9th International Conference on

Power Electronics for Plasma Engineering

May 14 – 17, 2018, Freiburg, Germany

Conference Proceedings

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CONFERENCE PAPERS

1. **Advanced materials enabled by plasma technologies**
   Prof. Dr. B. Szyszka, Technical University Berlin, DE
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   Dr. R. Korn, Singulus Technologies AG, DE
3. **Analysis of ICP plasma processes for crystalline silicon solar cell surface passivation**
   M. Hofmann, Fraunhofer Institute for solar Energy systems ISE, DE
4. **Hardware functionality driven PVD process optimization: a dual-output pulsed-DC plasma source utilization in CIGS photovoltaic cell production**
   P. Lesiuk, TRUMPF Huettinger, PL
5. **Efficiency and yield enhancing optical monitoring system for inline coaters**
   W. De Bosscher, Soleras, BE
6. **Simulation study on input power effects in magnetron discharges**
   M. Siemers, Fraunhofer Institute for Surface Engineering and Thin Films IST, DE
7. **Basic study on ZrO_x rotatable sputtering – target development**
   C. Simon, Materion, DE
8. **Success factors in ZrO_x target MF sputtering**
   Dr. M. Heintze, TRUMPF Hüttinger, DE
9. **Large area industrial PVD coatings**
   Dr. A. Kharchenko, Saint Gobain Recherche, FR
10. **Understanding crazing effect in large area coating – criticl factors and mitigation methods**
    Dr. W. Gajewski, TRUMPF Huettinger, PL
11. **HIPIMS-Deposited Nanoscale Multilayer Coatings to Improve the Quality of Friction Stir Welds in Aluminium Alloys**
    Prof. A. Ehiasarian, Sheffield Hallam University
12. **Challenges of HIPIMS for directional deposition**
    Dr. J. Weichart, Evatec AG, CH
13. **A comprehensive tutorial for successful HiPIMS application in mass production.**
    Dr. A. W. Oniszczuk, TRUMPF Huettinger, PL
14. **Recent progress in pulse magnetron sputtering at Fraunhofer FEP**
    Dr. M. Fahland, Fraunhofer Institute for Organic Electronics, Electron Beam and Plasma Technology FEP, DE
15. **Next generation of power supplies for plasma diffusion treatment**
    Dr. P. Kästner, Fraunhofer Institute for Surface Engineering and Thin Films IST, DE
16. **Multiple plasma source synchronization for improved process optimization: a Ti-Cr-based anticorrosion coating case study**
    K. Ruda, TRUMPF Huettinger, PL
17. **E-beam evaporation for packaging and security applications**
    R. Trassl, Applied Materials, DE

18. **Ultra-Clean and High Performance Substrates for Plasma Treatment technologies**
    V. von Morgen, DuPont Teijin Fims, UK
19. **Laser based rapid thermal processing**
    J. Wieduwilt, TRUMPF Laser, DE
20. **Defects and doping in oxides: case of doped TiO_2 films**
    Dr. N. Laidani, Fondazione Bruno Kessler, IT
21. **The road to predictability for industrial plasma coating: data-based process and up-time optimization**
    Dr. I. Luciu, TRUMPF Hüttinger, DE
22. **Silicon layers for application in lithium ion batteries**
    Dr. A. Georg, Fraunhofer Institute for Solar Energy Systems ISE, DE
23. **A Renewed Strategy for the EU Electronics Industry; Enhancing Europe's Position as Global Leader in the Digital Economy**
    E. Demircan, Semi Europa, BE
24. **"Dr. Production" and Predictive Maintenance: Lessons learned from Semiconductor Manufacturing**
    Dr. -Ing. M. Schellenberger, Fraunhofer Institute for Integrated Systems and Device Technology IISB, DE
25. **Gallium nitride power devices for MHz-switching applications**
    Dr. -Ing. R. Reiner, Fraunhofer Institute for Applied Solid State Physics
26. **Design for reliability and availability challenges in the development of plasma processing power supply**
    J. Kałowski, TRUMPF Huettinger, Poland
27. **RF Plasma enhanced method for the applications in modern semiconductor structures and devices**
    Prof. R. Mroczyński, Warsaw University of Technology, PL
28. **Controlled reactive HiPIMS – effective technique for low – temperature deposition of functional oxide films**
    Prof. J. Vlcek, University of West Bohemia, CZ
29. **High Voltage (HV) technology for ion energy management: current status and development trends**
    Dr. P. Ozimek, TRUMPF Huettinger, PL
30. **RhySearch - the new research and innovation center in the heart of the Alpine Rhine Valley - applied research in optical coating and precision manufacturing**
    Dr. R. Quaderer, RhySearch, CH
31. **Efficient PECVD chamber cleaning with F_2-based chemistry**
    R. Wieland, Fraunhofer Research Institution for Microsystems and Solid State Technologies EMFT, DE
32. **Requirements for modern semiconductor PECVD/ Etch applications**
    Dr. D. Krausse, TRUMPF Hüttinger, DE
33. **Multi frequency plasma systems for etch applications**
    W. Głazek, TRUMPF Huettinger, PL
34. **How small solution provider can help to improve your bottom line**
    P. Quaderer, SPM, DE
35. **Synthesis of electrochromic thin films by reactive co-sputtering**
    O.Kappertz, Fraunhofer Institute for Surface Engineering and Thin Films IST, DE

