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Abstract—We present a deterministic process-machine interaction (PMI) model that can associate different complex time-frequency patterns, including nonlinear dynamic behaviors that manifest in vibration signals measured during a chemical mechanical planarization (CMP) process for polishing blanket copper wafer surfaces to near-optical finish (R, ∼ 5 nm) to specific process mechanisms. The model captures the effects of the nonuniform structural properties of the polishing pad, pad asperities, and machine kinematics on CMP dynamics using a deterministic 2° of freedom nonlinear differential equation. The model was validated using a Bruel (Antomet 200) bench top CMP machine instrumented with a wireless (Xbee IEEE 802.15.4 RF module) multi-sensor unit that includes a MEMS 3-axis accelerometer (Analog Devices ADXL 335). Extensive experiments suggest that the deterministic PMI model can capture such significant signal patterns as aperiodicity, broadband frequency spectra, and other prominent manifestations of process nonlinearity. Remarkably, the deterministic PMI model was able to explain not just the physical sources of various time-frequency patterns observed in the measured vibration signals, but also their variations with process conditions. The features extracted from experimental vibration data, such as power spectral density over the 115 – 120 Hz band, and nonlinear recurrence measures were statistically significant estimators (R² ∼ 75%) of process parameter settings. The model together with sparse experimental data was able to estimate process drifts resulting from pad wear with high fidelity (R² ∼ 85%). The signal features identified using the PMI model can lead to effective real-time in situ monitoring of wear and anomalies in the CMP process.

Note to Practitioners—The semiconductor industry widely uses chemical mechanical planarization (CMP) process for realizing highly polished planar surfaces on inter-level dielectrics and metallic interconnects in the fabrication of integrated circuits. Accurate and timely detection of incipient process anomalies is critical for quality and yield assurance under emerging wafer density and performance specifications. While MEMS vibration sensors are considered a viable means for monitoring various real-world processes, the complexity of the vibration signal patterns from CMP process impedes their applicability for on-line quality monitoring. We have developed a deterministic process-machine interaction (PMI) model to delineate the physical sources underlying the various complex vibration signal patterns in CMP. Our experimental investigations suggest that the PMI model can capture the salient patterns of the measured vibration signals, and can therefore be effective for detecting process drifts, such as pad wear.

Index Terms—CMP condition monitoring, Cu-CMP, PMI model, vibration sensors, wireless.

I. INTRODUCTION

CMP IS A VITAL back-end-of-line (BEOL) process in semiconductor manufacturing for obtaining both local and global planarity on a variety of materials [1], [2]. CMP is often the last step before device testing and packaging stages [2]. As a consequence, wafer anomalies resulting from CMP operations will lead to excessive yield losses [3]. Advent of copper (Cu) semiconductor interconnects as a viable alternative to tungsten (W) and aluminum (Al) poses additional challenges to yield management. This is because, tantalum (Ta) and tantalum-nitride (TaN) barrier layers designed to prevent diffusion of Cu into the neighboring silicon dioxide (SiO₂) - low k dielectric have low selectivity with respect to Cu, and Cu interconnects are easily damaged during CMP due to their relative softness compared to W and Al [5]. Stringent control of operating conditions is therefore considered essential for defect-free realization in CMP process [1].

Industry predominantly uses off-line statistical process control (SPC) methods by surface characterization of test wafers for process quality assurance in CMP [6]. However, the use of test wafers for process monitoring can lead to ~35% reduction in throughput, and cause as much as 100% increase in cost of ownership [7]. These traditional SPC methods may fail to detect some of the subtle process drifts inherent to CMP [3], [8]–[10]. Consequently, real-time
in-situ sensor-based approaches have been pursued for CMP monitoring [3], [7], [11]–[14].

Contemporary CMP monitoring approaches primarily use piezoelectric vibration and force [15]–[27], acoustic emission (AE) [28]–[33], laser [34], [35], electro-chemical [36], [37], and thermo-optical [38]–[41] sensing elements. Apart from cost, these sensing systems require careful attention to calibration and location. In-situ optical sensing systems for CMP endpoint detection typically need specially designed polishing pads with optical filter windows [11], [35], [39]. Also, the added bulk and high power consumption of these sensing systems limits their applicability to non-intrusive close proximity monitoring. Hence, the majority of these approaches are mostly limited for detection of CMP endpoint as opposed to tracking anomalous process variations [12]. Wireless MEMS sensors have been used towards alleviating this issue [20], [21], [41]. These sensors also facilitate close proximity monitoring of the process.

However, the sensor signals acquired from the CMP process exhibit certain complex time-frequency patterns [19]. For instance, Fig. 1(a) shows a time portrait of a representative signal acquired from a wireless MEMS vibration sensor mounted on our CMP apparatus (See Section V). The signal exhibits a beat-like pattern with prominent periodic low frequency component, superimposed with aperiodic high frequency component. Such inherently complex signals can manifest broadband frequency spectra as seen in Fig. 1(b). Traditional methods use features, such as band limited energies, statistical moments, etc., that quantify the statistical patterns in a signal and not the inherent process dynamics in CMP.

A physical model capable of elucidating the multi-faceted aspects of CMP process dynamics can be used to define features that can track the process, as opposed to the mere signal variations. Existing physical models, however are largely focused on the wafer-pad asperity level mechanics, and explain the material removal regimes dominant at such a scale, such as hydrodynamic, mixed, and direct contact modes [42]–[47]. These models overlook the interaction among mechanics active at different scales, such as bulk pad structure, and machine kinematics. Consequently, the model solutions cannot be associated with complex patterns in the measured vibration signals, and therefore are not suited for process monitoring.

