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ROBUST OPTIMIZATION FOR SMART MACHINING SYSTEMS: AN ENABLER FOR AGILE MANUFACTURING

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ABSTRACT

This paper reports our efforts towards developing a mathematical and information framework for optimization of machining processes within a Smart Machining System (SMS). An SMS uses diverse integrated technologies that enable an enterprise to: (1) produce the first and every product correct; (2) improve the response of the production system to changes in demand (just in time); (3) realize rapid and agile manufacturing; and (4) provide data to the rest of the enterprise as needed. Optimization of machining processes is an important component of an SMS and contributes to realizing these capabilities. Based on a prototype, we demonstrate the concepts for robust optimization within an SMS and develop requirements and challenges for robust optimization in an SMS.

1 INTRODUCTION

Many manufactured products involve machining operations to shape the designed part from bulk material. As such, machining systems provide one of the best opportunities to reduce time and cost of transition from specification/inception to commercial birth of a product [1]. Furthermore, the productivity and responsiveness (or agility) of production systems as well as the product quality are important factors affecting the overall manufacturing competitiveness.

There has been a continual improvement in machine tools and machining systems to respond to the needs for fabricating better quality products at lower costs. Evolution from manual machine tools to numerical control (NC) and computer numerical control (CNC) machine tools and introduction of various sensing and control improvements have enabled machine tools to be more capable, effective, and productive [2-7]. However, machining systems still require long periods of trial and error to optimally produce a given new product design or component. They still require cryptic NC language to operate with limited knowledge of the quality of their work and process behavior. Furthermore, they rely on inefficient vendor-specific interfaces to receive partial information about design intent and the function of a product to be machined.

During this evolution, researchers and practitioners have continually improved methods of optimizing machining processes. For example, over a century ago, Taylor built his tool life model to improve machining performance [8]. Since then, researchers have developed many machining models to improve machining performance and further reduce costs [9, 10, 11]. With increased knowledge about the machines and processes [10, 12] and the development of inexpensive high performance computing, optimization of machining processes with respect to a wide variety of criteria is now possible. Such criteria may involve material removal rates, chatter avoidance, tool wear, machine availability, and performance, as well as the characteristics of the machined part such as dimensional and form accuracy, and surface integrity. Choosing which criteria to use and the associated optimization methods may vary by a number of factors such as task specific requirements, by available resources, or by company preferences. Therefore what is needed is not a single model or optimizer, but a framework that can accommodate the different criteria and methods of evaluating such criteria.

The National Institute of Standards and Technology (NIST) is in the initial stages of developing such a mathematical framework for optimizing machining processes.

This mathematical framework is a part of the Smart Machining Systems (SMS) program in the Manufacturing Engineering Laboratory at NIST. The SMS program aims to develop, validate, and demonstrate the metrology, standards, and other infrastructural tools that enable the manufacturing industry to characterize, monitor, and improve the accuracy, reliability, and productivity of machining.

Due to the uncertainty associated with models and data, design and development of optimization tools using robust methods coupled with on-line systems are important for optimization of machining systems. We provide an example of a robust optimization using linear programming for turning operations. In order to develop the framework, we built a prototype to solve the specific machining system optimization problem for this example. We tested and validated the prototype optimizer by machining parts; we then determined the requirements for developing a framework generalizing the implementation of the prototype. This paper describes the optimization approach we used, the prototype and the current state of the framework.

2 SMART MACHINING SYSTEMS

The characteristics of machining systems improve with the addition of advanced computing, sensing, and other technologies. Smart machining systems (SMS) are envisioned to have the following characteristics: self recognition and communication of their capabilities to other parts of the manufacturing enterprise; self monitoring and optimization of their operations; self assessment of the quality of their work; and self learning and performance improvement over time. These attributes can be realized by seamless integration of various hardware and software components into new or existing machining systems. With these attributes, SMS becomes an enabler for agile manufacturing. Within this context, an SMS can provide the following capabilities: 1) producing the first and every product correct; 2) improving the response of the production system to changes in demand (just in time); 3) realizing rapid manufacturing; and 4) providing data to the rest of the enterprise on an as needed basis. The current direction of SMS research at NIST [1, 2] is to identify the barriers for complete integration and functioning of SMS and develop solutions to overcome these barriers.

To understand the importance of optimization within an SMS we must first consider an SMS within the broader context of a product's life cycle. As seen in Fig. 1, a broad range of information sources must be considered such as design specifications [13], process planning [13], machine specifications [6], cutting tool specifications [10], and cutting parameters [9] as well as heuristic knowledge. Furthermore, SMS relies on a broad range of expertise from various disciplines and sources to constantly improve its performance and capability. Therefore, an SMS requires a high level of interoperability and communications infrastructure.

SMS must address the communication of all information needed to fabricate a product that satisfies customer and market needs. For complex products, it is virtually impossible to fully encapsulate all information needed for and from an SMS using tools and technology readily available today. This paper describes the data required for optimization purposes and how that data may be properly obtained and exchanged. As shown by several recent publications [15, 16], there is an increasing need to provide smarter data to enable enhanced interpretation and processing by computers. Semantic Web technologies and more logical languages are the foundations to systematically create "smart data" [14, 16], for use by Product Lifecycle Management (PLM) support tools (see Fig. 1).

