Smart machining systems: issues and research trends

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Abstract : Smart Machining Systems (SMS) are an important part of Life Cycle Engineering (LCE) since its capabilities include: producing the first and every product correct; improving the response of the production system to changes in demand (just in time); realizing rapid manufacturing; and, providing data on an as needed basis. Thereby, SMS improve the performance of production systems and reduce production costs. In addition, an SMS not only has to improve a particular machining process, but it also has to determine the best optimized solution to produce the part faster, better, at lower cost, and with a minimum impact on the environment. In addition, new software tools are required to facilitate the improvement of a machining system, characterized by a high level of expertise or heuristic methods. A global approach requires integrating knowledge/information about the product design, production equipment, and machining process. This paper first discusses the main characteristics and components that are envisioned to be part of SMS. Then, uncertainties associated with models and data and the optimization tasks in SMS are discussed. Robust Optimization is an approach for coping with such uncertainties in SMS. Current use of machining models by production engineers and associated problems are discussed. Finally, the paper discusses interoperability needs for integrating SMS into the product life cycle, as well as the need for knowledge-based systems. The paper ends with a description of future research trends and work plans.

Keywords: Smart Machining Systems, Life Cycle Engineering, Robust Optimization, Knowledge bases, Ontologies

1. Introduction

Many manufactured products involve machining. For such products, machining systems play an important role in the product life cycle as part of the connection between design and the finished product. The time and cost of transition from specification/inception to commercial birth may significantly affect the remaining phases of the life cycle. Furthermore, the productivity and the responsiveness (agility) of production systems as well as the product quality are important factors affecting product life cycle. All these characteristics are critical outcomes of machining systems used in production. There has been a continuous improvement in machine tools and machining systems to respond to the needs for 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 over the last several decades. Even after these improvements, 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 what they are producing or how well they are producing. Furthermore, they rely on inefficient vendor-specific interfaces to receive partial information about design intent and function of a product to be machined. They either break down unexpectedly or require costly periodic maintenance to avoid these breakdowns. These deficiencies cause significant delays in time-to-market, increase cost, and reduce productivity. Smart Machining Systems (SMS) are envisioned to have the capabilities of: self recognition and communication of their capabilities to other parts of the manufacturing enterprise; self monitoring and optimizing their operations; self assessing the quality of their own 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. Some of these components have already been incorporated in existing machining systems in a limited fashion. The current direction of SMS research at NIST [1] (National Institute of Standards and Technology) is to identify the barriers for complete integration and functioning of SMS with product life cycle and develop necessary tools to overcome these barriers. Within this context, a Smart Machining System (SMS) provides 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; 4) providing data on an as needed basis. These characteristics make SMS appealing for Life Cycle Engineering (LCE). The purpose of the SMS program at NIST is to lead the development of an infrastructural capability for realizing these SMS capabilities for a broad range of products and processes.

LCE [2] involves complex and timely communications of critical data on an as-needed basis. It also involves the large number of design and manufacturing tools, as well as architecture for product life cycle management [3]. Since the SMS is such a central part of the production system, it requires a high level of interoperability and communications infrastructure. This requirement is not trivial to fulfil because a broad range of information sources must be considered such as design specifications, process planning, machine specifications, cutting tool specifications, and cutting parameters as well as heuristic knowledge. Furthermore, SMS relies on a broad range of expertise from various disciplines, both internal and external to the company, to constantly improve its performance and produce innovative products, technologies, and methods. This drives the need for effective management of SMS-generated information for the product life cycle. Unfortunately, current machining systems are not capable of providing appropriate information for LCE. Given a means to share information appropriately, LCE tools should be able to capitalize on production capability more effectively. In this paper, a general view of SMS, their characteristics and functional components, along with the associated issues related to their development and integration into the PLC, are discussed.

