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Predicting Machine Tool Energy Use via Holistic Simulation

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Abstract

High visibility quality qualities of contemporary machine tools include low resource and energy usage. To remain competitive, and to lessen our environmental responsibility, it is essential that the energy used by machine tools, plants, and facilities be drastically decreased in relation to the value contributed. Model-based modeling and prediction of machine tools' anticipated energy consumption utilizing a complete simulation environment are presented in this article to provide a foundation for energetic improvements. Turning and milling processes will serve as examples of the capabilities of the simulation system. Adaptive control and optimization of the machine tool's energy states are added to this system by the use of artificial neural network controller networks and a supplementary expert knowledge data-base.

1. Introduction

In recognition of their seminal work on blue light-emitting diodes (LEDs), three Japanese scientists were given the Nobel Prize in Physics this year. Light sources that use less energy (white)" [1]. The Royal Swedish Academy of Science's nomination highlights the critical role energy efficiency plays in modern civilization. In addition to the social context, resource scarcity increases the price of legislative laws and energy. The industrial sector is also negatively impacted. To meet these problems, we need innovative solutions that can be easily applied in dynamic production systems that must adapt to rapid changes in demand, specification, and environment [2]. Potential solutions require simple, fast, and cheap evaluation techniques in order to be evaluated for their energy efficiency, cost savings, and environmental implications [2]. In light of this, the research project ECOMATION is creating a comprehensive simulation strategy. It's useful for mapping a whole production system, from the modeling of a single production machine's process all the way up to the simulation of the factory's material flow in order to assess energy consumption in great detail. This research proposes a model-based simulation strategy applicable at both the process and machine levels. This paper will have the following outline. The present level of study on energy process and production machine simulation is summarized in

Chapter 2. Reason for doing this study. In Chapter 3, we cover the basics of the modeling strategy and the simulation setup. Chapter 4 provides a case study that may be used to test the viability of the selected simulation method. Potential advantages for optimizing industrial machinery's energy use are discussed in Chapter 5.
In Chapter 6, we wrap up our key points and look forward to what the future holds in terms of research.

2. Theoretical Background & Motivation

There is a wide variety of options for making metal cutting machine tools more efficient in terms of energy use. Zein et al. state that there are three broad metrics to consider: energy input reduction, energy output reuse, and energy output recovery (see Table 1) [3]. The wide range of energy-saving strategies calls for a straightforward assessment tool that can provide machine-specific estimates of energy consumption. According to [3] [4], Table 1 provides an overview of energy-saving strategies for metal-cutting machine tools.

General measures	Action
Energy reduction	Reduction of process time
	Reduction of non-value adding time
	Use of energy efficient components
	Use of optimal dimensioned components
	Use of energy efficient control strategies for components
	Energetic optimized machining process
Reuse of energy	Reuse of kinetic energy
Energy recovery	Use of waste heat for other applications (TBS, ...)

There are currently no methods for accurately estimating the energy requirements of manufacturing equipment during the production planning stage [5]. Method of prediction that relies more on observational data models to predict how a machine would behave in a production setting. In general, simulation may be used for technological systems across the board, as stated by VDI3633: This allows for the verification of the system's projected behavior during product development, as well as the evaluation of prospective modifications to the use profile or retrofit measures prior to their implementation [6].

The Modeling and Simulation of Machines 2.1

Dietmair developed an empirical model for estimating the energy needs of machine tools using graph theory. There is a direct correlation between the manner of operation of a machine and the electrical power requirements of its various parts. Energy consumption may be calculated for a full machine or for individual parts by supplying a time-ordered sequence of machine modes [7]. Based on the work of Dietmair, Bettencourt expands the current model by associating transition trajectories between machine modes with a fixed need in terms of both power and time. The dynamical impacts are ignored in both models. There is a single power requirement associated with each machine mode [4]. Eisele [8] creates a method that is more dynamic. Eisele created a simulation library in the Matlab Simulink/SimScape® environment by combining empirical data obtained from datasheet material with mathematical models. Using the real NC software as input, the user may construct energy-demand estimation models for their machine tools with the help of the library. To further quantify torque and forces on the spindle and feed drives [8], Eisele used a fundamental cutting force model based on Kienzle [9]. Schrems used a similar strategy when he created a dynamic simulation tool to evaluate the energy requirements of process chains inside the ubiquitous Microsoft Excel® [5]. There are currently no methods for accurately estimating the energy requirements of manufacturing equipment during the production planning stage [5]. Method of prediction that relies more on observational data models to predict how a machine would behave in a production setting. In general, simulation may be used for technological systems across the board, as stated by VDI3633: This allows for the verification of the system's projected behavior during product development, as well as the evaluation of prospective modifications to the use profile or retrofit measures prior to their implementation [6].