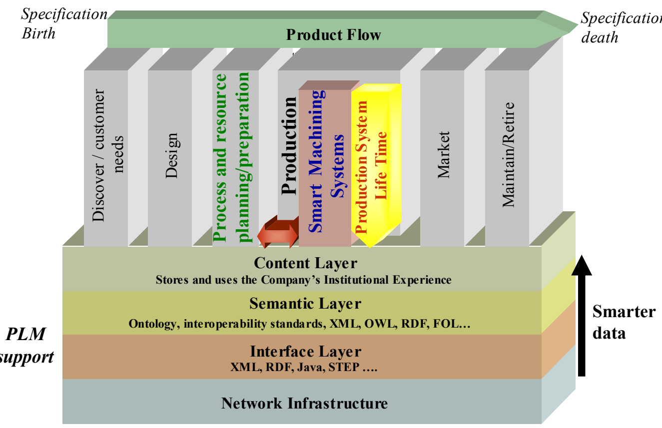


Fig. 1: SMS within the context of a product's life cycle

Fig. 2 provides a view of the SMS components. A Conceptual Process Plan (CPP) is the main input to SMS. The role of the CPP is to determine which general resources will be used. It represents the company's strategy for manufacturing the part and adds important global constraints to future optimization tasks. Based on this, a Detailed Process Plan (DPP) is developed to determine optimal machining parameters, tooling systems, and fixturing elements in order to satisfy design specifications. The SMS must optimize machining specifications before and during their realization, i.e., during planning, as well as during execution. Machining optimization uses Machining Models (MM) and data that involve uncertainty. Process monitoring and control (PMC) together with the Dynamic Process Optimizer (DPO) will adapt the machining models based on experience to reduce uncertainties. The DPO constructs objective functions and constraints using knowledge (models) about the machining process and equipment involved. The DPO also includes constraints from design such as: dimensional and geometrical tolerances, surface integrity, and surface quality. The DPO solves the resulting optimization problem to produce optimized machining operations. PMC modules execute these optimized solutions and work in conjunction with the DPM and MM to improve the DPP over time.

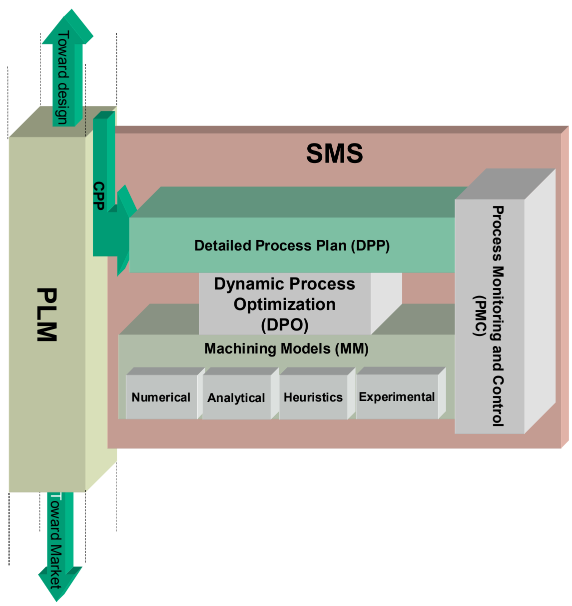


Fig. 2: SMS components

As discussed in section 3, machining optimization problems easily lead to ill-defined problems. Thereby, a DPP will become more robustly optimized using an optimization umbrella that can incorporate information from different types of models, such as numerical, theoretical, experimental, or heuristic, and represent it in such a form that it would be unambiguously understood by SMS components and the rest of the enterprise. In addition, a knowledge base for the DPO itself is required to properly construct the set of objective functions and constraints.

3 OPTIMIZATION IN MACHINING

Solving a general optimization problem means determining values for variables that satisfy an objective function and a set of constraints within a given parameter space. Depending on the type of problem, optimization may be solved using different approaches, such as linear programming [17], robust optimization [18], or multi objective optimization [19].

In machining, one challenge is that constraints are obtained from different sources of knowledge, represented as machining models (MM) in Fig. 2. These models can be numerical, analytic, heuristics or empirical. Numerical refers to Finite Element Model (FEM) simulation systems, e.g., [20], and other numerical solutions. Analytical refers to the type of knowledge captured in closed form mathematical relationships among various variables. Heuristic refers to knowledge gained from discussion with experts, such as a machinist who regularly uses the tool. Here knowledge bases [21] or expert systems are generally used to store, build, and exchange such constraints. Experimental refers to knowledge or information extracted from experiments.

Other important sources of constraints are design specifications and equipment capabilities. Part design specifications affect cutting parameters and equipment selection. Equipment capabilities may affect the quality of the machined parts. With such disparate constraints, the objective function is selected or built by different considerations such as (but not limited to):

- Business, including market windows, expected plant and facility usage from other work and time to acquire raw materials;
- Technological, for considering the equipment limitations (machine stability, tool wear …);
- Economical, to ensure a given machining cost/part;
- Required part quality.

This problem at first appears conceptually easy to solve, and it is in some machining applications. Within other configurations the optimization requires multiple objective functions and many constraints. Furthermore, machining systems and their equipment characteristics (e.g., their dynamic behavior, accuracy) change over time due to wear and maintenance. The following five characteristics of machining system optimization represent substantial challenges.

(1) Machining Systems data is uncertain or inexact. The principal elements of a machining system are the machine tool, the workholding system, the tooling, and the workpiece. The strong interaction that occurs between the different system components complicates analysis of the system response to excitation. As such, data collected in machining is uncertain or inexact because the system response to excitation is challenging to quantify. Well-defined procedures are necessary to quantify these uncertainties, such as proposed by the American National Standards Institute/American Society of Mechanical Engineering (ANSI/ASME) B5.59 draft standards [22, 23] for machine tool performance measurement.