2. Characteristics and components of SMS

SMS must address the communication of all information needed to fabricate a product that satisfies customer and market needs. A simple component can be produced easily through a conversation between a customer and a machinist, with the machinist operating the machine. As the complexity of the product, design and production process increase, the necessary scope of communications encompasses more people and more sources of information. For complex products, it is virtually impossible to fully encapsulate all information needed for an SMS using tools and technology readily available today. The machining strategy defines the collection of issues related to fabricating a part such as the machining process plan or NC tool path. A machining strategy can vary in complexity depending on the machining feature, costs, part geometry, technology, etc. The SMS must optimize machining process plans before and during their realization, i.e., during its planning, as well as during their execution. A machining process plan indicates the immediate objectives (i.e., the tactical choices), their priorities, executing times, and necessary resources. Machining optimization uses models and data that are incomplete or approximations, therefore any results will involve uncertainty. When these uncertainties lead to unexpected performance, the process monitoring and control

(PMC) will use adaptive control to return to optimal conditions. So for an SMS, design and development of optimization tools using robust methods coupled with on-line systems are a key issue. They would help enable an SMS to produce the first and every subsequent part on time and to specification through a science-based understanding and monitoring of the available machining processes and equipment without significant time spent on process development or setup. The Smart Machining Systems program at NIST 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 operations. Figure 1 provides a view of the SMS components. From a machining system analyst point of view [4], a Conceptual Process Plan (CPP) is the main input to SMS. The role of the CPP is to determine which and when general resources will be used. It represents the company's strategy for manufacturing and adds important global constraints to the future optimization tasks. Based on this a Detailed Process Plan (DPP) is built whose goal is to determine optimal machining parameters, tooling systems, and fixturing elements in order to satisfy design specifications. Traditionally, DPP adjusts these parameters using different approaches, including: 1) physics based models; 2) numerical simulations; 3) use of heuristic models; and 4) trial and error. Generally, conceptual and detailed process planning are more effective when the company's experience about its machining capabilities is used. The proper use of company’s experience is facilitated by LCE (see figure 1). In SMS, a Dynamic Process Optimization (DPO) will optimize a DPP. To maintain an optimized system, the SMS has to assess the quality of its work and outputs as well as improve itself over time. The DPO builds and then satisfies objective functions using Machining Models (MM in figure 1), including process, control, and machine tool. The DPO includes constraints from design such as: dimensional and geometrical tolerances, surface integrity, and surface quality. PMC modules execute these optimized solutions, i.e. the optimized DPP, and improve them over time. In the face of such optimization complexity, which can easily lead to ill-defined problems, we believe that 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 models, and represent it in such a format that it would be unambiguously understood by LCE. In addition, a knowledge base for the DPO itself is used to properly construct the set of objective functions and constraints. Consequently, development of optimization tools and associated models are key issues for SMS research.