We develop a deterministic process-machine interaction (PMI) model which incorporates the effects of the nonuniform structural properties of the polishing pad and machine kinematics on CMP dynamics at the wafer-pad interface using a deterministic 2° of freedom nonlinear differential equation. The PMI model is used to explain the physical sources of various time-frequency patterns observed in the measured vibration signals, and therefore are not suited for process monitoring. The signal features identified based on the PMI model can track inherent variations in CMP process as opposed to just statistical signal patterns, and thus would lead to effective real-time in-situ monitoring of drifts (wear) and anomalies in CMP process. The remainder of this paper is organized as follows: a review of the relevant literature is provided in Section II, an overview of the research approach is presented in Section III, the proposed process-machine interaction (PMI) model for CMP is described in Section IV, experimental validation of the PMI model in Section V, and the application of the PMI model for condition monitoring in CMP is discussed in Section VI.
in MRR and uniformity characteristics compared to un-stacked pads.

Integration of models capturing pad-asperity effects with those addressing pad structural non-uniformity may be necessary to delineate the physical sources of the spatio-temporal patterns in vibration signals from CMP and thereby facilitate process monitoring.

From the process monitoring viewpoint, prior sensor-based works for CMP process monitoring have used vibration [15]–[18], [22], [24], thermal [38], [40], [61], friction (including AE) [25], [26], [28], [33], and fluid pressure [46], [56] measurements. A common theme in these efforts has been to relate statistical features from the sensor signals, such as vibration amplitude, signal RMS, power spectral density (PSD), etc., with CMP process conditions – typically endpoint and MRR. For example, Carter et al. [16] used a piezoelectric displacement sensor (Micro-epsilon S601–0,5) mounted on the wafer carrier shaft to implicitly measure the drag (friction) force at the wafer-pad interface, together with an infrared (IR) pyrometer (Mikron Infrared MI-N500) to monitor oxide CMP process. They report close to 85% increase in PSD of displacement signals over a broadband 50–900 Hz frequency region as downforce is increased from 14.4 kPa (2 psi) to 42.2 kPa (6 psi), however, the trend is not linear. They also noted continuous bands of active frequencies, and significant interaction among process parameters, which pose challenges for CMP process monitoring. Hetherington et al. [17] mounted piezoelectric accelerometers (Endevco 7259A-500) on a CMP polisher (IPEC-472) spindle head. Using a $2^4 - 1$ fractional factorial design of experiment (DoE) to vary wafer carrier (spindle) speed, platen speed, and downforce for polishing plasma enhanced chemical vapor deposition tetraethyl orthosilicate glass (PE-TOS) coated SiO$_2$ wafers, they noted that vibration signal PSD in the 800–9000 Hz region increases from ~50 dB to ~30 dB as downforce is varied from 2 psi (14.4 kPa) to 10 psi (70 kPa), decreases from ~30 dB at 20 sec of polish to ~60 dB as polishing proceeds beyond 185 sec, and remains unaffected by changes in platen or wafer speed.

Jeong et al.’s [15] multi-sensor monitoring system for CMP uses a tethered piezoelectric force sensor attached to the spindle head, a Hall Effect sensor to monitor the current drawn by the spindle servo motor (as a consequence of polishing load), and an AE sensor attached to the backside of the wafer. These sensors essentially record variations in friction force at the pad-wafer interface due to material layer transitions during polishing. They detected a transition point from copper to tantalum (barrier) layer during CMP, at which point the force signal energy over the 80–100 Hz range increased 8 fold, and AE RMS signals showed a 3 fold increase at the material transition point. The Hall Effect sensor signal was found to be contaminated with extraneous sources, mainly motor impedance, and was therefore reticent in detecting these transitions. Tang et al. [28] mounted AE sensors on two different setups for polishing of spin-on glass, and PE-TOS wafer films. The AE RMS data showed large spikes whenever they induced defects on the wafer by using contaminated slurries (e.g., with 1 μm size diamond particles) and polishing pad having particulate residue. Ganesan et al. [29] used wavelet coefficients of AE RMS signals to track the process drifts, such as delamination defects, within a statistical process control (SPC) framework for CMP of patterned Cu wafers. Park et al. [32] mounted tethered and wireless AE sensors on a CMP apparatus. They conducted experiments in order to compare AE signal characteristics between Cu and oxide CMP process. Due to relative softness of Cu, scratches were observed on Cu deposited wafers when polishing conditions were maintained identical to those for oxide polishing. Consequently, the intensity in the 210–250 kHz frequency range was approximately 3 times greater for Cu-CMP. Chi et al. [27] tracked the residual errors from the Kalman filter predictions of piezoelectric force sensor signals to determine the polishing endpoint based on a predetermined statistical threshold. Allen et al. [62] mounted probes on the polishing platen that concurrently induce and sense eddy currents in the rotating wafer. The polishing endpoint is estimated by correlating eddy current intensity with wafer thickness. Meloni’s [37] endpoint detection method is based on estimating the concentration of reaction species, such as hydroxyl ions, which are typical byproducts of the chemical action in Cu-CMP, by relating the concentration of relevant reaction species with wafer thickness. Kojima et al. [24] used band limited frequencies from piezoelectric vibration sensors signals to detect endpoint in Cu-CMP. They correlated the intensity of vibration signals in the 1.5–4 kHz region with different phases of Cu layer thickness. Yamada et al. [23] used an in-situ dual axes strain gage probe in contact with the polishing pad to detect polishing endpoint in Cu-CMP. Their system is similar to a pin-on-disk tribometer and is designed to detect transitions in pad coefficient of friction. For example, the coefficient of friction decreased gradually with Cu removal (due to deposition of polishing byproducts on the pad) and reached a minimum value (approximately 30%) near the endpoint. A majority of the research in CMP monitoring relies on statistical, as opposed to physically motivated features for correlating sensor data with process conditions and outcomes. A PMI model that can relate the complex signal patterns with process mechanisms can facilitate extraction of signal features that are sensitive to variations in CMP process, and not just to signal patterns.