(2) Most machining models and optimization tools are deterministic or exact. In most cases, the uncertainties in a machining system are not represented in machining models at all. Additionally, most optimization tools are deterministic, and so they do not allow for uncertainty in the relations between variables and constraints or objective functions. Other than a few exceptions [11], most attempts to optimize machining operations mathematically have neglected the uncertainty inherent in the system. Initially, a conservative solution accounting for the uncertainty is preferable. Then, gradual adaptations may enable further optimization by reducing the uncertainties based on direct measurement of constrained process behavior such as tool life or surface roughness.

(3) Detailed process plans consist of many interdependent decisions. In detailed process planning, many interdependent decisions are made sequentially, such as selection of Machine A versus Machine B, then selection of carbide tools versus cubic boron nitride (CBN) tools, and finally selection of cutting parameters. A variety of approaches have been utilized to examine tradeoffs between upstream decisions (Machine A versus Machine B) by examining alternative scenarios downstream (carbide vs. CBN). In this paper, we examine a downstream scenario of cutting parameter selection including quantified uncertainty levels that can have a substantial effect on the resulting solution.

(4) The optimization may be a large-scale problem. Even if the optimization requires providing only a few variables (the optimal set of operational parameters), solving the optimization problem can become a large problem where many variables, constraints, and objective functions need to be considered. The number of variables depends strongly on the degree of detail that the process planner needs to consider but also on the way of treating uncertainties.

(5) "Metastable" optimal solutions are possible. Metastable solutions are those that become severely infeasible in the face of even relatively small changes in the conditions during machining.

The two common threads in these challenges are uncertainty (1,2,5) and complexity (3,4). Robust optimization methodology provides a means to overcome these difficulties inherent in machining optimization [18] without the need to associate uncertainties with explicitly defined probabilistic distributions as in stochastic optimization.

As presented in [1], a general machining optimization problem consists of determining decision variables $x_1, x_2, \ldots, x_n$, such as feed, depth of cut, spindle speed, in such a way that a set of given constraints are satisfied and a desired objective function is optimized. For SMS the constraints are determined either by empirical, heuristic, or theoretical considerations and they can usually be expressed as a system of inequalities. Then, if x is the vector of decision variables and $f_0(x)$ the objective function, the optimization problem can be written as

$$\text{Minimize } f_0(x) \tag{1}$$

$$\text{Subject to } f_i(x) \leq 0, i = 1,2,...,m. \tag{2}$$

If all f_i are linear then the optimization problem (1)-(2) becomes a linear programming problem (LP) that has been extensively studied, and for which efficient algorithms are known [6]. However, in most applications both the objective function and the functions defining the constraints can be nonlinear and additional algorithms such as robust quadratic programming, and robust semi definite programming, may be used such as discussed in [3, 14, 23]. In this paper, an LP approach for robust optimization is used. Other approaches will be tested in the future.

As discussed previously, uncertainty in data sources and models make the optimum solution only an approximation that is not always the best solution. Therefore we express uncertainties as a vector of interval variables ς for which:

$$\varsigma_i = [x_{i1}, x_{i2}] \text{ for } i=1,2, \ldots n. \tag{3}$$

Parameter ς_i is a vector of intervals for the variables considered in the optimization problem. The optimization problem then becomes:

$$\text{Minimize } f_0(x) \tag{4}$$

$$\text{Subject to } f_j(x,\varsigma) \leq 0 \text{ with } j = 1,2, \ldots. m. \tag{5}$$

The optimization problem stated by equations (1) and (2) produces a simple optimum. On the other hand, the optimization problem presented by equations (4) and (5) produces at least two solutions, S1 and S2. S1 is the maximum of the lower limits of the intervals, S2 is the maximum of the upper limits of intervals. Because S1 corresponds to the lower limits of the interval, it is the less risky optimum according to the process uncertainties. Therefore we called this value the **robust optimum**. On the other hand, S2 is the most risky and generally involves using the resources much closer to their upper limits than does S1. Therefore this value is called the **target optimum** because it is supposed to be the target set of parameters that the machining system may be able to achieve.

In practice, the robust optimum may be the starting point in the initial setup. Then, depending on process behavior and quality of machined parts, this optimum can be modified towards the target optimum. Nevertheless this modification cannot always be done instantly from robust to target optimum. Intermediate parameters may be used to avoid unexpected breakdown that are more likely to occur with the target optimum.

The key issue is determining uncertainty intervals, ς_i, that depend mainly on the variety of methods used to obtain the variables. In general, experimental results provide better estimations of uncertainty. However, they require well-defined procedures and the same experimental conditions to ensure repeatability. As a way of coping with the uncertainty in mechanistic and empirical models, we redefine the constants as random variables with unknown distributions. Estimations of the distributions are then formed on the combined basis of the inherent variability of the process and our uncertainty associated with the model's prediction of process behavior. Of course, with subsequent observations of actual process behavior, these estimations must be updated and if necessary the optimization problem can be revisited.

4 CASE STUDY IN TURNING

The part design used for our case study is presented in Fig. 3. The machining process plan to machine this feature is schematically represented in Fig. 4 and in Table 1. Five operation sequences[1] are required. Other machining strategies can be used, such as those referred to in [24]. Notice that the machining process plan choice is not addressed in this study. Two cutting tools have been chosen for the entire process plan, T1 and T2. Design constraints satisfied by each sequence are given in the fourth column.

