tournament
Crossover fraction	0.8
Mutation function	Adaptive feasible
Crossover function	Intermediate, Ratio=1.0
Migration direction	Both, Fraction=0.2, Interval=20
Multi-objective problem settings	Pareto front population fraction=1.0
Initial penalty	10
Penalty factor	100
Hybrid Function	None
Stopping criteria	Generations:10000, Stall generations:400, Function tolerance: 10^{-6}

In order to use the solver that is shown their interface, first a fitness function must be defined. This function that contains objectives and the required parameters is prepared in MATLAB and given in Appendix C.

Primarily, objectives are evaluated dually that is to say two objective functions are considered each time to see the interaction with each other. After the each generation, obtained Pareto-optimal fronts can be seen in Figure 5.6, Figure 5.7 and Figure 5.8.

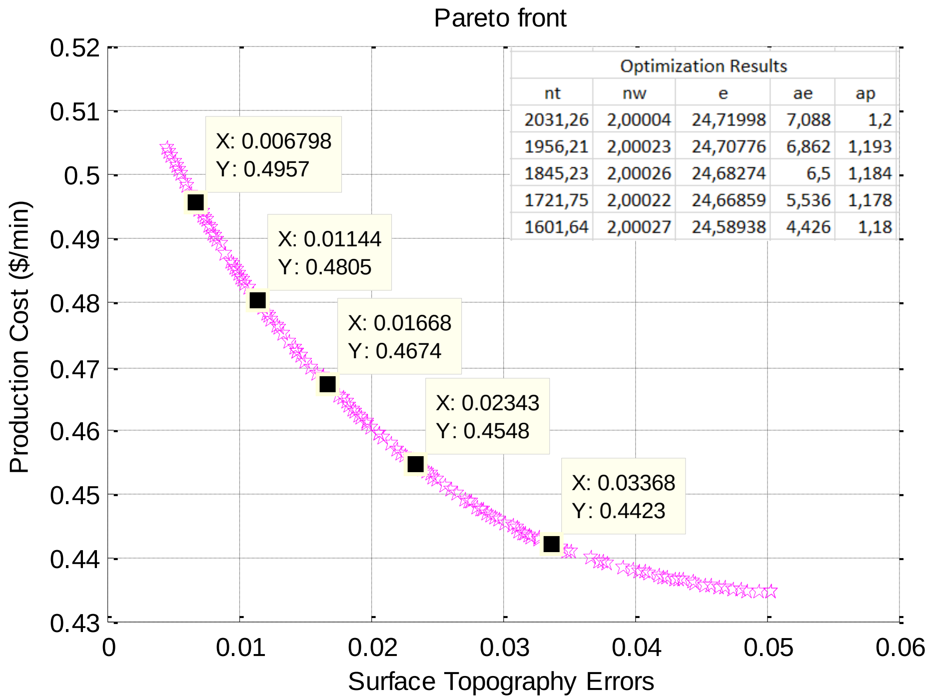
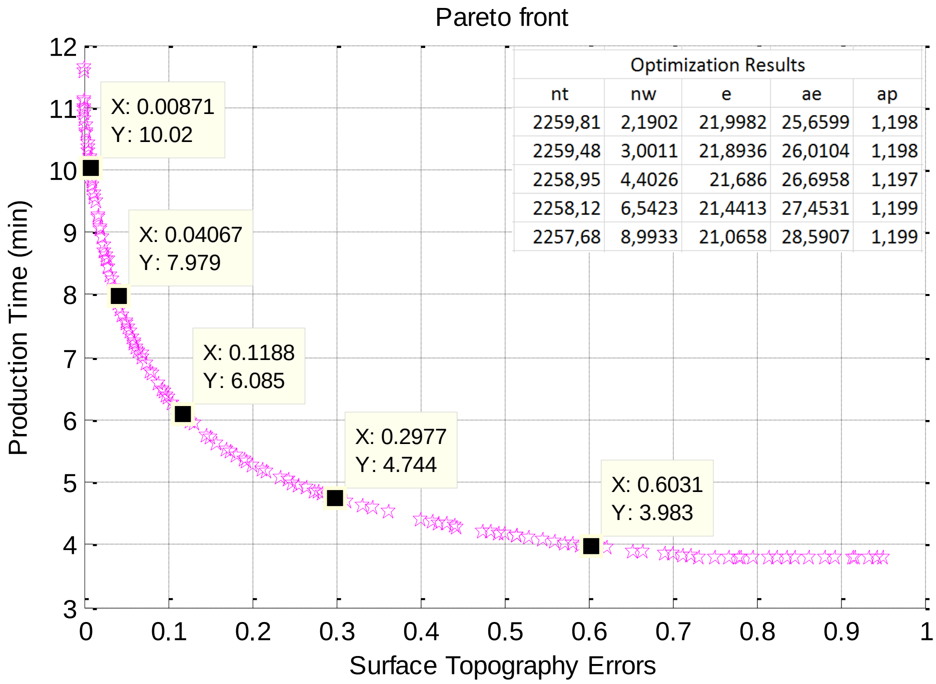


Figure 5.6: The Pareto front of non-dominated solutions for surface errors and cost.

NSGA-II algorithm, designed for the first case study, takes spindle speed, work rotational speed, cutter offset, axial feed rate, and cutting depth as inputs and predicts surface errors and production cost. Increasing cutting speed resulted in significant increase in tool wear development, however resulted in better surface roughness. On the other hand, increasing cutter offset after the critical value (21 mm in this case) shows better results for surface roughness but with tool life decreases.



nt	nw	e	ae	ap
2259,81	2,1902	21,9982	25,6599	1,198
2259,48	3,0011	21,8936	26,0104	1,198
2258,95	4,4026	21,686	26,6958	1,197
2258,12	6,5423	21,4413	27,4531	1,199
2257,68	8,9933	21,0658	28,5907	1,199

Figure 5.7: The Pareto front of non-dominated solutions for surface errors and time.

Since the selection of work rotational speed influences surface roughness and machining time conversely, minimization of surface roughness and minimization of machining time are contradicting objectives. In order to obtain a good surface finish, work rotational speed should be reduced, which then increases the machining time. Therefore, a compromise between surface roughness and machining time should be made. According to some candidate solutions listed in Figure 5.7, machining time can be reduced more than one minute with a 0.05 micron sacrifice in surface roughness estimation by setting the work rotational speed to n_w=3 rpm instead of n_w=2.2 rpm.

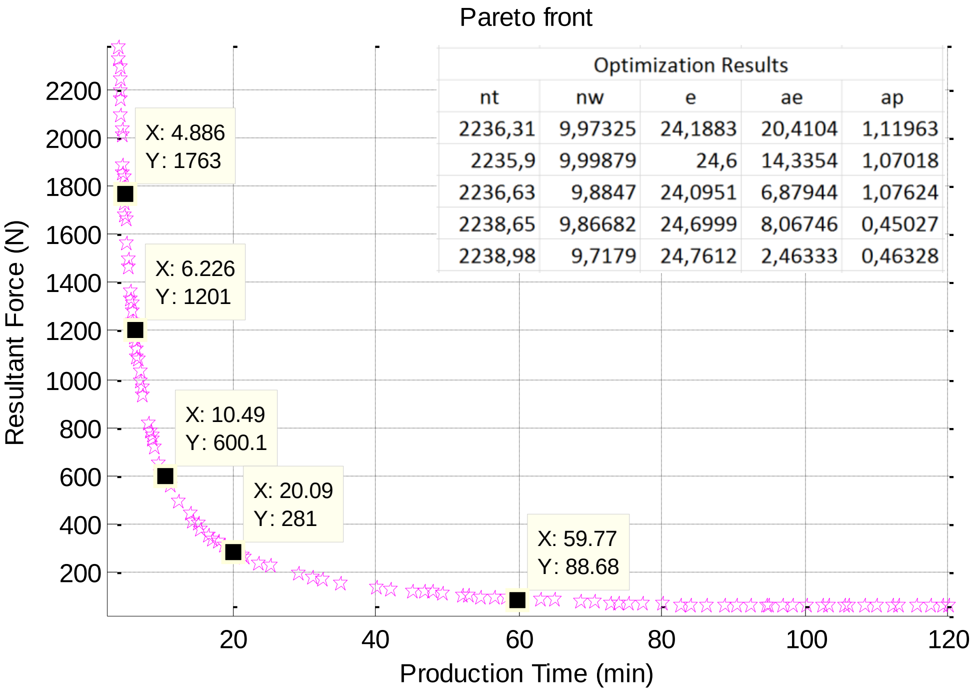


Figure 5.8: The Pareto front of non-dominated solutions for time and cutting force.

It has been observed that axial feed rate and depth of cut strongly effect production time and resultant cutting force conversely. Selection should be made with thinking of this trade-off.

Apart from these generations, also a Pareto front can be obtained as shown in Figure 5.9 for the main optimization problem. In this case minimization of surface topography errors, minimization of production cost and minimization of production time are aimed simultaneously.

