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A new paradigm for real-time machining optimization via an embedded near-zero latency heat flux sensor

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Abstract

This work presents a novel approach to sustainable manufacturing by integrating intelligent control with real-time thermal monitoring and modelling to optimize process parameters for improved productivity, surface integrity (SI), product lifecycle, minimized costs and reduced environmental impact. Manufacturing processes generate heat signatures that reflect underlying process mechanics and directly influence SI, which governs product durability and lifecycle emissions. A smart tool embedded with a Transverse Heat Flux Sensor (THFS) was developed to capture high-speed thermal data, including direct heat flux measurements, during machining. A key experimental finding is the correlation between normalized cutting force and normalized heat flux (R^2 = 0.564), validating Heatmetry as a reliable proxy for process load and energy transfer. The system enables predictive control of process parameters to minimize cumulative energy demand (CED) and CO_2 emissions while maximizing product quality and longevity. The outcomes support the development of digital twins and intelligent control systems for zero-emission manufacturing through real time data acquisition.

Keywords: sustainable manufacturing, surface integrity, heat flux sensor, intelligent control, digital twins

1. Introduction

Sustainable manufacturing has become essential as global industries seek to reduce environmental impact while ensuring high product quality and process efficiency. Machining operations generate significant heat and mechanical stresses that affect surface integrity and contribute to lifecycle emissions [1]. Surface integrity, which includes factors such as residual stresses, changes in microstructure, and surface finish, is highly sensitive to the mechanical and thermal loads induced during cutting. Excessive force results in energy losses and accelerated tool wear, while uncontrolled heat can degrade material properties and compromise dimensional accuracy [2]. To address these challenges, recent advancements have focused on integrating intelligent systems capable of monitoring and responding to real-time process data [3]. Sensor-based platforms capable of capturing both thermal and mechanical signals are being actively explored to support adaptive machining control strategies [4].

Recent studies have shown that most of the heat generated during machining originates in the primary deformation zone, where severe plastic shear initiates chip formation [5,6]. In this region, the workpiece material undergoes intense plastic deformation as it is forced to flow along the shear plane, resulting in significant energy dissipation in the form of heat [7]. This thermal energy arises from the mechanical work required to overcome the internal resistance of the material, and its generation is governed by the complex interplay between strain, strain rate, flow stress, and temperature [8]. The proportion of mechanical energy converted into heat is described by the Quinney–Taylor coefficient. Although this factor depends on material and cutting conditions, it is commonly assumed to exceed 85 percent for metallic alloys undergoing plastic deformation. The resulting heat is primarily transported away by the chip due to its direct exposure to the shear zone, while smaller portions are conducted into the cutting tool and the uncut material as depicted in Figure 1 [9]. This distribution of heat has a significant influence on surface integrity, tool wear, and overall process stability. Therefore, monitoring the heat generated in this region provides valuable insight into the efficiency and dynamics of the cutting process.

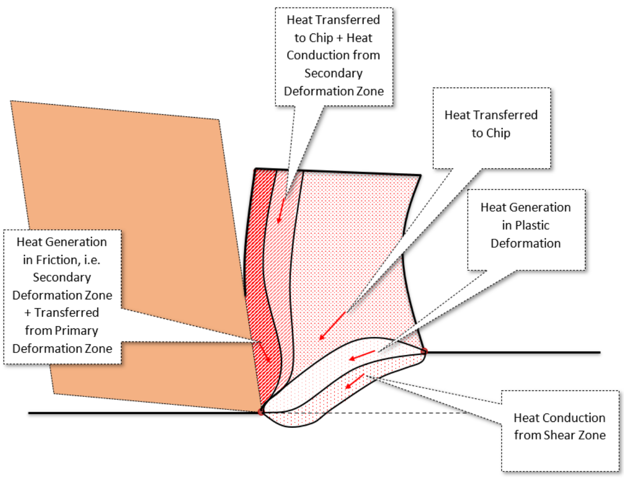

Figure 1. Heat Generation and Transfer in Orthogonal Cutting

Under adiabatic conditions, where heat exchange with the surroundings is negligible during deformation, the volumetric heat generation rate in the primary shear zone can be approximated by the expression:

$$\dot{Q} = \beta\sigma : \dot{\varepsilon}$$

where $\dot{Q}$ is the heat generation rate per unit volume, β is the conversion factor (typically between 0.85 and 0.95), σ is the flow stress, and $\dot{\varepsilon}$ is the plastic strain rate [10]. When integrated over the deformation volume, this yields the total thermal power input to the system, forming the basis for interpreting measured heat flux as an indirect indicator of cutting energy and chip formation intensity.

Although most research has focused on monitoring temperature, it is important to recognise that temperature is a consequence of the underlying mechanics of the process [11–14]. Therefore, real-time control requires the direct observation of heat generation rather than relying on downstream thermal effects. Conventional methods that involve reconstructing temperature fields through inverse heat transfer models are not practical for online applications due to their computational complexity and time delays.

This study introduces a direct sensing approach using a robust, high-speed, and high-sensitivity Transverse Heat Flux Sensor (THFS). Using this sensor, a new methodology called Heatmetry was developed. The basic principles of the THFS are described in [15]. When the heat passed through the sensor's material with anisotropy of thermophysical and electrical properties, the thermopower $E_{\perp}$ (called also electro-motive force) was generated in the normal direction to the applied heat flux vector $\overline{q}$, as shown in Figure 2.

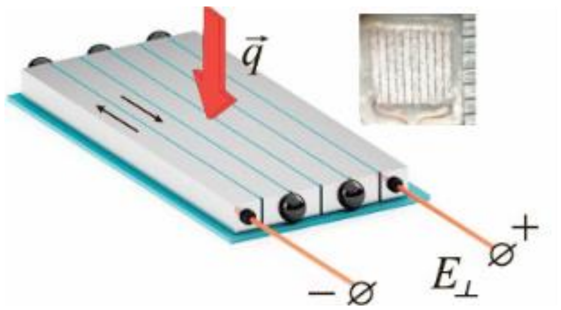

Figure 2. Schematic view of the transient heat flux sensors and real sensor next to mm scale

The ability of the THFS to directly measure heat flux enables a clearer understanding of how energy is dissipated during cutting and how it correlates with surface integrity outcomes. While heat flux sensing has been explored in various scientific and industrial domains [16–19], its direct application in machining remains limited. A recent review by Zhang et al. [20] underscores that most existing methods in machining rely on inverse heat transfer models or thermocouple-based approaches. These approaches often suffer from limited response speed, spatial averaging, or computational complexity, making them unsuitable for real-time applications. To address these limitations, the present study proposes Heatmetry, a novel methodology that integrates a transverse heat flux sensor directly into the cutting tool. This configuration enables high-speed, low-latency thermal monitoring with greater fidelity, offering promising opportunities for adaptive control and digital twin development in precision manufacturing.

Based on this framework, the present study demonstrates the use of a smart tool embedded with a THFS to simultaneously capture cutting forces and heat flux during machining.

2. Methodology

This study investigated the relationship between machining parameters and the corresponding mechanical and thermal responses during cutting operations. Cutting forces were recorded using Kistler Type 9129AA dynamometer, along the three orthogonal directions. The experimental setup is shown in Figure 3.