[1] In this paper an operation sequence is an atomic activity as defined in the Process Specification Language, PSL [25]. Depending on the context and application, other definitions may be used for a sequence.

4.1 Optimization problem

The optimization problem considered here is built upon machining constraints generally encountered in turning operations. The objective function is maximizing the material removal rate (MRR). This is a commonly used optimization function by process planners. Maximum material removal rate is achieved for high values of cutting speed, *Vc*, depth of cut, *ap*, and feed, *f*, which can induce process breakdowns. In turning this objective function is expressed as:

Max MRR = $F(ap, f, Vc) = ap \cdot f \cdot Vc$ (6)

Constraints that are to be satisfied while maximizing the objective function and considered in our study are:

- Cutting parameter ranges (C1 to C6);
- Machine tool spindle power limit (C7);
- Machine spindle torque limit (C8);
- Machine tool rpm constraint (C9);
- Tool life (C10);
- Part quality (C11 to C13).

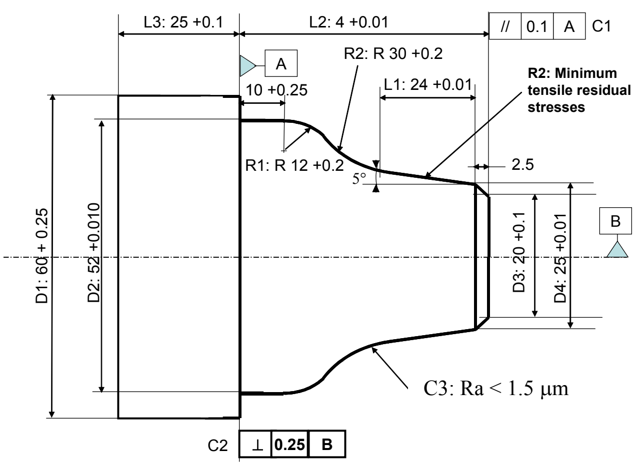


Fig. 3: Part design

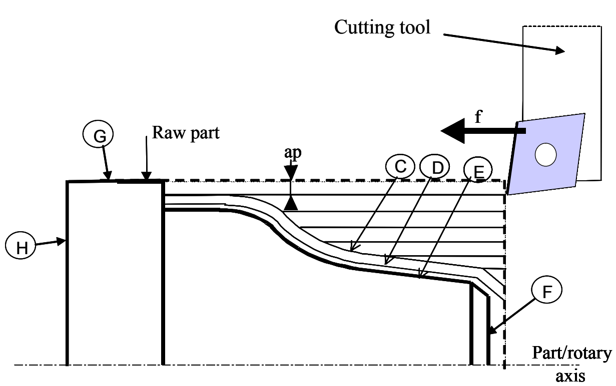


Fig. 4: Schematic process plan

Table 1: Process plan table

Ope. Seq. #	Process type	Surface	Satisfied Constraints	Tool
100	Set up	None	D4, L1, L2, C1, C2	None
110	Roughing	C	D1, R1, R2	T1
120	Semi finishing	D	D1,R1, R2, R2	T1
130	Finishing	E	D2, D3, D4, L1, L3, R1, R2, C1, C2, C3	T2
140	Finishing	F	L2	T2

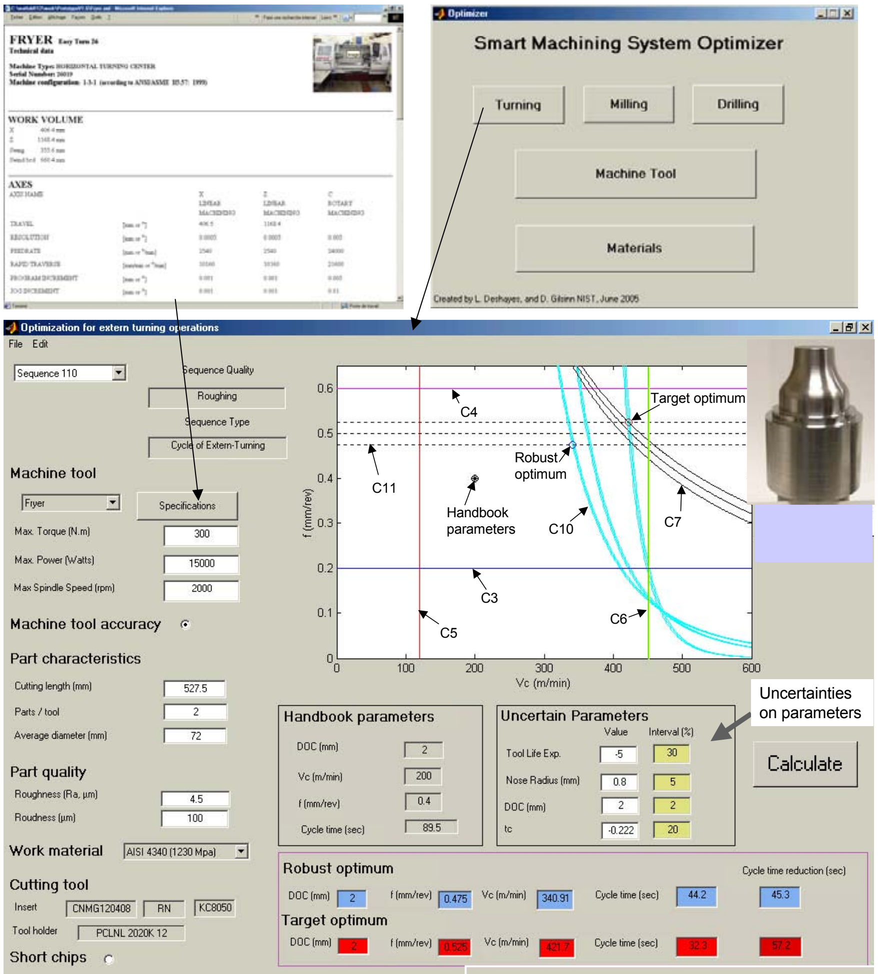
Calculations of the constraints are detailed in Appendix 1 and summarized in Fig. 5. Appendix 1 gives the nominal form of the constraints labeled C1 to C13. In order to solve the optimization problem using a linear programming approach, the equations were linearized using the logarithm function as documented in [9].

