Quality Improvement in Turning Process using Taguchi's Loss Function

L. Savadamuthu, S. Muthu, P. Vivekanandan

Abstract— This paper presents a advanced technique for quality improvement in turning operations. In this study, the Taguchi method is used to find the optimal cutting parameters in turning operations. The orthogonal array, the signal-to-noise ratio, and analysis of variance are employed to study the performance characteristics in turning operations of AISI 1030 steel bars using TiN coated tools. The model was developed initially for unidiameter case and then adapted to other workpiece geometries. An Adaptive Neuro Fuzzy Inference System (ANFIS) is proposed in this paper to control a constant cutting force turning process under various cutting conditions. The ANFIS consists of two parts: predictor and the fuzzy logic controller. The step size of the predictor, and the scaling factors of the fuzzy controller are adjusted for ensuring stability and obtaining optimal control performances. The Taguchi-genetic method is applied in this paper to search for the optimal control parameters of both the predictor and the fuzzy controller such that the ANFIS controller is an optimal controller. Computer simulations are performed to verify the effectiveness of the above optimal fuzzy control scheme designed by the Taguchi-genetic method. Experimental results are provided to illustrate the effectiveness of this approach.

Index Terms— Adaptive Neuro Fuzzy Inference System (ANFIS), Taguchi-genetic method, Fuzzy controller

I. INTRODUCTION

In modern industry the goal is to manufacture low cost, high quality products in short time. Automated and flexible manufacturing systems are employed for that purpose along with computerized numerical control (CNC) machines that are capable of achieving high accuracy and very low processing time. **Turning** is the first most common method for cutting and especially for the finishing machined parts. In a turning operation, it is important task to select cutting parameters for achieving high cutting performance. Usually, the desired cutting parameters are determined based on experience or by use of a handbook. Cutting parameters are reflected on surface roughness, surface texture and dimensional deviations of the product. Surface roughness, which is used to determine and to evaluate the quality of a product, is one of the major quality attributes of a turning product. To select the cutting parameters properly, several mathematical models [1–5] based on statistical regression or neural net-work techniques have been constructed to establish the relationship between the cutting performance and cutting parameters. Then, an objective function with constraints is formulated to solve the optimal cutting parameters using optimization techniques. Therefore, considerable knowledge and experience are required for this approach. In this study, an alternative approach based on the Taguchi method [6–8] is used to determine the desired cutting parameters.

There were two purposes of this research. The first was to demonstrate a systematic procedure of using Taguchi parameter design in process control of turning machines. The second was to demonstrate a use of the Taguchi parameter design in order to identify the optimum surface roughness performance with a particular combination of cutting parameters in a turning operation. There are many definitions of quality; however, the widely accepted definitions are 'fitness for use' [5], 'conformance to requirements' [6], and 'the totality of characteristics of an entity that bear on its ability to satisfy stated and implied need' [7]. All quality improvement programs have been focused on customer satisfaction with the quality of product in its core. The quality of product, as defined above, means elimination of defects of any kind from the product. The defect is a deviation from specification or, in other words, the performance gap between a desired result and an observed result. In Ref. [7] the defect was defined as the nonfulfillment of intended usage requirements. It should be noted that this definition covers the departure or absence of one or more quality characteristics from intended usage requirements. The source of a defect is an error. However, the errors may or may not lead to defects. Such defects are nonconformities to stated requirements or to human expectations. Defects may or may not lead to failure when meeting the required specifications, as a defective item may pass all quality inspections and tests. This is evidence of the fact that not every error leads to a defect and not every defect results in a failure. Also, a failure may arise from a combination of defects.

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L. Savadamuthu, Assistant Professor, SNS College of Technology, Affiliated to Anna University Coimbatore, India, (e-mail: savudamuthu@gmail.com, nandhika07@gmail.com).

Dr. S. Muthu, Principal, Srividya College of Engineering and Technology, Affiliated to Anna University Tirunelveli, India

P. Vivekanandan, Associate Professor, SNS College of Technology, Affiliated to Anna University Coimbatore, India .

The defect is a deviation from specification or, in other words, the performance gap between a desired result and an observed result. In Ref. [7] the defect was defined as the nonfulfillment of intended usage requirements. It should be noted that this definition covers the departure or absence of one or more quality characteristics from intended usage.