III. AN OVERVIEW OF THE RESEARCH APPROACH

Our approach to develop and experimentally validate a PMI model of CMP is summarized in Fig. 2. The PMI model combines the mechanics at the pad asperity level [53], [63] with the effects of the bulk pad material [57] and machine kinematics in the form of a deterministic 2$^2$ of freedom nonlinear differential equation model. The model solutions are corroborated with data acquired from experiments. The experiments were conducted on our Buehler CMP machine instrumented with wireless MEMS accelerometers. Process parameters, such as downforce (2 lb. (8.9 N) – 8 lb. (35.6 N)), spindle speed (30 RPM – 60 RPM), and pad condition were varied in these experiments. At each of the experimental conditions the PMI model parameterized with variables identical to the experimental conditions was validated.
using conventional time series techniques and frequency domain analysis [64], as well as, nonlinear invariants such as recurrence quantification measures [65]. Next, the sensitivity of these PMI model-directed features for in-situ monitoring of variations in process parameters (e.g. downforce, speed) and process conditions (here, pad wear) was assessed.

IV. DETERMINISTIC PROCESS-MACHINE INTERACTION (PMI) MODEL FOR CMP

A schematic representation of the CMP process (see Fig. 8(b) for an experimental setup) may be summarized as shown in Fig. 3. A wireless MEMS sensor is used to capture vibration patterns along tangential and normal directions, which are represented by the coordinate directions \( \hat{x} \) and \( \hat{z} \), respectively. Under ideal circumstances, this sensor axes \( \hat{x}\) and \( \hat{z} \) captures the process dynamics and machine axes, the sensor signal patterns acquired along the directions \( \hat{x} \) and \( \hat{z} \) are related to the instantaneous sensor coordinate along \( \hat{x} \) direction as

\[
x = v \sin \phi + \xi \cos \phi
\]  

The coefficient of coulomb friction at the wafer-pad interface (e.g., [66]). The displacements along the machine axes \( (\hat{\xi}, \hat{\nu}) \) are related to the instantaneous sensor coordinate along \( \hat{x} \) direction as

\[
\nu = -p_0 \sin \phi + \xi \cos \phi
\]

The nonlinear functional dependency of normal force \( F_X (\nu) \) on \( \nu \) will become evident from the following paragraphs. Additionally, \( c = 2 \text{ N-s/m} \), \( k = 1000 \text{ N/m} \) represent the (linearized) damping and stiffness coefficients, respectively, and \( m = 30 \text{ N} \) the inertial mass of the lumped mass system. The values of these parameters for our experimental CMP setup were determined via a thorough experimental modal analysis [67].

It may be noted that \( F_X (\nu) \) is expressed as,

\[
F_X (\nu) = P_0 - \dot{p}(\nu) \cdot A_\nu (\nu)
\]  

where \( P_0 \) is the applied downforce, \( \dot{p}(\nu) \) the effective load at the wafer-pad interface, and \( A_\nu (\nu) \) the effective contact area at the wafer-pad interface [53], [63]. The expressions for the dynamic RHS terms \( \dot{p}(\nu) \) and \( A_\nu (\nu) \) are obtained based on consideration of process dynamics at the following scales:

1) Wafer-pad asperity interface mechanics: The polishing action at wafer-pad interface is formulated according to Borucki’s model [53], which is based on the Greenwood and Williamson approach [63]. Unlike previous approaches, we capture the effects of vibrations and bulk pad behavior on the wafer-pad separation distance.

2) Bulk-pad structural dynamics: During polishing the bulk structure of the pad is considered to cyclically compress and relax in response to dynamic load \( \dot{p}(\nu) \). This aspect affects the mean separation \( d_\nu (\nu) \) between the wafer and the pad [49], [53], [68], as well as the effective structure stiffness.

3) Machine kinematic effects: Effects of geometrical inaccuracies of machine elements and eccentricity in spindle motion introduce low frequency cyclic displacements that are assumed to independently superimpose on the vibrations generated due to wafer-pad interface and pad structure effects.
A. Wafer-Pad Asperity Interface Effects

The Greenwood-Williamson (GW) approach [63] is used to compute the real contact area and pressure in wafer-pad asperity models by Luo et al. [42, 48, 52], Qin et al. [54], and Borucki [53]. The model by Borucki [53] is used in this work, since it provides a closed-form solution for obtaining the mean-separation distance between wafer and pad. Essentially the GW model suggests a probabilistic distribution of pad asperities primarily to determine the area of contact at the interface. Most abrasive finishing processes consider such an approach to model uncertainty in the nature of contact [44, 69, 70].

In addition to the assumptions made by the GW model [63], we impose the following conditions: (i) The pad asperity distribution \( \psi(z) \) is stationary Gaussian, and does not change with time – an assumption valid for at most a minute of polishing as shown by Borucki [53]; (ii) the dynamics effects of slurry particles and hydrodynamic pressure distribution due to the slurry film is negligible; (iii) pad deformations are purely elastic. The various constants used in the PMI model are identical to those used by Borucki [53], these are listed in Table I.

The polishing pad (Buehler MicroCloth) used in this work has a porous rayon top layer backed by a pressure sensitive adhesive layer (\(~2~\text{mm thick}\)). With respect to the CMP pads used in industry, such as SUBA and IC series [60]; the pad used in our study resembles the latter since, both MicroCloth and IC series have prominent asperities, and are relatively rigid [53].

The MicroCloth pad is adhesively fixed to a stainless steel bimetallic plate, which in turn is held (magnetically) on the bimetallic plate is considered as contributing to the overall bulk pad dynamics. We found that, applying the IC 1000 pad parameters [53] gives comparatively closer agreement with experimental data.

As the wafer is held down on the pad with an applied downforce \( P_0 \), the downforce and wafer separation distance (ignoring viscoelastic behavior of the pad) is assumed to settle to a nominal distance \( d_0 \) given by [53]

\[
d_0 = \arg \min_{d_0 \geq 0} \left| P_0 - \int_0 \left( z - d \right)^{1/2} \psi(z) \cdot dz \right|, \quad z > v (3a)
\]

The values of \( d_0 \) varied in the range of 35 \( \mu \text{m} \) – 38 \( \mu \text{m} \) as \( P_0 \) is decreased from 8 lb. (35.6 N) to 4 lb. (17.8 N). These values are consistent with literature [68].