4.2 Implementation and results

The case study was implemented using Matlab[2] and its GUIDE interface programming toolbox. The linear programming optimization has been programmed using the function "linprog" from Matlab. The optimizer user interface is shown in Fig. 5. The screen at the top right proposes to choose the cutting process to optimize; by selecting **Turning** the optimizer screen opens, as shown in the bottom of the figure. At this stage the following inputs to the optimizer are required:

- The DPP sequence, at the top left of the user interface identified by the sequence number and the required quality (roughing, semi-finishing, or finishing).
- The machine tool characteristics that are retrieved from a manufacturing resource database. An example of this type of data is presented in the top left of Fig. 5. This information is in extensible Markup Language (XML) format, according to ASME B5.59 draft standard [22, 23]. In this case study the machine tool spindle accuracy was used in the constraints (See Appendix 1).
- The part dimensions necessary for the machining operation. Here it consists of the average diameter, the cutting length, and the required number of parts by the tool specified by the process planner.
- The required part quality for each sequence. In our case only surface roughness and roundness are considered (See Appendix 1).
- The work-material.

[2] Commercial equipment and materials are identified in order to adequately specify certain procedures. In no case does such identification imply recommendation or endorsement by the National Institute of Standards and Technology, nor does it imply that the materials or equipment are necessarily the best available for the purpose. Official contribution of the National Institute of Standards and Technology; not subject to copyright in the United States.



Label	Name	Nominal form
C1	Minimum depth limit	$ap > ap_{min}$
C2	Maximum dept limit	$ap < ap_{max}$
C3	Minimum feed limit	$f > f_{min}$
C4	Maximum speed limit	$f < f_{max}$
C5	Minimum speed limit	$Vc > Vc_{min}$
C6	Maximum speed limit	$Vc < Vc_{max}$
C7	Spindle power	$Pc=Vc.ap.K_{cc(e0,\gamma0)}.K_{\lambda c}.\left(\frac{\sin\kappa}{e_0}\right)^{tc}.f^{1+tc}<Pu$
C8	Spindle torque	$\frac{D}{2}.ap.K_{cc(e0,\gamma0)}.K_{\lambda c}.\left(\frac{\sin\kappa}{e_0}\right)^{tc}.f^{1+tc}<Cmax$
C9	Spindle rpm	$Vc < \frac{\pi.D.Nmax}{1000}$
C10	Tool life	$(a_p)^l.(f)^{1+m}.(V_c)^{1+n} \geq \frac{N_{part}.lc.\pi lc.}{1000.Tr}.(a_{pr})^{-l}.(f_r)^{-m}.(V_{cr})^{-n}$
C11	Theoretical Roughness	$\frac{125.f^2}{r_\varepsilon} < Rth_{spe}$
C12	Arithmetic Roughness	$K1.f < Ra_{spe}$
C13	Roundness	$Vc<\frac{\pi.D.N_{synchr}}{1000}$

Fig. 5: Robust optimizer user interface

- The cutting tool name and its insert and tool holder codes.
- The desire for fragmented (short) chips.

Uncertain parameters considered in this study are the depth of cut, ap, the tool nose radius, r_{ε}, the Taylor exponent, n, and the specific cutting force exponent, *tc*. The uncertainty of ap is due to the tool wear and machine positioning errors.

Considering that tool wear is the dominant source, the estimated uncertainty of ap is 2 %. The estimated uncertainty of the tool nose radius is 5 % based on tooling tolerances provided by standards [24-25]. The next two parameters are obtained by experimental procedures. Depending on the number of experiments and other factors, the estimated uncertainties may be higher than the simple parameters mentioned earlier. For example, the Taylor exponent determination relies on measurements of tool wear under a microscope as well as precise setting of cutting parameters, all of which have uncertainties. Furthermore, experimental uncertainty associated with a small number of repetitions would increase the overall uncertainty. Therefore we chose the estimated uncertainty of the Taylor exponent as 30 %. On the other hand, since the experimental determination of *tc* only relies on the measurement of one force parameter, its uncertainty is expected to be smaller than that of the Taylor exponent. We therefore chose the expected uncertainty for *tc* as 20 %.

The output of the optimizer is a graph that presents the constraints and the optimum solutions. The graph indicates three points: one point for the handbook values, one for the robust optimum (S1), and one for the target optimum (S2). Values of cutting parameters for each optimum and each sequence are given in Table 2. The models were calibrated using experimental techniques described in [26, 27].

