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A digital twin-driven approach for process parameters selection in planarization technology

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ABSTRACT

Planarization technologies, such as lapping and chemical-mechanical polishing (CMP) are critical in achieving high-precision surface quality in various industrial applications. While predictive models of tool wear and material removal rate were developed in previous studies, recent advances in digital twins open new possibilities for integrating physics-based and data-driven approaches into a comprehensive decision-making framework. This paper proposed a digital twin-driven methodology for selection of process parameters in planarization technology. The framework combined lapping kinematic models, tribological equations and machine learning methods into a dynamic, adaptive system capable of predicting tool wear, optimizing parameters, and supporting real-time control. Case studies demonstrated the integration of predictive models into the proposed framework. Potential applications, limitations, and future research directions were discussed.

Keywords: digital twin, lapping, process parameters optimization, tool wear.

INTRODUCTION

Planarization is a key finishing process that enables the production of highly precise surfaces with strict flatness and parallelism requirements. Single-sided lapping, face grinding with lapping kinematics or chemical-mechanical polishing (CMP) are commonly used in manufacturing applications, such as valve plates, ceramic sealing rings, and semiconductor wafers. Despite decades of progress, selecting process parameters (e.g. plate and conditional rings rotational speeds, pressure, slurry and pad conditions, ring radial position) still involves multi-objective trade-offs among material removal rate (MRR), topography, and tool/pad wear and it is often managed via experience-driven trial-and-error. Recent advances in digital twins, which are high fidelity virtual replicas of physical processes, create an opportunity to formalize and accelerate parameter selection by fusing physics-based models with data-driven inference under real-time feedback [1, 2]. In this paper, a digital twin-driven framework for planarization parameter selection was proposed. It integrates kinematic, tribological modeling and machine learning within a closed-loop architecture for prediction, optimization, and control.

The planarization process is highly complex and depends on numerous technological factors. Its model comprises four main elements: the tool, abrasive slurry, workpieces, and the machine tool. Each of these elements has a significant influence on the surface creation mechanism, directly affecting the quality of the workpieces, tool wear, and the overall efficiency of the process. The input factors in the process may be categorized into controllable and uncontrollable. Controllable variables primarily include machining parameters, such as the applied pressure, the rotational speed of the lapping plate and conditioning rings, the characteristics of abrasive grains, the tool flatness, and the duration of machining. In contrast, uncontrollable variables include ambient temperature, grain size distribution, vibrations, internal stresses, and other external influences [3].

In the lapping process, the lapping plate is crucial for determining dimensional and shape accuracy, as well as the surface quality of workpieces. On the basis of the necessary material removal rate, the desired surface finish, the anticipated flatness, hardness, and geometry of the lapped components, the material, design, and technological parameters of the plate are selected [4, 5]. Key characteristics of the tool include its mechanical properties, material type, structure, macrogeometry, and the topography of its active surface [4, 6]. The mechanical properties and internal structure of the lapping plate material affect its wear resistance and the resulting surface quality. The topography of the machined surface is influenced by the macrogeometry of the plate, which also affects how the abrasive slurry and grains are distributed within the working gaps. Plate hardness is also important and when the plate is too hard, abrasive grains tend to roll rather than cut, causing stress-induced microcracks and particle embedding in the workpieces while reducing tool wear. Plates made from softer materials retain abrasive grains on the surface, promoting more sliding interactions and material removal in this case occurs mainly through scratching [7, 8]. To ensure proper flatness and high-quality surface finish, it is important to maintain stable process conditions and regularly correct the plate flatness. Excessive wear of the plate may lead to flatness errors such as concavity, convexity, or axial runout of the active surface of the tool [9]. It is essential to monitor and adjust plate flatness before and during machining. Therefore, periodic lapping of the plate (often with fine abrasives) is also recommended to maintain a smooth surface free of deep scratches.

Conventional approaches to modeling, such as kinematic simulations, have yielded insights into tool wear and material removal rate (MRR). Classical workpiece- or plate-scale descriptions of lapping often start with the Preston relation, which states that the local MRR is proportional to the product of the contact pressure and relative velocity [10, 11]. Although originally developed for glass polishing, Preston's models remain a practical backbone for process reasoning. It has also inspired numerous studies that incorporate contact mechanics, pad/asperity interactions, and chemistry-dependent terms. These models are attractive for transparency and low data requirements. However, they can struggle to capture non-linearities introduced by pad conditioning dynamics, slurry rheology, temperature, and tool kinematics that vary across the contact footprint.