3. The ECOMATION Simulation Environment

Here, we provide a high-level overview of the ECOMATION machine and process simulation environment, including its architecture and the flow of information inside it. The fundamentals Standard NC-programs written in DIN G-code format are read and translated by a software module that simulates a conventional NC-interpreter. It takes the series of instructions and transforms them into a stream of time data that represents the tool's location, velocity, and acceleration along the predetermined path. Information such as spindle speed, tool number (to implement the capacity to respond to tool changes), and M-commands accounting for fundamental machine operations such as coolant-lubricant flow, clamping devices, or general on/off states (e.g. chip conveyor) are also processed and made available. It is possible to modify the time step size so that the model dynamics are as required. The term "Offline-Mode" describes this way of operation. The input data will be sent in real-time (Online-) mode, straight from the actual machine tool's NC-control. Coupled process and machine models get all raw data. There is a simple connection between the machine model and the process model. Since the technique does not prioritize higher-level dynamics and stability, it lacks feedback in comparison to direct coupling. Process outputs such as real spindle torque and force loads on the machine axes are inherited by the machine model block. The axes, drives, and ancillary systems of the machine are represented as electromechanical models inside the machine model block (see fig. 1). There is a wide range of possible behaviors, from those based on basic linear power calculations to those involving complicated 2nd-order dynamics that take into account the operation of electrical converter systems and motion controllers. For each time step ('Immersion detection'), a process model is constructed by first determining the actual tool engagement circumstances and chip shape, and then calculating the cutting forces based on these parameters. The loads on the machine's axes are then calculated by projecting the cutting forces onto those axes. Additionally, the process model can estimate coarsely the resultant surface roughness and chip form as well as anticipate non-energetic impacts such as the basic heat load on chips, work piece, and tool.

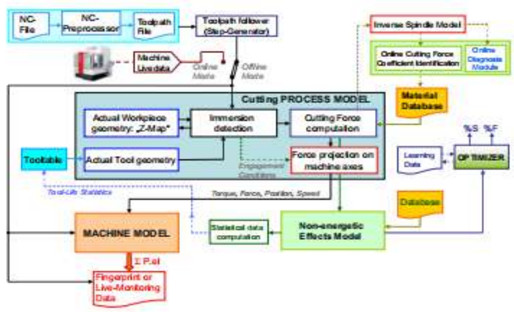
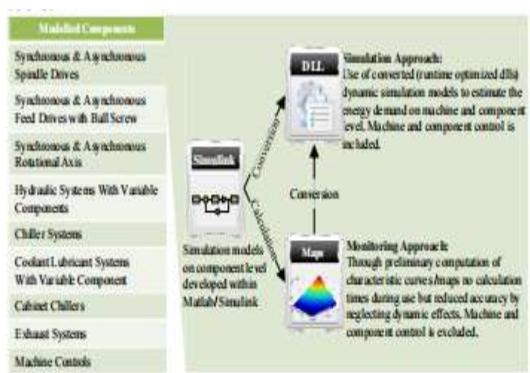


Fig. 1. Simulation Environment

3.1. Machine Tool Component Models

Different simulation models serve distinct functions within the ECOMATION research project: for continuous tracking of electrical energy use (without any power sensors) and predicting potential load patterns at the component level of machine tools [18]. Technical requirements on the simulation models also vary between the two applications. While real-time support is essential for monitoring, modeling load profiles on your own seldom causes a time crunch. In addition to the time needed for computation, demands on the management of the simulation model emerge. Additional data from the PLC and the machine control is provided for real-time monitoring of the power consumption of machine tool components. This means that monitoring simulation models may be run without include any control instances. Contrarily, simulation models for predicting the load profile show the opposite trend. Everything must be judged inside the simulation models itself due to the lack of knowledge regarding PLC switching states and control values. To accommodate these varying needs, we created a Matlab® and Matlab/Simulink® component model library for common machine tools. This library makes it straightforward to create simulation models for a variety of machine tool functional modules.