"DR. PRODUCTION®" AND PREDICTIVE MAINTENANCE: LESSONS LEARNED FROM SEMICONDUCTOR MANUFACTURING

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ABSTRACT

The semiconductor industry is a strong pacesetter in many technological areas - last but not least in "Industry 4.0"-related topics such as advanced data collection, data analytics and the use of data-driven production optimization. In this paper, an exemplary overview about both existing and evolving approaches for data-driven production optimization is given, with focus on predictive maintenance and other predictive analytics solutions. This overview is combined with the discussion of cost estimation for such implementations. A specific focus is set on how to quickly implement latest research results in the domain of "Industry 4.0" into complex production environments by utilizing the novel development and implementation approach of "Dr. Production®".

INTRODUCTION

The application of APC (Advanced Process Control) is state-of-the-art in all semiconductor production lines. Yet, the race towards broader and deeper utilization of data in a "smart factory" is going on, striving towards predictive analytics and implementation of machine learning, e.g., in the areas of predictive maintenance or prediction of process and machine behavior.

Thus, there is an ongoing need to implement latest research results on data analytics and "Industry 4.0" into production lines - and this affects not only current 300 mm fabs, but also 200 mm lines. Moreover, it affects not only the so-called frontend-of-line, but also the backend. APC-solutions are wide-spread and developing technically from the application of statistical process control, fault detection, fault classification and run-to-run control to the use of big data solutions for predictive analytics and machine learning. This progress from information-related to optimization-related data analysis is in-line with the four evolving areas of data analytics as defined by Gartner (see Fig. 1).

In order to quickly transfer latest research results from these domains into complex production environments, we created the new development and implementation approach "Dr. Production®". With this structured approach, lessons learnt from state-of-the-art R&D projects can be transferred and re-used in a quick manner. The current focus is on predictive analytics implementations and related economic aspects.

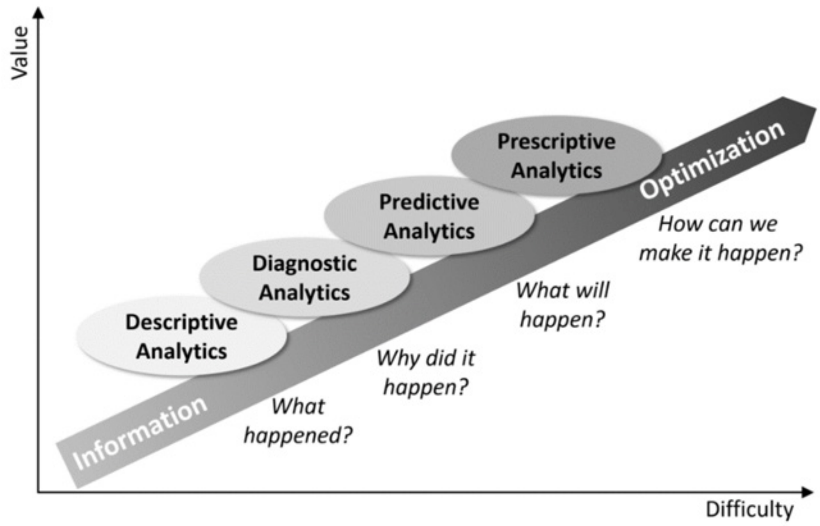

Fig. 1. Four areas of data analytics, as defined by Gartner (adopted from gartner.com)