Many kinematic and mechanistic studies have examined how trajectories, contact time, and velocity fields affect both MRR and pad/tool wear non-uniformity. For example, analytical studies of pad wear with conditioner kinematics show that cutting-path density and contact time are usually higher near the pad center. This explains the typical radial wear patterns and helps guide the choice of kinematic set-points and conditioning strategies. These findings show that wear and removal result from the combined motions of the plate, ring or wafer, and conditioner, as well as from boundary conditions and process geometry [12–14].

The data-driven methods for CMP and lapping have developed along with physics-based modeling, including supervised learning to forecast MRR and quality indicators from operational data. Decision-tree ensembles trained on tool traces, metrology, and recipe variables have achieved high predictive accuracy for wafer-scale MRR, while deep models and residual networks have shown promise for learning complex dependencies [15, 16]. Yet, purely data-driven models can extrapolate poorly outside the training manifold and typically lack physical interpretability, the limitations that are acute when recipes or hardware are modified. This has motivated physics-informed machine learning (PIML) that embeds mechanistic constraints or features (e.g. Preston-derived terms, asperity contact models) into learning pipelines, improving generalization and sample efficiency [17]. These hybrid strategies provide a natural methodological substrate for digital twins that must continuously adapt while respecting process physics.

Beyond predictive accuracy, digital twins promise a shift from post-hoc modeling to in-process decision support. Virtual experimentation, what-if analysis, and autonomous set-point updates under constraints (e.g., thermal budgets, tool life, surface targets) are made possible by DT deployments that synchronize sensor streams (force/torque, vibration, acoustic emission, temperature) with multi-fidelity models and optimization layers, according to reviews across the machining and grinding industries [18, 19]. While much of the literature focuses on material removal processes, such as milling, turning, and grinding, the architectural patterns, real-time data integration, co-simulation, and prescriptive optimization are directly transferable to planarization and have already been demonstrated for DT-assisted grinding parameter selection, pointing to a clear pathway for planarization twins [20, 21].

Digital twins have been widely deployed across machining and grinding, supporting functions that range from condition monitoring and predictive maintenance to state estimation, quality forecasting, and adaptive set-point control. By contrast, applications tailored to planarization remain comparatively nascent: the multi-body kinematics, evolving pad/plate topography, and slurry-mediated contact make direct transfer of machining-oriented twins non-trivial. A domain-specific integration of DT concepts with planarization tribology, linking kinematic models and Preston-type estimators with learning-based prediction, can bridge the gap between offline simulations and real-time, closed-loop optimization of key parameters (e.g., speed ratio, ring radial position, pressure), enabling proactive control of uniformity and material removal rate.

STOCHASTIC TOOL-WAER CHARACTERISTICS IN THE LAPPING PROCESS

One of the most critical planarization technologies is single-sided lapping. The fundamental mechanism in the process involves the rolling motion of abrasive grains suspended in a slurry within the gap between the lapping plate and the workpiece surface. In addition, grains may become temporarily embedded in the lapping plate or in the conditioning ring. Consequently, abrasive wear is one of the dominant mechanisms of the lapping process. This mechanism describes the separation of material induced by relative motion and occurs when, within the frictional contact zone of mating elements, either embedded or free abrasive particles interact with the surface. In abrasive machining, the objective is to minimize friction and tool wear while maximizing the abrasive removal of the workpiece. Within lapping, this balance is governed by the stochastic engagement of grains in the contact and by the evolving topography of the active surface. Therefore, process outcomes reflect the joint action of free-rolling particles in the slurry, intermittently fixed grains, and asperity-scale interactions at the tool–workpiece interface [22].

Two principal modes of material removal can be distinguished during abrasive wear: two-body and three-body abrasion. In the former, abrasive grains (or hard asperities) are rigidly attached to the counter face, allowing them to plough and cut deeply into the workpiece under sliding motion. In the latter, abrasive particles are free to move within the interface, as a result, they intermittently cut for part of the contact time and roll for the remainder. Under otherwise identical process conditions, the removal rate in two-body abrasion is commonly expected to be approximately three times higher than in three-body abrasion. In lapping, grains may both slide and roll within the gap between the workpieces and the lapping plate, so the effective removal mechanism is a mixture of two-body and three-body abrasion that evolves with operating conditions and surface state [23, 24].