Modeling using Subcomponents

The simulations in Simulink® and Matlab® are comprehensive, include built-in control techniques, and may be used for mapping. Behavior of a dynamic system [18]. The available data from the component manufacturers informs the general simulation technique for the individual machine tool components. For instance, characteristic curves included in most manufacturers' data sheets may be utilized to build empirical models for mapping hydraulic pumps. When it comes to electric drives, however, everything is modeled mathematically [19]. The prototype software environment ECIS (Energy Consumption Information System) created during the project [18] makes use of Matlab/Simulink® models converted to Dynamic Link Libraries (DLLs) to estimate the dynamic load profile and energy consumption of machine tools. Static models in the form of recalculated characteristics curves or maps, which contain the energy demand information of a machine component in dependency on different input variables (for example, drive speed and torque), can be used for real-time monitoring because the presence of control instances within such models is not required. The whole process is shown in Fig. 2.

Modeling the Process 3.2

Calculating the cutting force is a breeze. Mat lab® now hosts the turning and 3-axis-milling process model's real-time capable algorithm. The Kienzle-Viktor formulation (see eq. (1)) [9] or an alternate version with averaged linear cutting coefficients [12] provide the backbone of this theory. Tangential force Ft, radial force Fr, and axial force Fa all contribute to the total cutting force F.

$$\{dF\} = \begin{Bmatrix} dF_t = k_{tc1.1} \cdot dz \cdot h(\phi, z)^{1-m_c} \\ dF_r = k_{rc1.1} \cdot dz \cdot h(\phi, z)^{1-m_f} \\ dF_a = k_{ac1.1} \cdot dz \cdot h(\phi, z)^{1-m_r} \end{Bmatrix} \cdot K_{WV} \quad (1)$$

When calculating cutting forces, a correction factor KWV is used, with a range of 1 KWV 1.5, to account for the effects of tool wear. The tool wear prognosis model determines its true value.

$$h(\phi, z) = f_z \cdot \sin\phi(z) \qquad (2)$$

By calculating the geometric penetration of tool and work piece using a z-map, the real tool engagement conditions and the consequent chip shape may be determined. A surface geometry representation of the real work piece. As a result, the current scope of the program is restricted to 3-axis milling and 2-axis turning. Switching to boolean operations based on solid geometry would allow for more generalizability. The axis forces and main spindle torque are calculated by mapping the calculated cutting force F onto the machine's feed axes.

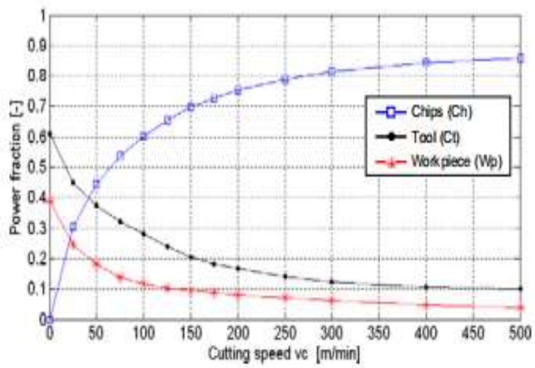
$$\begin{Bmatrix} dF_x(\phi(z)) = -dF_t \cdot \cos\phi(z) - dF_r \cdot \sin\phi(z) \\ dF_y(\phi(z)) = +dF_t \cdot \sin\phi(z) - dF_r \cdot \cos\phi(z) \\ dF_z = +dF_a \\ dM_{spindle} = \frac{D_{tool}}{2} \cdot z_{ct,engaged} \cdot dF_t \end{Bmatrix} \quad (3)$$

3.3. Non-energetic Effects Model

Both the coolant-lubricant need for adequate cooling and tool wear are affected by thermal factors during the cutting process. Energy savings may be achieved by dispensing coolant-lubricant in a cost-effective manner in response to the real temperature conditions. Since computing shouldn't take too long, we made our temperature forecast based on simple assumptions rather than fine-grained, precise physical models. First, the flow rate and pressure dependency of the cooling ability of the lubricant, given by the coefficient K, must be determined experimentally. Methodology is similar to that described in [20]. K characterizes the degree to which the coolant-lubricant dissipates heat relative to the overall amount of heat produced. K may be expressed roughly using time-records of heating- and cooling-curves with proper coolant-lubricant supply on the one hand, and under dry circumstances on the other.

$$K = \frac{\int_{t_0}^{t_{end}} \vartheta_{dry}(t)dt - \int_{t_0}^{t_{end}} \vartheta_{cooled}(t)dt}{\int_{t_0}^{t_{end}} (\vartheta_{dry}(t) - \vartheta_0)dt} \qquad (4)$$

The second method relies on the empirical finding that in dry cutting, almost all of the mechanical cutting power Pc is lost as heat energy and heat flux. According to fig. 3 [21], the process divides into three parts depending on the cutting speed VC: the chip (Q SP), the tool (Q SP), and the work piece (Q SP).