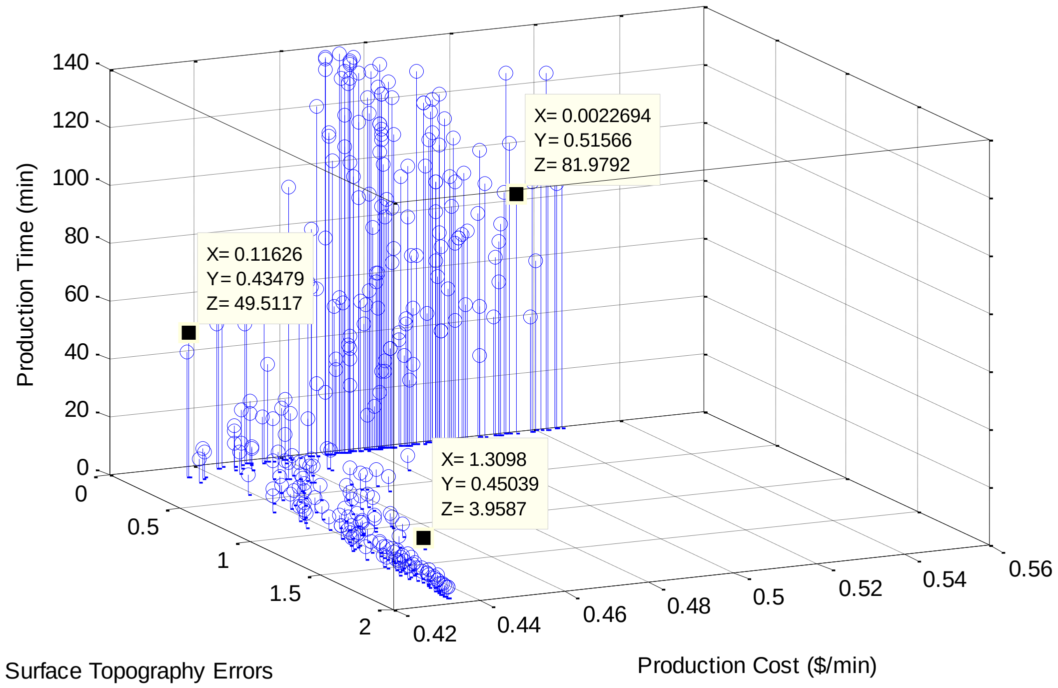


Figure 5.9: The Pareto front of non-dominated solutions for surface errors, cost and time.

After running simulations Pareto-optimal solutions were found. A large number of optimal solutions lying on the obtained Pareto front are available to the user as shown in Figure 5.9. Twenty of them are given in Table 5.11.

Table 5.11: Objective values of best solutions.

Solution	Surface Topography Errors	Production cost ($/min)	Production Time (min)
1	1,3098	0,45039	3,9587
2	0,11626	0,43489	49,5117
3	0,00226	0,51566	81,9792
4	1,88194	0,43538	3,7752
5	0,01012	0,4846	25,9952
6	0,01277	0,483171	19,1411
7	0,022481	0,465865	12,75347
8	0,033577	0,454878	15,65005
9	0,042138	0,447948	13,65727
10	0,670306	0,454365	4,50473
11	0,515190	0,443194	5,091605
12	0,271911	0,452171	6,144715

13	0,147938	0,445782	7,423064
14	0,1346931	0,437784	8,431299
15	0,0089562	0,488136	92,2955039
16	0,0140419	0,473494	137,3923211
17	0,0090931	0,4878663	38,8909670
18	0,0030116	0,5119000	72,3817337
19	0,0230934	0,4565486	33,0077772
20	0,2205298	0,4556209	6,224182

According to these solutions corresponding cutting parameters are given in Table 5.12.

Table 5.12: Optimal cutting parameters.

Solution	Spindle speed n_t, (rpm)	Work rotational speed n_w, (rpm)	Cutter offset, e (mm)	Axial feed, a_e (mm/rev)	Depth of cut, a_p (mm)
1	1694	9,7180	21,5065	24,964	1,19413
2	1600	2,7354	21	4,0664	1,2
3	2219	2,0008	24,91213	3,4090	1,17626
4	1648	9,9377	21,1931	26,9641	1,1998
5	1991	2,0016	23,9514	11,2436	1,1828
6	1983	2,05335	23,88489	15,3360	1,18318
7	1845	2,09541	24,59809	23,7660	1,18960
8	1785	2,14391	23,33291	18,5277	1,17304
9	1688	2,20323	23,15588	20,9408	1,18137
10	1777	7,10698	21,40437	25,47478	1,19910
11	1649	5,83031	21,4640	25,31064	1,187626
12	1764	4,58536	21,08218	26,00082	1,194724
13	1700	3,36035	21,79138	24,18717	1,194204
14	1624	3,00587	21,85496	27,35027	1,199942
15	2019	2,00073	24,85252	3,00517	1,177227
16	1896	2,00019	24,89382	2,04670	1,150634
17	2019	2,00172	24,62805	7,29325	1,186651
18	2194	2,00049	24,87654	3,85818	1,180606
19	1761	2,00541	24,42492	8,57204	1,193508
20	1775	4,301347	21,82785	24,146344	1,181682

All of the presented solutions are non-dominated that is to say they all satisfy optimization criteria. Of these solutions any solution set if compared with each other, superiority of one over the other cannot be established with five objectives in mind.

As emphasized on the previous chapter, in posteriori type of optimization all the best solutions are found first then decision maker involves to the procedure and among the solutions s/he selects one of them. So, decision maker should first evaluate result of the objective values in the Table 5.11 and he/she could choose one of the case which is best suited his/her demands (i.e. according to importance of the objectives). After determining the proper case (finishing, semi-finishing or roughing), relative cutting parameters can be read from Table 5.12, at the end they are selected to be used in orthogonal turn-milling process.

5.3.4 Sensitivity Analysis for NSGA-II

Sensitivity analysis are performed again in order to observe the effect of design variable variation on the optimal solution. Gradients of the objective functions are evaluated at the optimal point. Parameters given in the solution 1, 2 and 3 from the Table 5.12 are used as optimal points. Below the results can be seen for each objective function and for each solution:

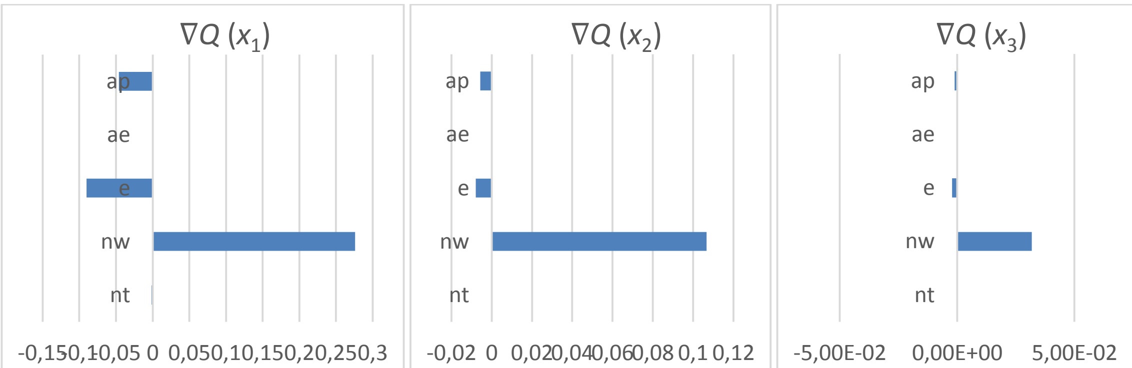


Figure 5.10: Sensitivities of Q for different solutions.

Sensitivity analysis results for the surface topography errors shows that the objective function is more sensitive to n_w, e and a_p.

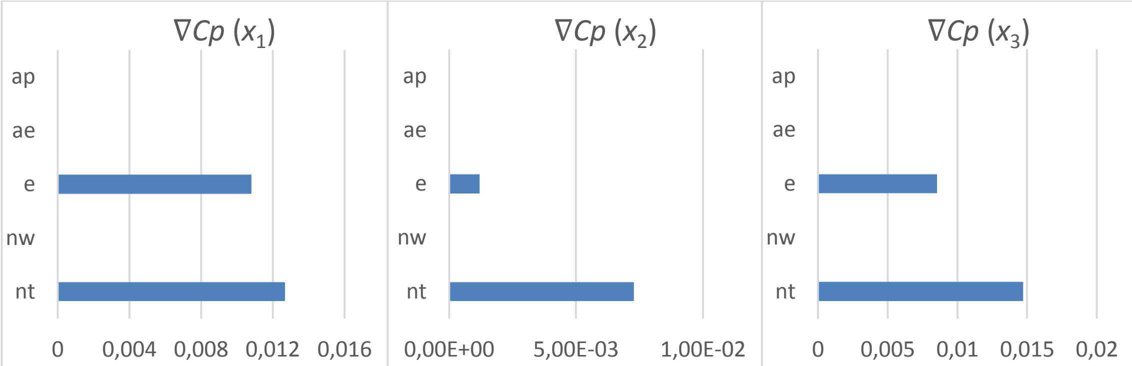


Figure 5.11: Sensitivities of C_p for different solutions.

According to results, it can be said that production cost most effected by n_t and e.

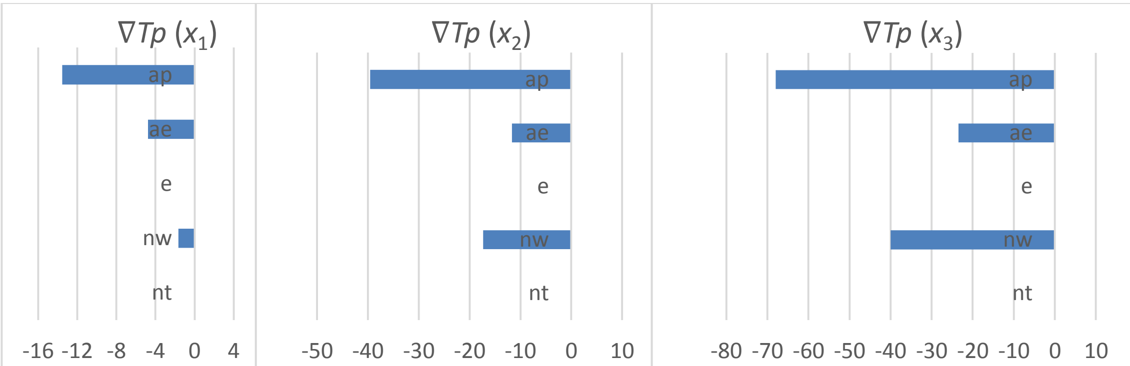


Figure 5.12: Sensitivities of T_p for different solutions.

In here it is seen that production time are more sensitive to changes on the n_w, a_e and a_p values.

5.4 Discussions

All in all, it can be mentioned about advantages of NSGA-II method over SQP as follows:

Using weighted sum methods, combining the different objectives into a scalar function, which actually made the multi-objective problem a single-objective problem before optimization. The deficiency in converting a multi-objective problem into a single-objective problem is that the scalar function in the latter problem cannot reflect the visibility of an individual objective function clearly. On the other hand, with NSGA-II method, it is more possible to find best results by optimizing objectives at the same time.

