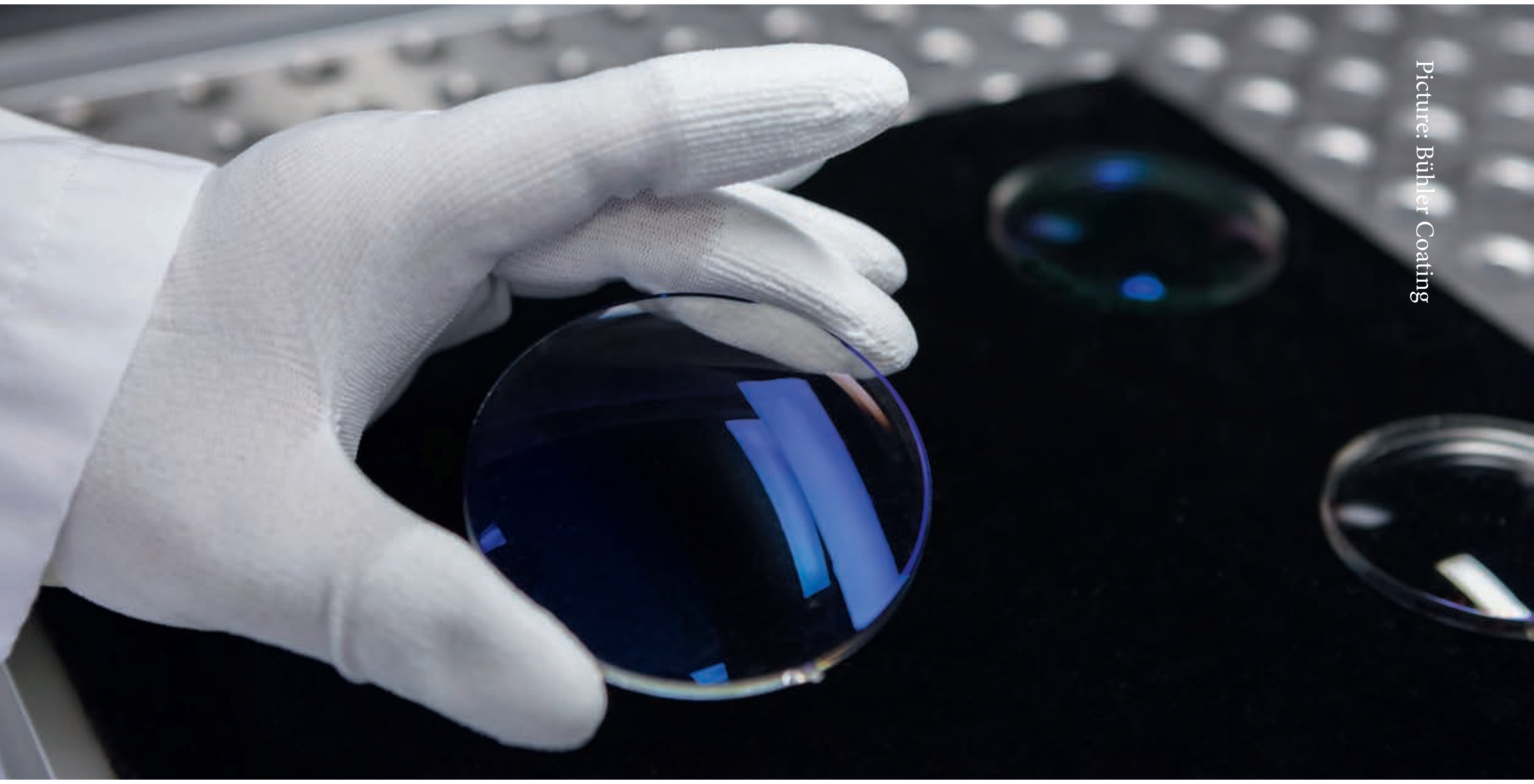


Picture: Bühler Coating

Anti-reflex coating and process control

Gaining control of process parameters by digital means. An approach to reduce scrap and rework.

