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Empirical Modeling Methods of Turning Process: A Review

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A B S T R A C T

This paper presents a review of the modeling methods which are widely used for empirical modeling of turning process. The review considered the scientific publications from renowned scientific resource bases from 2018 until the end of 2022. The main focus was to identify the applied empirical methods, considered turning process performances, turning process parameters, material of cutting tool and workpiece, type of turning operation (single or multi pass turning) and a number of performed experimental trials upon which mathematical model was developed. Research in this area provides ready-made information in one place that can be very useful to future researchers who decide to research in this direction, i.e., possibilities for modeling certain turning process performances as well as selection of process parameters and modeling method.

1. INTRODUCTION

In the manufacturing industry, knowledge, skills and experience of machine tool operators and process planners are usually used to assess optimal tools and cutting conditions. However, this approach may result in low productivity due to underutilization of machine tool and cutting tools capabilities.

The foundations on which today's production is based are: high market demands, new production technology based on knowledge, advanced production and information technologies, new materials and modern processing and production systems. The cutting process with modern tool materials is increasingly represented in many industrial plants. To increase the efficiency of the cutting process and achieve at the same time several mutually opposite criteria related to quality, cost, productivity etc., identification of the main process parameters for a given application and modeling mathematical relationships between these parameters (inputs) and different process performances (outputs) is of prime importance. Therefore, in today's fast-growing manufacturing sector, modeling methods in machining are essential to production to improve overall productivity, decrease costs (i.e., increase profit) while satisfying all imposed customer requirements related to machining quality, as well as all techno-technological constraints related to process itself, machining method, machine tool and cutting tool.

The main goal of modeling is to define mathematical models and other representations, which will adequately describe the studied process/system in the appropriate degree of accuracy. By developing a certain model of a machining process, process planners and engineers can perceive and analyze changes in output (certain performance characteristic) values with respect to changes in inputs, i.e., changes in machining regimes. Proper selection of input parameters in the machining process plays a significant role in achieving better quality products. This selection is also applicable for reducing the overall manufacturing cost and increasing productivity [29]. Models can improve the performance of the system in operation, so that model selected parts of the system and based on such set models perform analysis and reports conclusions about the actions to be taken on the real system. The main outputs (performance characteristics) of the metal cutting process which are modeled include: surface roughness, cutting forces, cutting temperature, material remove rate, cutting power, flank wear, tool wear, etc.

In this article, an overview of empirical modeling studies of turning is presented, which represents a research field that is always current and interesting for both development of modeling theory and practical industry applications.

2. TURNING AND MODELING PROCESS

Turning is one of the extensively used machining processes in industrial applications. It consists of removing material from an external or internal, cylindrical or conical surface. The workpiece is rotated at a particular spindle speed, and the cutting tool is fed against the workpiece (feed rate) at a certain level of engagement (depth of cut) [25]. In turning process cutting regimes consider the basic elements, which define relative position and movement of cutting tool and workpiece material, such as depth of cut, feed rate (or feed speed) and cutting speed, which represents the speed by which the cutting tool tip removes the included layer from the workpiece material. For modeling of turning process, it is necessary to know the key process performances as well as other performances as well as the influencing process parameters. By knowing the essence of the turning process and its dependence of the process parameters, it is possible to improve the quality of processing and efficiency, but also to reduce processing costs.

3. MODELING OF TURNING PROCESS

The model is a simplified representation of a real system made for a better understanding or better study of the observed system and experimentation with it. A model can be defined as an abstract system that is equivalent to a real system. Mathematical modeling of a real process means a set of mathematical relations that describe the functioning of the system in a quantitative way, i.e., in a quantitative way they describe the characteristics of the system depending on process parameters, input values, initial conditions and in the general case of time. Due to the complexity of the physical interpretation of the real cutting process, only its significant output characteristics are generally taken into account during its modeling. The purpose of modeling the turning process is to: realistically predict the results of the process, to gain new knowledge about individual phases of the process that will help design the process, quickly and realistically perform single or multi-objective process optimization with or without constraints.

For modeling new and complex processes and systems, experimental methods are useful. The modeling is based on the data obtained by the realization of the experimental test where the performance of the process is measured depending on the change of the input variables in the selected range. Using a set of input and output variables, a mathematical model is developed. Empirical modeling of all other modeling is the simplest and therefore the most used in industry. They use statistical models that are valid for the range of experiments performed that are not based on physical processes. The empirical model technique is based on an experiment plan for various input parameters of the turning process, such as cutting parameters, tool geometry, etc. This modeling approach relies on laboratory conditions, which reduces the field of application because a small change in test conditions leads to relevant changes in the model. The most popular methods used for empirical modeling the turning process are:

- Response Surface Methodology (RSM),
- Artificial Neural Networks (ANN),
- Fuzzy Logic (FL),
- Genetic Programming (GP).

