ID issm.2008.hideki.matsuhashi.pdf.solutions.final

BEOL parametric variation control with FDC data

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FDC data from inline sensors can be used to better control PCM variation using multivariate modeling. However, identifying which FDC sensor contributes most to PCM variability has been challenging since individual process equipment has hundreds of sensors, and the total number of sensors over the production line can be tens of thousands or more. In this paper, we demonstrate PCM variability control with multivariate modeling in a 65 nm mass production line using centralized FDC data management system [1, 2].

Fig.1 shows the work flow for the multivariate modeling demonstrated on via resistance (Rc) in via chain structures. Via resistance of Rc in via chain structure in product chip is used as the response variable across 2000 wafers. Sensor data relevant to Rc is collected from CVD, PVD, CMP, etch and litho equipment, and centralized at database using mæstria® CPCE, which allows tracking FDC data by wafer identification. The term “sensor” includes preventive maintenance records such as wafer count or process duration as well as physical sensors. The indicators were computed using mæstria® PCB for each sensor as inputs for multivariate modeling. The indicators were calculated for 2000 wafers. 7161 total sensors across all the equipment were included. The total number of indicators defined is 64,530. Using those indicators as input, multivariate modeling is performed to identify key indicators.

Via Rc varies from 2-15% over the period of observation which suggests an opportunity for improving variation control as shown Fig.2. Multiple via layers show similar trend over the time indicating common root cause of the variation. Figure 3 shows correlation between Rc and top dominant indicators which are identified by multivariate modeling algorithm out of 64,530 indicators, showing RF reflected power in plasma source of Ta deposition chamber and the duration time of TaN/Ta deposition are dominating the Rc variability. Fig 3(a) shows the strong non-linear behavior of via Rc vs RF power and is captured by our non-linear multivariate model. At lower values of RF power, via Rc begins to increase rapidly. Physically, those finding are reasonable because TaN and Ta at the via bottom dominates Rc since its resistivity is much higher than that of Cu, and low reflected power indicates high forward power into the deposition chamber that increase Ta deposition rate, which ends up thicker Ta, i.e. higher Rc. Figures 3 (b) and (c) show the correlation between via Rc and duration time for Ta and TaN deposition, respectively. The duration time and Rc are positively correlated as longer duration time can be translated to thicker Ta/TaN, which leads to high Rc and vice versa. The duration time for both Ta and TaN deposition dominates long term baseline variation as shown in Fig.2, since it shows positive liner correlation over the whole data scope.

To simulate impact of those key indicators on Rc variability, a multivariate model for Rc prediction has been built using the top dominant indicators. Fig.4 shows that the predicted Rc correlates well with measured Rc. Using this multivariate model of Rc, response of Rc was simulated from pseudo-indicators of multiple degrees of variation for RF reflected power and duration time for Ta/TaN deposition. Fig.5 shows the simulation result of Rc variation reduction from the reduction of variation from the top indicators. For example reducing the variability of RF reflected power can result in 20% improvement in Rc variation indicating immediate opportunity of variability reduction by optimizing reflected power while Ta/TaN deposition time variation don’t contribute variation reduction.

In summary, PCM variation control assessment is demonstrated using multivariate modeling to prioritize sensor level optimization. This is enabled by a centralized FDC data management infrastructure coupled with a process knowledge database and sensitive test chip that measures the response value.