As the downforce \( P_0 \) increases the pad stiffness increases. The pad structure parameters chosen were consistent with those of porous pads, such as MicroCloth and IC 1000. We use two sigmoid functions [71] to represent the nonlinear variation of...
Fig. 6. Behavior of the bulk pad material at different load conditions.

Fig. 7. Component representing spindle inaccuracy.

\[ E_{\nu}(\nu) = \begin{cases} 
1800 \text{kN/m} & \text{if } \nu < \sigma_z \\
1000 \text{kN/m} & \text{if } \nu \geq \sigma_z 
\end{cases} \]  

(3b)

where \( \sigma_z \) is the standard deviation of the pad asperity distribution \( \psi(z) \).

This behavior is consistent with observed polishing pad behavior documented by Bastawros et al. [49]. At high \( P_0 \), an increase in \( E_{\nu}(\nu) \) leads to increase in \( \bar{p}(\nu) \) and reduced \( d_0(\nu) \) (Eq. (2b) and (3a)). With the asperities compressed, the effective contact area between the pad and wafer \( A_{\nu}(\nu) \) also increases.

C. Machine Kinematic Effects

As shown in Fig. 7, a small angular error \( \theta \) in the spindle axis translates into additional periodic displacement

\[ x_m = 2r \cdot \tan(\theta) \cdot \sin\left(\frac{2\pi N t}{60}\right) \]  

(4a)

where \( r \) is the distance between the center of the wafer to the spindle axis, and \( N \) is the spindle speed. An inaccuracy \( (\theta=0.018') \) in the vertical plane was determined through extensive experimental studies [67] to be inherent to the system, leading to the low frequency pattern of \( x_m \). The governing equation of the spindle error-induced displacement \( x_m \) is formulated as

\[ x_m = \frac{2r}{}\sin(\theta') \]  

(4b)

Since, the time and length scales over which the effects due to spindle error occur are much larger than those of the asperity-pad induced vibrations, we ignore the effect of small time-scale asperity and pad-induced vibrations on the spindle error-induced displacements \( x_m \).

V. EXPERIMENTAL VALIDATION OF THE PMI MODEL

A Buehler (model Automet 250) metallographic polishing apparatus is instrumented with MEMS vibration (model ADXL 335 tri-axis accelerometer) and sound sensors (model ADMP 401 microphone) from Analog Devices [67]. Signals gathered from the accelerometer were employed for model validation. The accelerometer is capable of measuring vibration between \( \pm 3 \text{g} \), and has a maximum sampling rate of 1600 Hz for each axis. The signals are sampled at \( \sim 685 \text{Hz} \) using a XBee (IEEE 802.15.4 Protocol RF module) unit with an onboard analog to digital converter and transmitted wirelessly to a desktop computer having a coupled XBee receiver unit (see Ref. [67]). We mainly use the signals gathered from the tangential \( (V_X) \) direction (X-Y plane with respect to the rotating spindle) vibration sensor (Fig. 8). The sensors are placed within an aluminum enclosure affixed to the backend of the wafer. The entire wireless sensing platform rotates with a wafer carrier, as shown in Fig. 8(a and b) and therefore travels through the error in the spindle head.

Cylindrical copper (free-machining C14500 series) discs (wafers) of diameter 40.6250 mm \( \pm 0.1 \text{mm} \) (1.625 in.), and thickness \( \sim 12.5 \text{mm} \pm 2 \text{mm} \) (0.5 in.) are polished on this apparatus [72]. This particular copper series is 99.5\% pure with tellurium (Te) as an alloying element. Te improves the machinability rating of copper but limits the surface finish that can be achieved. Scratch free, near-optical finish with Ra \( \sim 5 \text{nm} \) is reported in this work (Fig. 8(c) and (d)). Experiments were conducted in accordance by varying downforce between 2 lb. (8.9 N) and 8 lb. (35.6 N), with spindle speed in the range of 30 RPM – 60 RPM, and platen speed fixed at 150 RPM.

We used a KOH-based alkaline colloidal silica slurry supplied by Eminess Technologies (Ultra-Sol S17, particle size 70 nm, 10 pH) with slurry flow rate maintained constant at 20 ml/min. Typical CMP operations were conducted for duration of 9 min. in three stages each lasting 3 min.
Since, the initial surface roughness of the blanket copper wafers can significantly affect the acquired CMP vibration signal patterns, the wafers used for CMP experimental studies were first lapped to a surface finish in the range of $R_a \sim 12.5 \text{ nm} \pm 2.5 \text{ nm}$. By tightly controlling the initial wafer surface roughness we ensure that the vibration signal patterns are consistent across experimental replicates. The wafer surface is therefore considerably smoother than the pad surface and thereby satisfies one of the key assumptions of the GW Hertzian contact formulation [63] (Eqs. 2(a–c)). Consequently, the vibrations resulting from the wafer surface morphology can be considered to be of negligible concern and dominated by vibrations from the padasperities and bulk-pad structure.

A. Examination of Time Portraits

We compared the time portraits of vibration signals obtained from experimental tests and the PMI model. Fig. 9(a) shows a 6-sec long vibration signal, gathered at $685 \text{ Hz}$ sampling rate from CMP tests conducted at 2 lb. (8.9 N) downforce and 150 RPM (0.5 Hz) spindle speed. We note a characteristic low frequency pattern occurring every 2 sec. This period corresponds to the spindle head speed. This low frequency pattern is replicated in the simulated vibration signal shown in Fig. 9(b). From these time portraits we also note that the high amplitude segments last for $\sim 1.25 \text{ sec}$.

