Title
Probabilistic Precision Process Planning- P4

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Abstract— Factories of the digital future would require simulation and optimization of processes and process chains before establishing the actual line using very specific procedures. There is tremendous scope for reducing significantly the lead time for production and costs by employing planning tools for virtual machining. P4 is designed to address challenges faced by automobile industries to integrate developments in technology based software and pave way for defect free process plans. P4 presents a novel way to plan each process as an independent entity that exists as part of a sequence. Face milling is used as an example in this report to demonstrate the various concepts that form the core of P4.

Keywords: process planning, probabilistic, precision.

1. Introduction

Process planning has taken two routes in the past, one focusing on capturing the expert knowledge possessed by planners, the variant planning systems and the other focusing on generating a plan given the geometry of the part along with specifications, namely the generative systems. During the late eighties and nineties hybrid systems began to evolve, primarily, to integrate scheduling and concurrent engineering concepts. Numerous schemes exist for either kind of approach; CAPP, MIPLAN, CAM-I, ACAPS to name a few [1]. Previous research in process planning at Berkeley focused on multi-agent process planning techniques producing alternate process plans dependent on the eventual goals like machining efficiency and lower cost or environmentally conscious decision making or higher machining quality [2]. The existing schemes tend to map the requirements to a set of inference rules resulting in sub-optimal solutions on numerous occasions. Statistical principles are used only in process control and design of experiments. These principles haven't been extended to judicious process selection. A way of visualizing factor of safety for manufacturing process is in terms of C_p or C_{pk}. The limitations of this approach and a way of more objectively using experimental data to design the process are demonstrated. This is intended to avoid tuning the process extensively during installation and, theoretically, ensure the ability of the chosen process and process parameters to satisfy the specifications.

2. Inspiration for probabilistic approach

A recent FAA report states: "Significant cost/weight savings for aircraft industry can be achieved by adopting probability based design" [3]. Probabilistic design involves the use of test results to assure success with a certain level of statistical confidence. These cannot be deterministically guaranteed. In manufacturing processes, the process outcomes generally tend to be stochastic. The process planners lean towards conservative plans that yield results much better than the requirements specified by the designer. If we consider a ratio of specification like C_p, for dimensional control as an equivalent for factor of safety generally used by a designer, it stays within reasonable bounds around 1.5. But applying similar ratios for a parameter like surface finish it can be seen that it would be of the order of 10's. To restate, the processes are mostly over optimized for a good number of specifications while one particular variable might be close to limits and under some circumstances difficult to control. The use of probability brings in a level of certainty for achieving each of the specifications by planning, leading to realistic "factor of safeties".

3. Framework development

Various components of a process, each piece of that chain, like tool path, tool geometry and fixturing can be modified to obtain better results in terms of burr formation, surface finish, flatness, etc. It should be noted that each process component mentioned here is a composite entity; e.g. tool geometry would mean defining attributes like rake angles, lead angles and special angles in some cases. Each optimization step for improving quality competes for the limited process resources. Allocation of the process resources along the chain to meet specifications while meeting the objective requires knowledge about each process outcome.

4. Modeling

<u>Constraints</u>

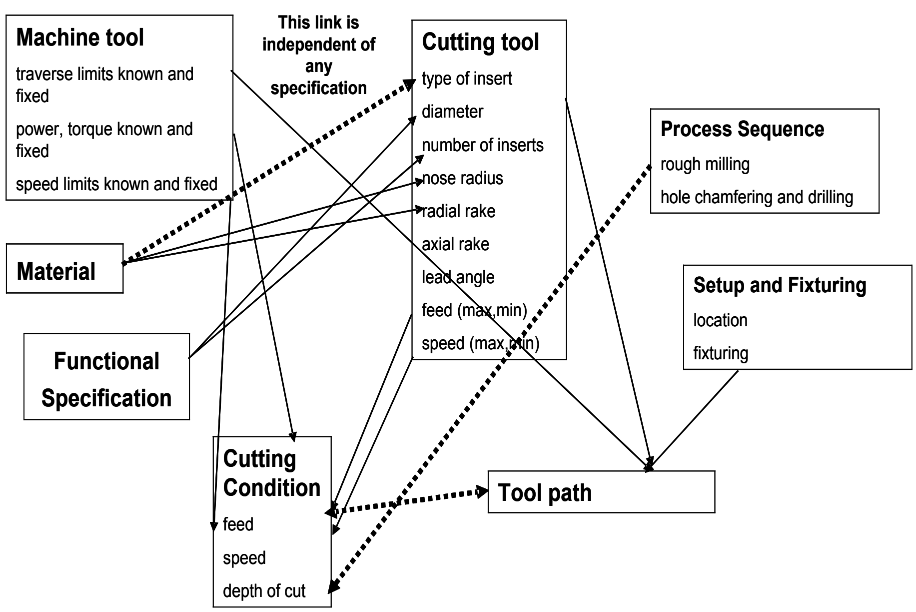

Figure 1. Constraint set for face milling.