International competition fuels manufacturing cost reduction, where scrap and rework land an immediate impact. Savings along this line of attack need dedicated process improvement, which in turn requires detailed knowledge of process parameters and their effects on a successful process result. Complex process chains, like anti-reflex (AR) coating, with their extremely large number of influencing parameters pose a considerable challenge for process engineering. By successively introducing tools of digitalization, and by merging them with deep process understanding, engineering will be enabled to take proactive measures before scrap or rework actually happen. A cooperative project of an equipment supplier, a lens manufacturer, and a university research group reached exciting results on the road to digitalization. *By Peter Weber*

To stand their ground in the harsh environment of international competition, manufacturers of ophthalmic lenses need to increase their efficiency continuously. Material procurement costs on the one hand and labor costs on the other are the main drivers to directly reduce production costs. Being successful there leaves a company in the comfortable situation to choose: increase margin, or increase competitiveness (by reducing selling prices).

Manufacturing costs reduction

On a first glimpse the approach via procurement of costs reduction seems to be a low hanging fruit: put some pressure onto your suppliers and harvest annual cost reductions. Still, to accomplish this without getting trapped in quality issues, a considerable investment into a straight supply-chain management organization is essential.

Especially for technologically driven companies a promising parallel approach is the deep-dive into one’s own processes. Increasing the efficiency of manufacturing processes will directly reduce production costs. In industrialized economies the key figure of efficiency is, for good reason, output per laborer. This means that via smart investment in automation, digitalization, and process quality, companies will reduce labor costs and subsequently reduce overall production costs.

Effect of scrap and rework on cost

Talking about process quality inevitably leads to scrap and rework. The good message about scrap and rework is: if reduced, it directly reduces both labor costs as well as procurement costs. And thus, it directly reduces overall production costs, i.e. better margin or competitiveness.

Any part that gets scrapped, already contains raw material to be scrapped. And any such part has gone through a considerable section of the process chain already, having piled up labor and machine costs. The effect of rework often is even more dramatic, as there is not only additional labor and machine time to be wasted. Even more, the unscheduled effort severely disturbs the regular production flow, creating work overload at the workplaces as well as in job preparation and shop-floor scheduling.

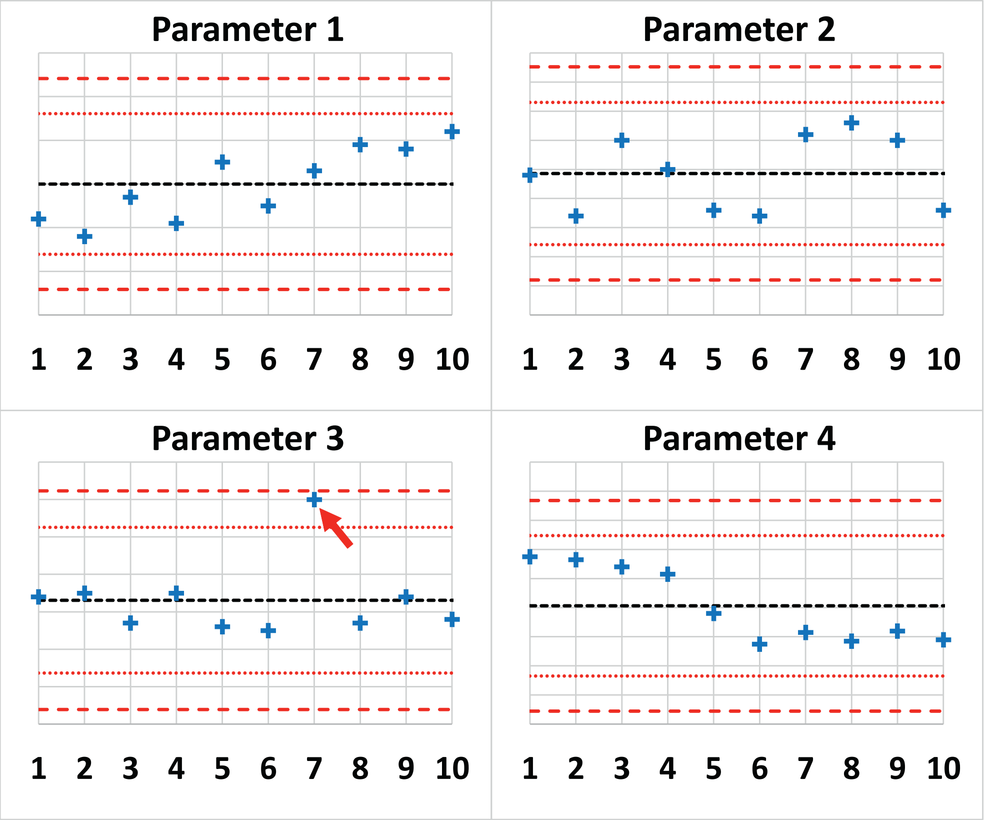


Fig. 1: *Control charts of four exemplary process control parameters for 10 batches. The black dotted line denotes the average, the red dotted lines mark the warning and control limits respectively of each parameter. In our thought experiment batch 7 is out of specification. The control-chart approach obviously helps to locate root causes. Adjust parameter 3 in the future and prevent this scrap/rework event to reoccur.*