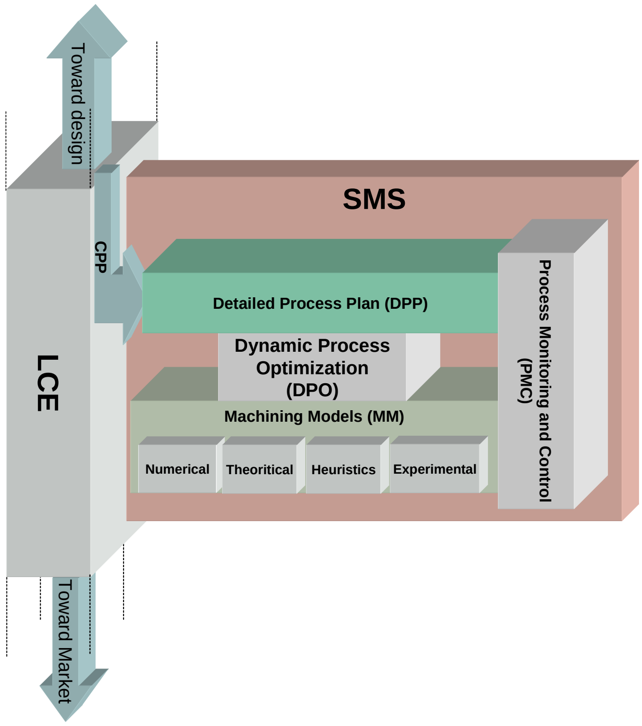

Fig. 1. Components of SMS

3. Optimization issues

Computer-based simulation and modeling will be an increasingly important part of the future in machining. There have been many studies looking at future manufacturing. One example from the 1990s states: "The Next Generation Manufacturing company will be characterized by its use of modeling and simulation, often coupled with agile and flexible manufacturing processes and equipment. …*Modeling and Simulation* will be pervasive throughout the enterprise as a new way of doing business. The modern manufacturing enterprise is the sum of the large and small decisions made by people and so-called intelligent machines."[5] The Smart Machining Systems program at NIST will address some of the important decisions involved in improving and optimizing machining processes.

Optimization trends

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. The constraints are determined by both empirical, heuristic, and theoretical considerations, and they can usually be expressed as a system of inequalities. If we denote by *x* the vector of decision variables and by $f_0(x)$ the objective function, then the optimization problem can be written as

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

$$\text{subject to } f_i(x) \le 0, i = 1,2,\ldots,m \tag{2}$$

An example of an objective function that we would like to minimize in machining may be the cutting tool deflection. The above general form of an optimization problem can also handle objective functions that we would like to maximize, like the material removal rate. This is accomplished by replacing $f_0(x)$ with $-f_0(x)$ in (1). If the objective function $f_0(x)$, as well as the functions $f_1(x), f_2(x), \ldots, f_m(x)$ defining the constraints (such as cutting force, machine tool power and torque, tool life, surface roughness, and spindle speed) are linear in the decision variables, 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 are nonlinear. By introducing an additional variable x_0, we can always consider that the objective function is linear. Indeed it is easily seen that the optimization problem (1)-(2) is equivalent to

$$\text{Minimize } x_0 \tag{3}$$

subject to

$$f_0(x) - x_0 \le 0, \tag{4}$$

$$f_i(x) \le 0, \ i = 1, 2, \ldots, m. \tag{5}$$

While in a traditional deterministic setting, where $f_0(x), f_1(x), \ldots, f_m(x)$ are considered determined precisely, the form (3)-(5) can be conveniently extended to deal with uncertainty in the data defining the optimization problem. Indeed, in real applications the functions $f_0(x), f_1(x), \ldots, f_m(x)$ depend on some parameters $\varsigma_1, \varsigma_2, \ldots, \varsigma_p$ that are only approximately known. In some cases we can define an "uncertainty set", or set of possible parameter values, $U \subset R^p$ that contain all possible values of the parameter vector ς. If U contains a single vector then we are in the traditional deterministic setting. Otherwise, we consider the robust optimization problem

Minimize x_0 (6)

subject to

$$f_0(x, \varsigma) - x_0 \leq 0, \quad \forall \varsigma \in U \quad (7)$$

$$f_i(x, \varsigma) \leq 0, \quad i = 1, 2, \ldots, m, \quad \forall \varsigma \in U \quad (8)$$

The robust optimization problem above aims at determining the vector of decision variables x such that the objective function is minimized and the constraints are satisfied for all possible values of the parameter vector ς. Although this solution seems hopeless, recent progress in optimization theory and practice shows that for many engineering problems we can formulate robust optimization problems that can be efficiently solved by modern optimization algorithms [7]. An alternative way to deal with uncertainty is to consider that the parameters $\varsigma_1, \varsigma_2, \ldots, \varsigma_p$ are random variables with given probability distributions. Then the optimization problem becomes a stochastic optimization problem (see the recent monograph [8] and the references therein). While for some problems of this type, like the stochastic linear programming problems, good solution methods are known, though they are in general more difficult to solve than their robust optimization counterparts. Another optimization paradigm in SMS is provided by multicriteria optimization. In this approach one aims at determining decision variables that satisfy the given constraints and simultaneously minimize several objective functions. For example we would like to simultaneously minimize the cutting tool deflection and to maximize the material removal rate [9]. This can be accomplished by constructing a "master" objective function as a weighted combination of the given objective functions, or to formulate the problem as a Pareto optimization problem [10-11]. A recent application of Pareto optimization in machining is presented in [9]. In the following sub-sections we introduce the types of models we will use in our optimization in the future.