B. Frequency Domain Analysis of Vibration Signals

Evident in Fig. 1(b) are four major frequency bands. The signal content in the 0.5 Hz – 1 Hz range is likely a result of spindle shaft eccentricity. The two broadband frequency regions centered around 25 Hz and 50 Hz are found to be a conjoined effect from sensor ambient characteristics, electromagnetic interference from machine elements, and extraneous vibration from the machine structure. The fourth, observed in the vicinity of 120 Hz was found to be sensitive to applied vibration from the machine structure. The fourth, observed in the vicinity of 120 Hz was found to be sensitive to applied vibration from the machine structure. The high-amplitude portion lasting for $\sim 1.25 \text{ sec}$.

Next, the effect of varying downforce on the frequency characteristics of the vibration signals was studied. Representative

![Image](https://via.placeholder.com/150)

**Fig. 9.** Representative time portraits of: (a) experimental and (b) simulated vibration signals for CMP process. (a) 6-sec long experimental vibration signal for CMP tests conducted at 2 lb. (8.9 N) and 30 RPM (0.5 Hz) spindle speed. (b) The corresponding simulated vibration time series, showing presence of low frequency pattern occurring at 2-sec intervals, and high amplitude portion lasting for $\sim 1.25 \text{ sec}$.

![Image](https://via.placeholder.com/150)

**Fig. 10.** Here the CMP tests were conducted under two different downforce conditions; 2 lb. (8.9 N, low downforce) and 8 lb. (35.6 N, high downforce). The spindle (head) and platen speed were maintained at 60 RPM and 150 RPM, respectively. We observe a 50% increase in the energy in the 115 Hz – 120 Hz region when downforce is increased from 2 lb. (8.9 N) to 8 lb. (35.6 N). These tests were replicated 9 times for each downforce setting, and a statistically significant increase in spectral energy content of (sum of squares of FFT magnitudes) 115 Hz – 120 Hz region with increasing downforce was observed.

![Image](https://via.placeholder.com/150)

**Fig. 11.** Time-frequency portraits of experimental and simulated vibration signals are shown in Fig. 10. Here the CMP tests were conducted under two different downforce conditions: 2 lb. (8.9 N, low downforce) and 8 lb. (35.6 N, high downforce). The spindle (head) and platen speed were maintained at 60 RPM and 150 RPM, respectively. We observe a 50% increase in the energy in the 115 Hz – 120 Hz region when downforce is increased from 2 lb. (8.9 N) to 8 lb. (35.6 N). These tests were replicated 9 times for each downforce setting, and a statistically significant increase in spectral energy content of (sum of squares of FFT magnitudes) 115 Hz – 120 Hz region with increasing downforce was observed.

![Image](https://via.placeholder.com/150)

**Fig. 11(b) and (d) show corresponding FFTs for simulation conditions imitating low (2 lb., 8.9 N), and high downforce (8 lb., 35.6 N) at 60 RPM spindle speed conditions. The model vibration data is in close agreement with the experimental data for the 115 Hz–120 Hz frequency region.**

**Table II**

<table>
<thead>
<tr>
<th>Quantifier</th>
<th>Simulated signal</th>
<th>Experimental signal</th>
</tr>
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| Spectral energy of 115 Hz – 120 Hz region for low downforce (2 lb., (8.9 N)) vs. high downforce conditions (8 lb., (35.6 N)) | Difference in (mean: 20.7%)| Difference in (mean: 54.5%)
| $p$-val: < 0.001                        | $p$-val: < 0.001 |
| Regression $R^2$                        | 92.22%           | 78.24%              |
| 91.73% (adj.)                          | 76.43% (adj.)    |

The observed increase in spectral energy, i.e., sum of squares of FFT magnitudes, is statistically corroborated using ANOVA (Table II). We used a non-overlapping moving window of length 3 sec to gather spectral energy values from simulated and experimental signals, $\sim 30 \text{ sec}$ of data each representing low (2 lb. (8.9 N)) and high (8 lb. (35.6 N)) downforce conditions were analyzed (since there are 3 replicates, we have a total of 30 measurements for each condition). As shown in Table II, there is a significant difference in spectral energy contained in the 115 Hz–120 Hz frequency band of both experimental as well as model-derived vibrations signals at the two downforce levels analyzed. The ANOVA regression $R^2$ (adj.) values are close to 75% for experimental, and 90% for the simulated cases.

C. Time-Frequency Analysis

Fig. 11 compares the time-frequency spectrogram portraits of the experimental (Fig. 11(a)) and simulated (Fig. 11(b)) vibration signals. These plots were obtained by taking a short-time Fourier transform (STFT) of the time portrait with
Fig. 10. Representative frequency domain fast Fourier transform (FFT) portraits of: (a) experimental, and (b) and (d) simulated vibration signals for CMP process obtained under different downforce conditions (spindle speed identical, at 60 RPM; i.e., 1 Hz). (a) FFT portrait of a 180 sec long experimental vibration signal (685 Hz sampling rate) for CMP tests conducted at 2 lb. (8.9 N) downforce and 60 RPM (1 Hz) spindle speed, showing the different characteristic regions. Inset shows the 0–2 Hz region zoomed in, with peaks corresponding to spindle speed (1 Hz). (b) The corresponding simulated vibration time series, showing presence of low frequency peaks (inset) as in (a), and 115 Hz–120 Hz region prominently replicated. (c) FFT portrait of a ∼180 sec long experimental vibration signal for CMP tests conducted at 8 lb. (35.6 N) downforce and 30 RPM (0.5 Hz) spindle speed. 115 Hz–120 Hz region shows an increase of ∼50% compared to (a). (d) Simulated vibration signal corresponding to (c) 115 Hz–120 Hz region shows an increase of ∼40% compared to (b).