Control charts – be proactive

There is one obvious and yet sometimes omitted fact: just by detecting scrap and rework, it is not prevented or reduced. To accomplish that, one needs to identify root causes. Here comes into play what you all know as control charts. The tracking of all those parameters along the process chain, which may influence the final product quality. Tracking these process control parameters makes it possible to correlate fluctuations of certain control parameters to scrap or rework.

Look at the example in figure 1: You see four control charts, each representing one crucial control parameter of a particular process for the last 10 batches. It turns out in final inspection, that part number 7 was not in specification, i.e. scrap. The process engineer could now easily grasp at a glance that the deviation of process parameter 3 might well correlate to the out-of-spec situation of part 7.

Now, the process engineer does not only know that part number 7 needs to be scrapped. He can localize the problem, with a certain probability, on process parameter 3 and take measures. By such experience, as well as by statistical means, warning limits for the control parameters are defined and continuously adjusted.

Practically this means, that a process engineer (or in best case even the operator) is regularly keeping an eye on the control charts and takes measures, whenever one of the parameters is violating an upper or lower warning limit.

In the example of figure 1 there might also be anticipated an issue with parameter 1, as it seems to have a tendency upwards, maybe violating the upper warning limit in a few batches. With sensibly chosen warning limits, the process engineer can already proactively adjust processes before any scrap or rework actually is produced.

Systematic process control needs effort

Now, in a real industrial environment with complex process chains, one deals with an enormous amount of possibly relevant control parameters. This is the bitter pill to swallow: effort is needed, to make as many of the crucial parameters measurable and accessible to a digital database as possible.

While there is no (or few) process data available (because no data acquisition is in place yet) no digital system can help at that point. An overall process parameter analysis has to be carried out by means of deep process-engineering know-how, to judge which of the parameters actually are relevant, and how to measure and acquire them digitally.

The less manual steps there are along a process chain and the higher the degree of automation is, the less effort it takes to acquire the data. Nowadays machines usually come with a set of integrated sensors and interfaces, to digitally get access to process and machine data. For older machines and manual process steps the effort is gradually higher.

Benefits in ophthalmic lens production

The process chain of eyeglass production spreads over the full range from basic manual to fully automated work steps. Subsequently, it is a considerable challenge to cover it completely with digital data acquisition.

Particularly the anti-reflex coating process features a blend of manual and automated process steps. Within a systematic approach, the first focus is put on the automated part of the process: coating in the vacuum-coating machine. A state-of-the-art vacuum coater measures, collects, and provides a wide range of digital machine and process data, which are, in principle, easily to be accessed for process control.

Dr. Stephan Küper of Bühler Leybold Optics, provider of vacuum coaters for ophthalmic industries, confirms the potential behind the coating process in terms of digital data acquisition. His project team has pushed this topic considerably in the last two years. In cooperation with the research group for Industrial Data Science (INDAS) at Frankfurt University of Applied Sciences, and optoVision, manufacturer of ophthalmic lenses, a big step forward was made in terms of systematic acquisition, presentation, and evaluation of process data.

Although it is well known that the flanking manual processes cause the larger part of scrap and rework, there is big potential in further stabilizing the coating process itself. There are advanced types of coating where process stability still is a challenge. And generally, for the benefit of matching lenses from different batches (with respect to color of residual reflex), better process control is highly desirable.

Anti-reflex coating of ophthalmic lenses

Anti-reflex coatings are a major feature of any ophthalmic lens. At an interface between two optical media (air, lens) back-reflection occurs. For an untreated standard glass roughly 4% of the incident light is reflected. Front as well as back side interface suffer from the effect, so you end up with losing a total of 8% of intensity. This holds for a "classical glass" with a refractive index of typically 1.5. To design thinner lenses, material with a refractive index of up to 1.8 is used. You buy this advantage at the expense of transmission. At each interface of these high-index materials you lose 8% of light intensity. In total only 84% of the incident light would reach the eye. With a good anti-reflex coating a transmission of up to 99.5% can be accomplished.