The purpose of defect detection is to sort conforming and nonconforming products or services through mass inspection. Defect detection assumes that defects will be produced; through this model, defects are, in many ways, expected. In this first stage of quality consciousness, there are no feedback loops or tools are available for correcting the factors that created the defectives in the first place. Once a defect is produced, it is too late to do anything but remove it from the process output [8]. Products and production processes are always subject to a certain amount of variation [3,9]. Understanding the concept of the variation is essential to the successful implementation of process improvements [10]. In this paper, the effect of operational variables affecting the performance of the process will be investigated. The operational variables and their effect on the process performance have several forms. One of these effects is related to the quality of the saleable product; when it contains defects it is considered to not conform to required specifications. These defects can be attributed, in some cases, to the capability of the system; in this case the number of defects in each produced unit would appear consistent or in a consistent range, while, in some manufacturing environments where the number of defects per unit of saleable product is not in a consistent range, this can be attributed to variations in the process variables contained within the manufacturing system. These variations differ from shift to shift, day to day, or month to month.

In many manufacturing plants, the item rejected by quality inspection contains a variety of defects. The word ‘reject’ is not a function of the number of defects on the produced item. An item with one defect is called a ‘rejected item’, as are items with two, three, or more defects. There is no differentiation between them. However, although one defect in an item is expected, many defects in an item require further investigation and should not be classed as an ‘expected’ occurrence. The manufacturing companies have the potential to achieve considerable gains, where a tool is employed to measure the expected defects and set measurements for deviation. Following this, the effect of process variables causing defects on the product can be optimized to achieve the objective of minimum or zero defects.

Machining inaccuracy is one of the major limitations of the product quality in manufacturing. Several kinds of inaccuracies have been reported in recent studies, such as thermal, geometric, kinematic and cutting force induced. The cutting force induced inaccuracies (errors) account for the majority of total machining error and constrains manufacturers to work with very low material removal rates in finishing. In spite of this fact, most of recent studies are concentrated to resolve some other types of machining errors, such as thermal errors. This is probably related with simplicity of thermal measurements in contrast to difficulties in cutting force measurements. In cutting force based studies, some researchers preferred real time or adaptive control applications. Yang et al. [1] proposed a real time error compensation system based on cutting force measurement. Shirashi and Sato [2] used an optical measurement

II. METHODOLOGY FOR QUALITY IMPROVEMENT

In this section, tools for defect assessment and an operational framework to deal with defects are introduced. The methodology is developed to assist manufacturing plants to increase ‘right first time’ quality performance. The defect life cycle and probabilities for occurrence of specific defects are discussed. In addition, a framework for quality improvement is introduced.

A. Defect life cycle

Equipment malfunction, process variation, and an improper process operation can generate a variety of defects [6]. Therefore, manufacturing system variables affecting product quality are related to operators’ skills, capability of machines, human actions during the production process, and workplace environment [3,9,10]. A standard process for the recording and analysis of defects should be developed.. The purpose of this model is to provide manufacturers with a standard set of states through which a defect occurs. These states are intended to help standardize defect reporting. This life history illustrates the time order of the various states of a defect, moving from when a case is first reported to when it is resolved. If measures based on defect status are gathered, they may be used to learn from the defects and thus improve the performance of the production line. Fig. 1 shows the proposed model for a defect cycle.

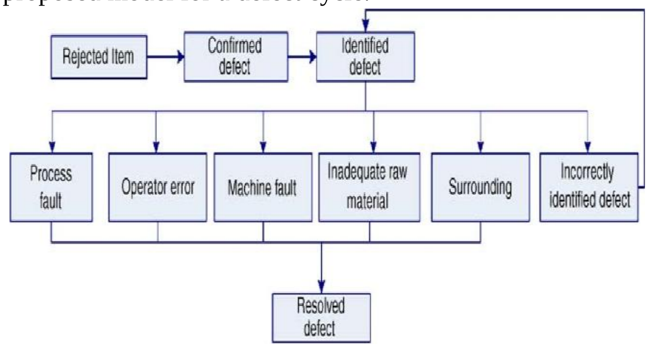


Fig.1. Defect life cycle

B. Framework for quality improvement

The framework is proposed for the inspection of finished products and investigation of the source of defects. Minimum or zero defects per produced unit is a function of minimum effect from manufacturing system variables. The objective is to minimize the number of defects per piece of product by control of the process variables that affect the quality of product. The framework comprises details of the elements of the manufacturing system that may affect the presence of defects in the produced items.

Also, it comprises the tool that is used for the inspection of defective items and the application of the lean manufacturing tool 'Jidoka'; this means stopping production when the quality of the product is compromised. The framework requires a statistical process control chart to define the average, higher, and lower levels expected for quality defects. A control chart will be chosen, which counts the number of deviation occurrences when the number chosen for sampling 'n' varies.