During single-sided lapping, relative motion causes some abrasive micro-grains to take an active position in the contact, while others remain inactive and exit the machining zone. Owing to size and shape effects, only a subset of all particles can actually enter the interfacial gap, the height H of which depends on the applied normal load F. Representative grain types present between the tool and the workpiece are illustrated in Figure 1, where grain A is too small to engage the surface, whereas grain B is too large to pass through the gap. Consequently, only a fraction of particles remains active and either rolls (grain C) or slides (grain D) within the contact. Notably, even particles of a nominally suitable size may be passive due to unfavorable shape/orientation, as exemplified by grain E. This size-shape selection mechanism underlies the inherently stochastic composition of the active cutting population in lapping [23].

Other phenomena also drive changes in the initial surface structure and tool wear. First, the most heavily loaded grains fracture, their fragments may participate in lapping depending on their size and shape. As a result, the population of grains on the lapping plate evolves: the number of larger particles decreases, while the number of smaller fragments increases. In addition, changing trajectories and relative velocities cause grains or fragments to collide, so that agglomeration and breakage can occur intermittently at any time. During lapping, the contact zone contains numerous particles, and the gap between the workpiece and the plate is populated by active grains that transmit normal forces to the opposing surfaces. These forces scale with the contacting volume (or effective indentation) of each active grain. To maintain a constant interfacial height, the sum of the normal forces carried by all active grains must equal the prescribed lapping load F [23, 25].

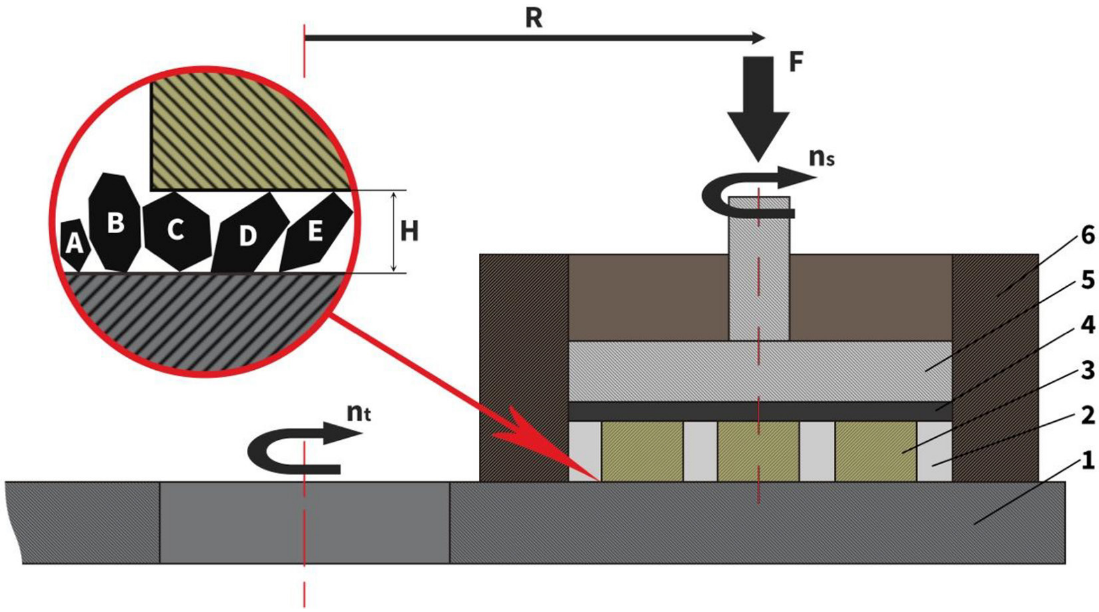

Figure 1. Model illustrating different positions of abrasive micrograins in single-sided lapping: 1 – lapping plate, 2 – separator, 3 – workpiece, 4 – pressure pad, 5 – pressure disc, 6 – conditioning ring

In the majority of lapping-plate wear models, it is assumed that the wear intensity is governed by the contact intensity between the tool and the workpiece, mediated by abrasive grains [26, 27]. One practical way to quantify this contact is to compute the density of the scratches produced on the lapping plate by the grains that are temporarily embedded in the workpieces and in the guide rings. An example of the scratch-density computation for a randomly selected grain set is shown in Figure 2. In the first step, the spatial distribution of grains is generated using a random function. The domain for point placement can be constrained to arbitrary surfaces, for instance restricted to the contact areas of the conditioning rings. In the next step, grain trajectories and the associated scratch paths are computed from the derived kinematic equations [13]. Figure 2a illustrates the resulting scratches after a specified simulation time. To obtain a uniform sampling along each path, an interpolation operator converts every generated scratch into a set of equally spaced points. Subsequently, the plate surface is tessellated into small, equal-area squares. The scratch density is then evaluated via a statistical counting function that tallies the total number of points falling within each square of the lapping plate. To visualize the concentration field, a kernel density estimator, implemented with Parzen windows, can be applied (Figure 2b). The kernel assigns the highest weight (1.0) to the point centered in the window and progressively smaller weights to the observations located farther from the window center.