Thus, for practical as well as cosmetic reasons, an anti-reflex coating is standard for ophthalmic lenses. The wearer of the glasses gets a clearer vision and a better contrast. In communication with other people there are no (or considerably less) disturbing reflexes interfering with eye contact.

> “One valuable outcome was the finding, that the period between cleaning cycles of the vacuum coaters could be considerably prolonged, significantly increasing the uptime and productivity of the machines.

An additional emerging feature of anti-reflex coatings is the selective filtering in the blue region of the visible light spectrum. This is a response to increasing exposure of our eyes in daily life to LEDs and TV or computer monitors, which is often perceived as distracting and exhausting.

Composition of anti-reflex coatings

Anti-reflex coatings are so-called dielectric coatings. Such a coating consists of a sequence of several sub-microscopically thin dielectric (non-metallic, i.e. transparent) layers of different refractive indeces (alternating high and low index).

The trick is to tune the thickness and the refractive index of each layer in a way that you get destructive interference between the back-reflected light of the different layer interfaces. Thus, the reflected light is cancelled out and all incident intensity (ideally spoken) is transmitted.

The desired layer thicknesses range in the order of or below 100 nm (which is the 10,000th part of a millimeter). Additional features must be integrated: E.g. a cap layer on top is needed to protect the thin-film system from ambience over life-time and an interface layer at the bottom makes sure that the system permanently adheres to the substrate (i.e. the lens). Altogether this may result in up to 10 or more layers of different materials and different thicknesses, which need to be precisely deposited onto the lens.