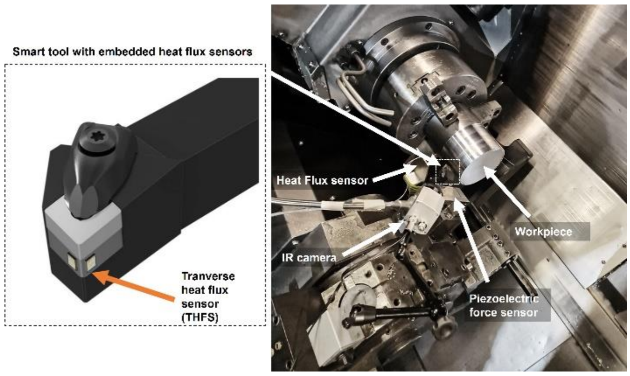

Figure 3. Tool with potential sensor locations (Left), Preliminary machining experiment setup (Right)

The resultant cutting force was normalised by the depth of cut to eliminate the direct size effect caused by varying engagement areas. This allowed the retained force values to remain responsive to changes in feed rate and cutting speed, thereby offering a more accurate representation of the mechanical load imposed during the cutting process. By removing geometric bias while preserving dynamic influences, the normalised force metric provided a reliable basis for evaluating cutting performance across different conditions.

Thermal energy generation was measured using a custom-designed THFS placed near the cutting zone. This sensor captured temperature gradients and converted them into voltage signals that reflect transient heat flow. The recorded data were pre-processed to remove baseline noise and aligned such that the onset of cutting defined the zero-time reference. Only the portion of the signal corresponding to active engagement between tool and workpiece was retained to ensure meaningful thermal analysis.

To account for the combined effects of all primary process parameters, the heat flux was normalised by the material removal rate. This approach distributed thermal influence across cutting speed, feed rate, and depth of cut without disproportionately weighting any single variable. As a result, the normalised heat flux served as a consistent and scalable indicator of thermal energy generated per unit of material removed, facilitating direct comparison across varied cutting scenarios.

All measured values were compiled along with the corresponding cutting parameters. Additionally, squared and interaction terms were computed to capture nonlinear and coupled effects. A Pearson correlation matrix was constructed to identify the dominant influences on mechanical and thermal responses and to assess interdependencies among variables as shown in Figure 4.

The cutting force exhibited strong dependence on the depth of cut and feed rate, while the normalised force remained strongly influenced by feed rate. This supports the chosen normalisation method as it preserves key process sensitivities. In contrast, the normalised heat flux showed moderate alignment with all three process parameters, with no single dominant factor. This confirms that dividing by material removal rate yields a balanced representation of heat generation intensity. The inclusion of higher-order interaction terms further revealed coupled effects, supporting their potential integration into intelligent control frameworks.

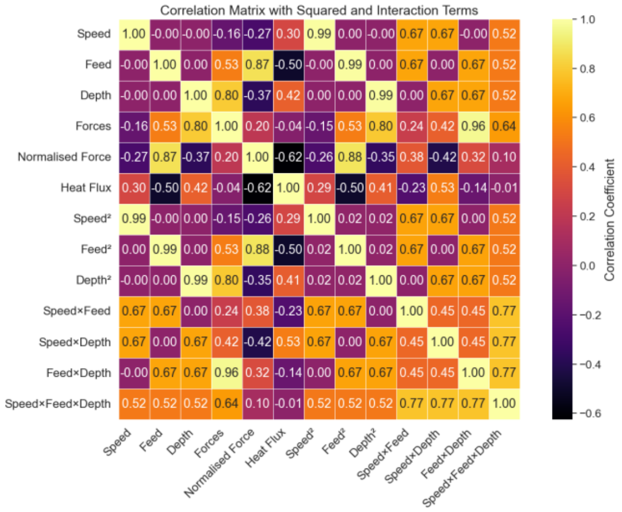

Figure 4. Correlation matrix of machining parameters, squared terms, interaction effects, and response variables. Superscripts indicate squared terms; multiplication symbols represent interactions

3. Results and Discussion

Contour plots were developed to investigate the influence of cutting speed and feed rate on both normalised cutting force and normalised heat flux. As presented in Figure 5, the normalised cutting force increases consistently with feed rate, whereas the effect of cutting speed appears relatively limited. This observation suggests that the mechanical load experienced during machining is predominantly determined by the rate at which material is engaged by the cutting tool. The consistent upward trend with feed rate reinforces its role as the primary factor influencing cutting force.

