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PRINCIPLES OF DESIGNING A DIGITAL TWIN AND USER INTERFACE FOR A MACHINE TOOL BASED ON SYSTEM MODELING OF THE GEAR CUTTING PROCESS

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Abstract. *Industry 5.0, as the next stage in industrial evolution, should put people back at the center of manufacturing processes. This can be achieved through the use of intelligent interfaces, where AI components will work in collaboration with professional operators on the production floor. This paper formalizes the basic principles for designing such interfaces for gear cutting processes.*

Keywords: *Digital twins, interface, design, gear cutting.*

Introduction

Gear transmissions are essential components of modern mechanical systems and remain fundamental for power transmission in a wide range of industrial applications. In power drives, reducers, gearboxes, and transmission assemblies, they perform the critical function of converting rotational speed, torque, and the direction of motion between interacting components. Owing to their reliability, efficiency, and ability to transmit significant loads, gears are widely employed across virtually all sectors of mechanical engineering.

The automotive industry alone accounts for approximately 80% of total gear production, manufacturing hundreds of millions of gears annually. With global vehicle production reaching tens of millions of units each year, this sector manufactures nearly one billion gears annually. Given additional demand from the aerospace, shipbuilding, robotics, machine tool, and heavy machinery industries, the global production of gears exceeds 1 billion units per year. This production volume highlights the strategic importance of efficient, flexible and sustainable gear manufacturing technologies for modern industrial production systems [1].

The economic importance of gear manufacturing is also reflected in the global gear technology market. The gear manufacturing market size is forecast to increase by USD 137.8 billion at a CAGR of 8.1% between 2024 and 2029.

The increasing technological complexity of modern machines, especially in sectors such as electric mobility, robotics, and aerospace systems, creates growing requirements for transmission precision, noise reduction, efficiency, and operational reliability. Consequently, gear manufacturing technologies must simultaneously ensure high accuracy, flexibility, productivity, and sustainability while maintaining economic efficiency. In response to these challenges, the overall goal of the project is to develop an AI-assisted gear manufacturing technology that significantly improves the efficiency, flexibility, and sustainability of gear production.

Purpose and Objectives of the Study

The purpose of this article is to formulate the basic principles for developing the foundations of artificial intelligence integrated into the gear cutting process to ensure the desired stability of the cutting tool. Also, considering the features of Industry 5.0, design the foundations for implementing digital twins and adaptive user interfaces.

Main section

The primary parameter characterizing the performance of cutting tools is wear, and the main criterion is the width of the wear zone on the rear surface of the cutting edge. To monitor this parameter, various approaches and methods are used:

– physical methods of direct monitoring based on contact and non-contact analysis, which utilize sensors, measuring instruments, and devices;

– indirect observation methods: of cutting forces, temperature in the cutting zone, oscillations and vibrations, power consumption, and the intensity of infrared radiation from the surface of the tool;

– statistical analysis methods for predicting the service life;

– methods of mathematical modeling and optimization of decisions – selection of operating modes, design and geometry of cutting tools, structure of the machining operation.

The latter research direction, in which the set goal can be achieved at the lowest material cost, without conducting complex and expensive experimental studies, and excluding the use of expensive equipment and special tools, is the most rational. The key prerequisite for maximizing the effectiveness of such a solution is the availability of reliable data and validated mathematical models. The methodology for researching complex gear-cutting processes, discussed in this paper and which can serve as a scientific basis for developing AI and a human-centered interface for the "CNC machine-operator" system, was developed at Lviv Polytechnic National University. The distinction and uniqueness of the proposed solution lie in a systematic approach and comprehensive computer modeling that covers all aspects of the processes involved in the formation of gear surfaces. In particular, a system of graphical-analytical and mathematical models has been developed that describe various secondary processes and phenomena accompanying the cutting and shaping of gear surfaces, the results of which are presented, in particular, in the works [3].

For example, the set of phenomena and associated processes, modeling objects, and the interrelationships between them – from the geometric modeling of the cut layers to the description of their wear using the example of gear cutting with a worm cutter – is shown in Fig. 1.