Heat transferred to the chip, tool, and work piece, as shown in Fig. 3 according to [21]. Power entering the off-flowing chip during dry cutting, as stated by Vieregge [22], causes a highest allowable level of

$$\vartheta_{Ch,\max} = \vartheta_0 + \frac{\dot{Q}_{Ch}}{\rho_{Ch} \cdot c_{Ch} \cdot v_c \cdot h \cdot b} \qquad (5)$$

Where h and b describe the chip's shape, c is the material's specific heat capacity, and U is its density. By adjusting Equation (6) with the cooling coefficient K, we get ballpark figure for the expected chip temperature with cooling lubricant:

$$\vartheta_{Ch,\max} = \vartheta_0 + \frac{K \cdot \dot{Q}_{Ch}}{\rho_{Ch} \cdot c_{Ch} \cdot v_c \cdot h \cdot b} \qquad (6)$$

The temperature change in the (dry) cutting edge segment of mass *mCt* also can be approximated roughly by

$$\dot{\vartheta}_{Ct} \cdot m_{Ct} \cdot c_{Ct} = \dot{Q}_{Ct,in} - \dot{Q}_{Ct,out} = \Delta\dot{Q}_{Ct} \qquad (7)$$

The flow of heat dissipation in this case

Cancel Q heat transfer from the cutting edge via the tool and tool holder into the machine structure, heat flux from radiation and convection, and the heat sink provided by the dripping coolant-lubricant. Since the cooling coefficient K has been empirically determined at the right cooling conditions, it is presumed that all these dissipative effects again collapsed into one single quantity.

$$\dot{Q}_{Ct,out} = K \cdot \dot{Q}_{Ct,in} \qquad (8)$$

$$\frac{dW}{dt} = A \cdot \sigma_N \cdot v_R \cdot e^{\left(\frac{-B}{\vartheta_{WZ}}\right)} \quad (9)$$

$$\sigma_N = \frac{F_{cN} - F_{cm} \cdot \mu}{VB_{ref} \cdot (a_p - \mu \cdot a_p)} \quad (10)$$

$$VB_m(t) = VB_m(t - \Delta t) + A \cdot \sigma_N \cdot v_c \cdot e^{\left(\frac{-B}{\vartheta_{WZ}}\right)} \cdot \Delta t \cdot K_{vc} \cdot K_{BS} \quad (11)$$

Chip form Estimation for Turning Operations

Unwanted long spiral chips or ribbon chips occur when the feed rate is too slow during turning operations. When set too high, the associated thermal and mechanical stress, wear included. A proper qualitative estimate of the predicted chip form is required in order to restrict feed and cutting rates while optimizing energy usage by adjusting feed and spindle speed. A feed-forward artificial neural network (FF ANN) is used in the selected method for this application. The configuration process is flexible, allowing for either self-learning or the use of pre-defined training data sets derived from the labeling of observed chip forms. Levenberg-Marquardt is used for the ANN's training procedure. The ANN-structure takes in seven different variables, including the material of the work piece, the cutting angle of the tool, the cooling-lubrication conditions, and the tool's wear state, as well as the technology parameters vc, f, and ap (normalized to suggested technology data of the tool's manufacturer). Predicted chipform (categorized according to fig. 4), heat load on tool, and predicted wear rate are the three outputs.

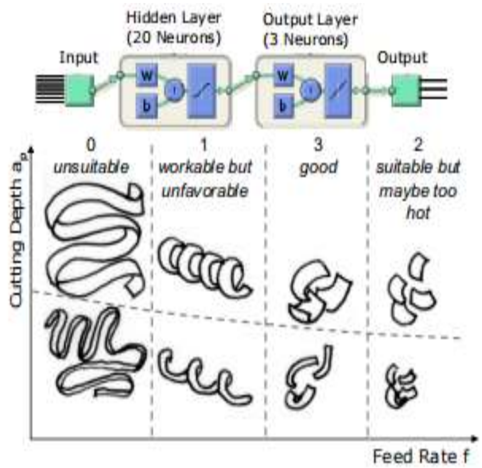


***Fig. 4. Chip form ANN and output-classification of chip for**ms*

4. Case Study

On a Digma EXERON HSC 600 milling center, an 8 mm diameter coated 3-flute cylindrical endmill was used to mill an AlMgSi1 aluminum workpiece. Course of action Figure 6 shows the contouring and pocket milling trajectories for four pockets made using various approaches. Good agreement may be shown between the simulated machining results and the actual machine tool power consumption. The machining process in five progressively deeper cuts is a good match to the measured power, and the main spindle run up is captured within 20% deviation of electrical power (see black arrow in fig. 5). Milling operation consumption is shown towards the right axis. There is currently a 62% contribution to the basic consumption (1). Axis drives (3) and the machine's main spindle (4) relate to the machine's periphery (2) (coolers, hydraulics, etc.).