Although it is possible to reach a solution rapidly in methods which include weight assignment for objective functions, obtained solution set is not the best one that enables DM request. When NSGA-II is used, in this case, all the best solutions are found and it is known that selected solution set will give the best result to the DM. But, when this type of MOOP solution methods are used computational time is much longer because they try to find all the best solutions.

Based on this chapter following guide can be created to generate and select optimal cutting parameters for turn-milling processes:

- Process models (tool wear, surface roughness, cutting force etc.) must be constructed in according to type of turn-milling for different tool and work piece materials.

- Decision space should be defined by the help of tool suppliers' catalogue and conducting some tests.

- GA parameters (population size, selection, mutation, crossover methods) should be specified for the algorithm.

- An elitist NSGA should be applied to rank the solutions.

- Among the solutions, optimal cutting parameters can be selected according to desired objective values.

5.4.1 Comparison of Optimal and Non-Optimal Solutions

Firstly it should be mentioned about what is optimal solution. To say a solution is optimal, obtained objective values with using parameters suggested by the solution must be match well with our demands. There are two issues which should be comprehend here. Within the best (non-dominated) solutions, a few of them actually match up with desired objectives, so these are the optimal solutions for us. When these few solutions compared to other best solutions, it would be observed that some objectives are upgraded however some others getting worse. As a result, objectives will be move away from the desired ones. For example, in roughing operation production time and cost are more important, it would be unreasonable to sacrifice these criteria to improve surface quality. On the other side, there are also non-optimal solution sets although their cutting parameters within the decision space. If these non-optimal solutions are compared with the optimal ones, it can be seen that all objectives are worse. Actually main reason of using optimization is to eliminate these solutions and gives the only best solutions.

Without optimization study, decision maker would have to select cutting parameters randomly within decision space. In that case process will lose their effectiveness. To understand importance of optimization, from the non-dominated solution sets twenty of them given in Table 5.13 would be compared with selected random values of cutting parameters in Table 5.14. In order to obtain Table 5.13, condition that is mentioned beforehand in this chapter is considered.

Table 5.13: Cutting parameters of non-dominated solutions.

Solution	Spindle speed n_t, (rpm)	Work rotational speed n_w, (rpm)	Cutter offset, e (mm)	Axial feed, a_e (mm/rev)	Depth of cut, a_p (mm)
1	1600	8,6427	21,000	27,267	1,0585
2	1632	9,9989	21,109	26,487	1,0788
3	1752	4,4176	19,320	25,009	1,0851
4	1665	9,8837	21,032	27,004	1,0693
5	1917	2,0000	23,504	9,2198	1,1094
6	1994	7,4436	20,048	24,735	1,1480
7	2004	6,3033	21,018	24,064	1,1368
8	1614	9,9999	21,000	27,267	1,0671
9	1898	9,0021	18,134	24,969	1,1139
10	1674	2,6052	21,426	21,490	1,0912
11	1656	9,9908	21,003	27,257	1,0632
12	1836	2,0003	24,816	3,057	1,1158
13	1691	2,0009	24,115	5,839	1,0352
14	1612	6,7041	21,175	24,064	1,0618
15	2069	2,0000	24,403	3,732	1,1561
16	1824	8,2331	21,032	24,989	1,1015
17	1921	2,0005	24,329	6,230	1,1320
18	1951	2,0011	24,521	3,929	1,1281
19	1808	2,0014	24,627	4,229	1,0779
20	1617	3,1131	20,004	27,155	1,0645

In second table, parameters are selected within the decision space that is to say these are the parameters suggested by the tool supplier or which allow by the machine tool.

Table 5.14: Non-optimal cutting parameters.

Parameter set	Spindle speed n_t, (rpm)	Work rotational speed n_w, (rpm)	Cutter offset, e (mm)	Axial feed, a_e (mm/rev)	Depth of cut, a_p (mm)
1	2032	8,23	4	2	0,40
2	1701	10	0	9,73	0,40
3	1600	10	1	28,51	0,40
4	2162	10	3	9,73	0,55
5	1600	9,99	15	28,51	0,40
6	2032	9,93	12	2	0,47
7	2008	10	3	9,73	0,40
8	1818	2,01	8	2,02	0,41
9	1605	10	0	4,80	0,43
10	1740	3,93	20	2,03	0,40
11	1740	8,80	9	2	0,43
12	2105	9,88	18	2	0,50
13	1772	3,31	11	2	0,42
14	1634	9,99	17	4,18	0,67
15	1820	4,70	6	2	0,42
16	1906	9,93	5	25,74	0,44
17	1820	5,48	13	2	0,41
18	1702	2,16	2	2,01	0,41
19	1740	9,99	4	28,51	0,42
20	1740	7,70	14	2	0,40

All objectives coming from second table were dominated by the first one. In other words generated cutting parameters in Table 5.13 gave better result considering tool life, surface roughness, circularity error, MRR and cutting force. Also there is no cusp height formation observed from the parameters Table 5.13. According to these cutting parameter sets, if user selects the process parameters among one of the non-dominated solutions i.e. for this comparison from Table 5.13 instead of Table 5.14, when considered average of twenty objective sets:

- Surface quality could be increased up to three times,
- Tool cost could be decreased by 50%,

- It is possible to reduce production time to one quarter using optimal solutions.

Note that this comparison can be made between all infinite number of non-dominated and dominated solutions. So in that case percentage of the improvements will be more or less different in every comparison, but in here principally important thing to be realized is simultaneously improving all the objectives is possible when optimization is generated and non-dominated solutions are selected.

5.5 Summary

Optimization of orthogonal turn-milling process is studied for defined work piece and tool. In this chapter, the task is to find optimum cutting parameters for the process. The methodologies for evaluation and selection of machining parameters are presented. Firstly weighted sum approach based on SQP method is used; elitist NSGA algorithm is then selected as an optimization algorithm. NSGA-II is based on ranking the solutions. First non-dominated solutions are ranked as one. Other individuals are sorted by the quantity of solutions being dominated by a particular solution. Then selection operation chooses the solutions with lower ranks. With this approach Pareto fronts are found as solutions of optimization problem. The optimum cutting conditions for each case study can be selected from calculated Pareto-optimal fronts by the user according to production planning requirements. Finally sensitivity analysis have been made to see the parameter effects on the objective functions. After determining proper procedure for parameter selection, in this chapter also optimal parameter sets are compared with non-optimal ones. According to presented results, it is recognized that optimization procedure carried a step further throughput of the process.

CHAPTER 6 COMPARISON OF MACHINED SURFACE QUALITY, PRODUCTION COST AND TIME OBTAINED BY CONVENTIONAL TURNING AND TURN-MILLING

The aim of this chapter is to present some results of investigations on machined surface quality produced by turn-milling and conventional turning and, to show differences on production time and cost.

There are several criteria for defining distinction between conventional and high-speed machining. These are: magnitude of cutting speed, revolution of spindle or rotating tool (spindle speed), dynamic behavior and work piece material.

Recently, with the advance in cutting tools materials and technologies, high-speed machining, (e.g., turn-milling process) has also been used in machining of alloy steels in their hardened state (above 30 HRC up to 60 – 65 HRC) [111].

6.1 Experimental Setup

The aim of this experimental investigation has been to compare results of turn-milling and conventional turning for roughing and finishing operations. The experimental work was carried out in the Manufacturing Research Laboratory (MRL), at Sabancı University. Mori Seiki NTX-2000 multitasking machine tool was used for both turning and turn-milling operations. This multitasking unit, Figure 6.1, makes possible achievement of work rotational speed up to 5000 rev/min and spindle speed up to 12000 rev/min.

Figure 6.1: Mori Seiki NTX2000 Mill-Turn center.

The tool holder used in conventional turning process is a Sandvik Coromant Capto® cutting unit with CoroTurn® RC rigid clamp design as shown in Figure 6.2. It is a screw clamp holder for rhombic 80° inserts. The cutting insert used in conventional turning tests is T-Max® P with CNMG-SM material and geometry code. Grade of the insert is 1105 which provides reliable machining and is truly versatile in all application areas from roughing through to intermediate and last stage machining especially for difficult to machine materials.

Figure 6.2: Tool holder and the cutting insert for conventional turning operations.

In turn-milling process a 50 mm Seco QuattroMill® milling tool with four cutting teeth is used as shown in Figure 6.3 and MS2050 grade inserts are selected which is recommended for machining superalloys .

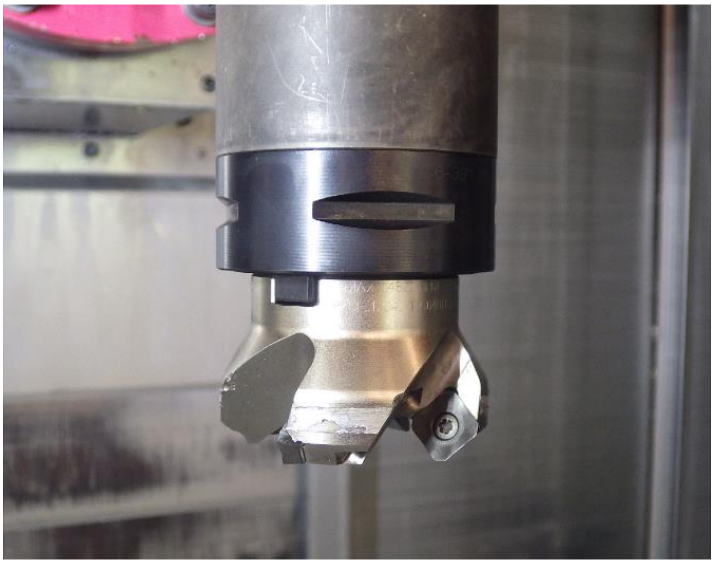


Figure 6.3: Tool holder and cutting inserts for turn-milling operations.