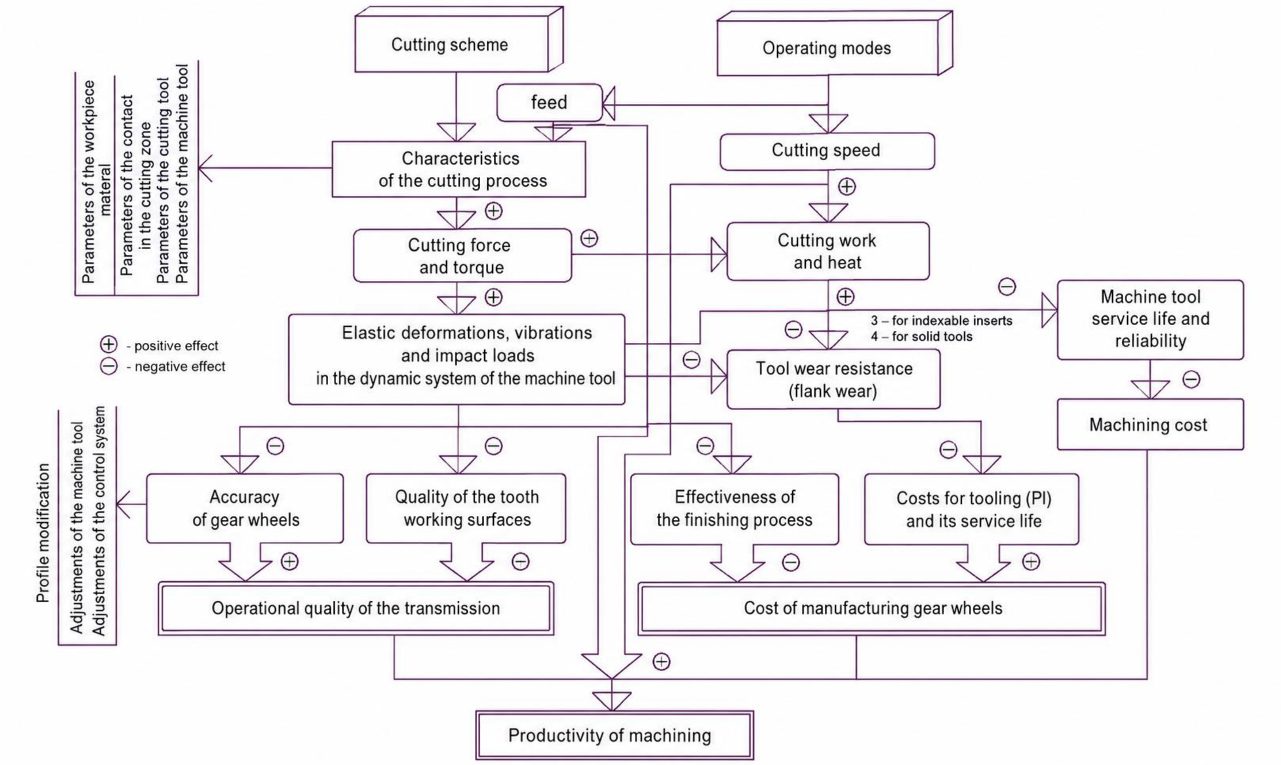

Figure 1 – The “-” sign indicates a negative correlation between the parameters

As can be seen from the flow above, the task of determining cutting parameters and optimal operating conditions is controversial and complex. For instance, to increase the productivity and efficiency of a machining operation, it is necessary to increase the feed rate and cutting speed, which will reduce the machining time and heat generation. However, increasing the cutting speed leads to reduced stability and higher tool wear, as well as creating a risk of vibrations and a deterioration in the quality of the machined surfaces. Increasing the feed rate leads to an increase in cutting force, energy consumption, cutting work, and heat generation, as well as increased oscillations and vibrations, and negatively affects the condition of the machine tool, the tool, and the quality of machining. Thus, taking all these conflicting factors into account is a critical challenge in process design and control.