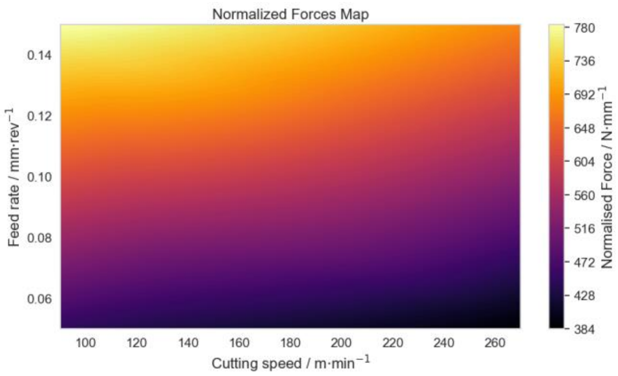

Figure 5. Contour plot of normalised cutting forces (N/mm) across cutting speed and feed rate

In contrast, the thermal response behaves in a more complex manner. The normalised heat flux, shown in Figure 6, demonstrates a nonlinear dependence on both cutting speed and feed rate. Localised peaks and valleys are visible within the heat flux distribution, indicating the presence of coupled effects related to tool dynamics, chip formation, and material behaviour. These variations imply that thermal generation during machining arises from a complex combination of physical interactions between tool dynamics, material flow, and energy dissipation.

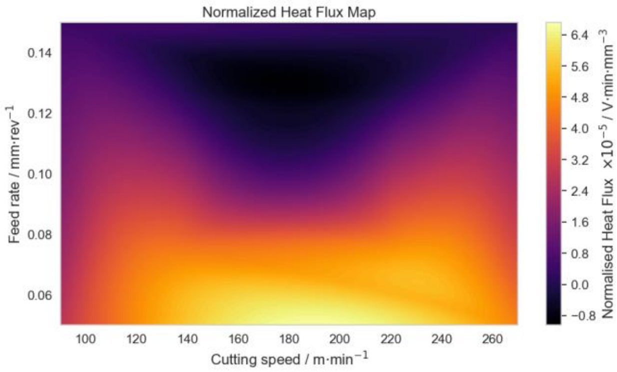

Figure 6. Contour plot of heat flux normalised by MRR (V·min·mm^{-3})

To investigate the time-domain correspondence between thermal and mechanical signals, raw sensor outputs were recorded for two experimental trials. As shown in Figure 7, both the resultant cutting force and heat flux signals exhibit similar activation patterns and transient behaviour across the duration of the machining cycle. Notably, sharp rises in cutting force align with simultaneous increases in heat flux, and both signals return to baseline levels upon tool disengagement. These synchronous changes indicate a clear temporal correlation between force and thermal response, reinforcing the premise that heat flux is physically linked to the mechanical load imposed during cutting. This preliminary observation supports the need for further quantitative analysis to explore the nature and consistency of this interdependence.

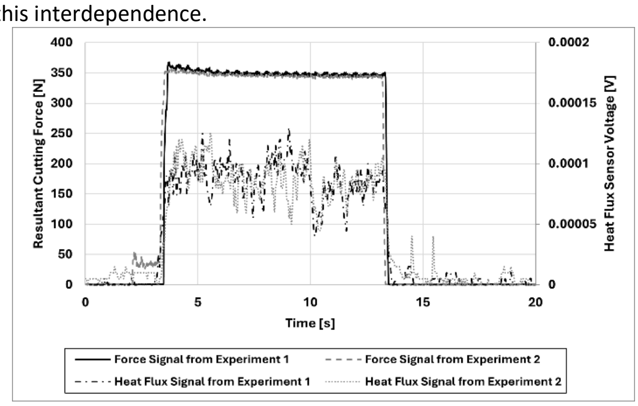

Figure 7. Time-aligned signals of cutting force and heat flux from two experiments, showing synchronous variations during tool engagement

To evaluate the interdependence between thermal and mechanical responses, a curve-fitting analysis was performed using the normalised heat flux and normalised cutting force data. Three regression models including quadratic, logarithmic, and exponential, were applied to capture the underlying trend. Among these, the exponential model demonstrated the highest consistency with the observed data and was selected as the most representative.