In order to make the comparison of surface quality and tool life between turning and turn-milling in a logical manner, it was necessary to define one common parameter as a reference feature. That parameter is selected as the material removal rate, MRR, of a work piece material. Cutting conditions were set up to the same feed and similar depth of cut in both cases, at the same time cutting speed has been calculated to obtain equal removal rate, MRR.

Type 316 stainless steel is selected as the material of the work piece; the chemical composition is given in Table 6.1

Table 6.1: Metallurgical properties of the machined steel.

Element	C	Cr	Mn	Mo	Ni	P	S	Si	Fe
Content (%)	0.08	16-18	2	2-3	10-14	0.045	0.03	1	Balance

AISI 316 is an austenitic chromium-nickel stainless steel containing molybdenum. This addition increases general corrosion resistance, improves resistance to pitting from chloride ion solutions, and provides increased strength at elevated temperatures.

Properties are similar to those of Type 304 except that this alloy is slightly stronger at high temperatures. Corrosion resistance is improved, particularly against sulfuric, hydrochloric, acetic, formic and tartaric acids; acid sulfates and alkaline chlorides. Typical uses include exhaust manifolds, furnace parts, heat exchangers, jet engine parts, pharmaceutical and photographic equipment, valve and pump trim, chemical equipment, digesters, tanks, evaporators, pulp, paper and textile processing equipment, parts exposed to marine atmospheres and tubing.

All experiments are conducted with coolant. Work piece diameter was of 115 mm, and length 220 mm. The average Brinell hardness of the work piece material is 149 HB. The main reason underlying this material selection is also to show machining performance of both turning and turn-milling operations with hard to machine materials.

6.2 Surface Quality Comparison

3 different MRR values are selected corresponds to finishing, semi-finishing and roughing operations. In each case surface roughness is investigated in axial direction for both processes. For turn-milling, critical axial feed rates are found as 27.1, 27 and 26.8, respectively. So, axial feed rate is selected as 25 mm/rev for all cases in order to prevent cusp height formation. Process conditions are given in Table 6.2.

Table 6.2: Process conditions for turning and turn-milling.

	Conventional Turning			Orthogonal Turn-Milling					
	V	f	d	V	f_n	e	a_e	a_p	MRR
finishing	200 m/min	0,05 mm/rev	0,1 mm	210 m/min	0,05 mm/(rev*tooth)	21 mm	25 mm/rev	0,15 mm	1000 mm^3/min
semi-finishing	150 m/min	0,1 mm/rev	0,15 mm	175 m/min	0,1 mm/(rev*tooth)	21 mm	25 mm/rev	0,2 mm	2250 mm^3/min
roughing	125 m/min	0,3 mm/rev	0,4 mm	140 m/min	0,3 mm/(rev*tooth)	21 mm	25 mm/rev	0,5 mm	14000 mm^3/min

Figure 6.4 and Figure 6.5 illustratively shows results for all experimental runs.

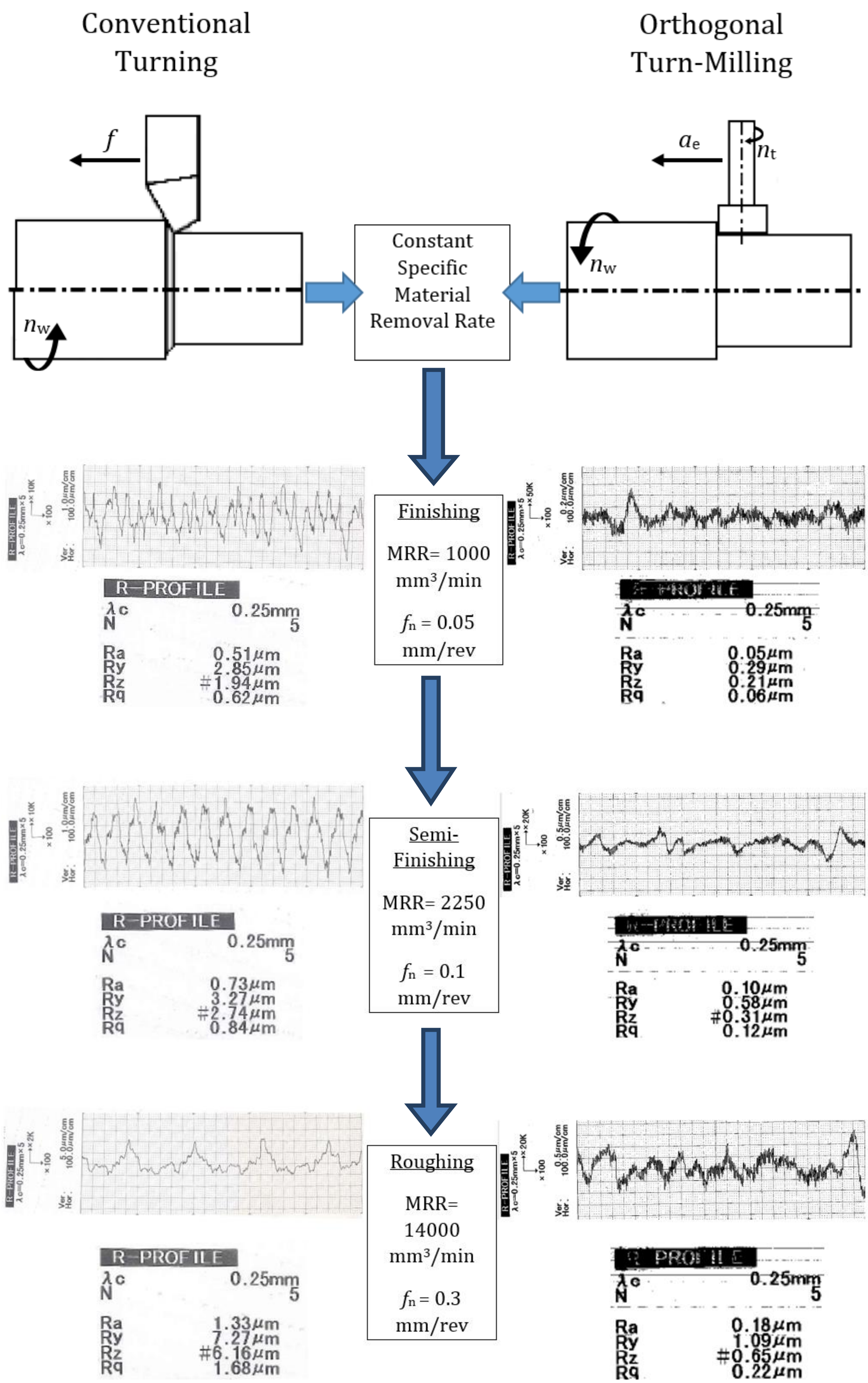


Figure 6.4: Experimental procedure and results.

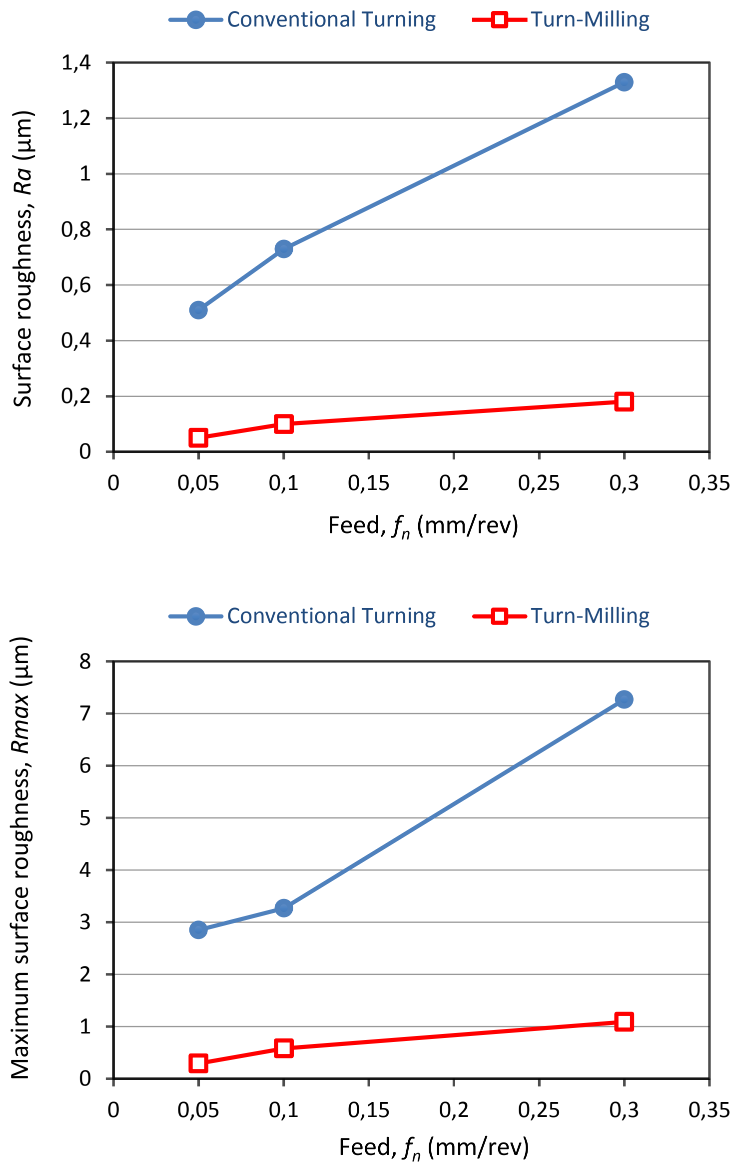


Figure 6.5: Graphical representation of measured surface roughness in different feeds.

On the basis of presented results, following conclusions can be drawn;

- The average value of the parameter Ra for conventional turning is 0.85 µm, and for high-speed turn-milling Ra = 0.11 µm. Ra is much lower for high-speed turn-milling.
- Increasing feed causes increase of Ra value for both machining processes.
- According to the obtained results, conventional turning produced the machined surface quality of N6 class by ISO 1302 classification. At the same time, high-speed turn-milling generate surface of N3 class quality by ISO classification.
- It is possible to get 10 times better surface quality with turn-milling especially in finishing operations.