Under such conditions, the task of determining operating modes that would simultaneously satisfy all the diverse requirements of the operation and yield the highest performance can be solved by intelligently integrating cutting data with predictions of tool condition, which changes over the course of the cutting process–

meaning the creation of a virtual twin of the machine tool with the gear-cutting process. A digital twin, combined with machine learning methods, will make it possible to bring together the entire data set, optimize decisions during the operation preparation stage, monitor the process in real time, control the process, and quickly adjust its parameters in critical situations.

At the same time, to improve the interpretability and transparency of the model, it is important to physically monitor the controlled parameter using a sensor integrated into the cutting process control system.

Modeling the temperature of the cutting wedge

The first step in creating a digital twin is a model that describes the relevant system. Based on the task of monitoring and controlling the gear cutting process according to the tool stability parameter, the factor that has the greatest influence on stability is temperature, as a numerical characteristic of the thermal state of the cutting wedge, and which is one of the main parameters of the cutting process. An increase in temperature in the cutting zone up to a certain limit facilitates the process by reducing the yield strength of the workpiece material; however, beyond this limit, the plasticity of the cut layers, the intensity of heat generation, and the cutting force increase. With a further increase in temperature up to the tool's heat resistance limit, it loses its strength, hardness, and cutting properties.

Depending on the set cutting conditions, temperature is a multi-parameter function in the sequence of processes occurring in the cutting zone: deformation, contact, tribological, force, and thermal processes, which ultimately determine the cutting temperature and the cutting wedge.

The results of temperature calculation and modeling, which can be used to create a digital twin of the power skiving process, are presented in the works [2] in the following form.

The maximum temperature at the contact surface belonging to the tool, as a result of the action of a uniformly distributed, fast-moving ribbon heat source.

$$\theta^{*}_{max} = \frac{2 \cdot q^{*}}{\lambda_0} \cdot \sqrt{\frac{b \cdot \chi}{\pi \cdot V}} \cdot K_{sh}, \tag{1}$$

where λ_0 is the thermal conductivity coefficient of the tool material, J/cm·s·°C;

χ is the thermal diffusivity coefficient of the tool material, cm²/s;

q – heat source intensity, J/cm²·s;

b – linear length of the source, equal to the effective width of the blade, mm;

V – cutting speed in mm/s;

Ksh – shape coefficient of the high-speed source.

In this formula, the parameter q represents the intensity of heat fluxes on the front surface of the working tooth:

$$q_{\gamma} = \frac{F \cdot V}{60 \cdot C \cdot b} \cdot \frac{1}{\xi}, \quad (2)$$

where $V / \xi = Vch$ – chip feed rate on the rake face in the secondary plastic deformation zone, m/min;

F – friction force on the rake face, N;

C – length of the plastic contact zone, mm;

b – chip width, mm.

The variables contained in these relationships were obtained preliminarily based on modeling of the cutting parameters, cutting force, friction, and cutting heat. Graphs of heat fluxes and temperatures on the blades of the skiver cutter during the power skiving process are shown in Fig. 2.