The importance of achieving the specifications has to be reiterated because the process must be designed for repeatable and reliable performance. But for a given process there is a set of relationships that exist and are independent of the specifications. This implies that they have to be enforced independent of the results we are trying to generate. If the production scenario is known, as is the case generally, there are certain links that become active and have to be enforced strictly from the beginning. Establishing the links restricts the space for the rest of the choices that have to be made. This in general guides and changes the flow of data during the actual numerical solution procedure. The focus on information flow is significant because in the future industrial scenarios like virtual manufacturing initiatives, application software would play a vital role in process improvement. Data management for such process flows is an important step that has to be addressed in the beginning of a virtual manufacturing framework. The external considerations necessary for each piece of software that deals with a specific part of optimization, for e.g. burr minimization, flatness generation, etc., have to be stored or obtained from these constraints. The links with no associated software or a theoretical model also indicate the necessity for establishing such a model for the future.

In Figure 1, the various links are a representation of mutual constraints that exist. For e.g., consider the links in thick dotted lines, the material of the workpiece limits the type of inserts that would be used on the workpiece to achieve a good tool life. At this point there are no considerations for the specifications like flatness or burr formation. Similarly, the cycle time automatically links the length of tool path at a given feed; this is independent of final results except the capabilities of the machine, which are indicated by other links.

The primary objective of the process is to consistently achieve the specifications. Cost, environmental concerns and machine utilization are secondary objectives which are important but come into consideration only when the primary objective is satisfied. To realize this we should be able to characterize, either through an analytical, semi-analytical or empirical model, the influences of the relevant parameters on the specifications. For most of the processes such models exist for each of the process outcome. The model should be based on process physics in addition to capturing the existing knowledge about the outcome. Integrating them in a way helpful for planning, and enforcing the constraints discussed previously, it is possible to generate a near optimal solution for the process. If the models are generated through a mechanism that would help group the effects, without having to do whole lots of experiments, it would lead to remarkable cost savings in experimentation.

Multiple stage face milling is planned to achieve a certain finish and flatness along with a good dimensional tolerance. There are significant trade-offs between each selection that has to be made for the process like tool, machine tool, fixture setup, tool path, and process parameters. The main goals for finish in a face milling process are good surface finish, flatness and dimensional tolerance. But there are unavoidable results of face milling like burrs and sub-surface damage. These are not generally specified in a technical drawing and are difficult to control but also have to be limited to maximum possible extent as it would necessitate subsequent processing. Flatness and burrs are modeled through an analytical scheme; Figure 2 shows the model for flatness. Finish is modeled empirically using interpolated data and some basic findings on its relations to various parameters. The diagram for empirical model can be seen as a post-processed Ishikawa or fishbone diagram. The effects are known to influence in a particular fashion but the model has unknown coefficients which have to determined for the specific case.

<u>Process Outcome</u>

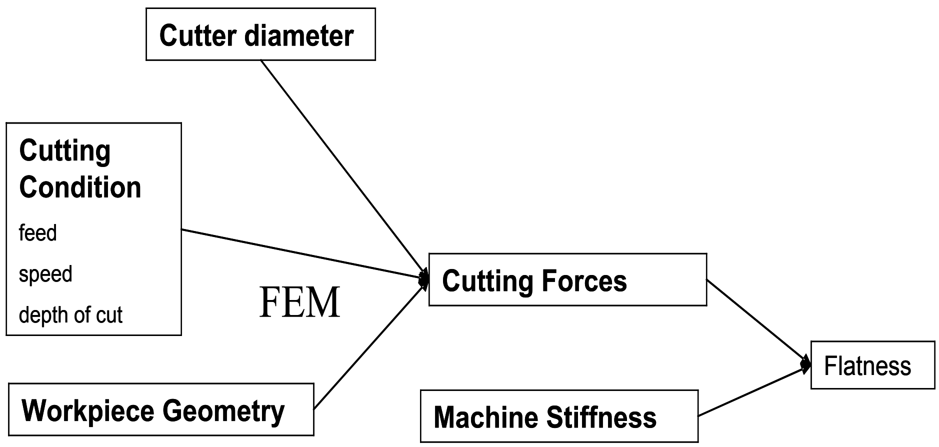

Figure 2. Analytical model for flatness.