DR. PRODUCTION®

Since the 1990's, a focused team at the Fraunhofer Institute for Integrated Systems and Device Technology IISB develops APC solutions aiming at data-driven production optimization, equipment and process optimization and yield enhancement. In order to make the lessons learnt from more than 20 R&D projects and the algorithms developed in more than 25 prototype implementations available in a structured manner, we created Dr. Production®, which was developed from an intrapreneurship activity within Fraunhofer.

Dr. Production® offers a holistic solution consisting of three consecutive, manageable modules (see Fig. 2):

1. Individual consulting and conception: The aim of this module is to clearly identify expected benefits (technical, quantitative and qualitative) and to elaborate a tailored approach towards data-driven production optimization. This includes the clarification of necessary prerequisites for realization, e.g., regarding data availability and data quality.
2. Analysis of production process and data collection: Within this core module, the respective production process is carefully analyzed and data is collected. For successful data analysis, the combination of data science with system overview and technological understanding is inevitable.
3. Development of intelligent algorithms: Finally, a prototype implementation of an algorithm is developed, based on the correlations identified in the second step.

   Steps two and three benefit most from Dr. Production's® pool of proven data analytics solutions and machine learning algorithms. A lean data framework , which was derived from a generic framework developed with industry partners [1] fosters the prototype implementation.

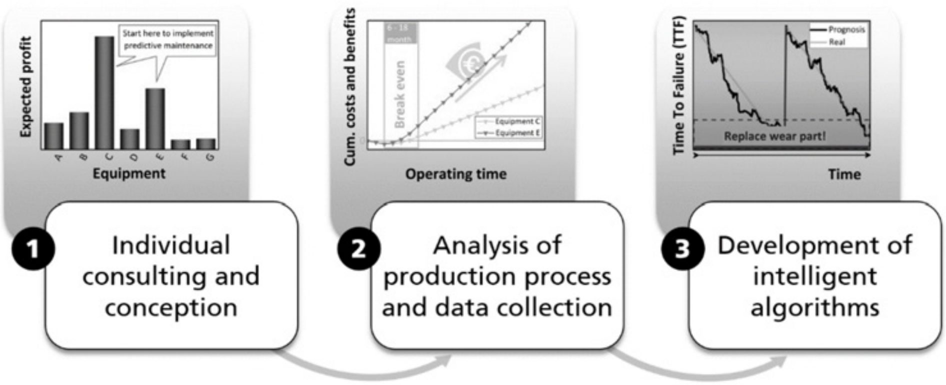

Fig. 2. Dr. Production®: a structured approach to quickly implement latest R&D results in complex production environments.

The benefits of this new development and implementation approach within R&D projects, for partners and customers are manifold:

- Expertise, concrete algorithms and lessons learned are collected and pooled in a structured manner – not only with regard to technological aspects, but also in areas like organization and collaboration.
- The pooled knowhow can be re-used and transferred to related application fields in semiconductor manufacturing, but also to other industries, and taking into account the needs of SMEs.
- This builds the bridge from latest research to application-oriented, tailored and fast research and development.

PREDICTIVE MAINTENANCE AND BEYOND

In semiconductor manufacturing, the implementation of advanced process control solutions has become essential for cost effective manufacturing at high product quality. Among the most prominent APC solutions are predictive maintenance and related solutions based on predictive analytics.

In the following sections, selected examples of predictive analytics solutions will be discussed that either contributed to Dr. Production® or benefited from its development and implementation approach. Since the examples are not elaborated to the last technical detail, reference to more detailed related publications is given where applicable.