Because of common modeling assumptions, many wear models neglect the factors and properties that substantially influence the magnitude of wear. In practice, the interaction intensity between the workpiece (through abrasive grains) and the active tool surface, as well as the interaction between the lapping plate and the machined surface, depends among others on the interfacial gap between these two surfaces. Since neither surface is perfectly flat, the instantaneous position of the workpiece in the coordinate frame attached to the rotating plate causes the point-to-point distance between the tool and workpiece surfaces to vary over time. The actual shape of both surfaces, particularly the flatness deviation of the active face of the lapping plate, therefore modulates the local gap and, consequently, the local wear intensity.

The primary kinematic parameters under operator control in lapping are the rotational speed of the lapping plate n_t and the radial position R of the conditioning rings with their separators and workpieces. In driven-ring machines, the rotational speed of the conditioning rings n_s can also be set independently. In practice, these kinematic parameters are largely selected heuristically, guided by prior experience and literature recommendations and then verified experimentally. To maintain the required tool flatness in single-sided lapping, parameter optimization is essential.

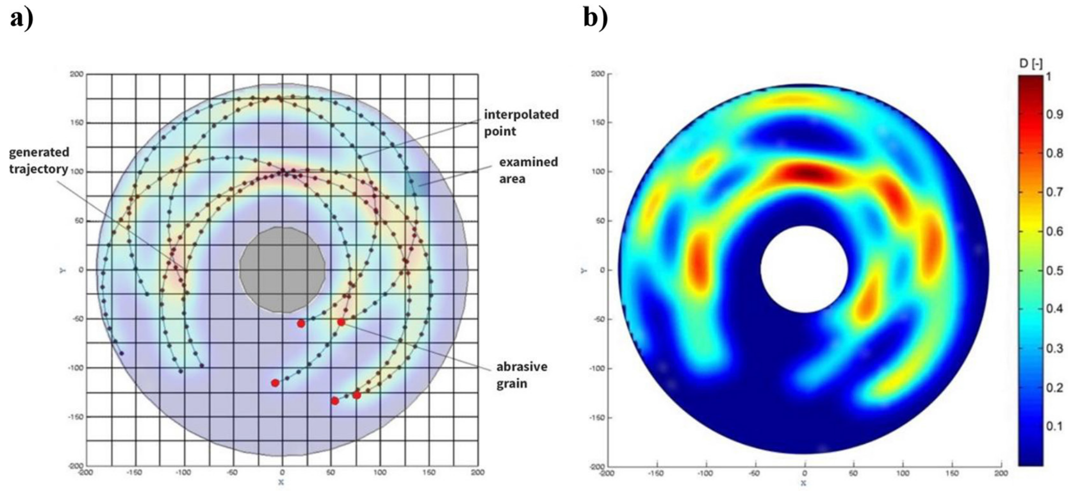

Figure 2. Example of scratch-density computation for a random set of embedded grains: (a) generated grain layout and kinematic trajectories; (b) kernel-smoothed density map

DIGITAL TWIN-DRIVEN FRAMEWORK

Digital twinning for planarization processes can be viewed as an end-to-end methodology that links the design and manufacturing workflows with computational modeling and optimization. Within this perspective, virtual experiments are run on a high-fidelity representation of the process to screen operating conditions before they are applied on the machine. A coherent Digital Twin-Driven Framework for planarization and lapping was presented in Figure 3. The framework links the physical process with its digital representation to enable systematic selection and adaptive updating of technological parameters. In contrast to traditional trial-and-error practice, the proposed approach allows predicting process outcomes and tool behavior over a wide parameter space using a limited experimental budget, thereby improving productivity and stability while maintaining strict quality requirements.