5. Specification coupling diagram (SCD)

A distinction is made at this point of the different kinds of specifications encountered while designing a process. They have to be treated differently in view of the fact that the effects of deviation from a given value are different. There are four basic categories, those with upper bound or lower bound; finish and flatness typically are of this category. Acknowledging the designers intent, any value that satisfies the bound can be deemed acceptable. The second category is bounded from above and below; a perfect example is dimensional tolerance. The deviation for this type can be measured in terms of Taguchi quadratic loss function. Furthermore, there are others which aren't necessarily specified on the drawing sheets but are nevertheless important. They have no bounds, but are detrimental to the process results. Burrs for example are of "lower the better" class and this in general is also associated with subsequent processing and cost savings in terms of tool life.

A specification coupling diagram is built by placing all the specifications on a frame and connecting them together. The individual process components that affect more than one outcome simultaneously are identified and placed on the links connecting the various process goals. This helps in transferring the relevant data from their respective individual models to another. Figure 3 shows one such highly simplified model for face milling. This comes into play during the software interface design.

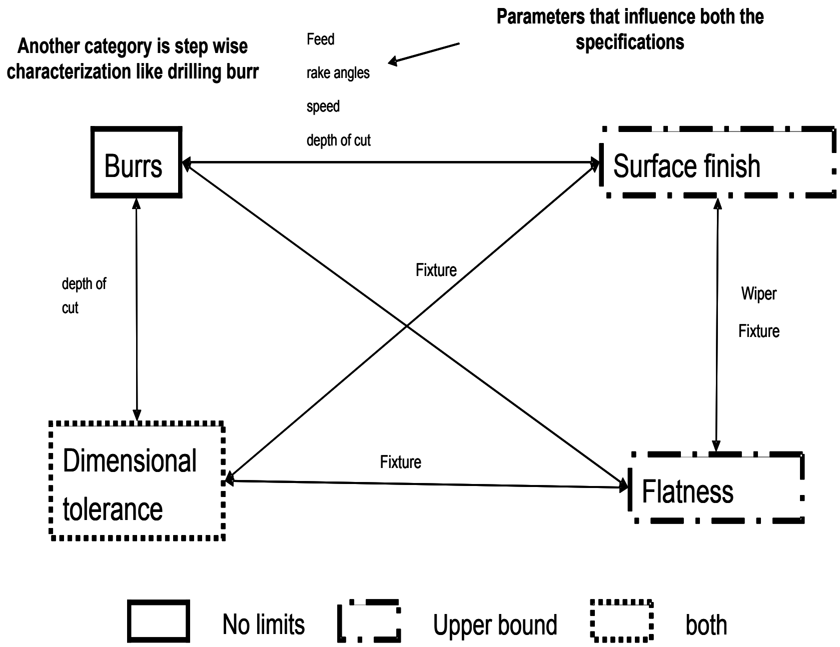

Figure 3. SCD for face milling.

6, Data management and probability model

The visualization tool developed for P4 performs the job of interpreting experimental data for the application in view. The various elements of the empirical model developed have to be tested experimentally to identify its influence. Parameters are either continuous as in feed and speed, or discrete steps like depth of cut and rake angles. In general, it is easier to change the continuous parameters compared to the discrete blocks. The axes are chosen from the most influential parameters, found either statistically when no prior information is available, or from semi-analytical models. The data points are interpolated using the appropriate regression model: linear, quadratic, or other commonly accepted relation. The variances can either be assumed constant or variable according to experimental conditions. The feasible region can be charted out from the interpolated surface imposing the relational condition:

Expected mean value [experimental values] + $t_{1\text{-}alpha/2}$ ** Standard deviation [experimental values] < Upper bound of specification or > Lower bound of specification or both*

Herein, alpha is the % confidence interval like 99.9% or 99.99% for the parameter we wish to control, and the value of *t* depends on the number of samples used to characterize variance. The mean and standard deviation can be improved with more data points and can be updated using a Bayesian approach as more experiments are conducted. The output after performing such an analysis is for each discrete step of influential elements a feasible region from parameter space. Examining the model for surface finish, feed, speed and depth of cut are known to play a role in the final value for various cutting angles and nose chamfer dimensions. Feed and speed are continuous parameters, while depth of cut and cutting angles can only vary in steps (user requirement). Experiments are performed on aluminum silicon alloy and multiple measurements are made for each feed and speed. Interpolating feed and speed, using an R_t requirement of 2 microns, we can see that the feasible region for each depth of cut is different (Figure 3). New regions come into play at different depths of cut, which would imply case specific choice for optimization. The information from this step is supplied as blocks for every depth of cut and rake angle to perform open optimization for burr formation and flatness. Moreover, additional information like stability of the chosen condition can be seen by examining the spacing of these lines. Closer spaced lines show unstable operating conditions. Inherent trade-offs between reliable design and aggressive design can be modeled relatively easily. It is also possible to reuse data and group experiments using the above scheme. For e.g., finishing face milling is performed on the various faces of cylinder heads, cylinder blocks. Data from a controlled set of experiments for face milling performed on a material with those blocks can be interpreted suitably for each application.

