A Critical Study on Computation of Cutting Forces in Metal Cutting

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Abstract. Tool behavior in metal cutting is inevitable since they are typically required to produce components with high precision. This would have a profound impact on efficiency and costs of machining. The cutting forces involved at chip tool interface and the surface finish of the machined surfaces are the two major facets to gauge the performance of tool. The prediction by a statistical model, and the experimental values recorded using various sensors especially dynamometers are different approaches to critically analyze the cutting forces. Many researchers use to extensively practice these methodologies for their research activity. The aim of current research is to critically analyze & summarize approaches i.e., experimental/predictive available for gauging the cutting forces with user suggestion.

1. INTRODUCTION

On the demand for high-precision parts from rising sectors, such as the electrical, automobile, aeronautical, medical, and industry, the Computer Numeric Control (CNC) machining industry is projected to rise to over $100 Billion by the year 2025. Asia Pacific economies including Japan, China, and India may be looked to as possible leading signs of progress in the usage of CNC machining equipment [1-3]. The relentless increase in manufacturing is taking forth changes in this machining method. It is important for industries concerned with machining to develop and refine these processes through enriching awareness regarding cutting forces, especially while selecting suitable fixtures and tools [4]. Extensively practiced empirical models including Kienzle’s formula use recorded values from experimental trials, FEM (Finite Element Modeling) and other statistical predictive models to gauge the cutting forces [5]. Apart from turning its application in milling has appeared useful for deciding suitable parameters (optimal) for machining of the components with high precision through exhaustively understanding the performance of tool, as well as, machinability of the selected workpiece material [6-9]. Furthermore, there are several issues, i.e., tool condition, overload and chatter vibration encountered while machining which can be remedied by understanding the involved cutting forces and suitable selection of cutting tool (Coated/ Un-Coated) including its optimization in geometry [10, 11]. Several researchers explored that improved machined component’s surface roughness and economics in machining (Optimized Tool wear & Enhanced Tool life) are dependent on various tool coatings which needs to be suitably selected [12].
2. LITERATURE REVIEW

We use predictor technologies to estimate cutting forces for various process optimization, i.e., machining (gear skiving) and 5-axis milling (Flank) [13, 14]. Several facets including selection of material, deflection of tool and system setup, so on influences in metal cutting contribute to difficulty in measuring cutting forces. Specifically, for the refinement of machining process, this cutting force prediction becomes impetus [15]. Furthermore, in certain cases of machining (five-axis), cutting force prediction is gaining technocrats attention as this result severe parametric variation (geometrical) in of the cutting area, due to machining complexities, remains uncertain. Thus, data acquisition and research experience its antagonistic effect [16]. Different statistical approaches have been employed to quantify cutting forces when machining composite. The reinforcements (isolated particulate and non-uniformly distributed) in these materials cause difficulty to foresee cutting power [17,18]. Interestingly, in several cases of FRPC (Fiber Reinforced Polymer Composite) warrants certain metal cutting simulation findings [19].

In the recent past significant researches examined surface finish and cutting forces using finite element Modelling (FEM) approach [20,21]. Simulations can enable the optimization of different stages including cutting force measurements while performing experiments. Furthermore, this approach will effectively reduce wastage of resources, including costly equipment, tools and the raw materials. Aside, its insight on morphology of chip and temperature of tool, cutting force useful to understand appropriate machining parameters selection, type of lubrication as well as, surface finish required in the context of tool wear, tool life and tool geometry. In case of turning, cutting forces produced at different nose radii affect each other. It’s evident from several research that large cutting forces results from smaller nose radii [22,23]. Yameogo et al. [24] reported variation of cutting forces due to the impact of several factors responsible for different chip morphology. Employing Finite Element modelling (Two-dimensional) technique this was examined and chip morphology and associated cutting forces were evaluated. During the process of machining using coated carbide insert (TiC/Al2O3/TiN) on Al 7075-T6 alloy, Sreeramulu et. al. [25] used a dynamometer to experimentally examine the cutting force along with machining temperature. Aside, the authors devised 3-D FEM replicating the boundary conditions as used in the actual experimental set-up. The outputs of the developed model were validated with experimental values. Such process is not only useful for time and cost saving but also refine process through scientific methods of evaluating potential component and to pave the way for useful machining equipment and design.

Brinksmeier et.al. examined advantages of high-speed machining (milling and turning using diamond tool) over conventional machining using FEM. They reported, the forces developed during metal cutting and time required for machining can be minimized using these methods, which will increase the longevity of tooling [26]. A recent research article evidenced the improvement in the machinability of Carbon Fiber Reinforced Polymers (CFRPs) using suitable tool geometry of cutting tool, wherein Duboust et.al. employed FE model to examine forces developed and wear of tool and correlation between them [27].