The starting point in the framework is a structured description of the physical space of the process, which is defined by five groups of inputs. The first group concerns the tool, characterized by the lapping/planarization plate material, its current wear state, and its geometry (for example initial flatness, working radius, groove pattern, or any corrective conditioning applied). The second group captures the abrasive medium, including abrasive material, grain size, slurry concentration, and rheological properties that govern the tribological conditions in the contact zone. The third group relates to process kinematics: rotational speeds of the plate and carriers/conditioning rings, their radial positions, and geometric dimensions that together determine the actual grit trajectories. The fourth group describes the workpiece, specified by its material, geometry, and initial thickness/shape error distribution. Finally, the fifth group includes machine characteristics such as the achievable normal load and its stability, possible superimposed oscillatory motions, and the thermal stability of the system, which may affect local contact conditions. These inputs form a complete snapshot of the real process configuration and constitute the data stream feeding the digital twin.

In the digital space, the framework employs an integrated modeling environment composed of two coupled modules. The first module is kinematic and reconstructs abrasive-grit motion on the tool surface. On the basis of the imposed rotational speeds and system geometry, grit trajectories are computed and transformed into trajectory density distributions as a function of radius. The output of this module therefore consists of spatial maps of contact intensity and relative velocity fields, which are the primary drivers of both material removal and tool wear. The second module is tribological–mechanistic and converts the kinematic descriptors into local removal and wear rates using Preston relation. In practical terms, the relative velocity and pressure distributions are mapped to the predictions of local and global material removal rate (MRR), time-evolving wear profile of the tool, and wear uniformity indicators that are critical for sustaining flatness. Because the tool geometry changes progressively, the two modules are iteratively coupled: the predicted

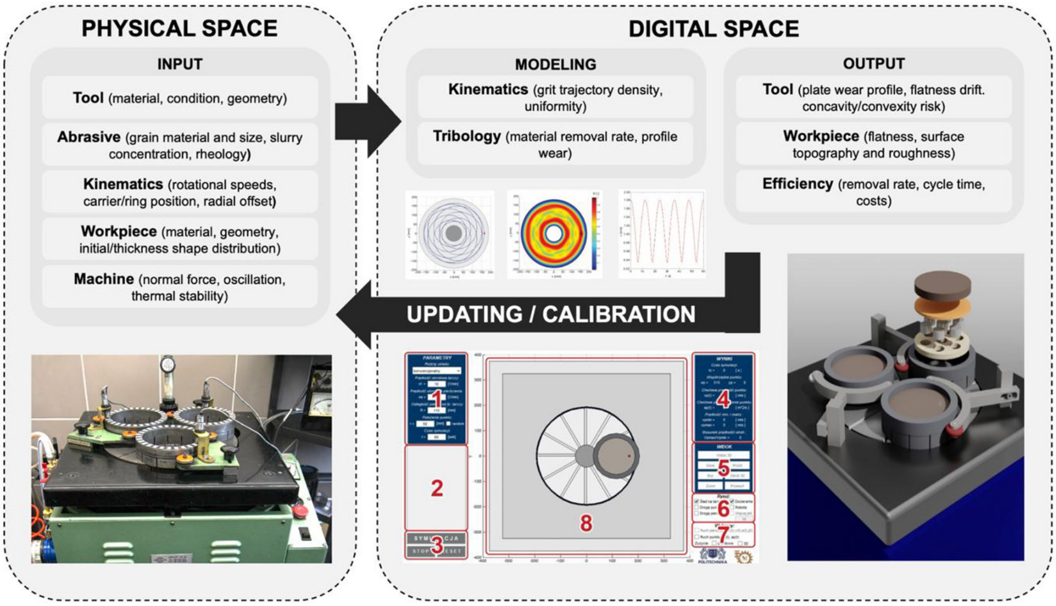

Figure 3. Integrated modeling concept for a digital twin system

wear profile updates the effective contact geometry, which modifies kinematics and, in turn, affects subsequent wear and MRR predictions.

The digital twin provides three complementary categories of outputs. First, it predicts the tool state, including the wear profile of the plate, the tendency toward concavity/convexity, and the expected progression of these deviations if parameters remain unchanged. Second, it predicts workpiece quality, such as final flatness, surface topography, and roughness proxies resulting from local abrasive action. Third, it delivers efficiency measures: global removal rate and cost-related indicators. A central element of the framework is the updating loop. After processing a batch, feedback from the physical process is incorporated into the digital twin. Such feedback includes measured tool wear maps (e.g. profilometry or flatness inspection), machine-recorded process parameters, and metrology of finished parts (flatness and roughness). With each update cycle, the twin becomes a more faithful representation of the actual process state, increasing the reliability of subsequent parameter recommendations. Importantly, this mechanism supports not only offline parameter planning but also online adaptation as the tool evolves.