To validate the optimization, three parts were machined using the handbook values, the robust optimum values, and the target optimum values. The roughness on the finish-machined surface labeled E in Fig. 4 was measured and taken as the quality criterion for comparing the three sets of parameters. All three were good parts according to the design specifications (See Fig. 3); the arithmetic mean roughness, *Ra*, was below the required 1.5 µm. But it is noticed that the robust optimum presents the best roughness value compared to the two other settings. This shows that the target optimum, even if the part is good, seems to be too close to the machine tool limits. On the other hand, the handbook values clearly underestimate the real optimum of the process. We observe that the robust optimum setting reduces the cycle time by 46 % and surface roughness by about 30 % compared to handbook values. The target optimum setting reduces the cycle time by almost 60 %.

Table 2: Experimental results of the tests realized with the three settings: the handbook parameters, the robust optimum, and the target optimum

Setting	Ope. Seq. #	f (mm/rev)	V_c (m/min)	Seq. Cycle Time (s)	Measured Roughness (Ra) (μm)
Handbook parameters	110	0.4	200	89.5	-
	120	0.4	200	10.5	-
	130	0.12	300	21.7	**1.3**
	Total	-	-	**121.7**	-
Robust optimum	110	0.47	341	44.2	-
	120	0.47	377	4.7	-
	130	0.14	320	16.5	**0.8**
	Total	-	-	**65.4**	-
Target optimum	110	0.52	422	32.3	-
	120	0.52	377	4.2	-
	130	0.16	352	13.6	**1.2**
	Total	-	-	**50.1**	-

5 A FRAMEWORK FOR OPTIMIZATION

A formalization of the optimization is necessary to develop a generic optimization system capable of handling diverse sets of constraints and objective functions for various machining processes. The requirements for such formalization are:

- Communicating with diverse sources of information while interacting with multiple levels of manufacturing enterprise involving multiple disciplines,
- Handling/processing diverse types of knowledge (numeric, heuristic, etc.) with different types of sources of uncertainty,
- Capable of functioning in changing environments (technical, economic, etc.).

These requirements present the following technical challenges:

- Creating unambiguous and machine processable information structure (e.g., XML, ontology languages, etc.)
- Computer representation of different types of models and data and their associated uncertainties
- Dynamic arrangement of optimisation.

XML-based data specifications and structures have proven to be very effective tools for better interoperability in various fields including manufacturing [15]. Therefore, we believe that the robust optimizer for SMS could benefit from this information technology to represent and store all parameters, functions, mathematical expressions, and associated uncertainties. Our first implementation is based on XML and MathML representations of our prototype optimization.

However, even though the current XML structure provides an adequate specification of the optimization problem at hand, extending the representation capabilities of XML may be necessary to achieve full functionality of the generic formalization. Representation schemes that can convey the meaning and interrelationships of the data are needed for improved functionality of applications. In the case of robust optimization, the representation of an objective function or a constraint can be a single human-understandable sentence, (but unstructured data for a computer) just to avoid misunderstanding, or a more sophisticated logical notation to be used by reasoning systems. In addition, different scientific concepts with very subtle differences and implications that are not trivial to represent have to be incorporated. This can be done in two ways: 1) using technologies provided by the Semantic Web [16] such as RDF (Resource Description Framework) and OWL (Web Ontology Language); 2) using more logical structures, such as First Order Logic as used in PSL [28]. We believe the use of such structured information will reduce ambiguities for humans as well as machines.

6 CONCLUSION AND NEXT STEPS

The goal was to develop a prototype to show the concepts for robust optimization within a SMS. Based on the prototype, we developed the requirements and challenges for a framework to satisfy.

The robust optimization requires developing, testing, and validating various optimization algorithms capable of solving complex machining problems. It also requires a machine-processable framework rich enough to represent the subtlety of the objective functions and constraints used in machining. Furthermore, it requires a proper representation and confidence level for the information/models used in the objective function and constraints.

The immediate next steps for such a generic optimization system are:

- Testing and validating robust optimization algorithms (quadratic, semi-definite, etc.).
- Building improved data models for objective functions and constraints. This may involve testing several machine-processable languages to specify machining objective functions and constraints.
- Specifying a framework for such an optimization system.

For the long term, we envision robust optimization playing a role to assist in selecting not only cutting parameters, but also machining resources. It may also help in constructing detailed machining process plans.

7 ACKNOWLEDGMENTS

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APPENDIX 1: CONSTRAINTS FORMULATION

Constraints used in section 4 (and Fig. 5) are presented.

Let assume the following experimental equation [25] for the cutting force, Fc:

$$Fc = Vc \cdot ap \cdot K_{cc(e0,\gamma 0)} \cdot K_{\gamma c} \cdot \left(\frac{\sin\kappa}{e_0}\right)^{tc} \cdot f^{1+tc} \quad (1)$$

where $Kcc(e_0, \gamma_0)$ is the specific cutting force (in N/mm^2) experimentally determined for a chip thickness, e_0, and a rake angle, γ_0; κ is the cutting edge angle, V_c is the cutting speed (in m/min), a_p the depth of cut (in mm), f the feed rate (in mm/rev). $K_{\gamma c}$ is a coefficient taking into consideration the normal cutting angle effect on specific cutting force, Kcc.

Generally $K_{\gamma c} = 1 - a.(\gamma_n - \gamma_0)$ where a is a constant determined experimentally, and γ_n the normal cutting angle. tc is an exponent determined experimentally such as shown in Fig.6. In this study tc was determined for a single tool geometry in order to simplify the model. More complex models for tc may be used to incorporate tool geometry effect into the model. Notice that the tool rake face geometry effect is represented in equation (1) by the coefficient $K_{\gamma c}$ that is assimilated to a correcting factor for the tool normal cutting angle, γ_n. Nevertheless, tool nose radius and edge radius are not considered in this model.