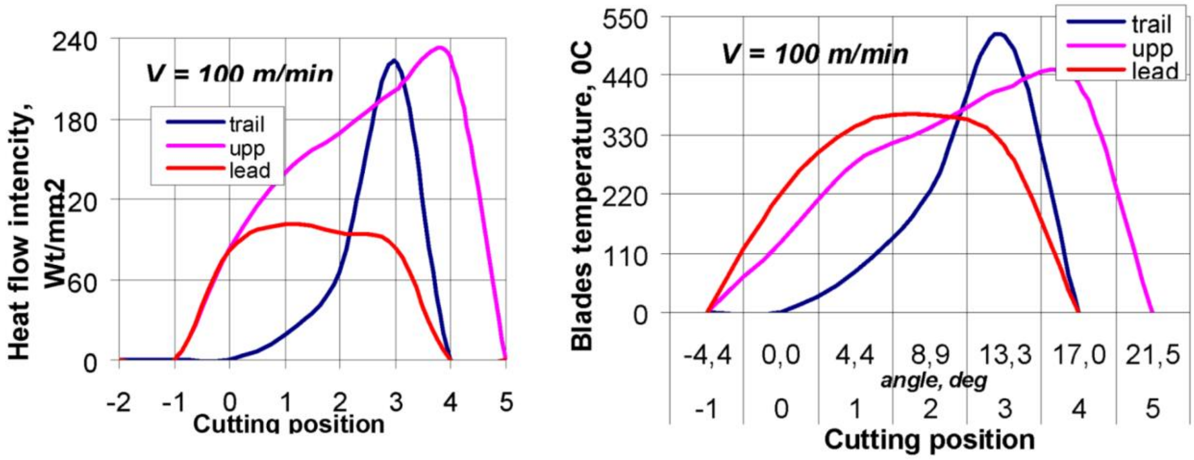

Figure 2 – Heat fluxes (a) and temperature (b) at the tool tooth edges
$\lambda = 0.094$ cal/cm·s·°C = 0.04 J/mm·s·°C; $\chi = 6.6 - 7.2$ mm²/s; $Ksh = 1$.

For the given initial conditions, the maximum temperature reached on the driven side blade does not exceed 540°C and is well below the temperature limit of the hard alloy. However, if we take into account the heat accumulation factor with each machining cycle, then after k revolutions of the tool, the heat generated on this blade, accounting for the balance of thermal processes, will amount to 4.55 J ($k = 22$, Fig. 3) according to the formula, and the final blade temperature will be 1270°C.

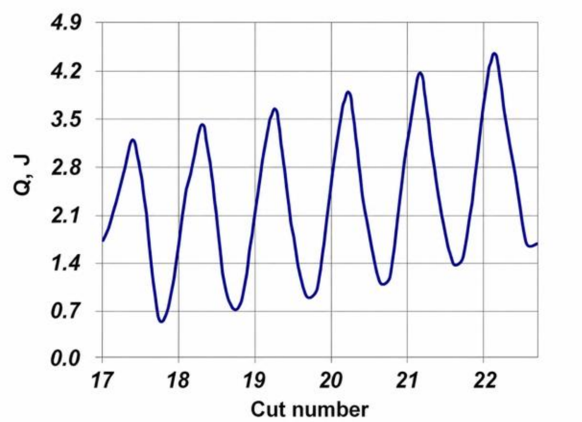

Figure 3 – Balance of thermal processes

This temperature represents the heat resistance limit for the hard alloy; therefore, exceeding it while the machine continues to operate will cause the tool to fail.

Therefore, if the function of controlling the gear-cutting process based on this parameter is assigned to a digital twin, it will be able to terminate the process in a timely manner or adjust the process parameters – specifically, change the cutting modes based on the acquired information and mathematical models [3].

Human-Centric Design

This pillar ensures transparent and user-friendly operation, facilitating adoption by a wide range of operators.

Interface design:

– development of a human-centred visualization platform displaying AI predictions, process status, and optimization decisions in real time [5];

– support for decision-making at automatic, semi-automatic, and manual levels.

Usability testing and optimization:

– evaluation of the UX/UI will be conducted through structured user testing with machine tool operators under both simulated and real operating conditions. Current operators as well as potential candidates from the relevant industrial sector will be invited to participate in the trials in order to collect qualitative feedback and systematically analyse user interaction and behavioural patterns during system operation [2];

– iterative improvements to ensure clarity, trust, and efficient human-system interaction. The methodology follows an iterative Research and Innovation (R&I) cycle. Close integration of experimental results, AI-based optimization, and digital twins ensures rapid feedback and continuous improvement. Each phase is evaluated using quantitative metrics aligned with project objectives, enabling measurable impact. This structured approach ensures the achievement of ambitious yet realistic results, maximizes TRL progress, and prepares the solution for rapid industrial deployment.

