

SUSS DISPENSE SYSTEM – AUTO CALIBRATION / SELF LEARNING

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The SUSS Dispense System (SDS) is a pressure based dispense system, which is used to dispense chemicals for coating and developer processes with a repeatability of $\pm 1\%$ and an absolute accuracy of $\pm 2\%$. The system setup uses standard components and intelligent software algorithms to achieve precise dispense results.

To optimize this a new automated calibration and self-learning/self-optimizing algorithms needed to be evaluated and implemented, to simplify the system setup and maintenance in the field and also to improve the cost of ownership.

Now in the new update, the system intelligence is improved further with the complexity being taken away from the user. Thus, the system is more intelligent, more stable and with reduced tolerance to errors, and offers significant reduction in time and effort for setup and calibration.

AUTO CALIBRATION

The system is using a pressure based dispense and a flow sensor for accurate dispenses. These components together with the system behavior need to be calibrated in an optimal way to achieve precise and repeatable results.

The dispense behavior can be separated in three different phases:

1. Start phase

- During the start phase the flow rate is ramping up to the flow set value, depending on system settings also including an overshoot at the beginning
- 2. Stable flow
 - Time in which the flow rate is as stable as possible
- 3. Stop phase
 - After stopping the system (closing valves etc.) the flow rate is ramping down, but there is still some amount which is dispensed even after stopping the system

The next picture shows these three phases with overdrawn start and end phases to better visualize the behavior in general:



Figure 1 Drawing dispense phases

To achieve the most accurate results the software needs to predict the optimal stop time, therefore not only the calibration of the components, but also the calibration of the system behavior is very important.

In the first version of the system, it was necessary to do all required calibration manually; now with the new version the change of parameters is handson. Every needed parameter can be changed in real time from dispense to dispense without any further steps. This dramatically reduces the time taken for the first setup of tools as well as the time to get the process running after any hardware change in the system.

The calibration for all required parameters can be done in an automated process. After starting the auto calibration only a zero offset and three dispenses are required to calibrate the system to a specific resist.

After starting calibration, the real time dispense graphs are shown in Figure 2.

After each performed dispense, the user is requested to provide the real measured amount in weight and density or amount in ml (Figure 3).

After this short procedure, the system is calibrated and ready for production. If the resist needs to be changed, then also by just repeating this procedure, the system can be taken back to production in little time.



Figure 2 Realtime dispense chart



Figure 3 User input for measured amount in calibration mode

SELF-LEARNING

Caused by the pressure based dispense, the system is sensitive to temperature changes. In the previous version, this was compensated by the system by adjusting the dispense time. Now the software is one step ahead. Any variations in e.g. the clean room temperature will be compensated by self-learning algorithms, which actively adapt the pressure and therefore flow rate rather than the dispense time. Therefore, the system ensures consistent flow rate, resulting in a static dispense time.



Figure 4 Two dispenses without self-learning

SELF-LEARNING PRINCIPLE

The new software uses principles from machine learning to optimize itself from previous dispense results. Therefore, the software collects the quality (errors) in former dispenses and starts to train itself to predict better performance for future dispenses.

The optimization for future dispenses is started after at least three dispenses are performed. One issue of this optimization is overfitting (learn noise instead of real errors), this would result in a bad repeatability performance, as shown in the next picture (blue Gaussian distribution vs. red).

A Finite Impulse Response Filter (FIR) and an asymmetric filter is used to omit old recorded errors, which are not relevant anymore. This optimizes the adaption to temperature or viscosity drifts and limits the influence of statistical inaccuracy at the same time.



Figure 5 Second dispense with bad compensation by noise



Figure 6 Blue new worse Gaussian distribution

EXPERIMENTAL RESULTS

The provided test results are showing the capabilities of the system. The system was calibrated using resist at 21.4 °C (room temperature), afterwards resist was cooled down to 19.5 °C, which is 1.9 °C delta from the temperature during calibration. The corresponding data can be seen in Figures 7-9. These results are presented to demonstrate the error caused by the temperature change and the efficiency of the new software. According to the new update, Self-Learning became effective after three dispenses.

As you can see in Figure 7, once the temperature is changed the previous calibration does not fit anymore. That's the reason for the jump in the 9th, 10th and 11th dispense. As mentioned earlier, the system learns the change in flow rate and error correction is activated after three dispenses (started at the 12th dispense). Thus, already after the fourth dispense, the error is just under 5 % and the system keeps close to the set value. In a real world application, a jump in the dispensed amount would not occur, as temperatures typically change slowly and the system continuously adjusts to the changing conditions.

The biggest advantage comes with the time taken for dispense, as shown in the next picture. Even after $1.9 \,^{\circ}$ C of temperature change, the time taken for dispense is kept constant at +/- 100 ms with no compromise in the system specification.

In addition, a miscalibrated system will optimize itself automatically as shown in Figure 9, where a bad calibration (used on purpose) demonstrates, how the total amount is compensated to match the set value.

As you can see in the above graphs, the temperature has a huge impact on the system performance. Yet, the self-learning takes care of the changes and keeps the system within the specification i.e. 2 % accuracy and 1 % repeatability.



Figure 7 Stable flow rate









Thus, without any extra effort needed for calibration, the system performs to its specification with almost no change in the dispense time.

LOGGING

The SUSS dispense system is seamlessly integrated in the optional SUSS data logging concept. In case data logging is available, all dispenses can be reviewed offline using the viewing software. It is possible to see the flow behavior and the dispensed amount for each dispense, which were performed in the past.



Figure 10 Dispense data view in SUSS data logging

SUMMARY

The SUSS dispense system is designed with the concept to make it universal and user friendly. Additionally, it supports automatic dummy dispenses in case of detected bubbles. The dispense system can be used between 3 ml to 25 ml with $\pm 2\%$ accuracy and $\pm 1\%$ repeatability. The system features great possibilities of monitoring and controlling of dispense in real time. This helps the customer to use various ranges of viscosities and let them optimize the whole dispense for process specific requirements. With the latest addons along with the existing exceptional system performance, the SUSS Dispense System now made a further step forward. The new system not only offers an improved user friendliness and stability against environmental changes, but also significantly reduces the time and effort required for system setup.

Björn Böckle studied Electronics and Information Technology at the University of Heilbronn. He graduated with focus on software development in 2002.

After starting his career in the area of digital image processing, he developed sensors based on optical coherence topography (OTC) for Metrology applications whereby he collected first experience in the semiconductor industry. He joined SUSS MicroTec in 2011 as Lead Engineer Software Development. Since 2018 he holds the position of Manager R&D Software and is responsible for the software development for the bonder and coater product line.