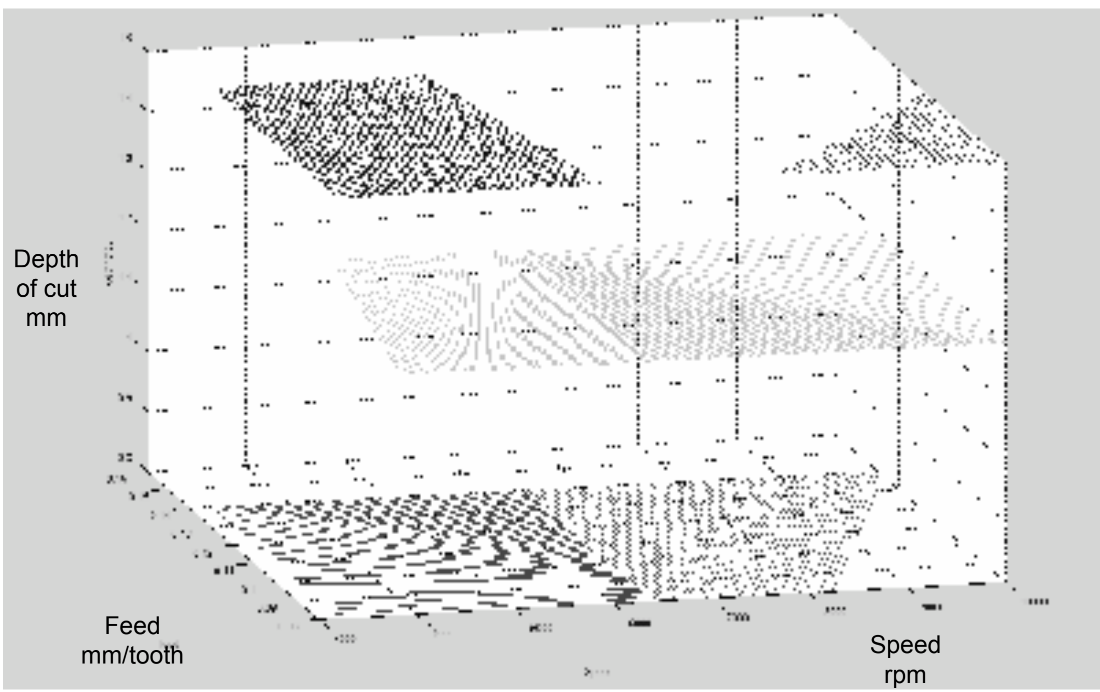

Figure 4. Feasible region for surface finish in an AlSi alloy.

The use of probability in achieving each specification helps veering away from using high factor of safeties for certain specifications. Identical probability scale, which only depends on the amount of knowledge possessed means that each specification is considered as important as the other for any given value. By choosing appropriate alpha values for t distribution it can be ensured that only one part in million produced with this plan would be out of specification. Therefore, this can be seen as a six sigma approach extended to process planning.

7. Solution procedure

To finally solve the problem to obtain numeric values that have to be supplied to the shop floor we undertake the following steps:

- Define the feasible space for the various parameters that influence the specifications with limits like finish, flatness and dimensional tolerance.
- Merge the regions for common parameters on the links that exist in the specification coupling diagram.
- Optimize the open ended specification without bounds like burr size. Modify feasible space for the common parameters like feed, speed, depth of cut.
- Further optimize to improve quality for specifications with both upper and lower bound.
- Finally optimize the open-ended choices still not clamped down to reduce the overall cost for process.

8. Conclusion

This report is the first step in establishing a framework for machining process optimization in a virtual factory setup for mass production. This is designed as a mathematical tool that could be used by a process planner for optimizing a skeleton plan. By rigorous use of experimental data, the concepts of six-sigma from process control can be extended to process planning, which we hope would eventually lead to defect-free process plans. Working in the realms of probability enables aggressive manufacturing leading to optimality with respect to planning and parameter selection. The concept will be tested in the future using case studies from automobile industry. The future work involves creating some of the appropriate software pieces and establishing the links to create an integrated virtual machining tool for face milling. This concept will also be extended for other basic machining processes like drilling and turning.

References

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