Machining models

The variety of criteria used in machining optimization involves material removal rates, chatter avoidance, dimensional and form accuracy, surface integrity of the machined part, and tool wear. Generally two main categories of machining models are used to represent such criteria; models describing the cutting process and models describing the machine tool and its components. These two categories are represented in figure 2 where the hatched zone represents the cutting process, i.e., the tool workpiece inetraction. Of course other models are used to describe the interaction occurring between those two categories. The cutting process is the interaction between the cutting tool and the workpiece and is the excitation source for the machining system. Extensive research has been done in these two domains. Here we provide a brief overview of the approaches that will be used in SMS. The first set of models generally involves decisions in specifying cutting parameters by predicting cutting forces and controlling cutting process quality criteria. Thereby, one of the keys to making good decisions is to accurately predict cutting forces in a particular machining process. By accurately predicting cutting forces, the power and torque needed for a specific machining operation can be calculated. Knowing the cutting forces is also important for fixturing and tooling decisions. From cutting force predictions, the total energy input by the machining process can be calculated, which is essential for predicting cutting temperatures and tool wear. Approaches to predicting cutting forces include (a) traditional experience-based models; (b) machining experiment methods using mechanistic models; and, (c) models that use standard material properties rather than specific machining experiments. The experienced-based models, including the use of “physical models”, is the oldest approach. Anytime there is an existing machining process similar to the one being studied, this may be the best approach to accurately predict cutting forces. Recently, a set of standards for describing a method to realize such experiments in industry has been developed [12]. This ideal scenario is rarely the case in product development. Models that use generally accepted material properties such as hardness or ultimate strength, rather than machining generated properties, have an advantage for predicting cutting forces in situations where the process or material are new to the company. Starting in the 1940s, approaches of this type have been developed that are based on simple geometry and rather simple material models, such as the well known Merchant model [13-14] or Lee and Shaffer's study [15], Since the 1980s, Finite Element Methods (FEM) have been developed that can handle both the complicated geometrical aspects of metal cutting as well as sophisticated material relationships. These FEM models [16] can be extremely accurate at predicting cutting forces, but require a great deal of knowledge about the cutting tool geometry and other machining parameters plus highly accurate constitutive models for the material. The FEM approach can also be very effective at predicting temperatures in the cutting zones and residual stresses in the workpiece after machining. The use of FEM machining models may be limited in SMS applications because of the time required to solve a problem - several hours to days of computer time - and current limitations of adequate constitutive material models. Current work at NIST [17] and several other laboratories, is aimed at determining reasonable values of the flow stress and constitutive model parameters for machining modeling. The NIST work includes using a high strain-rate testing device, called a split Hopkinson Pressure bar or Kolsky bar, with electric pulse heating to determine flow stress values useful for predicting cutting forces [18]. This work is aimed at providing flow stress values to aid the simple model force predictions, as well as providing detailed constitutive models expressing the stress as a function of strain, strain rate, temperature, and heating rate that will aid the use of finite element approaches. The dimensional and form accuracy of a machined part is affected by the quasi-static performance of the machine tool, as well as environmental effects on both machine tool and the machined part [19-22]. Quasi-static performance of machine tools includes positioning accuracy and repeatability, geometric errors of linear and rotary motions, as well as alignment and locations of moving axes with respect to each other. The environmental effects are primarily in the form of temperature changes and gradients resulting in deformation of machine structure. In addition, errors associated with the coordination of multiple axes during the creation of complex tool paths are also contributors to machine performance. Furthermore, static and dynamic stiffness of the machine tool/cutting tool/workpiece structural loop contributes to the accuracy of the machined part. Similar to modeling the cutting process, there are various approaches to modeling machine tool performance. Most models are based on a combination of a kinematic model and experimental data [23, 24]. Such a modeling approach uses sample performance data along the main axes of the machine, and then uses kinematic models to estimate performance in the whole work zone of the machine (in 2D or 3D). Other models rely more on correlating the representative measurable inputs to the machine performance [25]. These models are used for improving the accuracy of machine tools and processes [26]. Research at NIST aims to incorporate these diverse models and the associated measurement data into the available set of objective functions and contraints used by SMS and its dynamic optimizer. Ideally, a sophisticated Smart Machining System will utilize all of these types of approaches from time to time. It will also need to recognize the limitations and range of uncertainty based on the different methods. Finally it will have to identify what information is needed by each of the modeling approaches and how to exchange it effectively with the other parts of LCE.