Electronic industries and aerospace industries extensively use composites based on ceramic matrix and various fiber reinforcements for development of various components with high precision. Milling of these materials were considered for prediction of developed cutting force and its critical analysis through a stochastic model (novel method) strategized by Zhang et al [28]. This model accounts both the tool wear (aggravated stochastic in nature) and carbon fibers’ distribution (random) in order to estimate the cutting forces. The reports demonstrate material deformation (plastic / elastic), cracks in fiber (development / propagation) and debonding at interface of fiber-matrix lead to the development of cutting forces at those regions experience under ploughing and deformation (i.e., friction / shear) which is different from metallic materials. Also, the predicted values of stochastic model confirmed
experimental values obtained from milling trials. Furthermore, irrespective of the machining conditions it exhibited its capability for cutting force prediction.

Accounting material removal modes, for example, brittle and ductile fracture, during ultrasonic machining (rotary type) of CFRP composite due to edge surface ground Wang et al. demonstrated a model to estimate a key performance measure i.e., cutting force in the direction of feed alone [29], whereas, in a separate article they explored in different directions i.e., depth-of-cut and feeding [30]. The experimental values confirmed the values predicted by the developed model. size & concentration of abrasive-grain, depth-of-cut, rate of feed, tool RPM and ultrasonic amplitude are the different control variables that significantly influence the components of the cutting force.

Analysis Based on RCS (Receptance Coupling Substructure) and TPA (Transfer Path), Wang et al. [31] formulated a model based on frequency response to understand the force compensation while machining to ease the complexities arises during measurement of the cutting force which is dynamic in nature. The influence of dynamometric frequency response plays key role to explore the control parameters wherein for certain geometries FEM is employed for the development of the model based on frequency response. They validated the model predicted values with experimental (milling) values. During machining (Milling /Turning) the authors demonstrated the model as a successful approach to understand (optimizing / forecasting / regulating) cutting forces.

In the cases of hard- to-machine materials, the machining operation require in-depth knowledge on cutting force for understanding of the process and optimization. Especially, in case of Al 6060-T6 alloy milling, Tsai et al. [32] formulated two model i.e., ‘Recursive Least Square’ and ‘Altintas’ to estimate the cutting force accounting impetus of diameter of tool and feed/tooth. Experimental validation revealed that there appeared certain points where experimental values contradicted the ‘Altintas’ predicted values, whereas it agreed for all the predicted values of the ‘Recursive Least Square’. The research reported that the development of tangential cutting forces resulted due to increased feed rate.

In case of five-axis metal cutting, variation in orientation of tool during metal cutting of intricate shapes responsible for complexity in assessment of cutting force. In a recent research emphasized a predictive model i.e., ‘cutting-edge element moving method’ formulated by Zhu et al. [33] useful to estimate the thickness of Chip (undeformed) in real time hence remedied the issue to understand the cutting force developed in five-axis metal cutting. Furthermore, in another research Olvera et al. [34] formulated another predictive model considering different control variables like process angles, lead, orientation tilt and tool geometry to understand cutting force in milling operation (five-axis, Workpiece: Al 7075-T6 alloy, cutter shape: barrel). The high-performance, chatter-free, difficult to machine aeronautical components production extensively use these tools. The predicted values exhibited a reasonable agreement with experimental values. These models play significant role, not only for process optimization while machining, but also for tool testing and their suitable geometric development.

In case of micro milling, the knowledge of cutting force is paramount and this becomes impetus of various predictive techniques as evidenced in current researches. In line to this, based on geometry of tool for micro-end-milling of alloys of aluminum and steel, Rodriguez and Labarga formulated a predictive model accounting significant control variable i.e., angles (exit and entry), size, deflection, and run-out of the tool used for machining [35]. Accounting material strengthening effects and edge radius, in case of NAK80 steel’s micro-end-milling, the cutting forces predictive model formulated by Zhou et al. [36], basis traditional models i.e., slip line and oblique cutting. The experimental validation of the demonstrated model exhibited errors within reasonable agreements in different directions i.e., X: 5.23% & Y: 8.02%. In continuation to this research in case of steel (AISI 1045), accounting the chip thickness while machining (micro-milling), Wojciechowski et al. [37] formulated another model (numerical) understanding the developed cutting force. The model demonstrated force’s variations using the dominant control variable i.e., deflection of tool, geometrical variation while metal cutting, thickness of chip with lowest value and burnishing along with the circumstances behind it. It was reported, while
metal cutting stability can be influenced by chip thickness, which is responsible for the variation in cutting force. Furthermore, Zhang et al. [38], has focused on both positions i.e., exit and entry of tool to formulate a predictive model wherein coefficients of cutting force indicate the size effect, as well as, for computing thickness of chip (instantaneous, uncut), they considered effect of runout in the tool. The predicted values remained within reasonable agreement (0.6%) as compared to the experimental values. In case of P20 steel micro-milling, Sahoo et al. [39] not only demonstrated the control and dynamics of machining, but also formulated FEM model (predictive) to describe the effects of geometry (limiting angles) and coating (TiAlN) of tool on the cutting forces by computing its coefficients. Values of cutting force remained within reasonable agreement in different directions i.e., X: 16.26% and Y: 15.84%. Aside, the model was also validated using experimental values for a different cutting tool (WC uncoated) which exhibited high value of errors in different directions i.e., X: 33.15% and Y: 29.56%.