3.1 Response Surface Methodology (RSM)

RSM is a set of statistical and mathematical tools for modeling and optimizing process or system, with respect to single or multiple objectives, based on the use of design of experiments [1, 2]. It is a simple and widely used method for testing the relationship between independent and dependent parameters of the process. The method is an empirical statistical technique used for regression analysis of data obtained in experiments, by solving a system of equations. Measurable process output is called response. Response is a measurable size of the processing process.

3.2 Artificial Neural Networks (ANN)

ANN is a computer model based on existing knowledge about the functioning of the human brain. The ANN in computer science is a highly interconnected network of data-processing elements called neurons or nodes which are arranged in single or multiple hidden layers. They can cope with problems that are difficult to solve with the traditional approach. One of the most important features of ANNs is their ability to learn from a limited set of examples. The advantage of ANN over other modeling techniques is the ability to model complex nonlinear relationships [25]. ANN networks are systems that use the acquired knowledge from experience they can accumulate and acquire knowledge. An ANN mathematical model consists of an input layer used to present data to the network, then an output layer for performing predictions of output and one or more hidden layers between inputs and output [28].

3.3 Fuzzy Logic (FL)

FL is a suitable tool for developing models in engineering which contains complex, imprecise information which cannot be handled by traditional tools. Fuzzy rules are a set of linguistic statements which establishes the relationship between the input and the output in a fuzzy system [30]. The number of fuzzy rules in a fuzzy system is related to the number of fuzzy sets for each input variable. The primary steps involved in developing models using fuzzy logic are definition of number and type of membership functions, design of fuzzy rule base to simulate the decision process and scaling the factors with the help of variables [26].

3.4 Genetic Programming (GP)

GP is a systematic method for automatically problem solving starting from a high-level statement of what needs to be done. Specifically, GP iteratively transforms a population of computer programs, i.e., mathematical models, into a new generation of programs by applying analogs of naturally occurring genetic operations [27]. Inspired by biological evolution and its fundamental mechanisms, GP software systems implement an algorithm that uses random mutation, crossover, a fitness function, and multiple generations of evolution to resolve a user-defined task.

4. RESULTS AND DISCUSSION MODELING OF TURNING PROCESS

In researching of cutting process, modeling of turning process has attracted the attention of a large number of researchers due to the importance and contribution of the methods. Application of the methods, namely RSM, ANN, FL and GP, for empirical modeling of turning process are shown in Table 1. Review period is observed from 2018 until today. In addition to the modeling method, the following are presented: process parameters and performance, material of tool and workpiece, single or multi pass turning process and the number of experiments.

The research of papers was conducted using scientific resource bases, such as Elsevier, Springer, Taylor and Francis, Emerald, and others.

The review of the literature clearly shows the chronological application in the period from 2018 until today of RSM, ANN, FL and GP for modeling turning process, Fig 1.

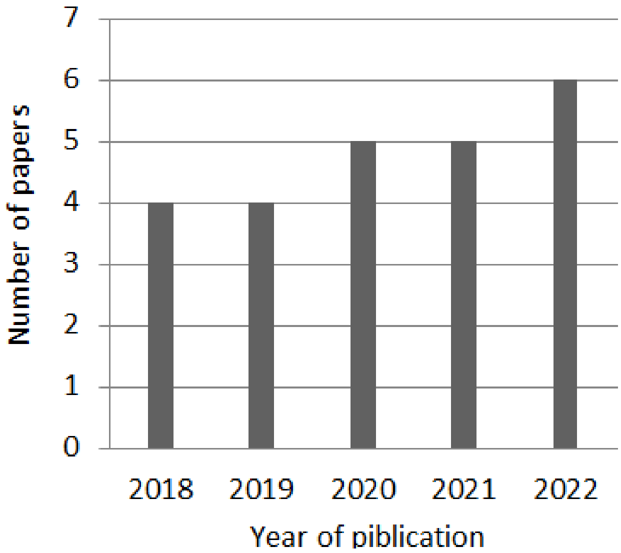

Fig. 1. Yearly distribution of publications.

The application of different methods used for modeling of the turning process is presented in Figure 2.

The figure shows the most used modeling method is RSM, followed by ANN and FL, whereas the application of GP for turning process modeling is limited. RSM is the most applied method because it has a clear formalized application structure, is very efficient for testing a large number of variables, a small number of tests are sufficient, relatively simple to understand, and there are many software tools that allow its application.