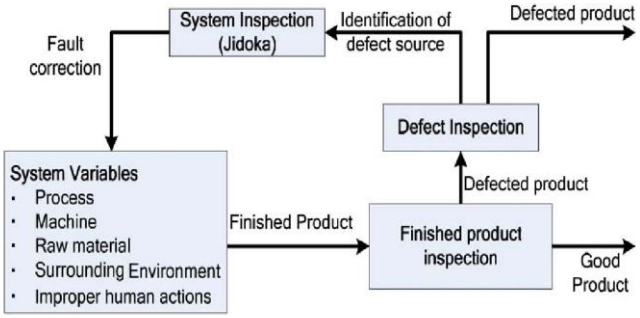
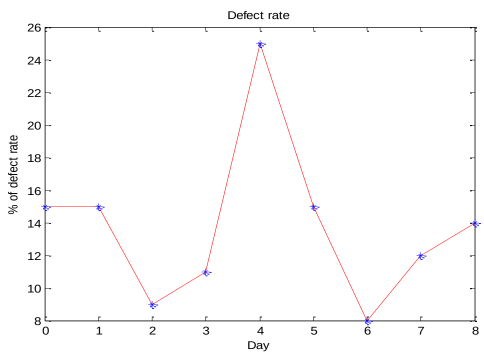


Fig. 2. Framework for quality improvement of defective production

Statistical process control is needed to count and analyze the number of defects in the rejected items. This enables the definition of the process variables that affect the quality of the product. Jidoka can then be introduced into this plant. It is important to note that in some manufacturing industries, such as automotive painting and electroplating industries, once a quality problem is identified on a final product, it has already appeared on many other products. The defect rate plot is shown in Fig.3. Even if a correct action is immediately taken at one stage of a multi-stage process, there will still be a certain number of products with the same problem as those products have already been manufactured in the process after that stage. The statistical process control (SPC) analysis is performed on all the robotic paint lines to verify if the process is in a stable condition. Each paint application has a certain program to follow when painting a particular product. Upper and lower control limits, based on the amount of paint sprayed (cubic centimeters reading), are set while the program is designed. During production, the readings of the amounts of paint sprayed are noted down. In cases when the readings of amount of paint sprayed are falling above or below the set levels, the robot is stopped and the fault is resolved.



III. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis to its appropriate membership value. Two well known types are Mamdani-type and Sugeno-type. Both can be implemented in fuzzy logic toolbox. These two types differ in the way output's are determined. Mamdani-type inference expects the output membership functions to be fuzzy sets, and requires defuzzification. A Sugeno fuzzy model has a crisp output, the overall output is obtained via weighted average, thus neglecting the time consuming process of defuzzification required in a Mamdani model[9]. In practice, the weighted average operator is occasionally replaced with the weighted sum operator to reduce computation further mainly in the training of a fuzzy inference system.

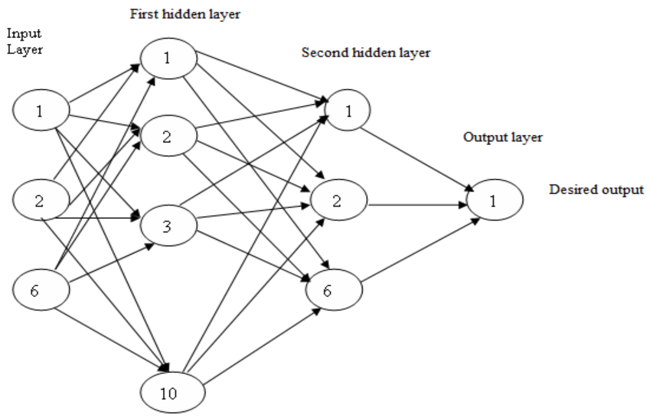


Fig.4 Neuro fuzzy training

The process of identifying a fuzzy model is generally divided into the identification of the premises and that of the consequences. And each of the identifying processes is divided into the identification of the structures and the parameters. The structures of a fuzzy model mean the combination of the input variables and the number of the membership functions in the premises and in the consequences. Sugeno's method finds the best fuzzy model by repeating the followings: (i) the selection of the structures in the premises, (ii) the identification of the parameters in the premises, (iii) the selection of the structures is the consequences, and (iv) the identification of the parameters in the consequences. This identifying process is time consuming. Our experience tells us that the characteristics of a fuzzy model depend heavily on the structures rather than on the parameters of the membership functions. The selection of the structures is first done once in the process. The selection of the structures of types I and II is done only in the premises since the structures of these types in the consequences are automatically determined with those in the premises[7]. After the structures are selected, the fuzzy neural network(FNN) identify the parameters of fuzzy models automatically.