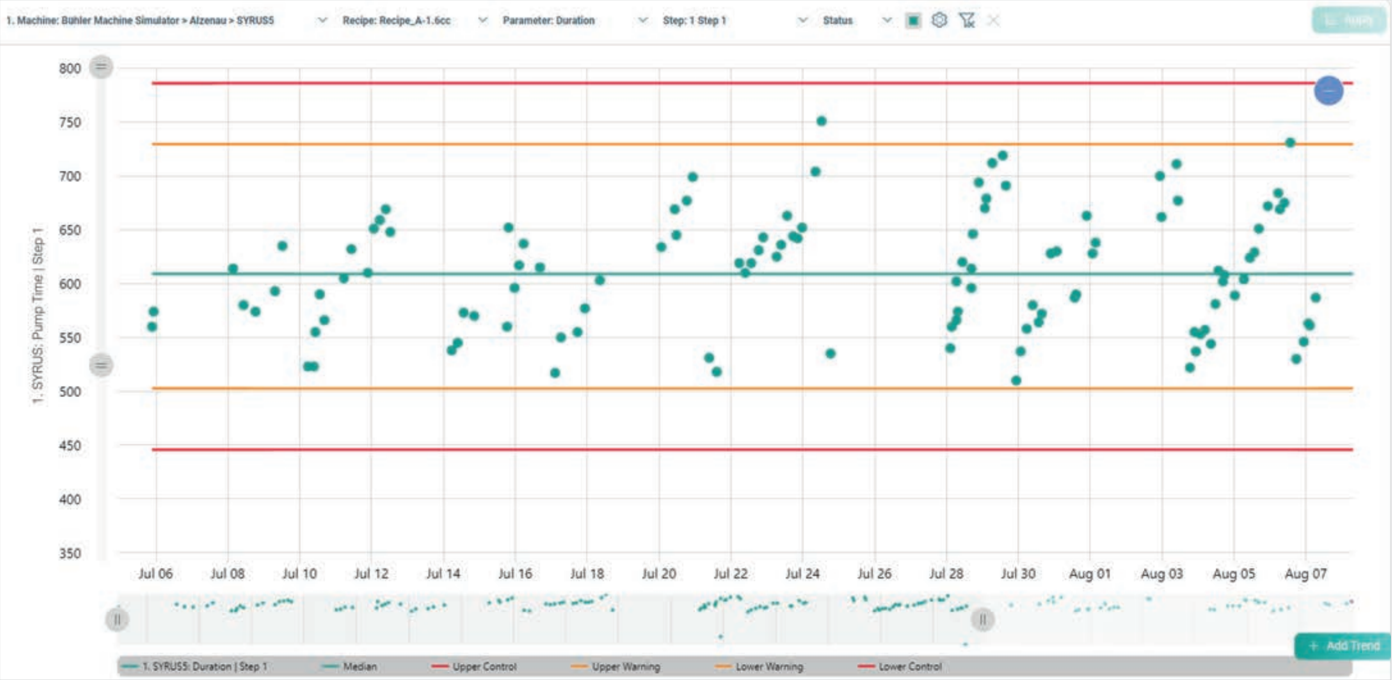
Operation of a vacuum coater

The single layers of an anti-reflex coating consist of different dielectric materials. These silicon-oxide and metal-oxide layers provide an alternating system of high/low refractive index. For deposition on the substrate (the lens), coating material is heated and subsequently evaporated in a crucible at the bottom of a vacuum chamber. The lenses are positioned at the top of the chamber.

In vacuum, the evaporated atoms or molecules propagate (ideally undisturbed) from the bottom to the top and deposit on the lenses, growing a thin film. The heating and evaporation of the material is usually accomplished by an electron beam being targeted at the material.

The thickness of the deposited film on the lenses is mainly controlled by the length of exposure via shutter and by the rate of evaporation via electric power of the beam.

Basically, there are two different approaches. One possibility is to directly evaporate the oxide material onto the substrate. The other is to evaporate the pure silicon or metal, and create an oxygen plasma in the chamber, which reacts with the evaporated material, forming the



1. Machine: Bühler Machine Simulator > Alzenau > SYRUS5

Recipe: Recipe_A-1.6cc

Parameter: Duration

Step: 1 Step 1

Fig. 2: *Exemplary control chart from Bühler Leybold Optics database cockpit. The data shown here simulate the cycles of increasing pump-time from batch to batch till next cleaning run simulated data, as no real customer data can be shared here.*

desired oxide film on the lens. In both cases the stoichiometry, the composition of metal and oxide, significantly controls the refractive index of the respective layer.

Key parameters of the AR coating process

Key output parameters of the AR coating process are: low residual reflex, correct color of residual reflex, no significant surface defects, and, finally, adhesion of the coating over lifetime.

The three first-mentioned are usually judged in a visual inspection, while the latter is checked in an accelerated life-time test and via customer-complaint statistics. Key process parameters for the fulfilment of these output parameters are the thicknesses of each layer and their refractive indices (stoichiometry).

While the thickness is directly accessible from measured data, the refractive index is not. It is controlled indirectly by other process parameters. And even though the thickness is measured directly, it is controlled by several more parameters.

This leads to a complex multiplicity of parameters, which need to be tuned properly for a successful outcome of the process (pressure over time, power of the electron beam over time, partial pressures over time, time of exposure, cleanliness of the vacuum chamber, to name just a few).

Big data needs digitalization

The coating process provides us with a load of relevant process control parameters to deal with. A state-of-the-art vacuum coater comes off-the-shelf with the sensory system and the digital interfaces to straightforwardly get access to these data. “These data” precisely spoken means: time resolved process and machine data for each coating run (batch). These data can be fed into a database and be evaluated to gain better control of the process. Although relatively comfortably available, it is not yet state-of-the-art, to use these data on a big scale. One reason for that is the lack of proper interfaces into a comfortably usable database. This is now provided by the team of Dr. Küper.

Level I of digitalization

When digital data acquisition is in place for the relevant parameters, the next challenge is to plot them in an expressive way. Technically spoken, process parameters span a vast multidimensional space of variables, which depend on time, on batch number, and in many cases on each other. And there are two classes of variables: first the process control parameters, and second the output parameters, where the former shall be tuned to optimize the latter.

Level I of digitalization is accomplished when process engineering is provided with an interactive cockpit where they can flexibly get access to any representation of the data. It has to be possible to pick just any pair of parameters and plot them against each other in a chart. This helps to find correlations between parameters, particularly between control and output parameters. Furthermore, parameters can be plotted over time or over batches to make visible significant changes and possibly correlate them with certain events (e.g. from the machine log, e.g. cleaning or maintenance).

Plotting parameters over batch finally leads to the classical control chart, where by statistical means, the stability of each process parameter can be tracked. Dr. Küper showed that his team accomplished to provide a full-scale cockpit in this sense (see example in figure 2). Process

Process control parameters show important information that can help users to optimize processes.

engineers can click through the data, choose parameters, choose graphical representations, choose scale, zoom in, zoom out, jump between different graphs, to get the best overview on the interdependencies between the parameters.