1. Predictive Maintenance

A significant part of the operational costs in a semiconductor manufacturing plant is related to the frequent need for maintenance of the manufacturing equipment, which causes unscheduled downtime, scrap production and logistic challenges. In addition to random equipment failures, some of these maintenance necessities emerge periodically due to wear and tear of certain parts. The length of such a periodic maintenance interval is not always constant, due to the influence of actual processing conditions, as well as random factors, e.g. the quality of the spare parts used and of the maintenance actions.

To prevent unscheduled downtime and scrap production, today’s most common maintenance strategy (Preventive Maintenance, PM) aims for the time-based replacement of spare parts at an early stage, so as to prevent sudden equipment failures. This strategy results in additional, early maintenance actions, and therefore causes unnecessary non-productive downtime and increased spare-part consumption. For better equipment and spare-part utilization, Predictive Maintenance (PdM) aims for predicting the exact point in time when the system will fail. Utilizing, e.g., multivariate statistical learning methods, these PdM predictions aim at achieving improved maintenance planning and at preventing unscheduled equipment downtime, waste of spare parts, and scrap production.

As an example, in close collaboration with an IC manufacturer, we created PdM models for prediction of the filament breakdown in ion-implanter sources, taking electrical parameters as basis for calculation [2]. Fig. 3 shows the “time-to-breakdown” curves (real and predicted) for two maintenance cycles. As a modeling method, Bayesian Networks regression was selected, resulting in a good average prediction error and thereby permitting an optimized maintenance planning.

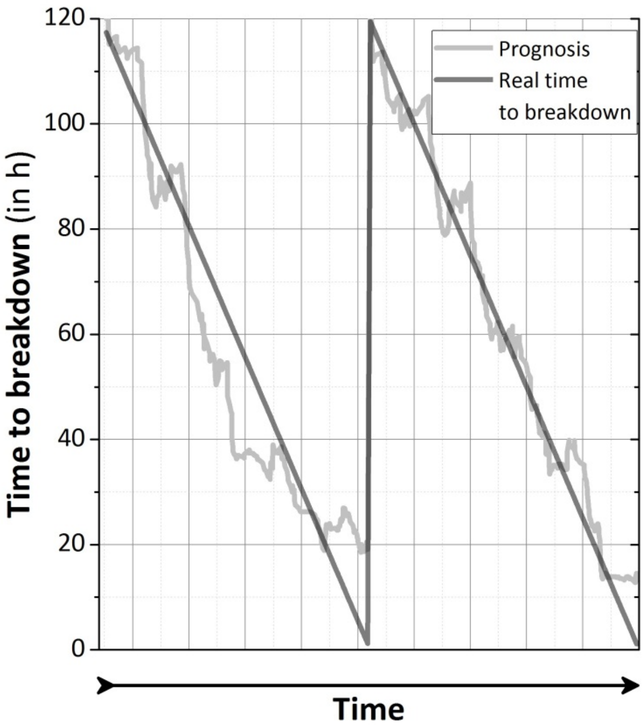

Fig. 3. Observed and predicted “time-to-breakdown” curve, representing the degradation of two ion source filaments.

2. Virtual Metrology

While predictive maintenance has the manufacturing equipment in focus, virtual metrology (VM) is targeted to the manufactured product: With VM, post-process quality parameters are predicted from process and wafer state information. Just as PdM, VM is often based on statistical learning methods, and a large variety of potentially applicable algorithms is available. A key challenge of the virtual metrology application is proving its capability to produce precise predictions even in complex semiconductor manufacturing processes.

We assessed the applicability of virtual metrology for a complex dry etch process which is conducted on different chambers, for different products, and for two levels of etch depth. Stochastic gradient boosting tree models were applied for algorithm development, and the application of ensembles of trees, including update strategies, were investigated [3]. Even in this complex process scenario, precise VM predictions together with the provision of reliance indicators are achievable (see Fig. 4). As result, time-consuming physical depth measurements, that are done at a fraction of processed wafers only, can now be amended by valid VM predictions for every single wafer.