From an operational standpoint, the Digital Twin-Driven Framework follows a clear decision sequence. First, constraints are defined in three domains: machine capability (allowable speed, load, and positioning ranges), product quality (e.g. minimum wear uniformity or maximum permissible flatness drift), and productivity (minimum MRR or maximum cycle time). Second, the digital twin simulates a broad set of candidate parameter combinations to identify a feasible region where all constraints are satisfied. Third, within this feasible region, a multi-objective selection is performed, typically maximizing MRR while maintaining uniform wear, or minimizing flatness deterioration while preserving a required removal rate.

INTEGRATION WITH PREDICTIVE MODELS

This case study focused on the integration of data-driven predictive models into the digital twin environment for planarization. Physics-based simulations are a natural backbone of digital twins for planarization, because they offer interpretability and allow scanning broad parameter spaces. Nevertheless, the predictive power of purely mechanistic approaches is limited by the assumptions required to keep computations tractable. In single-sided lapping, these assumptions include simplified abrasive interactions, constant tribological coefficients, and model outputs that remain largely dimensionless. This kind of simplifications can distort absolute predictions of material removal or tool wear under specific operating regimes. To mitigate these limitations, the digital twin is enriched by a data-driven predictive layer that learns the input and output relationships directly from experimental evidence and improves continuously as new samples are collected.

A key challenge in the lapping plate wear studies is the lack of high-quality datasets. Experiments require many precise, time-consuming measurements that are difficult to perform on industrial machines, and the wear rate is low due to the high hardness of plates. The small number of labeled observations increases the risk of overfitting for advanced models such as deep neural networks. To address this, both the base study and the current approach control model complexity using small-sample learning techniques, including cross-validation, feature selection, output bucketing, and lightweight classifiers suited for limited data. This kind of approach supports the digital twin concept. The physics-based layer defines the overall process structure, while the data-driven layer corrects biases and captures unmodeled effects, such as slurry transport variability, stochastic grit embedding, or minor machine disturbances. When updated, the statistical module incorporates new labeled data, allowing for gradual improvement without altering the mechanistic core.

The experimental dataset used to train the predictive models was gathered from a representative single-sided lapping setup equipped with a standard lapping plate and three conditioning rings, with controllable ring direction and rotational speed. The database spans multiple operating conditions, including different workpiece materials and geometries, abrasives of varying type and concentration, and different initial tool states. To reflect the small size of the dataset and to avoid inflating the feature space, only the two most influential operational parameters were retained as predictors: k_1 – speed ratio between conditioning rings and the lapping plate, R – radial position of the conditioning ring. Wear uniformity U was computed from the experimental wear profiles and then discretized into five ordered classes (A–E) spanning the range from 55% to 79% uniformity. This bucketing step converts a noisy regression task into a robust classification problem. Instead of predicting a single continuous uniformity value, the model outputs an interpretable quality regime that can be mapped directly to accept/reject logic in the digital twin (Figure 4).

The experimental dataset (Figure 5) shows a clear and systematic dependence of wear uniformity U on both k_1 and R. Uniformity increases within a narrow corridor of the (k_1, R) space while dropping rapidly outside this region, confirming that these two inputs can be sufficient to discriminate stable and unstable wear regimes. While the shape of the experimental response surface is consistent with the physics-based kinematics–mechanistic prediction, the absolute uniformity levels measured in practice are higher: the best conditions approach 80% experimentally, whereas simulation peaks near 60% [28]. This discrepancy is informative for the present digital twin. It implies that the mechanistic layer captures the correct global structure of wear behavior, but systematically underestimates attainable uniformity in real. Therefore, the statistical predictor is embedded not as a replacement of physics but as a calibration and reality-alignment module that adjusts the twin's outputs into the industrially achievable range.

Three lightweight supervised classifiers were evaluated to predict the wear-uniformity class from the parameter pair (k_1, R): k-Nearest Neighbors ($k = 3$), decision trees, and Naïve Bayes with kernel smoothing. The dataset was randomly split into 80% training and 20% test subsets. To remove dependence on any single split, training/testing was repeated ten times with different random partitions and the mean accuracy was reported. The comparison showed a clear ranking: decision trees provided the best generalization (94.52% accuracy), followed by Naïve Bayes (87.53%), while kNN was substantially less accurate (76.45%). Confusion-matrix analysis confirmed that decision trees most reliably separate high-uniformity regimes (D–E) from low-uniformity regimes (A–B), and that remaining errors occur mainly between adjacent classes, acceptable for process-window screening. Figure 6b presents the confusion matrix summarizing the accuracy results for decision tree.