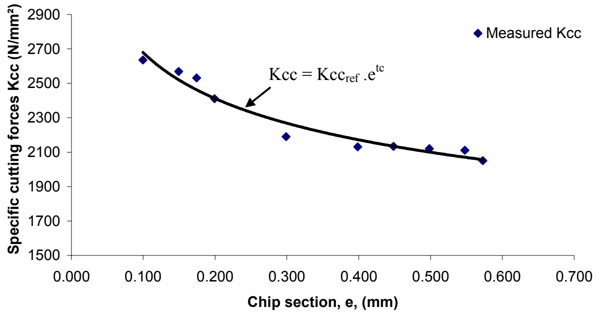

Fig. 6: Determination of tc

1- Constraints associated with cutting variables (C1 to C6)

These constraints are imposed by the interaction between the tool and work material. They limit the range of validity for each cutting parameter (variable), ap, f and Vc, such as:

- $ap_{min} < ap < ap_{max}$ (2)
- $f_{min} < f < f_{max}$ (3)
- $Vc_{min} < Vc < Vc_{max}$ (4)

These three inequalities represent 6 constraints (C1 to C6) which are:

C1: $ap > ap_{min}$
C2: $ap < ap_{max}$
C3: $f > f_{min}$
C4: $f < f_{max}$
C5: $Vc > Vc_{min}$
C6: $Vc < Vc_{max}$

2-Constraint associated with available machine tool spindle power (C7)

The power consumed by the cutting process, Pc, is :

$$Pc = Vc \cdot Fc \quad (5)$$

The cutting force, Fc, is given by equation (1), then :

$$Pc = Vc \cdot ap \cdot K_{cc(e0,\gamma)} \cdot K_{\lambda c} \cdot \left(\frac{\sin\kappa}{e_0}\right)^{tc} \cdot f^{1+tc} \quad (6)$$

Therefore, in order to perform the cut, **C7,** the cutting power has to be below the nominal power available to the machine spindle, Pu, i.e.:

$$P_C < P_u \quad (7)$$

Then:

$$Vc \cdot ap \cdot K_{cc(e0,\gamma 0)} \cdot K_{\lambda c} \cdot \left(\frac{\sin\kappa}{e_0}\right)^{tc} \cdot f^{1+tc} < Pu \quad (8)$$

3-Constraint associated with spindle torque (C8)

The cutting torque Cc, i.e., the torque produced by the action of the tool on the work-piece, is :

$$Cc = Fc \cdot D/2 \quad (9)$$

Where D (in mm) is the machined part diameter. Cc has to be below the maximum torque, Cmax, available on spindle:

$$Cc < Cmax. \quad (10)$$

Then the constraint is:

$$\frac{D}{2} \cdot ap \cdot K_{cc(e0,\gamma 0)} \cdot K_{\lambda c} \cdot \left(\frac{\sin\kappa}{e_0}\right)^{tc} \cdot f^{1+tc} < Cmax \cdot \quad (11)$$

4-Constraint associated with spindle speed (C9)

The cutting speed Vc is related to spindle speed, N (rpm) as

$$Vc = (\pi \cdot D \cdot N)/1000. \quad (12)$$

Therefore the cutting speed has to be below the maximum available spindle speed, Nmax. The constraint is:

$$Vc < (\pi \cdot D \cdot Nmax)/1000. \quad (13)$$

5-Constraint associated with tool life (C10)

The tool life has to be greater or equal to the time, t_{cut}, necessary to machine a given number of parts:

$$T \geq t_{cut}. \quad (14)$$

The cutting time is :

$$t_{cut} = (N_{part} \cdot lc) / (f \cdot N) \quad (15)$$

where N_{part} is the number of parts, lc the cutting length, N the spindle speed (rpm).

Using the generalized Taylor tool life equation [9]:

$$T = Ct\,(a_p)^l (f)^m (Vc)^n$$

where T is the tool life, n, m and l are parameters determined experimentally, the constraint is:

$$T_r \left(\frac{a_p}{a_{pr}}\right)^l \left(\frac{f}{f_r}\right)^m \left(\frac{V_c}{V_{cr}}\right)^n \geq t_{cut} \quad (16)$$

where Tr is the measured tool life for a tool flank wear of Vb = 0.3 mm with a chosen set of cutting parameters a_{pr}, f_r and V_{cr}. With equations (13) and (15), the final form of the constraint is:

$$(a_p)^l (f)^{m+1} (V_c)^{n+1} \geq \frac{N_{part} \cdot lc \cdot \pi \cdot D}{f \cdot 1000 \cdot Vc \cdot Tr} (a_{pr})^{-l} (f_r)^{-m} (V_{cr})^{-n} \quad (17)$$

6- Constraint associated with quality (C11, C12 and C13)

Roughness constraints (C11 and C12)