It must be noticed that when surface quality is considered, surface roughness in the feed direction should be also examined for turn-milling. Roughness in this direction actually is referred as circularity error in turn-milling processes. Surface roughness measurements obtained from turn-milling experiments in the direction of helical feed are given below for finishing, semi-finishing and roughing operations, respectively:

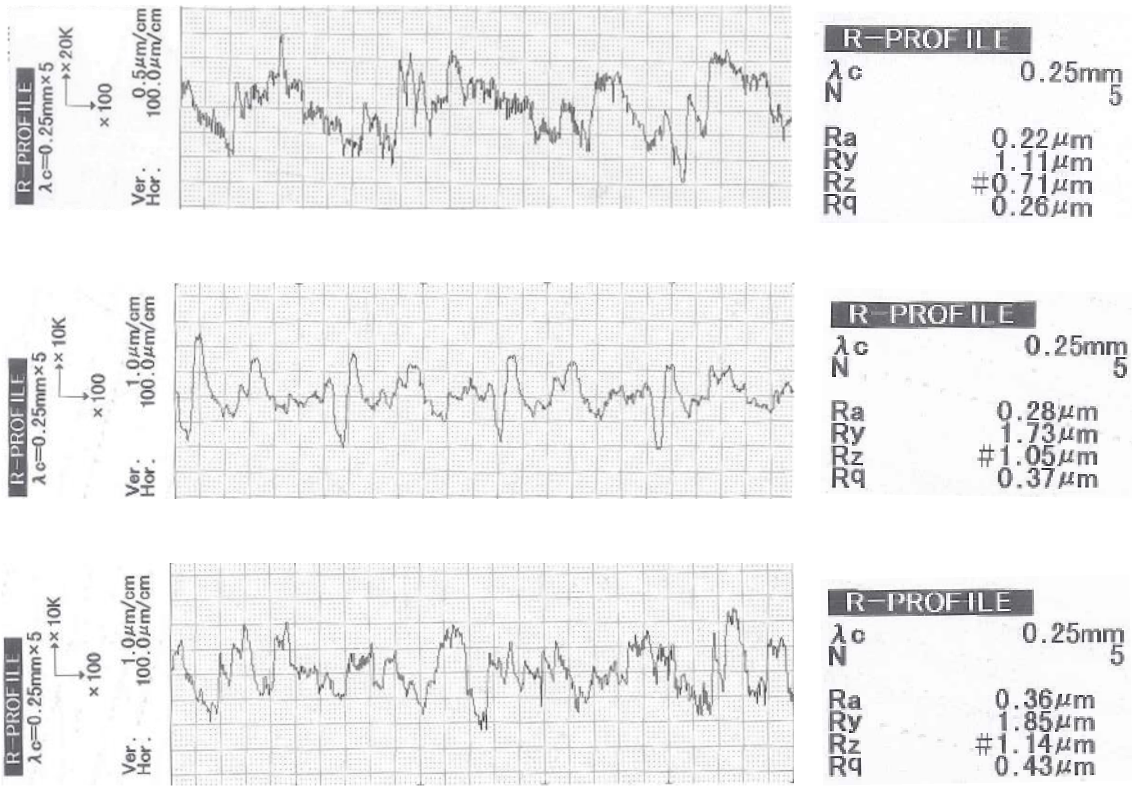


Figure 6.6: Turn-milling surface roughness results in feed direction.

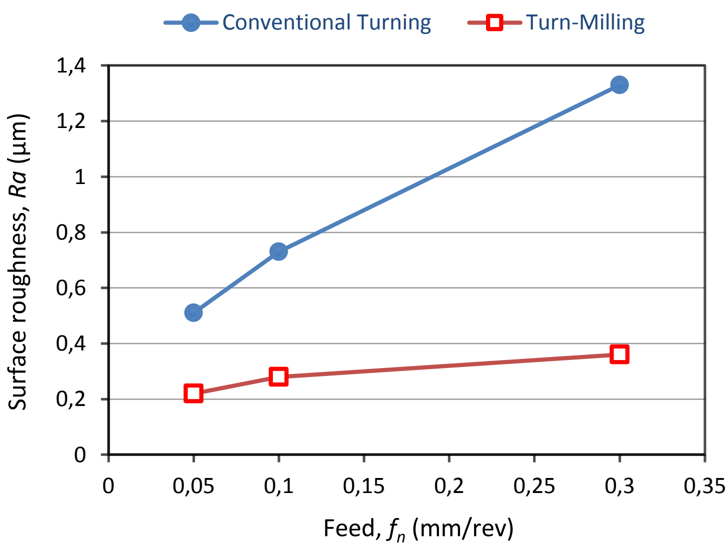


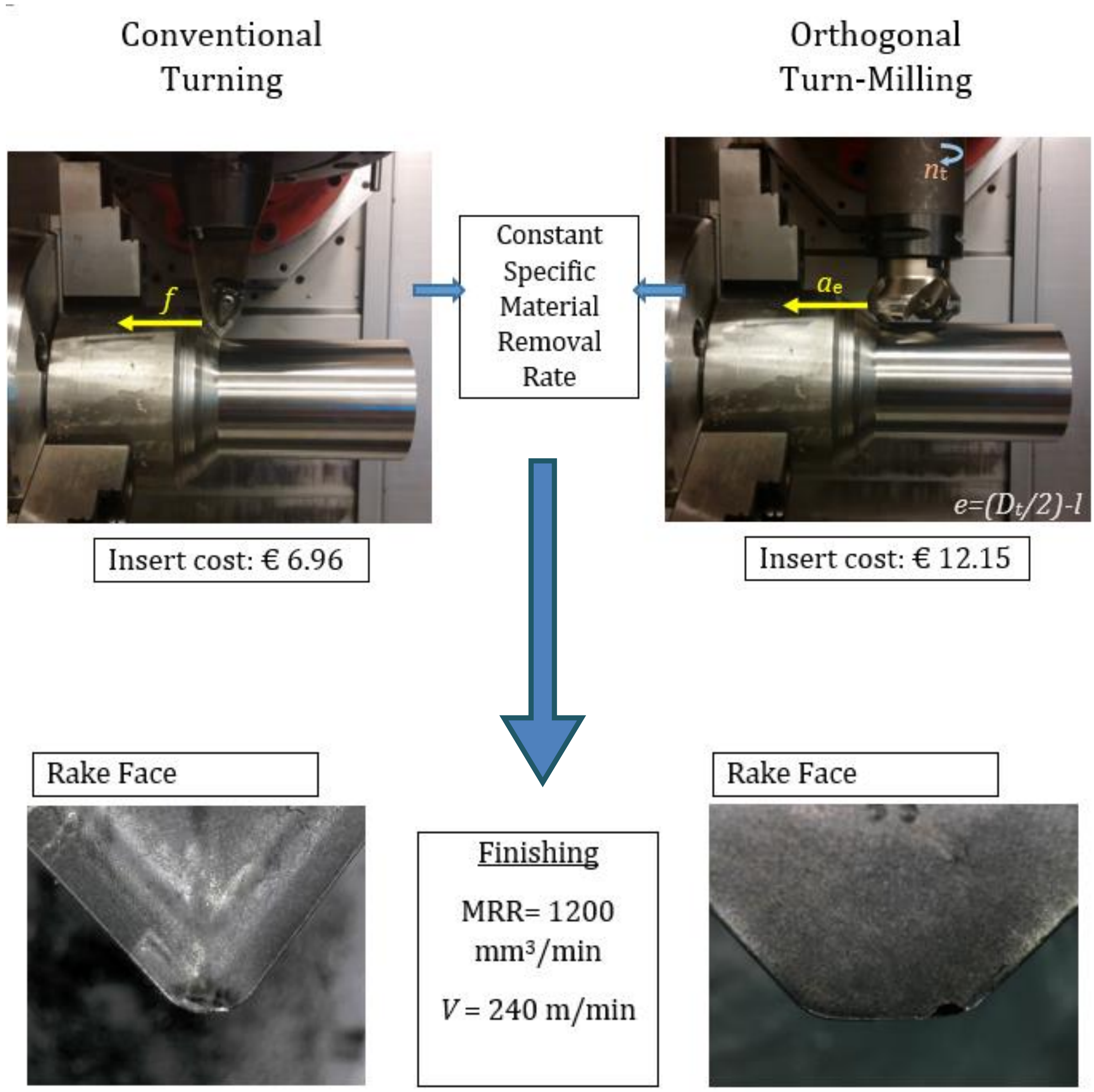
Figure 6.7: Comparison of measured surface roughness in feed direction.

According to these results, it is evident that, even values of circularity error are much smaller than roughness values observed in turning process. In addition no cusp height formation is observed.

So, generally speaking, from the aspect of surface quality, the experiment confirms advantage of high-speed turn-milling over conventional turning.

6.3 Production Cost Comparison

Other than the initial tool cost, tool life used in machining operations is one of the most important factors affecting total production cost. Next figures show tool life comparison between turning and turn-milling operations.