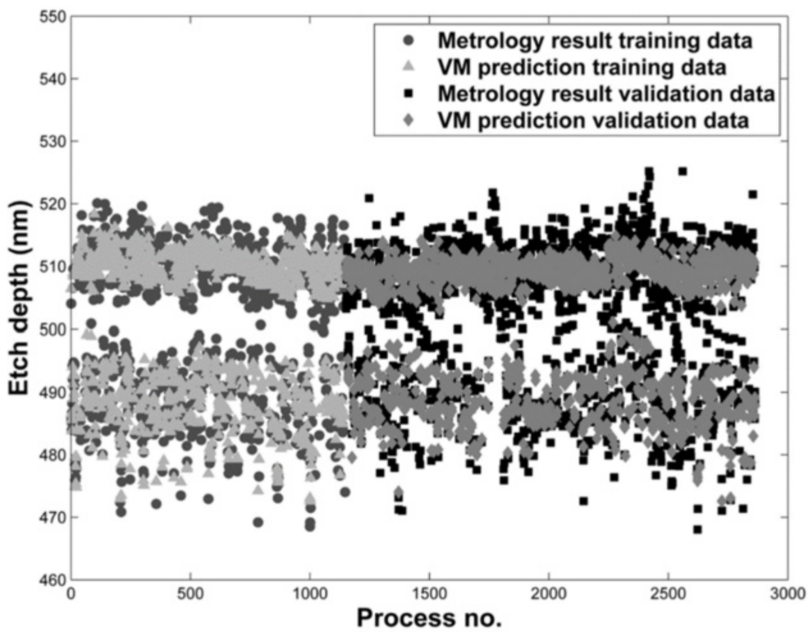

Fig. 4. Comparison of VM predictions versus the metrology reference data for the case that the model is updated after every incoming case with metrology data and the prediction is performed on the next predictor data set.

3. Prediction of Mechanical Setup Conditions

In the example of PdM for the filament of an ion implanter discussed before, the condition of the filament was obviously related to electrical parameters that could be measured at the filament. Yet, in many cases, the status of equipment parts cannot be monitored, because there is no direct or evident correlation to equipment parameters. This is especially the case for mechanical settings performed by an operator.

In joint research with an industry partner, we demonstrated that scheduled mechanical interventions on wire-bonding equipment can severely affect bonding quality and equipment health in semiconductor mass production. Typical faults in mechanical setup for example include weak clamping due to undefined torque of the associated screws.

A systematic big data analysis of potential correlations between mechanical setup states and available equipment parameters revealed that by utilizing a total of 6 equipment parameters, the actual condition of the mechanical setup could be predicted with an average accuracy of 92 % [4]. Fig. 5 illustrates a part of this correlation between the setup conditions "weak/strong clamping" and the equipment parameters "current" and "deformation".

While up to now mechanical setup conditions could only be controlled outside the operating time, the novel data-based algorithm enables inline control for every single bonding event. This enhanced control of the mechanical setup conditions, otherwise being strongly affected by the responsible equipment operators, improves bonding quality, equipment health and process stability.

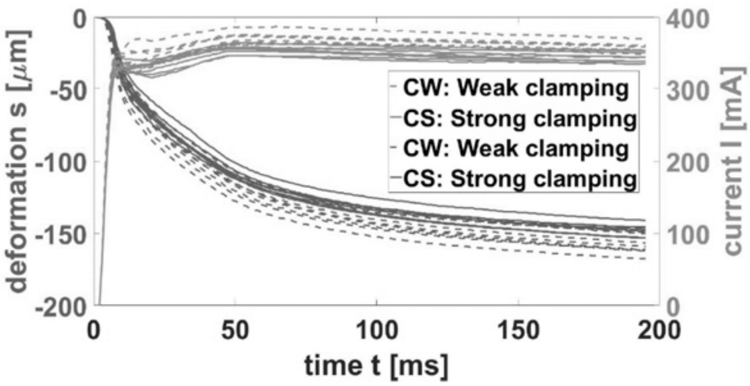

Fig. 5. Deformation (left axis) and generator current (right axis) traces of the mechanical setup states, weak clamping (CW, dashed lines) and strong (CS, solid lines) clamping.

4. <u>Predictive Probing</u>

The prediction methods discussed so far were targeted on the manufacturing equipment or the product properties after a certain production step. Beyond that, the application of sophisticated test procedures during final test guarantees high quality of the final product. E.g., in LED manufacturing, high effort is spent to probe every single LED chip: in dedicated probing equipment, ultra-thin needles are used to contact an LED and measure its brightness, color and electrical properties. With thousands of LED chips to be tested per wafer, this is a time-consuming and expensive step.