Experimental system diagnostics and validation form a central methodological pillar of the project. The experimental programme provides the data required for validation of the manufacturing system, calibration of the digital twin models and generation of datasets for the development and training of AI-based optimisation models.

After manufacturing the individual components and upgrading the machine tool, a structured experimental testing programme will be carried out to characterise the behaviour of the manufacturing system under realistic operating conditions. The testing activities focus on four complementary diagnostic domains describing the behaviour of the complete machining system:

– machine tool accuracy and dynamic behaviour;

– tool behaviour and thermal stability;

– tool-workpiece interaction and local process physics;

– resulting gear geometry and transmission quality.

Machine-level studies will analyse geometric and kinematic accuracy, structural stiffness and dynamic properties of the system. Measurements of vibration behaviour and frequency response will support the modelling of machining stability and the identification of potential vibration phenomena.

Tool behaviour will be characterised through measurements of tool geometry accuracy, thermal stability and operating conditions during machining. These data will support the analysis of how tool deviations and temperature effects influence machining accuracy and process stability.

The interaction between tool and workpiece will be studied by analysing cutting forces, torque, temperature and lubrication conditions in the cutting zone. These studies characterize the local physical processes governing the machining operation.

Finally, the resulting gear geometry and quality will be evaluated through measurements of pitch errors, profile deviations and other accuracy indicators. These measurements provide the basis for analysing the relationship between manufacturing parameters and gear transmission behaviour.

In addition, selected gear samples will be analysed with respect to their dynamic and acoustic performance under realistic operating conditions. These studies examine how manufacturing deviations affect transmission error, dynamic excitation, and noise generation in gear systems.

Dedicated gear test rigs will be used to analyse the dynamic behaviour and acoustic emissions in the gear system. The combination of gear measurements, system-level experiments and numerical models enables a systematic link between manufacturing process parameters and the dynamic performance of the resulting gear transmission.

The experimental data will be integrated into the digital twin framework of the project. Experimental measurements will support the calibration and validation of multiphysics simulation models and provide training data for AI-based optimisation algorithms.

Beyond the validation of the concept, the experimental studies could also generate transferable knowledge on the dynamic behaviour and stability of advanced gear manufacturing systems. These insights will support the future design of more reliable machine tools, improved process control strategies and next-generation gear manufacturing technologies.

This experimental framework provides the essential link between manufacturing process development, digital twin modelling and AI-based optimisation, ensuring that the proposed technologies are grounded in experimentally validated system behaviour [5].

This approach has the potential to transform gear manufacturing from highly specialised production systems into flexible, intelligent manufacturing environments capable of adapting to changing production requirements. Such a transition represents a significant improvement toward more flexible and intelligent gear manufacturing technologies.

The fundamentals of designing digital twins and adaptive interfaces for their subsequent integration into Industry 4.0-5.0 manufacturing processes are presented in Table 1.

Table 1 – Current Status and Proposed Fundamental Principles

Aspect	Current state-of-the-art gear manufacturing	Recommended solutions
Machine architecture	Dedicated gear-cutting machines designed for specific gear types	Universal multi-axis machine platform capable of producing multiple gear types
Cutting tools	Specialized tools (hobs, shaping cutters, skiving tools) for each gear geometry	Single multi-purpose disk milling cutter
Production flexibility	Limited flexibility; tool and machine changes required	Highly flexible programmable kinematic generation
Process optimisation	Mainly empirical parameter adjustment by operators	AI-assisted real-time optimisation using neural networks [5]
Process modelling	Partial empirical models	Integrated multiphysics digital twin
Human-machine interaction	Conventional machine interfaces with limited decision support	Human-centred intelligent interface following Industry 5.0 principles
Production efficiency	Multiple machines and operations are often required	Integrated cutting and finishing on a single platform
Sustainability	High tooling consumption and energy use	Reduced tooling demand and improved energy efficiency

Research findings

The methodological framework of the digital twin will be based on the following principles:

Hybrid structure: a combination of models describing processes and phenomena during gear cutting with machine learning models, using artificial intelligence to adjust process parameters and variables.