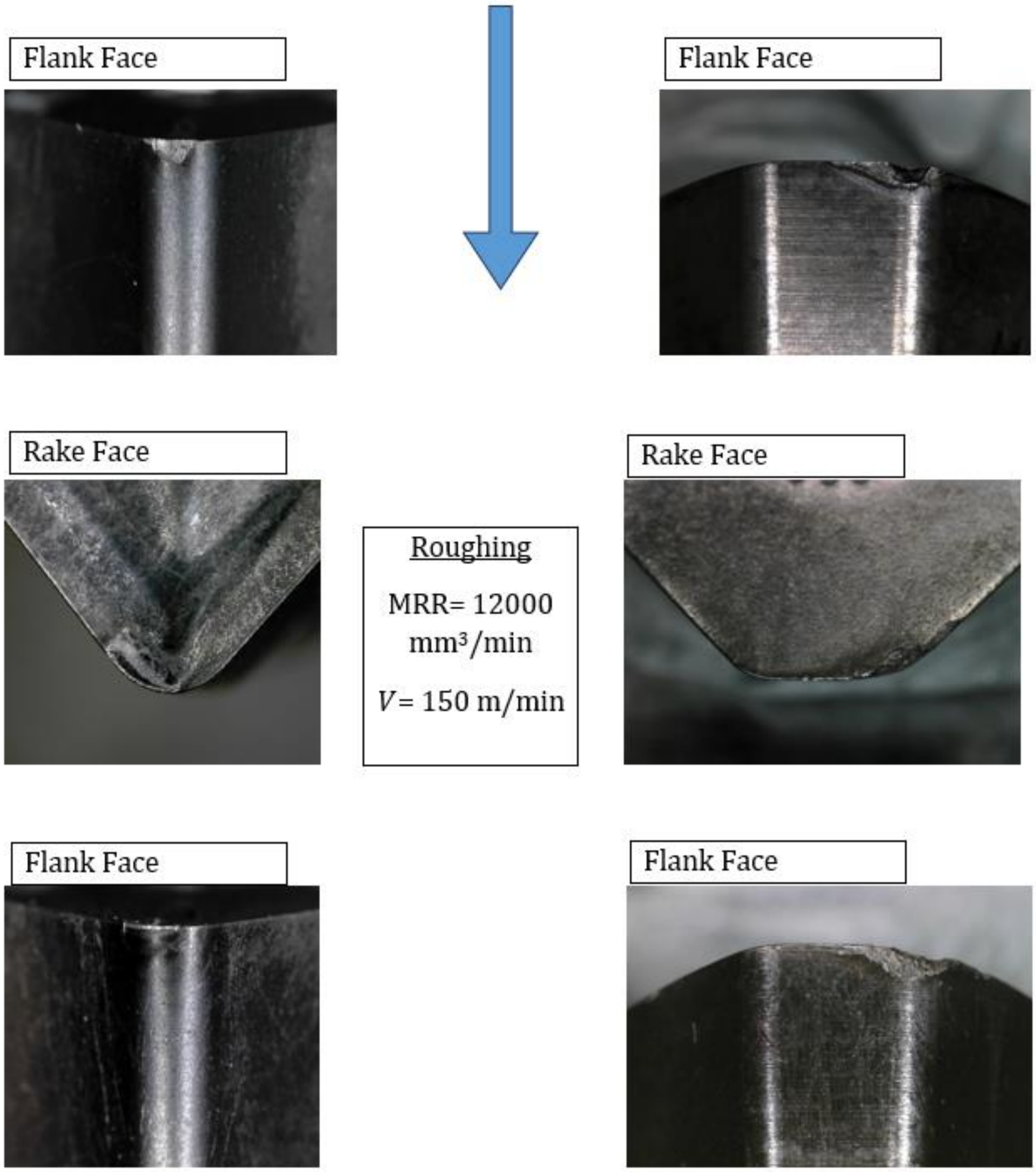


Figure 6.8: Experimental procedure and results.

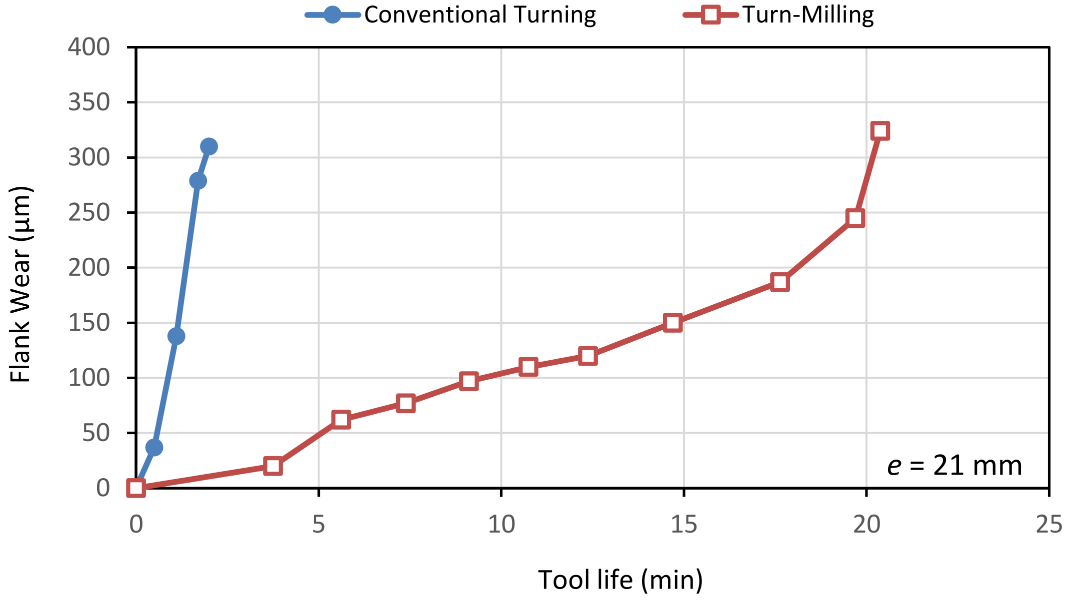


Figure 6.9: Tool life comparison for finishing operation.

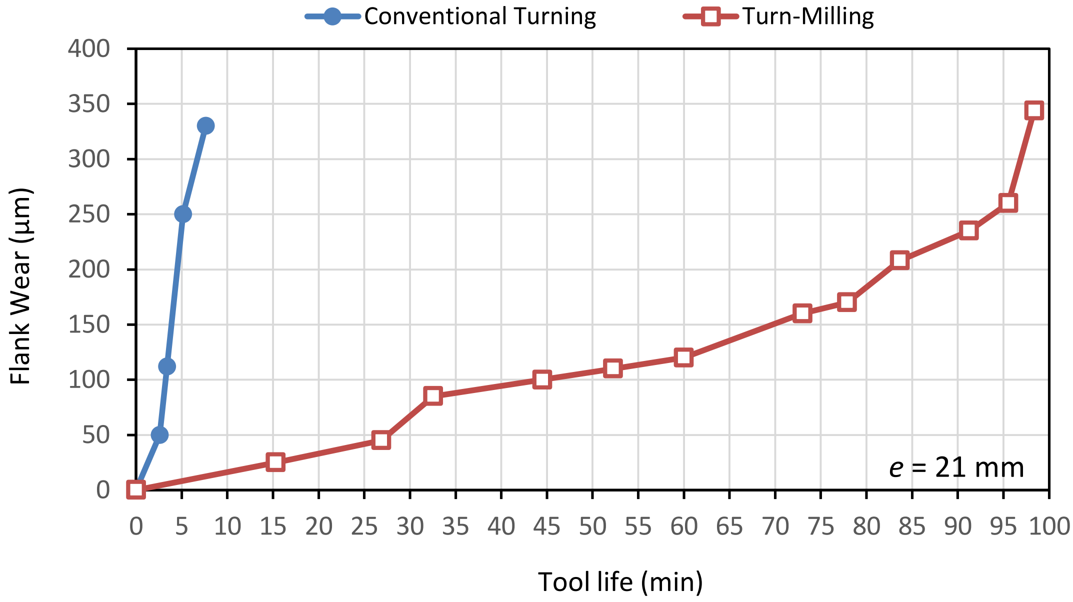


Figure 6.10: Tool life comparison for roughing operation.

Figure 6.9 and Figure 6.10 show tool life results for turning and turn-milling tools. It should be noticed that since the turn milling tool has four inserts, the tool life results must be normalized by dividing the elapsed cutting time by number of cutting teeth when comparing it with conventional turning data. In other words, life of the inserts should be compared instead of the total cutting time.

From the above results, followings conclusions can be drawn;

- In finishing operations life of the insert for turning is T = 2.14 min, and for a turn-milling insert T = 5.09 min.
- In roughing T = 7.65 min is also much lower for turning compared to the turn-milling tool life of 24.59 min.
- The test results confirmed that the cutting speed has a great effect on the tool life as expected. Decreasing the cutting speed, cause increase of tool life for both machining processes.
- Although in turning operations insert cost is cheaper, tool life is considerably higher in turn-milling processes.
- To sum up, in the aspect of tool cost and tool life, production cost can be decrease up to 26 % and 45 % for finishing and roughing operations, respectively, using turn-milling process instead of conventional turning process.

So far, the same MRR values are used for both processes when comparing with each other and advantages of turn-milling over turning process is observed with the aid of experiments.

6.4 Production Time Comparison

Production time is directly related to MRR values in machining operations and it is important to increase that as much as possible to decrease time. In this section, in order to show higher productivity of turn milling, similar surface roughness values and similar tool costs are aimed for turning and turn-milling where resulting MRRs are compared.

Below selected parameters with resulting MRR values can be seen:

Table 6.3: Cutting parameters used in the test.

Conventional Turning			Orthogonal Turn-Milling				
V	f	d	V	f_n	e	a_e	a_p
240 m/min	0,05 mm/rev	0,1 mm	250 m/min	0,25 mm/(rev*tooth)	21 mm	25 mm/rev	0,4 mm
MRR = 1200 mm^3/min			MRR = 16000 mm^3/min				

After cutting tests carried out with these parameters, results shown in Figure 6.11 and Figure 6.12 are obtained for surface quality and tool life.

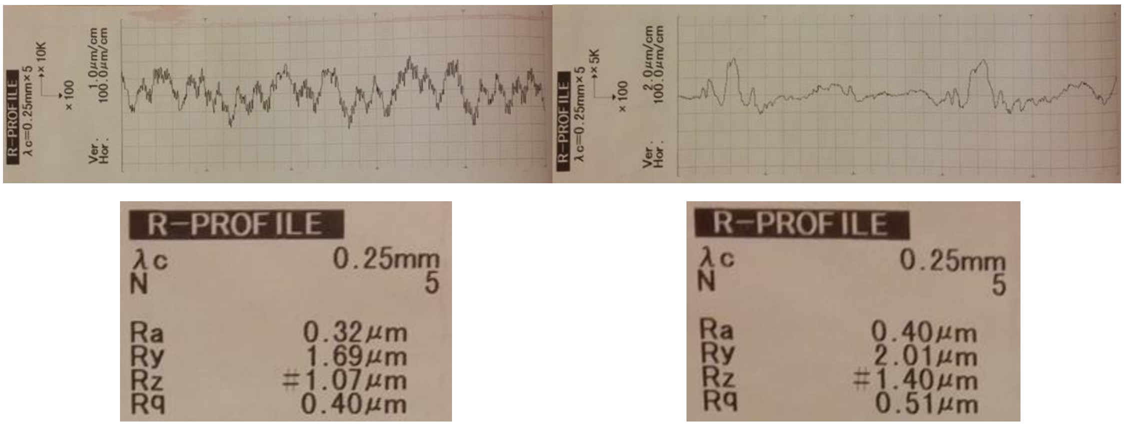


Figure 6.11: Surface roughness results for turning and turn-milling respectively.