References

[1] Mike W. at al. Proceedings AEC/APC 2007, US session

[2] Hideki M. at al. submitted to AEC/APC 2008, US session

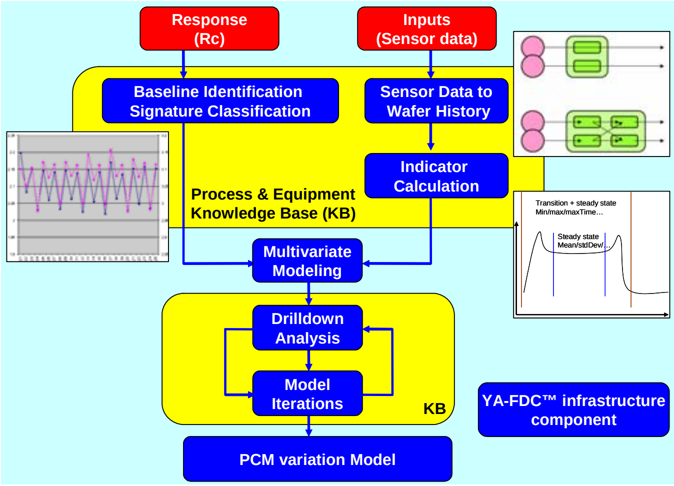

Fig.1 work flow for the multivariate modeling with YA-FDC™ infrastructure

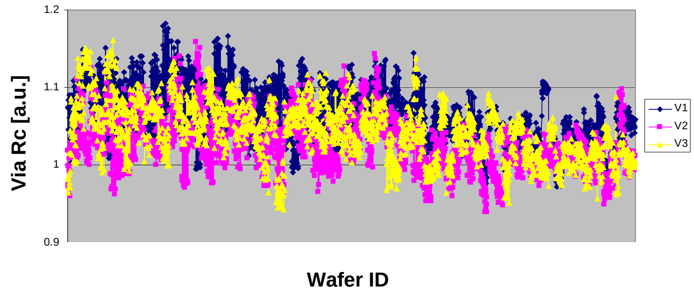

Fig.2 Via Rc trend

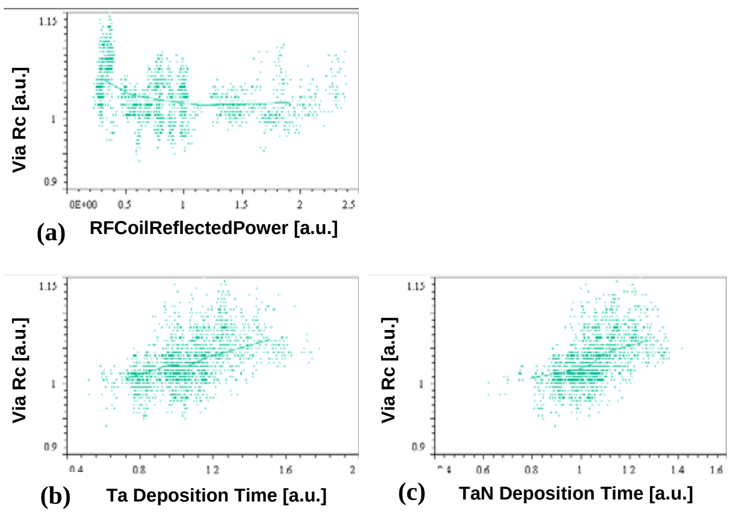

Fig.3 Correlation between Rc and top dominant indicators identified by multivariate modeling algorithm

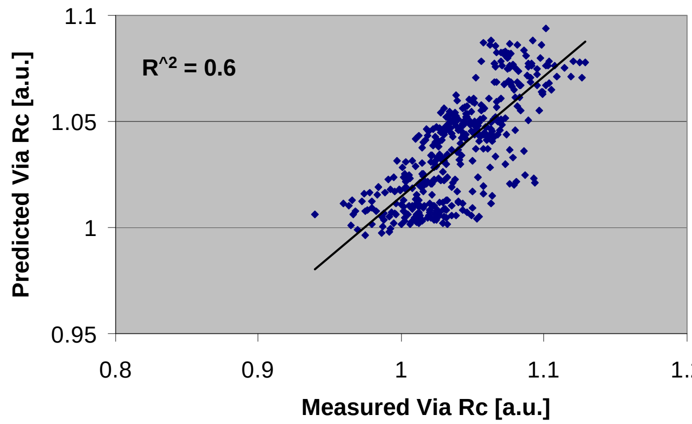

Fig.4. Correlation between predicted Rc from sensor data and measured Rc

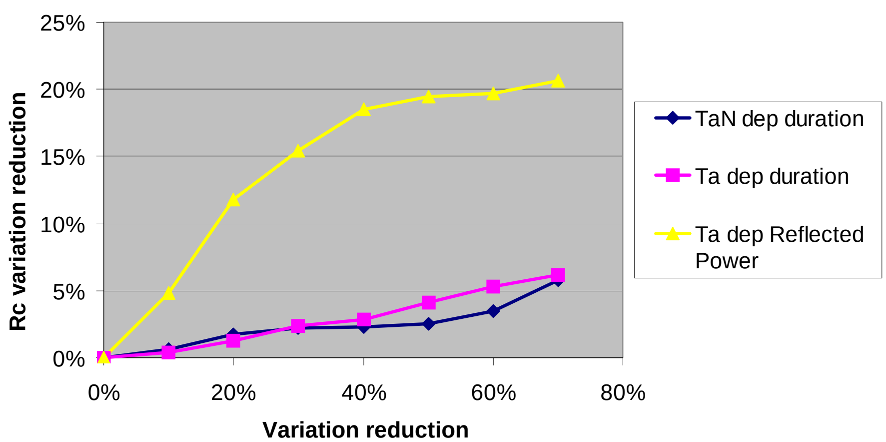

Fig.5 of Rc variation reduction from the top indicators with multiple level variations