As shown in Figure 8, the exponential model provided the best overall fit. This result reveals a monotonic inverse relationship: as the normalised thermal output increases, the corresponding mechanical force tends to decrease. Physically, this may be attributed to improved material softening or more efficient energy conversion in the cutting zone. The curve demonstrates a diminishing mechanical load under high thermal response, indicating a possible optimisation window for reduced tool wear and energy input.

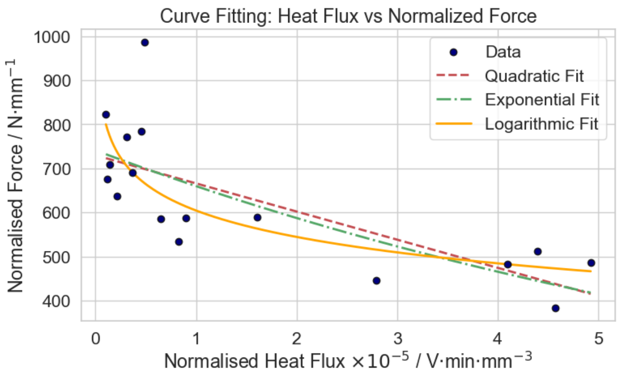

Figure 8. Regression fits between normalised cutting force and heat flux. The exponential model shows the best inverse correlation, indicating heat flux as a reliable process efficiency indicator

The fitted model captures this behaviour with moderate accuracy and supports the interpretation of heat flux as a meaningful indicator of process efficiency.

The exponential fit is represented by the following equation:

$$F_{norm} = 741.2 \times \left(e^{-11607 \times H_{norm}}\right)$$

where F_{norm} is the normalized forces and H_{norm} is normalized heat flux.

The coefficient of determination (R^2) for the exponential fit exceeded 0.56. While not exceptionally high, this value suggests a moderate yet meaningful predictive capability. The strength of the relationship supports the hypothesis that heat flux, when normalised by material removal rate, can serve as a practical indicator of process efficiency. It also implies that heatmetry based sensing can be integrated into data-driven control frameworks to estimate mechanical load conditions without requiring complex dynamometer setups.

Overall, the regression analysis not only reinforces the validity of using THFS for intelligent process monitoring but also highlights the importance of thermal response as a control variable in sustainable machining.

4. Conclusion

This study validates heatmetry as an effective and practical approach for intelligent machining control. By capturing thermal and mechanical responses in real time using an embedded THFS, the method offers a direct and responsive means of understanding process behaviour. The use of normalised metrics enables fair comparison across varying cutting conditions and facilitates the integration of sensor data into predictive frameworks.

The observed exponential inverse relationship between normalised heat flux and cutting force suggests that higher thermal input leads to reduced mechanical resistance. This supports the interpretation of heat flux as a meaningful process indicator that reflects both energy transfer efficiency and material response. Such a relationship offers the potential for adaptive optimisation of cutting parameters without reliance on complex force measurement systems.

The findings demonstrate that thermal signatures, when interpreted through direct sensing, can inform process decisions in ways that enhance both performance and sustainability. By providing reliable input for digital twins and closed-loop control systems, heatmetry contributes to the advancement of real-time, energy-aware machining strategies.

In summary, this work establishes a solid foundation for the practical use of embedded heat flux sensors in zero-emission manufacturing. Future research will focus on refining the sensing approach, exploring multi-sensor integration, and extending validation to more complex industrial scenarios.

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