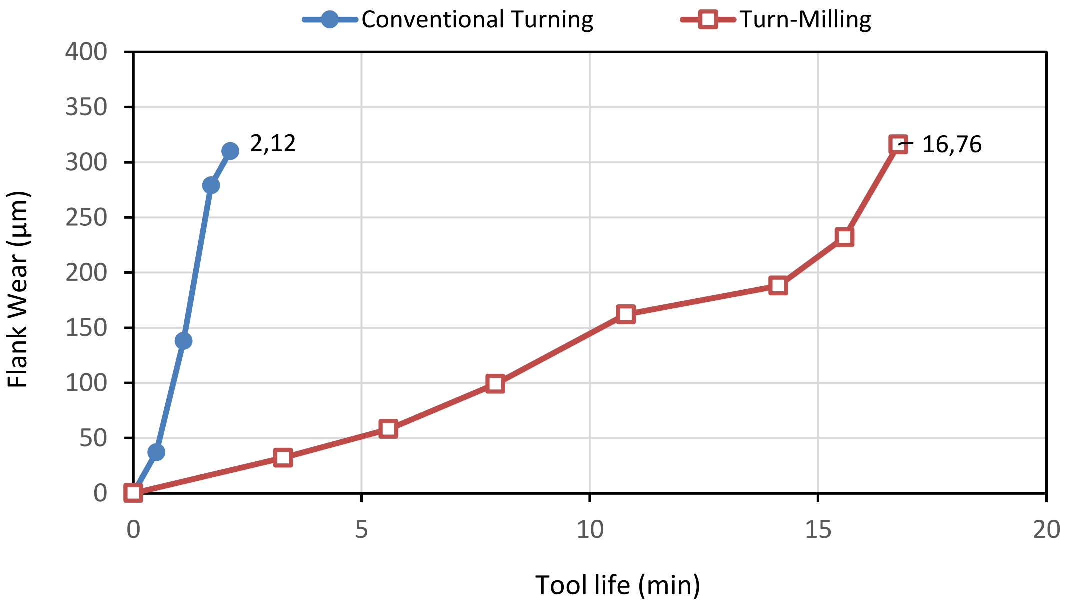


Figure 6.12: Tool life results for turning and turn-milling in different MRR.

Followings can be drawn from these results;

- Productivity can be increased by turn-milling almost 13 times without degrading tool cost and with small aggravation in surface roughness.
- Higher number of inserts increases time efficiency since less time is wasted for changing the insert after they are worn. For finishing operation, Figure 6.9 shows that turn-milling machine can work for 20.38 min non-stop whereas in turning machine has to be stopped after every 2.12 minutes. Similarly, in

roughing operation Figure 6.10 shows that turn-milling machine can work for 98.37 non-stop whereas in turning machine has to be stopped after every 7.65 minutes for insert change.

All in all, when turn-milling process compared to conventional turning process, great advantages are appeared. Considering these advantages, it can be said that turn-milling process will become more popular among machining processes.

6.5 Summary

Machined surface quality demands significantly affect cost of production and increase the price of a product. Hence, obtaining a good quality of surface while lowering production costs and decreasing production time has been main target in machining operations. One possible approach for solving that problem is introducing high-speed machining facilities into production. High-speed machining (e.g., turn-milling) allows higher productivity, excellent surface finish and good dimensional accuracy in the manufacturing process. Therefore, in this chapter possibilities of turn-milling process are explored by comparing conventional turning process. Both processes are analyzed with regard to surface quality, production cost and production time under the same conditions. Superiorities of the turn-milling over turning process have been clearly demonstrated by the experiments.

CHAPTER 7 CONCLUSIONS

In recent years, as products become more complex, machining processes have become more sophisticated. Conventional turning and milling has been difficult to meet requirements, especially in aviation, aerospace and other military products. Therefore, new efficient processes have become more popular day by day. Turn-milling is also relatively a new cutting process which combines two conventional manufacturing processes; turning and milling. This promising technology becomes an alternative to turning due to its advantages such as higher productivity and lower cutting temperatures, which provide longer tool life. Intermittent characteristics of turn-milling helps maintaining lower cutting temperatures and making high cutting speeds possible.

Building a parameter selection methodology for turn-milling processes has been main concerned of this study. In order to do that, objectives that is considered in the optimization context are investigated and formulated. In the analysis, tool life and machined part quality are formulated including cutter offset effects with the aid of experiments. Minimum surface errors, minimum production cost and minimum production time are selected as targets of the optimization study considering tool life, surface roughness, circularity error, cusp height, cutting force and material removal rate (MRR). Cusp height form error is considered and indicated as a constraint in the optimization problem. Introducing this to algorithm, parameters which are not allow to cusp height formation are then possible to be generated. Also cutting force is limited to specified value according to machine tool dynamics. Once the reliable model for orthogonal turn-milling process has been constructed, optimization algorithms are then applied to the model for determining optimal cutting parameters. Furthermore in this study, advantages of turn-milling process are explored by comparing it with conventional turning process. From this study following parameter effects can be drawn for orthogonal turn-milling:

- One of the biggest factor which affects the tool wear is the cutter offset. It is better when the cutter offset equals half of the tool radius minus cutting edge length during the rough machining, while the cutter offset is a little more than this critical value during the finish machining. In this way, cutter wear is well-distributed and the surface quality of the work piece is better.

- Adopting more teeth of a cutter can make both tool wear and surface roughness smaller.

- The axial feed rate has little effect on tool wear and surface topography. So the axial feed rate can be selected as high as possible in order to improve machining efficiency. But in that case it should be remember, cutting forces raise and it is become more possible to formation of cusp height.

- It has been observed that decreasing feed rate helps obtain a good surface finish but increases machining time. High cutting speeds may help reduce the surface roughness and circularity error, but since tool life at high cutting speeds is just a few couple minutes this solution is not applicable. In some cases surface roughness is improved with increasing tool wear; therefore, attention should be paid to the relation between tool wear and surface roughness. It is therefore crucial to obtain a group of optimum conditions, which may serve different purposes under different circumstances.

- Spindle speed has effect on tool life, surface roughness, circularity error and cutting force. Despite, increasing spindle speed drop tool life dramatically, too little improvements occur on the surface quality and force. Besides, tool life highly related to spindle speed, surface roughness and force dependent almost all parameters. Therefore, spindle speed should be selected near to lower boundary as suggested by optimization results in order to keep tool life longer.

- Selecting low work rotational speed cause lower MRR, on the other hand high work rotational speed leads to increased surface errors and cutting forces.

Specific contributions of the presented study are listed as follows:

- Mathematical formulations of tool life and surface roughness are developed by including cutter offset. By this way, an accurate approach are provided with respect to previous models.

- Optimization methods are applied in the context of this thesis to orthogonal turn-milling processes in order to find optimal cutting parameters. This is not present in the literature. It is seen that by using the methodologies proposed in this thesis the productivity and part quality can be improved with cost savings. Moreover this study is one of the pioneer study in turn-milling that solves three dimensional multi-objective problem.

- It is demonstrated that NSGA-II algorithm for optimization of surface quality, production cost and production time is an adequate approach. Rather than using classical optimization methods, NSGA-II provides more reliable results.

- In order to generate and select optimal cutting parameters, a guide is also created. Especially, to be able to use for other materials, tools and types of turn-milling.

- Orthogonal turn-milling process is compared with conventional turning process in all aspects for the first time in the literature. It is observed that better surface quality is possible in turn-milling. Production cost can be also reduced according to conventional turning. Besides, when we compare them in terms of time efficiency, it is obtained that total manufacturing time is reduced substantially in turn-milling process. Especially in roughing operation it provides more advantages. From the given data and according to given results, it is obvious that widespread of turn-milling will provide great benefits to machining industry in the view of time, money and product quality.

- This thesis forms a basis for the forthcoming studies in simulation and optimization of turn-milling processes.

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Appendix A: Evolutionary Optimization Terminologies

Evolutionary algorithm (EA): A generic name given to an algorithm which applies Darwinian survival-of-the-fittest evolutionary principles along with genetically motivated recombination and mutation principles in a stochastic manner usually to a population of solutions to iteratively create a new and hopefully better population of solutions in the context of a stationary or a dynamic fitness landscape.

Evolutionary optimization (EO): An EA which is designed to solve an optimization problem.

Generation: An iteration of an EA.

Genetic algorithm (GA): An early version of an EA, which uses three main operators – selection, crossover and mutation – on a population of solutions at every generation. In binary-coded GAs, solutions are represented in a string of binary digits (bits). In real-parameter GAs, solutions are represented as a vector of real-parameter decision variables. Other representations can also be used to suit the handling of a problem.

String: In a binary-coded GA, a population member, made of a collection of bits, is called a string.

Niching: A niching is an operator by which selection pressure of population members are controlled so as to not allow a single solution to take over the population. Thus, niching helps to maintain a diverse population.

Elitism: An operator which preserves the better of parent and child solutions (or populations) so that a previously found better solution is never deleted.

Fitness: A fitness or a fitness landscape is a function derived from objective function(s), constraint(s) and other problem descriptions which is used in the selection (or reproduction) operator of an EA. A solution is usually called better than the other, if its fitness function value is better.

Population: A set of solutions used in one generation of an EA. The number of solutions in a population is called ‘population size’.