From the literature review, it is clear that a large number of turning process performances have been investigated. The performances of turning processes that are mostly modeled by applying modeling methods are surface roughness and MRR, Fig. 3. Surface roughness is mostly investigated due to the quality of the product. Low surface roughness improves several characteristics of the processed product, such as tribological properties, fatigue strength, corrosion resistance and aesthetic appearance. Accordingly, the most important tasks in the scraping process are the measurement and characterization of surface properties [19].

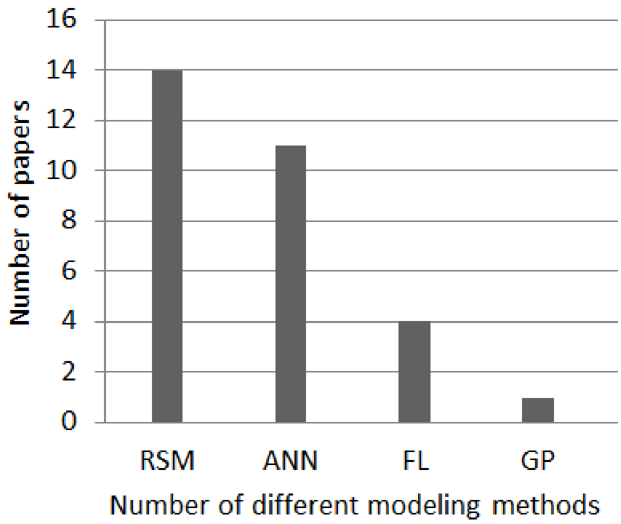

Fig. 2. Number of different modeling methods.

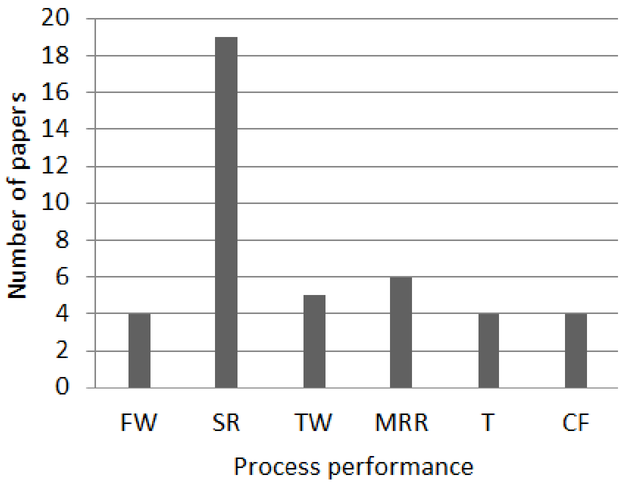

Fig. 3. Modeling of process performances.

From the review of the literature, it can be concluded that the researchers mainly used single pass turning process and various turning process models were developed in terms of the following parameters: cutting speed, feed rate and depth of cut, whose range can be seen in Table 1.

Table 1. Review of empirical modeling of turning processes.

Ref.	Modeling method	Process performance	Process parameters	Material workpiece	Material tool
[1]	RSM	FW SR	v (40-70-100) m/min f (0.1-0.125-0.15) mm/rev a_p (0.5-0.75-1) mm T (30-315-600) °C	Monel-400	TiN coated
[2]	RSM	SR (MQL) SR (wet)	v (145-350-650-950-1155) m/min f (0.07–0.12–0.19– 0.26-0.31) mm/rev a_p (0.66–1.0–1.5–2.0–2.34) mm	AA6061-T6	uncoated carbide
[3]	ANN	TW MRR	v (83.87-135-210-285) m/min f (0.08-0.20-0.32-0.40) mm/rev a_p (0.26-0.60-1.10-1.60) mm	AISI 1050 steel	HSS tool
[4]	RSM	SR T	v (125-175) m/min f (0.05-0.1) mm/rev a_p (0.25-0.75) mm	Al/Al2O3 MMC	carbide inserts
[5]	RSM	SR MRR	n (1000-2000) rpm, f (0.1-0.2) mm/rev a_p (0.1-0.3) mm	EN31	diamond shaped carbide
[6]	FL	CF FW SR	v (60-80-100) m/min f (0.14-0.17-0.20) mm/rev EP additive (5-10-15) %	AISI 1040 steel	coated carbide
[7]	ANN	SR	v (100-110-120-130-140) m/min f (0.1-0.15-0.2-0.25-0.3) mm/rev a_p (0.1-0.2-0.3-0.4-0.5) mm Q (100-200-300-400-500) ml/hr	AISI 4340	carbide inserts
[8]	RSM	SR MRR	n (1200-1500-1800) rpm f (0.15-0.20-0.25) mm/rev a_p (0.5-1-1.5) mm	AA6061	carbide inserts
[9]	ANN	T	v (80-90-120-160-180) m/min f (0.05-0.1-0.2-0.25) mm/rev a_p (0.07-0.1-0.22-0.45-0.5-0.7) mm	EN 90MnCrV8	CBN inserts
[10]	ANN	SR MRR	v (125-150-175-200) m/min f (0.05-0.010-0.15-0.20) mm/rev a_p (0.30-0.60-0.90-1.12) mm	AZ61 magnesium alloy	VCGT160404 FN-ALU
[11]	RSM ANN	SR T FW	v (200-300-425) m/min f (0.12-0.18-0.24) mm/rev a_p (0.15-0.30-0.45) mm	AISI 316L	Coated carbide
[12]	RSM ANN	SR CF	v (100-200-300) m/min f (0.08-0.14-0.20) mm/rev a_p (0.25-0.5) mm tool (GC5015-CC6050-CC650)	AISI D3 steel	Ceramic inserts
[13]	FL	SR MRR	v (200-2100-4000) r/min f (2.0-7.0-12) mm/min a_p (10-25-40) μmm	PMMA contact lens polymer	monocrystallin e diamond tool
[14]	RSM	SR	v (220-292-375) m/min f (0.1-0.2-0.2) mm/min a_p (1-1.5-2) mm	EN 8 steel	cemented carbide
[15]	FL	CF	v (192-325-420) rpm f (0.05-0.1-0.2) mm/rev a_p (0.2-0.6-1.0) mm	AISI D3 steel	carbide inserts
[16]	GP	FW	v (100-150-225-250) m/min f (0.125-0.15-0.175-0.2-0.25-) mm/rev t (0.25-2.2.5-3.5-5.5-12) min	AISI 4340 steel	TiCN-coated carbide inserts
[17]	RSM	SR TW CF	v (70-120-170-220) m/min f (0.10-0.15-0.20-0.25) mm/rev a_p (0.2-0.4-0.6-0.8) mm	Hastelloy C-276	PVD coated carbide inserts