There is a plethora of surface texture quantifications. Many of them characterize the surface “roughness”. The surface roughness required of the part is specified by the design and this may be transposed in machining by the following constraint:

$$Rth < Rth_{spe} \quad (18)$$

Where Rth is the theoretical roughness, and Rth_{spe} is the required theoretical roughness. Rth is generally calculated, in micrometers, by the following equation:

$$Rth = \frac{125 \cdot f^2}{r_\varepsilon}, \quad (19)$$

where r_ε is the tool nose radius (in mm). Therefore constraint **C11** is:

$$\frac{125 \cdot f^2}{r_\varepsilon} < Rth_{spe} \quad (20)$$

Other roughness models can be used for this constraint. For example, a linear equation for the average roughness, Ra, obtained by measurements in function of feed rate f is given in Fig. 2. The diamonds represent measured arithmetical mean roughness obtained by direct measurement on the part surface after machining. Therefore in that case constraint **C12** is:

$$K1 \cdot f < Ra_{spe} \quad (21)$$

Where K1 is a constant, K1 = 11.233 in Fig. 7

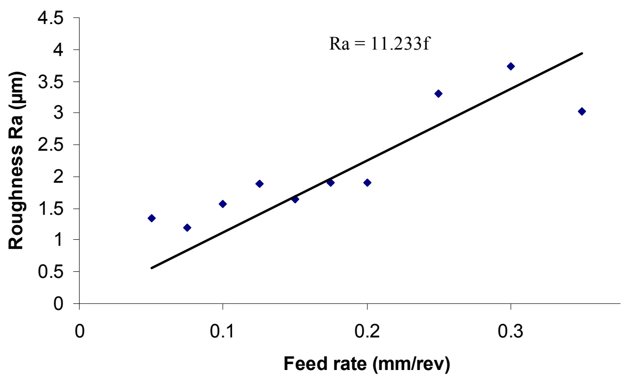

Fig. 7: An experimental linear equation of the measured average roughness (Ra) as a function of feed rate f

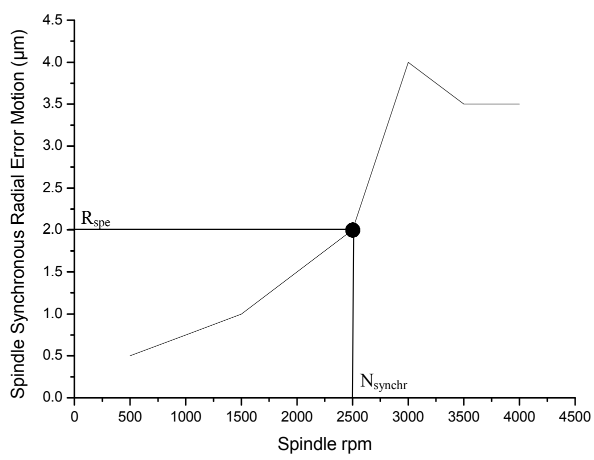

Fig. 8: Spindle Synchronous Radial Error Motion as a function of spindle speed

Roundness constraint(C13)

Here, as an example, the synchronous error motion of spindle is used as a constraint on the cutting speed. Synchronous radial error motion plot is shown in Fig. 8 as a function of the spindle rpm. The roundness is associated with the spindle synchronous radial error motion. Therefore for a specified roundness of Rd_{spe}, the constraint is:

$$Rd < Rd_{spe.} \quad (22)$$

To make this constraint useful with the previous constraint it needs to be specified as a function of cutting parameters. As shown in Fig. 3, a spindle speed, $N_{sycnhr,}$ is associated with Rd_{spe}. Therefore, the constraint can be expressed as:

$$Vc < \frac{\pi \cdot D \cdot N_{synchr}}{1000}. \quad (23)$$

APPENDIX 2 LINEARIZED CONSTRAINTS

The linear optimization requires rearranging the constraint inequalities and writing them in a linear format. Using logarithm scale, the following table gives the linear formulation of these same equations presented previously. The following notation has been adopted for the linearized equations:

$F = \log(f)$; $A = \log(a_p)$; $V = \log(V_C)$; and

$$kf = K_{cc(e0,\gamma0)} \cdot K_{\lambda c} \cdot \left(\frac{\sin\kappa}{e_0}\right)^{tc}$$

Label	Name	Linear form (Logarithm space)
C1	Minimum depth limit	$A > \mathrm{Log}\,(ap_{min})$
C2	Maximum dept limit	$A < \mathrm{Log}\,(ap_{max})$
C3	Minimum feed limit	$F > \mathrm{Log}\,(f_{min})$
C4	Maximum speed limit	$F < \mathrm{Log}\,(f_{max})$
C5	Minimum speed limit	$V > \mathrm{Log}\,(Vc_{min})$
C6	Maximum speed limit	$V < \mathrm{Log}\,(Vc_{max})$
C7	Spindle power	$A + (1+tc)\,F + V \le \log\left(\frac{P_u.60}{k_f}\right)$
C8	Spindle torque	$A + (1+tc)\,F \le \log\left(\frac{2.C_{Max}}{k_f.D}\right)$
C9	Spindle rpm	$V < \mathrm{Log}\left(\frac{\pi..D.N_{max}}{1000}\right)$
C10	Tool life	$1.A + (1+m).F + (1+n).V \ge \mathrm{Log}\left(\frac{N_{part}.lc.\pi lc.}{1000.Tr}.(a_{pr})^{l}.(f_r)^{-m}.(V_{cr})^{-n}\right)$
C11	Theoretical Roughness	$F < \left(\frac{Rth_{spe}.r_\varepsilon.}{125}\right)^{1/2}$
C12	Arithmetic Roughness	$F < \mathrm{Log}\left(\frac{Ra_{spe}}{K1}\right)$
C13	Roundness	$V < \mathrm{Log}\left(\frac{\pi.D.N_{synchr}}{1000}\right)$

Notice that the objective function (Max MRR = $a_p \cdot f \cdot V_c$) must also be linearized, such as:

$$\text{Max } \log(MRR) = A + F + V.$$