In order to save both, testing time and cost, we developed the novel approach of "predictive probing" to measure just a certain fraction of LED chips on a wafer but still get optical and electrical parameters from all LEDs (see Fig. 6). Predictive probing relies on long-term and short-term historic data: a basic identification of to-be-probed chips is derived from historic probing data from different wafers and products, revealing typical areas of uncertainty on a wafer. This basic identification is amended by utilizing measurement data collected during the processing of the very wafer that is ready for probing. Among those upstream metrology data are particle measurements, ultrasonic measurements or photoluminescence measurements. The results from the reduced set of probed LED chips are finally used to also calculate the optical and electrical characteristics of the non-measured ones.

Finally, it was possible to omit the measurement of 93% LED chips on a wafer and still predict the brightness, color and electrical parameters of all LEDs – with an accuracy that fulfils the specification of the manufacturing partner.

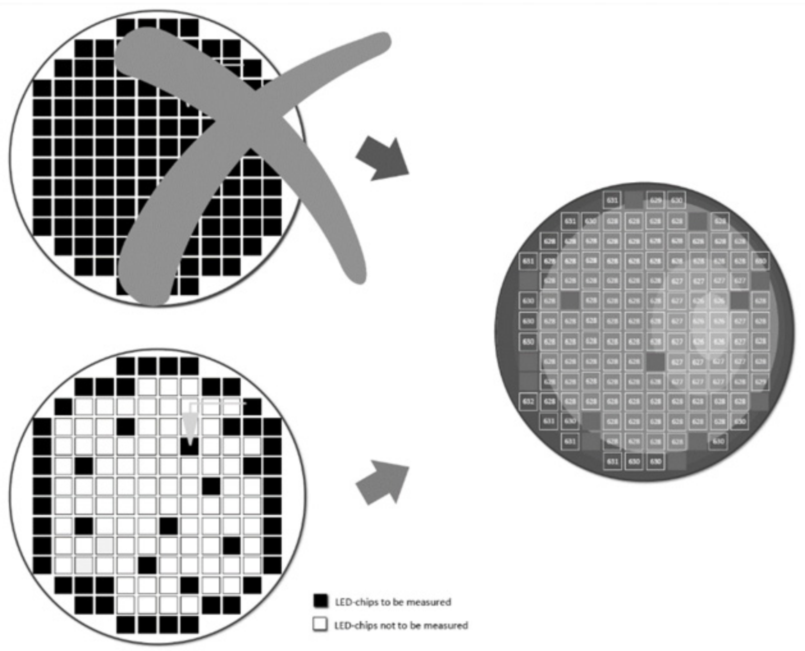

Fig. 6. The concept of predictive probing: Identify those LED chips that have to be probed in order to reconstruct the optical and electrical parameters also from those LED chips that were not probed.

ECONOMIC ASPECTS OF PREDICTIVE MAINTENANCE SOLUTIONS

So far, technological aspects of predictive analytics were discussed. However, for application of respective solutions in an industrial environment, it is inevitable to also consider economic aspects.

Since process tools in semiconductor facilities represent a huge amount of capital expenditure, it is essential to maximize the use of these assets and to minimize maintenance cost. The implementation of PdM yields the following effects:
- Reduction of maintenance costs due to focusing on inevitable maintenance actions and optimized timing of the work.
- Increased equipment utilization due to less time reserved for maintenance.
- Reduction of yield losses, scrap wafers and rework due to reduced equipment failures.
- As a negative, new risks are added by the fact that maintenance predictions may be incorrect. Those risks include, e.g., uptime loss and decreased device yield.

Together with leading European semiconductor manufacturers, we developed a PdM-related cost model to quantify these effects [5]. The model compares costs to benefits and calculates investment assessment figures such as payback period, return on investment and net present value. Fig. 7 shows the economic benefits due to the implementation of PdM at various equipment types. It was found that the potential savings of maintenance costs is an important contributor to the overall benefits. Reduction of scrap wafers is very important for batch equipment (e.g., furnaces). For most equipment types, the benefits outweigh the costs, reaching the break-even within 24 months or less.