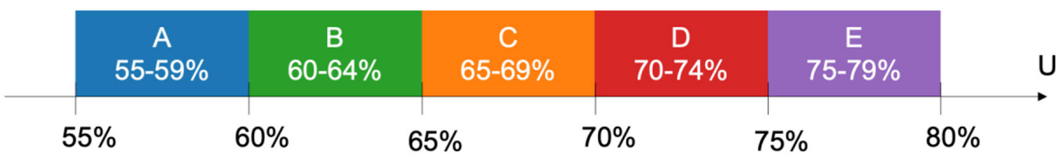

Figure 4. Plate wear uniformity U classes used for predictive modeling

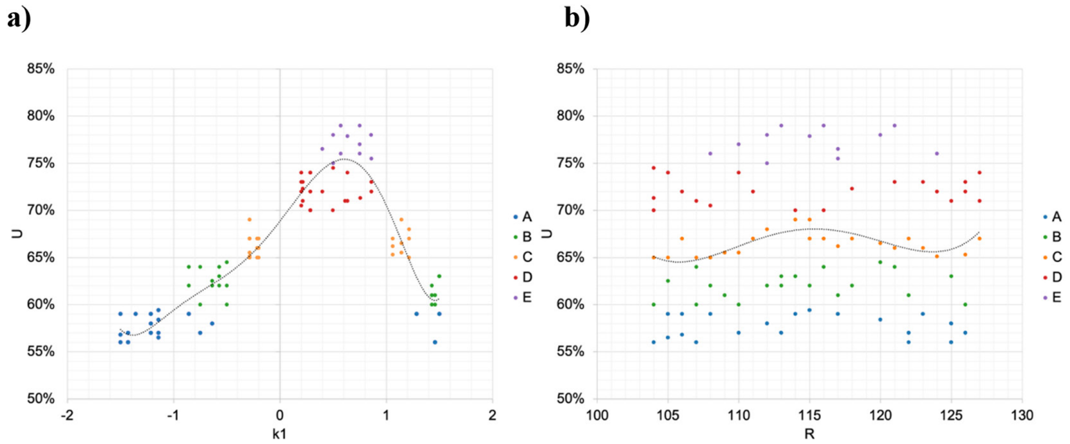

Figure 5. Dataset used in data-driven model: (a) influence of the parameter k_1 on the uniformity of U; (b) influence of the parameter R on the uniformity of U

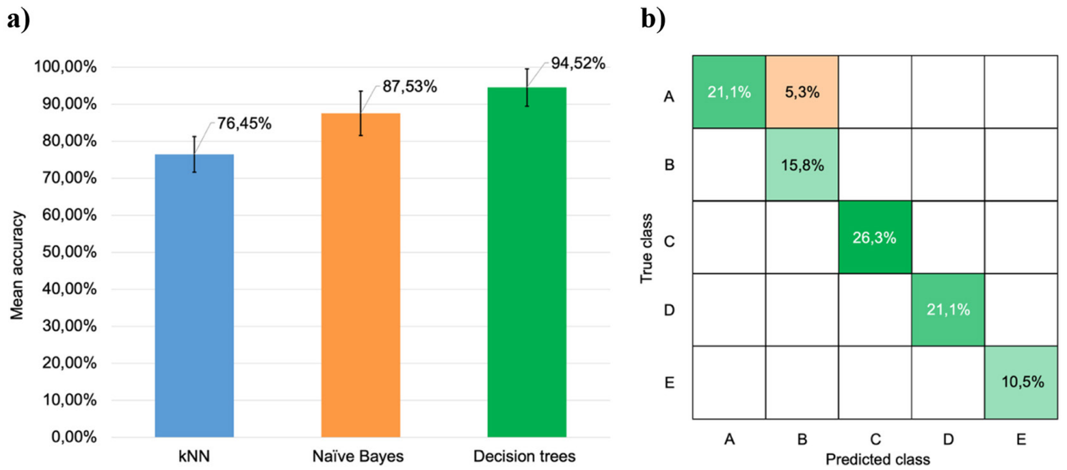

Figure 6. Performance of data-driven classifiers for wear-uniformity prediction: (a) Mean classification across 5-fold cross-validation for the three evaluated models (kNN, Naïve Bayes, Decision Tree); (b) Confusion matrix obtained for the decision-tree classifier