[18]	ANN	SR TW MRR	v (35.53-62.49-89.45) m/min f (0.07-0.08-0.09) mm/rev a_p (0.2-0.4-0.6) mm	Inconel 825	cryogenically treated carbide insert
[19]	RSM ANN	SR	v (80-120-170-240-340) m/min f (0.08-0.012-0.16-0.2-0.24) mm/rev a_p (0.1-0.2-0.3-0.4-0.5) mm	martensitic stainless steel AISI 420	coated mixed ceramic cutting inserts
[20]	FL	SR T	v (382-414-446) rpm f (0.125-0.135-0.155) mm/rev a_p (0.4-0.45-0.5) mm	medium carbon steeAISI1045	Untreated, deep cryogenic treated tool
[21]	RSM	SR TW	v (100-150-200) m/min f (0.1-0.2-0.3) mm/rev a_p (0.4-0.6-0.8) mm	AISI 52100	TiCN-coated carbide insert
[22]	RSM ANN	SR	*n (750-100-1250) rpm* *f (10-20-30) mm/rev* *a_p (0.1-0.2-0.3) mM*	EN-36 alloy steel	Coated Tungsten Carbide
[23]	RSM ANN	SR	v (80-100-120-140) m/min f (0.2-0.3-0.4-0.5) mm/rev a_p (2.5-3.0-3.5-4.0) mm nr (0.8-1.2-1.62.4-) mm	Duplex 2205 (ASTM A276)	WC-Co coated carbide inserts
[24]	RSM ANN	TW	v (80-140-200-260-320) m/min f (0.02-0.1-0.18-0.26-0.32) mm/rev a_p (0.15-0.3-0.45-0.6-0.75) mm t (2-4-6-8-10) min	hardened die steel AISID3	Multilayer CVD coated, uncoated PVD coated ceramic inserts
v-cutting speed, *f*-feed rate, a_p-depth of cut, *Q*-quantity of mixture, *t*-time, *n*-spindle speed, *nr*-nose radius SR-surface roughness, MRR-material remove rate, *T*-temperature, CF-cutting force, FW-flank wear ,TW-tool wear,					

5. CONCLUSION

This paper presents an overview of recent research and the application of different methods for empirical modeling of turning process. The aim was to identify which methods, in the last five years, are among the most used for modeling turning process, which process performances are most often used for modelling, range of process parameters, material of workpiece and cutting tool. The review shows that RSM is most used for modeling turning process. In addition to the use of RSM, ANN, FL and GP for turning process modeling future studies could also focus on the application of other important modeling approaches, such as dimensional analysis, and development of hybrid empirical models. By coupling these models with optimization methods one can determine optimal cutting regimes with respected to different response characteristics. Surface roughness, cutting force and MRR are process performances most commonly considering for modeling turning process. The review revealed that there is a steady high research activity in modeling of turning process, wherein the majority of studies considered single pass turning of metal alloys workpieces.

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