IV. TAGUCHI-GENETIC METHOD

Taguchi has developed a methodology for the application of designed experiments, including a practitioner's handbook [1].

This methodology has taken the design of experiments from the exclusive world of the statistician and brought it more fully into the world of manufacturing. His contributions have also made the practitioner work simpler by advocating the use of fewer experimental designs, and providing a clearer understanding of the variation nature and the economic consequences of quality engineering in the world of manufacturing [1,2]. Taguchi introduces his approach, using experimental design for [2]:

i) Designing products/processes so as to be robust to environmental conditions;

ii) Designing and developing products/processes so as to be robust to component variation;

iii) Minimizing variation around a target value.

The philosophy of Taguchi is broadly applicable. He proposed that engineering optimization of a process or product should be carried out in a three-step approach, i.e., system design, parameter design, and tolerance design. In system design, the engineer applies scientific and engineering knowledge to produce a basic functional prototype design, this design including the product design stage and the process design stage. In the product design stage, the selection of materials, components, tentative product parameter values, etc., are involved. As to the process design stage, the analysis of processing sequences, the selections of production equipment, tentative process parameter values, etc., are involved. Since system design is an initial functional design, it may be far from optimum in terms of quality and cost.

The objective of the parameter design [9] is to optimize the settings of the process parameter values for improving performance characteristics and to identify the product parameter values under the optimal process parameter values. In addition, it is expected that the optimal process parameter values obtained from the parameter design are insensitive to the variation of environmental conditions and other noise factors. Therefore, the parameter design is the key step in the Taguchi method to achieving high quality without increasing cost.

V. CONCLUSION

The proposed quality improvement methodology caused significant reductions in the defect rate in a very short period of time. This reduction in defects implies that the selected tools are suitable for establishing the required improvement. The integration of improvement tools within one framework was found to be an effective way of making substantial improvements in manufacturing performance. In this paper, the ANFIS control scheme is applied to control the turning process with constant cutting force under various cutting conditions. The Taguchi-genetic method is applied to search for the optimal control parameters of both the predictor and the fuzzy controller such that the ANFIS controller provides optimum output. Computer simulations are performed to verify the effectiveness of the above optimal fuzzy control scheme designed by the Taguchi-genetic method.

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AUTHORS PROFILE

L. Savadamuthu, received his Bachelor of Engineering degree in Mechanical Engineering from Government College of Technology, Bharathiar University, Coimbatore, India in 1997, Master of Engineering degree in Production Engineering from PSG College of Technology, Bharathiar University, Coimbatore, India in 2004. He is currently a Research Scholar in the department of Mechanical Engineering, Anna University, Chennai, India. He is a Life member of ISTE, and member of ISHRAE. He has vast industrial experience in various areas such as Designing Jigs and Fixtures, Development of Tooling's for Special machines, preparation of Process sheet etc. Currently he is working as an Assistant Professor in the department of Mechanical Engineering, SNS College of Technology, Coimbatore, India. His areas of interest are Production Engineering, Process Planning and Cost estimation, Quality Management, Design of Tooling's etc.

Dr. S. Muthu received his Bachelor of Engineering degree in Production Engineering from PSG College of Technology, Coimbatore, University of Madras,, India in 1978, Master of Engineering degree in Industrial Engineering from PSG College of Technology, Coimbatore, University of Madras, , India in 1980. He is a Life member of ISTE,IE and Fellow member in IIIE. He had 30years of academic experience at various capacities. Currently he is serving as a principal in Sri Vidya College of Engineering and Technology, Virudhunagar. He published 5 International Journals and presented 47 national and International Conferences. He has been guiding 14 Research scholars and his areas of interest are Production Engineering, Quality Management, Maintenance Managements etc.

P.Vivekanandan received his Bachelor of Engineering degree in Mechanical Engineering from Maharaja Engineering College, Bharathiar University, Coimbatore, India in 1998, Master of Engineering degree in Engineering Design from Maharaja Engineering College, Anna University, Chennai, India in 2004. He is currently a Research Scholar in the department of Mechanical Engineering, Anna University, of Technology - Coimbatore, India. He has long academic career of 13 years of experience at various capacities from Lecturer to Associate Professor. Currently he is working as an Associate Professor in the department of Mechanical Engineering, SNS College of Technology, Coimbatore, India. His areas of interest are Engineering Mechanics, Composite materials, Process Planning and Cost estimation, Design of machine elements, Robotics etc.