Fig. 11. Representative time-frequency domain analysis – spectrogram portraits of: (a) experimental, and (b) simulated vibration signals for CMP process obtained under identical conditions (2 lb. (8.9 N) downforce, spindle speed 30 RPM, i.e., 0.5 Hz). (a) Spectrogram of a 30 sec long experimental vibration signal (685 Hz sampling rate) for CMP showing two distinct regions: (i) high energy portions corresponding to high amplitude sections in the overlaid time series (marked in black), and (ii) low energy portions corresponding to the low amplitude sections of the time series (marked in green). (b) The corresponding simulated vibration time series, showing similar characteristics.

an overlapping moving window of length 0.5 sec (345 data points), with an overlap of 0.0125 sec (8 data points). The time-evolution is shown along the abscissa, while the frequency in Hz is plotted along the ordinate axis. The highest magnitude portions of the STFT are colored red, and the lowest magnitude portions take a dark blue hue. Thus, the spectrogram plot allows for visualization of the signal in both time and frequency domains.

For spectrogram plot of a vibration signal obtained from CMP tests at 2 lb. (8.9 N) downforce, 150 RPM platen speed, and 30 RPM spindle speed (Fig. 11(a)), two distinct regions can be discerned: (i) region marked in black corresponds to the high amplitude portions of the time series, and (ii) region marked in green, corresponds to the low amplitude portions. We notice that, the high amplitude portions (dark red hue) appear at every 2 sec intervals corresponding to the spindle speed and last for ∼1.25 sec (Fig. 9(a)). One also notes the prominent presence of significant signal components in 25, 50 Hz and 120 Hz bands, along with another component in 240 Hz region. The spectrogram for the equivalent simulated vibration signal is shown in Fig. 11(b). Comparison between the experimental and simulated vibration signals attests to the ability of the model in capturing the CMP process dynamics, both in the time and frequency domains.

We compare the length of the low amplitude portions of the time series for different downforce conditions – 2 lb. (8.9 N) and 8 lb. (35.6 N). Visual examination of the 120 Hz region of the spectrograms plotted indicated that the length of the low amplitude region is shorter for the high downforce case. The interval lengths were determined based on a statistical clustering methods to segment signals based on dynamic behavior [73]. Here, we used a recurrent Dirichlet classifier [74] to estimate the duration of the low amplitude portions. Time duration information corresponding to the low amplitude portions is extracted for low (2 lb. (8.9 N)) and high downforce (8 lb. (35.6 N)) conditions (thirty measurements for each condition) from simulated as well as experimental data. The ANOVA results are summarized in Table III. We note a statistically significant difference in the length of the low amplitude portion between low and high downforce conditions, with mean difference of 10.78% for the model vs. 16.31% for experimental data.

D. Comparison of Nonlinear Dynamic Quantifiers

Next, we compared certain topological properties, such as recurrence [65] and space-time separation characteristics [64] of the state-space of the dynamics derived from experimental data vs. the PMI model. Application of a battery of tests suggested that the model correctly captures the dimensionality (m = 4) of the CMP process state space [75], [76]. The acquired vibration time series were embedded in a four dimensional state-space using a delay reconstruction procedure [64], [77]. The Euclidean distance of each data point in the reconstructed state space with every other data point is evaluated
(b) High magnitude patterns are also contaminated with noise, mostly emerging from 25, 50 Hz frequency regions.
(a) High magnitude patterns are high magnitude in time domain (i.e., high Euclidean distance in state-space). At 685 Hz sampling rate, the yellow to red hues are considered as regions of notice the recurrent periodic behavior for the 0.95 fraction (top line), cyan) where the distance between successive periods is ∼ 4 time steps in state-space. Similar corroborating patterns can be discerned for fraction size down to 0.60. Each of the eight lines uses a specific fraction between 0.60 and 0.95 with a step increment of 0.05. The bottom most line (cyan), has a fraction specified at 0.60, while the second (yellow) has 0.65, and so on. In our case, comparison of the space-time separation plots for experimental (Fig. 13a), and simulated (Fig. 13b) vibration patterns, shows a close corroboration at various specified fractions. For example, we notice the recurrent periodic behavior for the 0.95 fraction (top most line, cyan) where the distance between successive periods is ∼ 4 time steps in state-space. Similar corroborating patterns can be discerned for fraction size down to 0.75 (5th line from top, black line).

Next, we quantitatively compared the characteristics of the experimental and simulated vibration signal dynamics using features obtained from the recurrence plot [65]. Consider the un-thresholded recurrence plot shown in Fig. 12, the Euclidian distance measured from these plots is now converted into a matrix of ones and zeros applying a Heaviside step function, i.e., if the Euclidean measurement is greater than a set fraction it is assigned a value 1, and 0 otherwise. The appropriate threshold (neighborhood size) is selected based on the space-time separation plot (Fig. 13). We selected a fraction of 0.75 (fifth line from top, black line), and note the corresponding average neighborhood size (ε) around the point at which a specified density of measure (roughly the specified fraction of points in the state space) is reached. In other words, we evaluate the size ε of the Euclidean ball, required to accommodate a fixed percentage of points in the state-space.

For example, consider a representative space-time separation plot in Fig. 13a), obtained from a CMP experiment conducted at low downforce (2 lb. (8.9 N)) and 60 RPM spindle speed. There are eight prominent lines in the plot, each of the eight lines uses a specific fraction between 0.60 and 0.95 with a step increment of 0.05. The bottom most line (cyan), has a fraction specified at 0.60, while the second (yellow) has 0.65, and so on. In our case, comparison of the space-time separation plots for experimental (Fig. 13(a)), and simulated (Fig. 13(b)) vibration patterns, shows a close corroboration at various specified fractions. For example, we notice the recurrent periodic behavior for the 0.95 fraction (top most line, cyan) where the distance between successive periods is ∼ 4 time steps in state-space. Similar corroborating patterns can be discerned for fraction size down to 0.75 (5th line from top, black line).

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The appropriate threshold (neighborhood size) is selected based on the space-time separation plot (Fig. 13). We selected a fraction of 0.75 (fifth line from top, black line), and note the corresponding average neighborhood size (ε, along the ordinate axis) for both cases. For the experimental case the neighborhood size, ε = 0.03, and for simulation ε = 0.04 are selected. These neighborhood sizes are used as the thresholding for the Heaviside step function.