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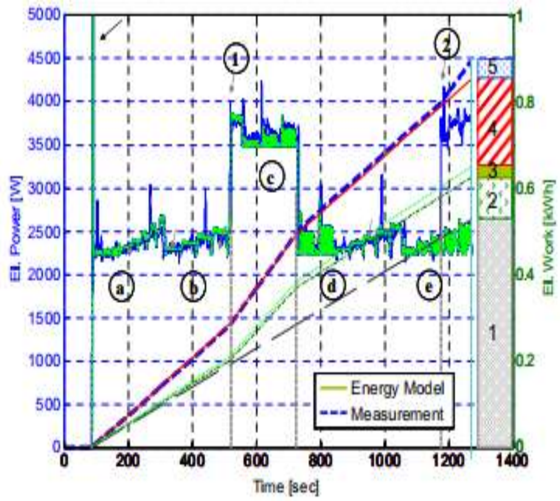

Fig. 5. Measured and simulated power draw and energy consumption during milling of AlMgSi-1 with successively increasing depth of cut

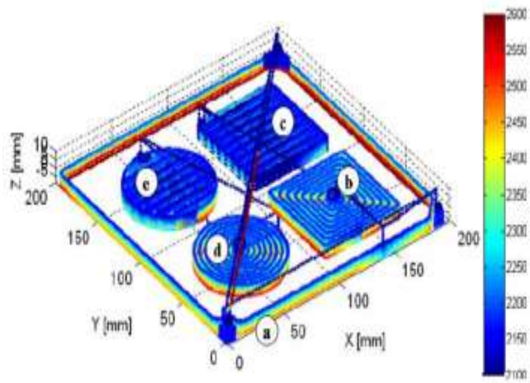

Figure 6: The tool path trajectory shown against the simulated power consumption of the main spindle and axis drives (limited to 2.1 to 2.6 kW).

The contouring procedure and pocket segments are shown in fig. The four pockets that need milling are labeled "a" through "e," and their accompanying tool path segments are labeled similarly in Figure 6. The machine's air conditioner kicks on between 1 and 2. While the model does a good job of recreating the first period of cooling, it fails to account for the second activation, which occurs a little bit later than shown in the graphic. It demonstrated the need of accurately modeling power-intensive peripheral aggregates like coolers or hydraulic pumps to reliably capture such switching intervals. The proper calculation of thermal power losses that comprise the input loads to cooling units or the exact hydraulic fluid demands to the hydraulic units seem to be the essential element, even when the dimensions and features of the units themselves may be described pretty well. Such variables affect the total electrical work (power) required by the process. Figure 5 shows that the model accurately represents the power consumption up to time point '2', 1180 seconds, but then deviates in the ultimate consumption at 1270 seconds (see chunk (5) in bar on the right).

5. Potentials and Strategies for Energetic Optimization

Several options for affecting manufacturing machine tools' electrical consumption on the process and machine levels are made available by the ECOMATION method. If implemented in a non-digital setting, before a single chip is ever cut, the process planner may use the energy simulation model to pinpoint the power-hungry stages of a machining process (shown in fig. 6), optimize the machining process, and estimate the machining operation's energy efficiency. In addition, if numerous resources are available for a certain function, it enables efficiency comparisons across machines and the selection of the best one. Energy controlling, when utilized as an online monitoring tool, may help raise machine operators' energy consciousness and provide guidance on how to reduce power use in manufacturing. Machines can have their energy states controlled or intervened upon by semi-autonomous energy optimizers operating on the NC-control during operation, leading to greater energy efficiency without sacrificing acceptable non-energetic outcomes of the process like tool wear, heat generation, chip forms, or surface quality.

6. Summary & Conclusion

This work proposes a comprehensive simulation technique integrating existing models to shed light on the energy requirements of metal-cutting machine tools without resorting to costly hardware measurements. Simulation of cutting processes and machine tool parts using models. The created simulation method is intended for real-time tracking of machine tools' energy consumption and foretelling of their future energetic behavior. The advantages of the selected simulation method are shown inside a well-executed case study.
A framework of energy optimizer is constructed based on the proposed simulation method, which does things like adjust feed rates, spindle speed, coolant lubricant volumes, and the switching states of peripheral devices based on the projected conditions.

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