In case of turning of steel i.e., AISI 4340 and AISI 52,100, Orra and Choudhury [40] formulated a predictive model (type - mechanistic) considering radius of nose and morphology of chip to estimate the cutting forces. The experimental validation exhibited predicted values within reasonable agreements with significance P value 0.05. Such researches pave the way for low cost and feasible production of high precision components.

In case of Hastelloy C267 turning, considering variations in both the developed temperature (machining) and different force components i.e., feed force, thrust force and cutting force due to coolant (cryogenic in nature) Kesavan et al. [41] simulated the real environment to formulate a Deform 3D predictive model. The experimental validation of the developed model exhibited the predicted values within reasonable agreement (<5%). Unlike dry turning, it reported temperature with a low value (57%) under Lagrangian optimal conditions.

Rinaldi et al. [42] not only focused on turning of Inconel 718, but also considering several milieus along with the variation in temperature, rate of strain and value of strain they demonstrated a model based on FEM to forecast variation on machined surface at microstructural level along with the involved cutting force. The experimental validation revealed the close relationship (<5%) with the predicted values.

In case of turning the developed forces i.e., ploughing and cutting, basis Kienzle force model, was focused by Salehi et al. [43]. They demonstrated a predictive model employing ‘Bayesian Inference’ and ‘Least Square Fitting’ that are nonlinear in nature. Authors recommended ‘Bayesian Inference’ due to the ease of simulating values from with fewer experimental trials with reasonable accuracy. Basis of required value of surface roughness and the number of tool pass in turning (Inconel 718), Toubhans et al. [44] demonstrated a force (cutting) predictive model considering force component in the direction of chip flow. It was found that the development in cutting force is resulted due to a significant control variable i.e., tool wear.

As an economical alternative for the high-cost commercial dynamometer, such predictive methodologies are gaining technocrats attention. Consequently, such approaches present a variety of difficulties, primarily time limitation and need to know proper inputs. The instruments to gauge cutting force are often coupled with such strategies, in order to make the predictions more consistent and precise. In-depth knowledge machine health and cutting milieus obtained from such methods plays crucial role, thereby allowing the machining optimization i.e., tool wear, tool life & surface roughness. For cutting forces prediction/determination, Preez and Oosthuizen [45] highlighted ‘Machine Learning Methods’ for quality improvement, saving in material, time and cost, increased. Acquired data from different sources including ‘Finite Element Method’ and turning, milling so on used to train the model in this technique to forecast the components of forces during metal cutting.

Wenkler et al. [46] demonstrated model based on Artificial Neural Network (ANN) which focuses on forecasting of components of forces during metal cutting (milling). This methodology continues to
learning itself adjusting ANN milieus i.e., the no of layers, no of neurons in each layer and assigned weights etc. till low value for Mean Square error and high value for coefficient of determination achieved. For remaining metal cutting application, authors recommended use of such methodology. Furthermore, Peng et. al. [47] focused on MLM which operate on hybrid data acquisition system from different sources 2D FEM (Refer Fig. 1) & dynamometer, in order to forecast tool wear and component of forces in turning.

These emerging methods are cumbersome due to the reliance on data acquisition (components of forces) through complex FE analysis, whereas, MLM appears to be a very influential method for better machining through forecasting suitable tool geometry and cutting environment, thus increase machining efficiency.

![Figure 1. Schematic illustration of machine-learning architecture with approach hybrid in nature [47].](image)

3. CONCLUSIONS

The increasing expertise and sufficient data availability based on experimental trials has contributed to development of improved model with precise prediction capability which are typically focused on such statistics. Computational models and techniques for forecasting components force in metal cutting have been established and tested, are now regarded as very accurate. Apart from computing the components of cutting force, the Surface finish of machined surface, temperature (Workpiece/Tool/Coolant) and Tool wear, such models including FEM are found to be useful.
Through a thorough exhaustive study, aim of the present research includes the modification and enhancement of established simulation techniques and statistical models for different metal cutting, as well as the development of innovation & invention of new cutting-edge technique. Aside, this research also remedied the hinderance in computing the components of the forces for high precision metal cutting of components with intricate shape and difficult to machine material. Table 1. shows the literature summary of computation of cutting forces in metal cutting including its recommendations and limitations.

**Table 1. Summary of Computation of Cutting Forces in Metal Cutting**

| Issues | Advantages/Recommendations | Limitations |
|--------|-----------------------------|-------------|
| Enhancement on prevailing technique | • High precision;  
• New machining processes can use validated model;  
• Validated models require low initial investment (as compared to dynamometer) | • The complex modelling computations involve a huge time which is cumbersome.  
• Use of dynamometers appears easier for assessment of cutting force.  
• Completely dependent on statistical data. |
| Innovation & invention of new cutting-edge technique | • Improved machining methods.  
• Delivers estimates for reducing powers.  
• Results of implementations have been consistent for composite material.  
• Apart from components of forces, Surface finish, tool wear, tool life etc. required to improve the economics in metal cutting | The complex modelling computations involve a huge time which is cumbersome.  
• Use of dynamometers appears easier for assessment of cutting force.  
• Needs confirmation and is usually combined with sensors for force measurement. |

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