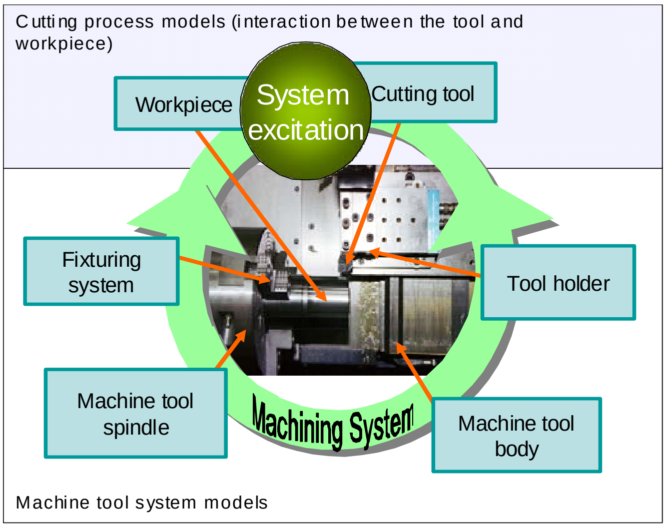

Fig. 2. Chain components machining system and its model categories

3.1. Improving robustness of machining process models

In order to provide meaningful improvement to the robustness of predictions from machining process models, we must first define and distinguish the various sources and forms of uncertainty and variability involved in the models, the predictions, and the machining process. The performance of any machining process has some level of inherent *variability*. This performance can be characterized through various measurements. There is *uncertainty* associated with how well the measurement represents the process performance. If the process is continued or repeated, additional measurements will demonstrate some degree of variability with some statistical distribution. If process parameters such as feed or depth of cut are adjusted, the distribution may shift or change shape. Empirical machining models are based on experimentally derived relationships between process parameters and process measurements. Given values for process parameters, this type of model typically produces an exact value. In order to relate this exact value to an expected distribution of future measurements, we must combine our uncertainty associated with the model and our uncertainty associated with the variability associated with the process itself. Balancing these factors against the various priorities of the overall strategy will be handled through robust optimization, as described in section 3.1. We are changing the form of mechanistic and empirical constraints to incorporate the inherent uncertainty of machining process models and the inherent variability of the machining process. For example, a typical force constraint has the following form:

$$F_c = K_f \ f^r a_p^s \qquad (9)$$

where values for the constants K_f (4500 N/mm^2), r (0.7), and s (1) have been determined experimentally. As a way of coping with the uncertainty in mechanistic and empirical models, we propose to 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. With subsequent observations of actual process behavior, these estimations must be updated and anytime adequate information has been obtained to change our estimations of the expected distributions, the optimization problem can be revisited. Our initial formulation of the machining optimization problem will involve a weighted sum of production time, cost, and product quality, where the weighting of each factor depends on the strategy and priorities indicated by production and design. A collection of constraints of the same type as the force constraint in Equation (9) will be used to fully define the problem, including allowable cutting power and torque, a surface roughness constraint, and a tool life constraint. Additionally, upper and lower limits will constrain the cutting speed V_f and the feed f. More details of this formulation are presented in [27].