The statistical tools for control charts are implemented. Furthermore, warning and control limits could be edited individually for each parameter. This first level of digitalization already provides engineering with an enormous head start. With this set of information, one does not just react on scrap and rework events when output parameters are already off specification. Proactive measures can be taken already when control parameters start to become critical – before scrap and rework actually occur.

Level II of digitalization

As stated before, in complex manufacturing environments, process engineering is confronted with an enormous amount of possibly relevant parameters. It is unrealistic to assume that the resulting control charts can be checked on a sufficiently regular basis visually.

The second level of digitalization provides algorithms, which check all the control charts automatically for violations. Obviously, level I needs to be in place.

From a data science point of view this is just if-then-else queries. The bigger challenge is to have the proper workflows and the qualified personnel in place for action: in case of violations of control limits, the relevant engineers get informed automatically. They would then jump into the situation with their process know-how and decide upon necessary measures of stabilization.

Level III of digitalization

With level I and level II digitalization in place, process engineering is able to react proactively to violation of warning limits of control parameters. This presumes that the influence of each control parameter onto the output parameters is known. In real life, this is not the case.

One is confronted with a large number of control parameters, and for many of them, the correlation towards the output parameters (specifications) is at best vaguely known. Here comes into play the third level of digitalization. It introduces algorithms, which check all parameters for correlations with any other. This may include inter-correlations between the control parameters, but particularly focuses on correlations between each control parameter and the output specifications.

The result of this algorithm is a classification of how much each process parameter actually influences one or more output specifications.

This information is invaluable for proactively controlling the process. It helps a great deal to focus engineering activities on the right parameters. Also, with respect to cost or cycle time reduction as well as new products´ development, these data can be most useful.

Level IV of digitalization

Finally, machine-learning comes into play. A machine-learning algorithm can be fed with available process data and predicts the outcome of the process, i.e predicts whether the output parameters will be met, or not (scrap or no scrap). The research group Industrial Data Science (INDAS) at Frankfurt University of Applied Sciences tuned their machine-learning algorithms on this challenge.

They got the opportunity to feed the algorithm with long-term real process data from optoVision, manufacturer of lenses and partner in the cooperation. After teaching the algorithm with historic process data (process control as well as output parameters, so called labelled data), it was possible to predict whether a particular coating run produced an in-spec or an out-of-spec batch. After each coating run its process data were fed into the algorithm, and the outcome prediction was afterwards counter-checked by standard quality-control procedure.

As Peter Ludewig, Head of Department IT/IS at optoVison, points out, one valuable outcome was the finding that the period between cleaning cycles of the vacuum coaters could be considerably prolonged, significantly increasing the uptime and productivity of the machines.

According to Prof. Schäfer of Frankfurt University's INDAS group, expectations towards machine-learning still need adjustment.

Machine-learning is not a silver bullet which answers all questions without further effort. It is definitely a powerful tool but often the black box nature of standard machine-learning algorithms requires further human insight. And particularly, this project showed: although all the data were basically available, there was a considerable effort to be invested by optoVison's engineering team to classify the data in a technologically meaningful way before finally getting good results from the machine-learning algorithm.

KI – the answer to all questions?

A widespread vision is an "artificial intelligence", where to enter your problem, and get the proper solution suggested right away. In manufacturing, the challenge of this task is a lot about process understanding, about grasping cause and effect, about metrology and data acquisition.

In most cases, there is a lot of "old-school" process analysis to be done before digitalization with its full potential can actually kick in. An algorithm only yields useful answers when asked meaningful questions.

Conclusion

The database and its engineering interface, as presented by Dr. Küper and his team, are a successful realization of level I and level II digitalization. They provide a full-scale cockpit for comfortable and flexible navigation as well as graphical representation of the coating process' complex parameter space.

The team of Frankfurt University's INDAS group succeeded in the proof of principle that by teaching a real-life extensive dataset, provided and interpreted by lens manufacturer optoVision, their machine-learning algorithm was able to predict the outcome of single coating runs based on their individual process data. All three partners in unison judge the project as great example of how rewarding a collaboration between equipment manufacturer, producer and researchers can actually be. Bühler Leybold Optics will now make the interface available for customers within the scope of their service packages. The joint project will continue to implement further features of level III and level IV digitalization successively. ◆

Interview partners

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