A number of recurrence quantifiers were extracted from the thresholded recurrence plot as suggested by Marwan et al. [65]. First, ∼ 7.25 sec long (5000 data points) non-overlapping sliding window is applied to the vibration signals obtained from both experiment and simulations. Recurrence measures were then extracted for each window. We
VI. CONDITION MONITORING OF CMP USING PMI MODEL

The developed PMI model was shown to capture some of the salient dynamics of the CMP process. We now illustrate the application of the PMI model for condition monitoring applications in CMP. Apart from using spectral features, we used various recurrence measures gathered from the signal, as discussed in Section V (Table IV) to monitor the following three types of variations in CMP process:

(i) downforce is varied from 2 lb. (8.9 N) to 8 lb. (35.6 N),
(ii) polishing pad gradually deteriorates, and glazed portions become apparent, and
(iii) both downforce and pad condition vary.

A. Effect of Varying Downforce

We used experimental and simulated vibration data for two downforce conditions, 2 lb. (8.9 N, low downforce), and 8 lb. (35.6 N, high downforce). For each downforce condition 9 data sets, each representing 3 sec of vibration signals (30 sec total) are considered. From these data sets, 16 different quantifiers including 14 recurrence measures, spectral energy content in 115 Hz – 120 Hz range, and duration of low amplitude portions (see Section V) were used as candidate features.

First, a best subset regression analysis was conducted to determine the subset of these quantifiers which can differenti ate between varying downforce conditions. Then, conventional linear regression models are constructed with the selected candidate features (identified from the best subset regression step) regressed on downforce (dependent variable). We can thereby identify the common parsimonious feature set capable of explaining the process variation (due to varying downforce) for experimental and simulated signals.

The regression results are briefly summarized in Table V. Compared to cases where only the signal spectral and time features were used (Table II and Table III of Section V), a significant improvement in predictability on using recurrence-based features is observed. Furthermore, the simulated signals seem to capture over 95% (R²) of the process variation, and can provide a means to anticipate process anomalies.

B. Effect of pad wear

The effect of pad wear has been experimentally studied by Bajaj et al. [57]. They observed the evolution of morphology of polyurethane polishing pads to explain the decay in material removal rate with polishing over time. They observed blockage of pad pores in worn pads which subsequently hinders slurry flow to wafer-pad interface. Byrne et al. [78] observed that the polishing pad undergoes thinning overtime, with a worn pad being ∼ 10% thinner than a fresh pad. They also note that, while worn IC 1000 pads are more compliant than a fresh pad with the elastic modulus decreasing by ∼ 13%, the pad hardness (shore D) for worn pad is nearly 3% higher.

Lu et al. [79] observed significant changes in surface roughness, pore geometry and spectral properties of the polishing pad due to wear. In comparison to a fresh pad, the average surface roughness (Rₐ) of worn pads decreased to ∼ 6.5 μm from ∼ 8.5 μm, the pore geometry became more elongated along the direction of rotation with use, and worn pads showed almost two fold increase in infrared absorbance magnitude.

Models proposed by Wang et al. [43], [44] and Borucki [53] incorporated the gradual degradation observed in the pad asperity distribution (mean and standard deviation of asperity heights decrease) to explain the decay in removal rate with time. The degradation of the pad asperity distribution affects the wafer-pad separation distance (d₀) in Eq. (3a). For worn pads, d₀ reduces in comparison to fresh pads. Borucki [53] estimated a decrease of close to 2 μm and 8 μm in d₀ after 8 min. and 45 min. of polish, respectively.

Lapped copper wafers (Rₐ ∼ 10 nm – 15 nm) were polished on the CMP setup in 3 min. intervals with silica slurry. The polishing conditions were as follows: platen speed 250 RPM, head speed 60 RPM, and downforce 4 lb. (17.83 N) The platen speed is deliberately increased to this high value in order to accelerate pad wear. Such high platen speed is not advisable for long runs, since we observed a significant vibration of the machine rests and workbench. These extraneous vibrations manifested in a dominant peak at around 75 Hz in the frequency spectrum (Fig. 15).

After 3 min. of CMP the average wafer Rₐ improved to nearly 7 nm. Subsequently, pad wear was accelerated by soaking the pad in slurry for 45 min., followed by drying in air. By soaking and subsequent drying of the pad, the silica particles in the slurry tend to crystallize in the gaps between the asperities (pad glazing) [57]. This constrains the flow of slurry at the wafer pad interface, and deprives the wafer of adequate slurry. Secondly, by employing high relative velocity the hardened asperities (due to pad glazing) are easily sheared off (pad wear). As a consequence, we observed sheared pad material residue in the slurry reservoir.

The CMP process is carried out in 4 stages of 3 min. each with the pad soaked and dried in the interim. After the end of 12 min. of CMP, significant glazing of the polishing pad is observed (Fig. 14(a)). In the same interval, prominent scratches were seen on the wafer (Fig. 14(b)), and Rₐ increased to approx. 22 nm. The FFT of the tangential direction (Vₓ)
vibration sensor obtained after 3 min., and at the end of 12 min. (when glazing of pad is observed) are compared in Fig. 15(a) and (b) respectively. The magnitude in the 115 Hz - 120 Hz region increases by nearly 30–40% at the end of 12 min. (Fig. 15(b)) of CMP, indicating the effect of pad deterioration on vibration data.

To emulate the effect of pad wear in the PMI model, the static separation distance \(d_0\) (in Eq. (3a)) was reduced by 10% from \(\sim 36 \mu m\) for the unused pad to \(\sim 33 \mu m\) for a moderately worn pad case [53], [78]. The results from the simulation are shown in Fig. 16. We note an increase of 20–30% in magnitude of FFT for the worn pad case (Fig. 16(b)) compared to fresh pad (Fig. 16(a)).