Integration issues in SMS

This section gives a general description of the implementation to be accomplished with the intention to automate and integrate the SMS information within the product life cycle management tools. The most important issues concern dynamic modification and maintenace of the system according to heuristic knowledge, which is generally changing in production environment.

Software development needs

Each model previously described in section 3.2 and 3.3 presents a small part of an optimized solution. In order for an SMS to be robustly optimized over time, and in addition to the use of robust optimization algorithms, these models must be integrated such that the product life cycle engineer views one coherent optimization. This coherence must be performed automaticly selecting the particular models used into the optimization. In addition, the software that implements the previously described models must be able to work seamlessly as a unified package with other product life cycle software. To accomplish this goal of seamless integration, the software must be interoperable and there must be additional software that enables each company's strategy. SMS is envisioned to facilitate the information integration to the rest of the product life management tools. Interoperability is achieved through a common understanding of the semantics and the syntax of the data passed between software components. The easier problem is syntax, and today there are a variety of representations such as XML to handle syntax. The more difficult problem is semantics. Because people frequently communicate with each other[1], many have difficulty understanding why getting the semantics correct for software is so difficult. The reason is that software is precise. Any small differences in meaning may become exaggerated and cause software to cease working, or behave in an unexpected way. The current state of semantics in manufacturing and engineering is described in the next section. Enabling a company's strategy in machining to be followed means that there is a way for the product life cycle engineer to communicate with the SMS such that a coherent and global optimization will be formed by the machining decisions that are made at various points along the product life cycle. To bridge the gap between what is needed for each company's product life cycle, we believe knowledge-based software will require that can both communicate the strengths and weaknesses of the different models to a life cycle engineer, as well as capture what is important to the engineer, so that the best machining decisions can be proposed. Knowledge-based software is described in the last subsections.

3.2. Towards a semantic world in machining

Currently the most developed level of exchange for product information during its life cycle concerns data models and notably through ISO 10303, informally known as the STandard for the Exchange of Product model data (STEP) [28]. The objective of this standard is to allow the development of new application protocols, on the basis of integrated resources and by applying the STEP description and implementation methods. This standard must allow representatation of product data from its conception, through its realization and ultimate recycling. Although work has been done to develop STEP models for manufacturing and machining processes [29-31], it must be recognized that this approach is at present limited to modeling the product structure information such as geometry, dimensions and

[1] Getting the semantics right for people is also difficult. People regularly have semantic arguments and use dictionaries to make certain that they understand. Many interactions between people are simple and either do not require precise communication or are so simple that precision is easy to achieve.

tolerances [32-34]. For this type of information, risks of nonsense (or miscomunication) are relatively limited. Information relative to different professions with high degrees of specific knowledge are difficult to represent in a uniform way. It is often very complex to represent a consensual schema of data which does not cause misunderstanding. The case of machining is concerned with such context [35] and to be competitive, companies need to represent their knowledge using different approaches [36]. This is mainly the reason why some researchers work on defining machining process concepts. In the USA, standards for data specifications, such as the ANSI B5.59-1[37] for machine tool performance tests and the ANSI B5.59-2 [38] for properties of machining and turning centers, represent data using the XML syntax which gives more definition to the concepts. For cutting resources the ISO 13399 [39] effort provides a glossary of terms for tooling and recently, data models have been proposed using some STEP parts and application protocols. The last example concerns STEP NC [31] whose role is to clearly define Numerical Control information in order to integrate it with STEP models. This approach seems promising for SMS to capture on-line information and make it available during the product life cycle. To exemplify the problem that these researchers are facing, the description of a cutting tool can be taken as an example. Some experts will see only the insert in the end of the tool, while others will be more concerned with the combined insert and tool holder, or still others will focus on their semantics for the active part of the tool constituted only of two faces and a cutting edge. This difficulty is more prevelant today due to the globalization of partners, which means that a company does not deal only with local partners but with worldwide practices and knowledge. Ontologies allow capturing both the semantic and the syntax description of the information. The purpose of ontologies engineering is to make explicit, for a given domain, the knowledge contained in engineering software and in business or companies' procedures [40]. An ontology expresses, for a particular domain; a set of terms, entities, objects, classes, and relations among them. It supplies formal definitions but also axioms whose role is to constrain the term interpretations. An ontology allows one to represent a very rich variety of structural and non-structural relations such as generalization, inheritance, aggregation, and instantiation. It can supply a precise model for software applications. Finally, an ontology is able to represent relations defined in taxonomic or data models by adding to it axioms which constrain the interpretation or implicit relations of terms. Ontologies are generally represented by using a wide variety of legible and logical languages which are understandable both by humans and machines. Such as shown in [41] Propositional Logic (PL) is one way to model ontologies, but PL lacks the expressive power to model concisely an environment with many objects and facts. First Order Logic (FOL) has much more expressivity and can represent much more complex relations between objects. The Ontology Web Language (OWL) is the language widely used by the semantic web community. In comparison to FOL, OWL is weightier and based on a taxonomic model. Some attemps concerning process ontologies [42] and machining [35, 43] have been done and are intended to be used as base models for the SMS implementation.