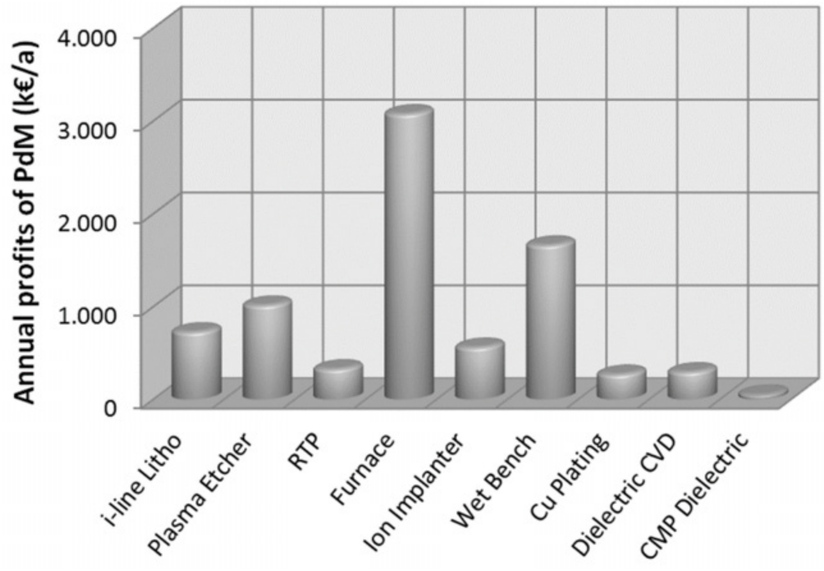

Fig. 7. The profit of implementing predictive maintenance is greatly depending on the target equipment (here: analysis in semiconductor manufacturing).

CONCLUSIONS

We shared and discussed examples for the application of predictive analytics in semiconductor manufacturing. Beyond the technical achievements and benefits, a cross-cut analysis revealed the following lessons-learned:

- Collaboration is key: Data analytics comprises a field of high complexity and makes collaboration with universities, institutes and even competitors a must.
- Technology understanding is inevitable: In complex production environments, it is not sufficient to only take care of statistics and analytics – it must be linked to equipment and technology knowledge.
- Standards are of high importance: This includes technical standards, such as communication standards, but also process-oriented standards such as CRISP-DM (Cross-industry standard process for data mining [6]).
- Data quality is often underestimated: Reliable data analytics and intelligent algorithms rely on quality input data.
- Implementation is to be planned carefully: It is a good approach to start with single process optimizations and to go for low-hanging fruits first. However, it is important to keep the overall "automation picture" in mind and to avoid island-solutions.

We also showed that starting from “classic” predictive maintenance, the structured development and implementation approach “Dr. Production®” facilitates the evolvement towards the application of related predictive analytics in the areas of virtual metrology, the prediction of mechanical setup conditions and predictive probing.

The general concepts discussed here can be transferred to other areas in semiconductor manufacturing, but also to other industries with complex production sites.

ACKNOWLEDGMENTS

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REFERENCES

[1] Schellenberger M. et al. (2011, October). Developing a Framework for Virtual Metrology and Predictive Maintenance. *Future Fab International, Issue 39.*

[2] Schöpka U. et al. (2013, May). Practical aspects of virtual metrology and predictive maintenance model development and optimization. *Advanced Semiconductor Manufacturing Conference (ASMC).*

[3] Roeder, G. et al. (2014, August). Feasibility Evaluation of Virtual Metrology for the Example of a Trench Etch Process. *IEEE Transactions on Semiconductor Manufacturing 27(3):327-334.*

[4] Klingert F. et al. (2017, May). Condition-based maintenance of mechanical setup in aluminum wire bonding equipment by data mining. 28*th* *Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC).*

[5] Koitzsch M. et al. (2012, September). A calculation model for the economic effects of implementing predictive maintenance algorithms into semiconductor fabrication lines. *Advanced Process Control Conference (APC), Ann Arbor, MI, USA.*

[6] Shearer C. (2000). The CRISP-DM model: the new blueprint for data mining. *J Data Warehousing (2000); 5:13—22*