Next, we proceeded to construct a linear regression model for data sets representing experimental, as well as, simulated vibration patterns. The experimental vibration patterns obtained from the first 3 min. of CMP represent the fresh pad case, whereas the signals obtained between 9 to 12 min. was chosen to represent the worn pad case. For each of the two representative data sets, we extracted 9 non-overlapping segments each measuring 20 sec. As in the previous case, we computed 16 different quantifiers for each of these segments. Similar steps were taken with simulated vibration patterns from the PMI model.

We then combined the simulated and experimental data sets in order to compensate for the sparseness of available experimental data (see for example, Ref. [80]). Thus, we have 36 different data points representing fresh and worn pad cases (18 data points each). We used integer indicator variables (1 and 2 for fresh pad vs. worn pad case, respectively) to differentiate between pad conditions. Similar to the previous case, we extracted 8 non-overlapping segments from each condition, giving a total of 32 (= 8 \times 4) data points. We then computed the candidate features for each segment. Thereafter, the simulated and experimental data sets were combined (64 total data sets) and the candidate features regressed on integer coded process states. Five features, as listed in Table VI, are found to be significant, with \(R^2\) in the vicinity of 88%. We also note that, the set
of statistically significant features identified from regression analysis for each of the three cases illustrated in this section are largely unique (Table V – Table VII). This uniqueness of feature sets sensitive to different types of anomalies mitigates the possibility of confounding. For example, while spectral energy in 120Hz range undergoes similar variation with increase in downforce as well as pad wear, the recurrence feature lomlarity is found to be significant for the pad wear case (Section VI-B), but not a relevant predictor of downforce (Section VI-A). In other words, based on the behavior of different features sets, a robust inference can be made regarding the type of anomaly.

Furthermore, by using the vibration patterns from the PMI model different types of anomalous conditions can be simulated offline. Consequently, the statistical feature set indicating the onset of such anomalies can be anticipated apriori from the simulated data. Therefore, instead of merely tracking a fixed set of statistical features, some of which may not necessarily be sensitive to process variations; the PMI model can be used as a means to select the most cogent features based on understanding the process dynamics.

Table VII: Regression analysis combining both simulated and experimental data

<table>
<thead>
<tr>
<th>Factor</th>
<th>Statistical significance (p-val)</th>
<th>Regression R² (adj.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral energy of 115 Hz – 120 Hz region</td>
<td>0.019</td>
<td>88.8%</td>
</tr>
<tr>
<td>Recurrence rate</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Meso diagonal fret length</td>
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<td></td>
</tr>
<tr>
<td>Divergence</td>
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<td></td>
</tr>
<tr>
<td>Trapping time</td>
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<td></td>
</tr>
<tr>
<td>Regression R²</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

VII. CONCLUSIONS

We have forwarded a deterministic multi-scale process-machine interaction (PMI) model of CMP in the form of a 2° freedom differential equation, which in combination with experimentally acquired vibration signals can help identify onset of process anomalies.

Specific contributions of this work are as follows:

1) A deterministic 2° of freedom nonlinear differential equation process-machine interaction (PMI) model for CMP was formulated encompassing the responses at three different levels, namely: (i) pad-asperity, (ii) bulk pad structure, and (iii) machine kinematics levels. The model was validated on a CMP apparatus instrumented with multi-channel wireless vibration sensors. Despite being deterministic, the PMI model simulated vibration patterns closely emulated ($R^2 \sim 90\%$ for some cases) the signals obtained from CMP tests. Remarkably, apart from capturing the spectral aspects of the measured vibration signals, the PMI model solutions was also able to replicate complex time-frequency and nonlinear topographical aspects of experimentally acquired vibration signals.

2) The PMI model solutions were used off-line to simulate different types of process drifts. The resulting simulated signal patterns were analyzed apriori for identifying the appropriate statistical feature set responsive to process variations. The features so extracted are closely related to physical changes in the process as opposed to mere signal statistics. Consequently, signal features identified based on PMI simulated signal patterns were observed to capture the process variation and resulting anomalies with $R^2$ in the range of 80 - 90%.

3) The PMI model solutions, due to their close dynamic similarity with measured vibration signals, can augment the sparse experimental data typical to CMP. For example, in case of process defects such as pad wear, availability of prior observations can be rare or at best evanescent. Under such conditions, the features extracted from the PMI simulated signals can be used as surrogates to experimental data.

It may also be noted that for reasons of tractability, the CMP experiments in this work were conducted on blanket copper (dia. 40.625 mm, thickness 12.5 mm) wafers, whereas the wafers used in industry are both significantly larger and thinner (dia. 300 mm, thickness <1 mm), and composed of multi-material phases. The effect of these different wafer dimensions on the vibration signal patterns may be non-negligible. For example, we have observed that the raw magnitude of vibration signals in the 115 – 120Hz region is close to 60–70% lower when 25 mm (1 in.) dia. copper wafers were used for preliminary tests. With larger diameter wafers used in industry, we contend that the vibration signal patterns will be dependent on the radial location of the sensors. In order to isolate and thereby model the effect of sensor location, several sensors can be mounted at different radial locations on the wafer carrier in close proximity to the substrate. We are currently investigating Bayesian-based analytical approaches for data fusion from multiple sensors.

Also, since industry uses a multi-step CMP approach for copper interconnects, it is reasonable to anticipate a change in the vibration signal patterns as the process evolves from blanket copper removal phase to copper clearing and barrier removal stages. It is therefore expected that additional experimental efforts may be necessary towards extending the concepts presented in this work to an industrial semiconductor production scenario.

These practical challenges notwithstanding, we contend that the overall approach of modeling the various multi-scale PMI phenomena in CMP and subsequently integrating the model with observed signal patterns, as presented in this work, can be valuable from a quality assurance perspective.

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DEDICATION

The authors dedicate this article to the fond memory of Dr. Ranga Komanduri (1942–2011), a scholar and a mentor whose presence would be deeply missed.

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Sanjay Byalal Photograph and biography not available at the time of publication.

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