3.3. Knowledge-based models

In the previous section the concept of an ontology was introduced to help an SMS deal with interoperability problems. An ontology helps us deal with issues surrounding the semantics of terms and their precise usage. As such an ontology represents one kind of knowledge. Earlier in section 3, mathematical optimization trends and how an SMS might take advantage of those trends was discussed. This represents a different type of knowledge, that of solving problems that fall into the category of mathematical optimization. This is a critical component of machining process improvement. There is a third type of knowledge that helps with both the tactics and the strategy of improving the machining process. Tactics from the the point of view of helping a mathematical optimizer compute one of the functions the optimizer is evaluating. As described in section 3.1 there are different ways of computing cutting forces: (a) traditional experience-based models; (b) machining experiment methods using mechanistic models; and, (c) models that use standard material properties rather than specific machining experiments. When the mathematical optimization program needs a cutting force function, a tactical decision must be made about what is the best way to compute that function. The decision depends on: (a) what data is available; (b) how difficult is the data to obtain; (c) what stage of life cycle the product is in; and (d) various other questions that may depend on the organizations capitalized experience. This type of decision-making is based on heuristic knowledge. Frequently this knowledge is hard-coded into a system based upon interactions between domain experts and system analysts. The difficulty with this approach is that one ends up with a system that represents one view point, and for which there is difficulty representing multiple and changing viewpoints. The approach is to move away from capturing this knowledge as one unified program, but rather to use a mechanism that allows smaller fragments of knowledge to be captured at about the level of single sentences in a natural language. The formal languages used to capture this knowledge are the same as those used in ontologies described earlier. This has the advantage of allowing the domain expert and the system analyst to focus on single components of the knowledge base. When the tactical and strategic knowledge are captured, then generic programs (theorem provers, production rule / blackboard systems) can be used to make the tactical or strategic decisions. In conclusion, knowledge based systems will play two roles in SMS. First the role of helping to decide what to opitimize in the detailed process plan, and second what tactics to apply when optimizing the detailed process plan during its realization, i.e., using on-line monitoring and adaptive controls.

4. Conclusion and discussion of future work

The research presented in this paper is in its initial stages. Although significant information related to performance of machine tools, machining processes, cutting tools, and materials already exist, there is no unified methodology to combine this information to generate optimum machining conditions with expected outcomes. Our research aims to address this need by developing necessary tools and architectures. During this development, we plan to assess the robustness of available models and provide further improvements in models and data. For example, recent improvements in both FEM modeling techniques and sensors such as high speed visible light and thermal cameras are rapidly improving our ability to verify and improve machining models. Improvements in chip formation modeling are also expected as a result of this effort. Our immediate effort will be focused on demonstrating a simple version of the dynamic process optimizer with a specific example in turning including a knowledge base and mechanistic models. Loaded with high fidelity process and performance models and optimization tools, SMS will behave in a predictable and controllable manner well integrated with the rest of the manufacturing enterprise and life cycle engineering.

Disclaimer

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