Within the digital twin-driven framework, the trained classifier becomes an embedded predictive block that complements the physics-based simulation in three ways. First, it enables feasibility filtering: candidate parameter sets generated by the twin are rejected if the predicted class indicates insufficient uniformity. Second, it supports quality-aware optimization: among feasible candidates, regimes classified as D–E are prioritized to ensure long-term flatness stability. Third, it allows continuous improvement: after each machining batch, the measured wear profile is appended to the dataset and the classifier is retrained or incrementally updated. This update step systematically reduces prediction bias over time and tightens the feasible process corridor as the plate geometry and slurry conditions evolve. In effect, the data-driven predictor supplies the adaptive intelligence of the planarization digital twin, aligning mechanistic forecasts with real machine behavior and enabling stable parameter selection under industrial variability.

CONCLUSIONS

This paper proposed a digital twin–driven approach for selecting and updating process parameters in planarization technologies, using single-sided lapping and CMP-like kinematics as the main reference domain. The main contribution is a closed-loop framework that connects a structured description of the physical process (tool, abrasive slurry, kinematics, workpiece and machine characteristics) with a coupled digital model on two levels: kinematic simulation of abrasive trajectories and mechanistic or tribological estimation of removal and wear. By exchanging information between these layers, the twin predicts both instantaneous material removal tendencies and the time-evolving wear state of the tool, as well as its impact on workpiece flatness, surface topography and process efficiency. This framework shifts the planarization parameter choice from experience-based trial-and-error to a systematic, model-supported decision process.

The study also underlined the stochastic and multi-factor nature of lapping wear. Only a fraction of abrasive grains becomes active in the contact zone, and their sliding/rolling engagement changes over time due to grain size, shape, fracture and agglomeration effects. These stochastic micro-scale mechanisms translate into macro-scale non-uniformity of plate wear and, consequently, into deviations of tool flatness. The presented kinematic scratch-density modeling provides a practical route to quantify the spatial distribution of contact intensity, which is a primary driver for non-uniform wear. Integrating this information with Preston-type tribological relations yields physically interpretable predictions of wear profiles and removal rate distributions that are directly relevant for planarization quality.

A key result of the paper is the demonstration that physics-based modeling alone, while essential for understanding trends and exploring broad parameter spaces, can underestimate achievable wear uniformity in real processes because of unavoidable simplifications. For this reason, a data-driven predictive layer was embedded into the digital twin and validated on an experimental dataset. The learning task was formulated as a small-sample classification problem through discretization of wear uniformity into ordered quality classes. This strategy improves robustness to measurement sparsity and noise, in addition to aligning directly with industrial decision needs (selection of feasible, stable parameter windows). Among the tested models, decision trees provided the highest and most reliable prediction accuracy, with errors mainly confined to neighboring uniformity classes. Overall, the proposed digital twin driven methodology provides an actionable route toward productivity-quality co-optimization in planarization. It supports fast screening of candidate kinematic settings, identification of high-uniformity operating parameters, and adaptive adjustment as the tool state evolves. The approach is general enough to be transferred to related planarization variants (fixed-abrasive lapping, face grinding with lapping kinematics, CMP), provided that the corresponding kinematic and tribological descriptors are supplied.

Looking forward, several clear pathways exist to expand and strengthen the framework. First, the physical layer can be extended beyond purely kinematic and tribological formulations by introducing more detailed contact mechanics, slurry hydrodynamics and temperature-dependent effects, enabling better prediction of absolute MRR and wear magnitude. Second, richer sensing and metrology (in-situ force, vibration, acoustic emission, temperature and full-field surface topography) would increase the observability of the process and allow the updating loop to operate at higher fidelity and shorter time scales. Third, the data-driven module can evolve from simple classifiers toward physics-informed learning pipelines that embed mechanistic features or constraints, improving generalization when parameters, abrasives or system are changed. Finally, as datasets grow, the twin can incorporate uncertainty quantification and confidence-aware recommendations, which is critical for safe online adaptation in industrial environments.

This work established a unified digital twin architecture for planarization parameter selection that is both physically based and data adaptive. By integrating mechanistic simulation with machine learning, the framework enables systematic optimization of planarization performance and provides a scalable foundation for future autonomous, wear-aware control of lapping and CMP processes.

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