Reproduction: An EA operator which mimics Darwin’s survival of the fittest principle by making duplicate copies of above-average solutions in the population at the expense of deleting below-average solutions. Initial EA studies used a proportionate reproduction procedure in which multiple copies of a population member are assigned to the mating pool proportionate to the individual's fitness. Thus, this operator is used for maximization problems and for fitness values which are non-negative. Current studies use tournament selection which compares two population members based on their fitness values and sends the better solution to the mating pool. This operator does not have any limitation on fitness function.

Selection: Same as "reproduction", defined above.

Crossover: An operator in which two or more parent solutions are used to create (through recombination) one or more child solutions.

Recombination: Same as "crossover", defined above.

Crossover probability: The probability of performing a crossover operation. This means, on average, the proportion of population members participating in crossover operation in a generation.

Parent: A solution used during crossover operation to create a child solution.

Mutation: An EA operator which is applied to a single solution to create a new perturbed solution. A fundamental difference with a crossover operator is that mutation is applied to a single solution, whereas crossover is applied to more than one solution.

Mutation probability: The probability of performing a mutation operation. This refers to, on average, the proportion of decision variables participating in a mutation operation to a solution.

Children: New solutions (or decision variable vectors) created by a combined effect of crossover and mutation operators.

Offspring: Same as "children", defined above.

Mating pool: An intermediate population (usually created by the selection operator) used for creating new solutions by crossover and mutation operators.

Individual: An EA population member representing a solution to the problem at hand.

Solution: An EA population member, same as an "individual".

Appendix B: MATLAB Codes for Turn-Milling Process Optimization Using SQP

```
%----------------------Turn_milling_ObjFun.m-------------------------

%Definition of objective function

function [func,Grad] = Turn_milling_ObjFun(X)

%Variables
nt=X(1);
nw=X(2);
e=X(3);
ae=X(4);
ap=X(5);

%Design Parameters
Dw=70;      %avg. workpiece diameter
Dt=50;      %tool diameter
z=4;        %number of teeth

Ct=13.55;   %insert cost ($)
Cl=0.31;    %labor cost ($/min)
Co=0.08;    %overhead cost ($/min)

V=197920;   %volume of the removed material
Ts=1;       %setup time
Tc=2;       %changeover time
Ti=1;       %time during which tool does not cut


%Formulas
ft=(nw*pi*Dw)/(nt*z);

%Tool Life (min)
T=((1756000/(pi*Dt*nt))^2.6)*(-0.012*e^3-0.06*e^2+12*e+123)/123;
%Surface Roughness (mm)
SR=(25-sqrt(625-(nw^2*(ae^2+(2*pi*(35-ap))^2))/(8*nt^2)))*(-
0.03*e+0.9);
%Circularity Error (mm)
CE=(Dw/2-ap)*(1/cos((pi*nw)/(z*nt))-1);
%Material removal rate
MRR=(nw*pi*Dw*ap*ae);


%Boundary calculations

Tmin=((1756000/(pi*Dt*2300))^2.6)*(-0.012*25^3-
0.06*25^2+12*25+123)/123;
Tmax=((1756000/(pi*Dt*1600))^2.6)*(-0.012*0^3-0.06*0^2+12*0+123)/123;

SRmin=(25-sqrt(625-(2^2*(2^2+(2*pi*(35-1.2))^2))/(8*2300^2)))*(-
0.03*25+0.9);
SRmax=(25-sqrt(625-(10^2*(30^2+(2*pi*(35-0.4))^2))/(8*1600^2)))*(-
0.03*0+0.9);

CEmin=(Dw/2-1.2)*(1/cos((pi*2)/(z*2300))-1);
CEmax=(Dw/2-0.4)*(1/cos((pi*10)/(z*1600))-1);

MRRmin=(2*pi*Dw*0.4*2);
```

```
MRRmax=(10*pi*Dw*1.2*30);


%Objectives

%Surface quality (minimize roughness and error)
Q=(SR-SRmin)/(SRmax-SRmin)+(CE-CEmin)/(CEmax-CEmin);

%Production cost (minimize) ($/min)
Cp=Ct/T+Cl+Co;

%Production rate (minimize cycle time) (min)
Tp=Ts+V*(1+Tc/T)/MRR+Ti;

Qmin=0;
Qmax=2;

Cpmin=13.55/Tmax+Cl+Co;
Cpmax=13.55/Tmin+Cl+Co;

Tpmin=Ts+V*(1+Tc/Tmax)/MRRmax+Ti;
Tpmax=Ts+V*(1+Tc/Tmin)/MRRmin+Ti;

%Weights of the objectives
w1=0.3;
w2=0.4;
w3=0.3;

%Function
func=w1*((Q-Qmin)/(Qmax-Qmin))+w2*((Cp-Cpmin)/(Cpmax-Cpmin))+w3*((Tp-
Tpmin)/(Tpmax-Tpmin));
%func;

syms nt nw e ae ap

if nargout>1
%Define gradient of the objective functions

    Grad(1,1)=diff(func,nt);
    Grad(2,1)=diff(func,nw);
    Grad(3,1)=diff(func,e);
    Grad(4,1)=diff(func,ae);
    Grad(5,1)=diff(func,ap);

end


%----------------------Turn_milling_ConstFun.m-----------------------

function [c,ceq,gc,gceq] = Turn_milling_ConstFun(X)
%Reassign the variables.
nt=X(1);
nw=X(2);
e=X(3);
ae=X(4);
ap=X(5);

%Nonlinear inequalities
c(1)=ae-(2*sqrt(25^2-(e+(35-ap)*tan((pi*nw)/(4*nt)))^2));   %axial
feed constraint
```

```
c(2)=1200-10^5*(ap*ae*nw^0.1)/((1+1.25*e^0.2)*(nt^0.8));     %cutting
force constraint

%Nonlinear equalities
ceq = [];

% Gradient calculation
syms nt nw e ae ap

if nargout > 2

gc(1,1) = [diff(ae-(2*sqrt(25^2-(e+(35-
ap)*tan((pi*nw)/(4*nt)))^2)),nt),diff((10^5*(ap*ae*nw^0.1)/((1+1.25*e^
0.2)*(nt^0.8))),nt)];
gc(1,2) = [diff(ae-(2*sqrt(25^2-(e+(35-
ap)*tan((pi*nw)/(4*nt)))^2)),nw),diff((10^5*(ap*ae*nw^0.1)/((1+1.25*e^
0.2)*(nt^0.8))),nw)];
gc(1,3) = [diff(ae-(2*sqrt(25^2-(e+(35-
ap)*tan((pi*nw)/(4*nt)))^2)),e),diff((10^5*(ap*ae*nw^0.1)/((1+1.25*e^0
.2)*(nt^0.8))),e)];
gc(1,4) = [diff(ae-(2*sqrt(25^2-(e+(35-
ap)*tan((pi*nw)/(4*nt)))^2)),ae),diff((10^5*(ap*ae*nw^0.1)/((1+1.25*e^
0.2)*(nt^0.8))),ae)];
gc(1,5) = [diff(ae-(2*sqrt(25^2-(e+(35-
ap)*tan((pi*nw)/(4*nt)))^2)),ap),diff((10^5*(ap*ae*nw^0.1)/((1+1.25*e^
0.2)*(nt^0.8))),ap)];

gceq = [];

end


% ------ Solve the optimization problem using SQP method --------

clear all
close all
clc

options =
optimset('Algorithm','sqp','DerivativeCheck','off','GradConstr','on');

% Set the boundary of the variables.
Lb = [1600; 2; 0; 2; 0.4];
Ub = [2300; 10; 25; 30; 1.2];
for i=1:1:30
X0(1,i) = [1600]+700*rand(1);
X0(2,i) = [2]+8*rand(1);
X0(3,i) = [0]+25*rand(1);
X0(4,i) = [2]+28*rand(1);
X0(5,i) = [0.4]+0.8*rand(1);

% Find the minimum of the function for the given initial condition
ti=cputime;
[x(:,i),fxval,exitflag,output] =
fmincon('Turn_milling_ObjFun',X0(:,i),[],[],[],[],Lb,Ub,'Turn_milling_
ConstFun',options);
te=cputime;
t(:,i)=te-ti;
fval(:,i)=fxval/10^7;
outputt(:,i)=output;
```

```
end
X0=X0.';
x=x.';
t=t.';
fval=fval.';
```

Appendix C: MATLAB Code for Fitness Function of Turn-Milling Process Optimization Problem

```
function f = mymulti3(x)

%variables
nt=x(1);
nw=x(2);
e=x(3);
ae=x(4);
ap=x(5);

%Design Parameters
Dw=100;
Dt=50;
z=4;

Ct=13.55;
Cl=0.31;
Co=0.08;

V=197920;
Ts=1;
Tc=2;
Ti=1;

%Formulas
%Tool Life
T=((1756000/(pi*Dt*nt))^2.6)*(-0.012*e^3-0.06*e^2+12*e+123)/123;

%Surface Roughness
SR=(25-sqrt(625-(nw^2*(ae^2+(2*pi*(35-ap))^2))/(8*nt^2)))*(-
0.03*e+0.9);

%Circularity Error
CE=(Dw/2-ap)*(1/cos((pi*nw)/(z*nt))-1);

%Material removal rate
MRR=(nw*pi*Dw*ap*ae);

SRmin=(25-sqrt(625-(2^2*(2^2+(2*pi*(35-1.2))^2))/(8*2300^2)))*(-
0.03*25+0.9);
SRmax=(25-sqrt(625-(10^2*(30^2+(2*pi*(35-0.4))^2))/(8*1600^2)))*(-
0.03*21+0.9);

CEmin=(Dw/2-1.2)*(1/cos((pi*2)/(z*2300))-1);
CEmax=(Dw/2-0.4)*(1/cos((pi*10)/(z*1600))-1);

%Objectives
%Surface quality (minimize roughness and error)
f(1)=(SR-SRmin)/(SRmax-SRmin)+(CE-CEmin)/(CEmax-CEmin);

%Production cost (minimize, $/min)
f(2)=Ct/T+Cl+Co;

%Production rate (minimize cycle time, min)
f(3)=Ts+V*(1+Tc/T)/MRR+Ti;
```