Data segmentation by active teeth and cutting tool blades under multi-tooth cutting conditions.

Use of time series. Processes that are the subject of AI, in particular wear, are modeled as the result of sequential processes (RNN/LSTM) preceding the wear mechanism, and the wear process itself is considered during the cutting time as a function of the previous states of the blade.

Real-time integration of the machine's CNC system with a digital twin using a sensor system to monitor the gear cutting process.

Ensuring systematic online updating of models based on machine status information (elastic deformations, cutting forces, vibrations and oscillations, cutting temperature).

Based on the results, the header wireframe for the user interface design is proposed in Fig. 4.

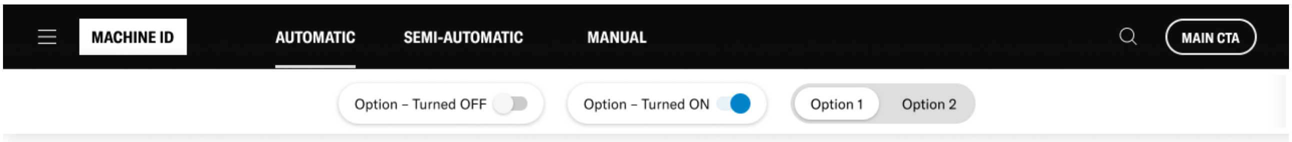

Figure 4 – Conceptual UI/UX solution for the header

In the image above, we can see the following key interface elements, which can be divided into three main groups: status indicators (machine ID, background color), three main mode switches, and a row containing filters and options for fine-tuning the production process.

Conclusions

This study formulates the methodological and technological foundations for the development of a human-centred AI-assisted system for gear cutting processes within the paradigm of Industry 5.0. The proposed approach combines mathematical modelling, digital twin technologies, sensor integration, and machine learning methods to create an intelligent manufacturing environment capable of supporting both automated and operator-assisted decision-making [4].

The research demonstrates that the stability of the cutting tool is determined by a complex interaction of thermal, force, tribological, and dynamic phenomena occurring in the cutting zone. Among these factors, temperature was identified as the dominant parameter influencing tool wear and operational reliability. The developed thermal models make it possible to predict the thermal state of the cutting wedge, analyse heat accumulation effects during repeated machining cycles, and determine critical operating conditions leading to tool degradation and failure.

The obtained results confirm the feasibility of integrating validated analytical and graphical models into a digital twin framework for real-time monitoring and adaptive control of gear cutting operations. Such integration enables continuous assessment of machining conditions, prediction of tool behaviour, timely correction of cutting parameters, and prevention of critical thermal overloads. The proposed hybrid architecture, combining physics-based models with AI-driven learning algorithms, provides the basis for adaptive optimisation under multi-parameter and conflicting process requirements.

An important contribution of the work is the formulation of principles for human-centric interface design in intelligent manufacturing systems. The proposed UI/UX concept supports transparent interaction between operators and AI systems through real-time visualization of process states, predictive analytics, and optimisation recommendations. The inclusion of automatic, semi-automatic, and manual control modes ensures flexibility of operation and facilitates practical industrial adoption.

The developed experimental framework establishes the necessary connection between physical diagnostics, numerical simulation, digital twins, and AI-based optimisation. The integration of experimental measurements into the digital twin environment enables systematic model calibration, validation, and continuous improvement of predictive capabilities. Furthermore, the proposed methodology creates the foundation for future research aimed at increasing machining stability, improving gear quality, reducing energy consumption, and enhancing the sustainability of advanced gear manufacturing systems.

Overall, the presented approach demonstrates significant potential for the development of next-generation intelligent gear manufacturing technologies aligned with the principles of Industry 5.0, where artificial intelligence acts not as a replacement for the operator, but as a cooperative decision-support instrument within a human-centred production environment.

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