Identification of cleaning mechanism using machine learning methods

Diploma thesis written by Dipl.-Ing. Wolf Freiherr Marschall

Supervisor: Dipl.-Ing. Christian Golla

Examiners: Prof. Dr.-Ing. habil. Jochen Fröhlich, Dr.-Ing. Frank Rüdiger

Extended Summary

Product safety is paramount in the food industry. To ensure this, there are high hygiene standards that manufacturers must comply with. However, cleaning processes are designed on the basis of experience and with high safety factors, so they are often oversized. This is exacerbated by the fact that frequent product changes mean that systems are cleaned several times a day.

In the dairy industry, up to 28% of water and 13% of energy is used to clean equipment, with up to 80% of the energy used coming from gas. According to the literature, the potential savings in cleaning processes are 30-80% of cleaning time and 30-75% of cleaning costs, provided that the processes are optimally designed.

The mentioned potential can be tapped by simulating cleaning processes. The Chair of Processing Machines and Processing Technology and the Chair of Fluid Mechanics have been researching in this area in applied projects for more than ten years. One approach used here is the modelling of soils as a boundary condition of a numerical flow simulation. This means that a multiphase simulation is no longer necessary for the cleaning simulation since the flow field and the soil are decoupled. This approach drastically reduces the computational effort to a level suitable for industrial use. An essential basis of this model approach is the classification of the soils according to their cleaning mechanism, i.e. their behaviour during detachment. The cleaning mechanisms are diffusive dissolution, cohesive separation, adhesive detachment, and viscous shifting. Figure 1 shows a schematic representation of the cleaning mechanisms. Diffusive dissolution describes the transport of soil molecules into the cleaning fluid, driven by a concentration gradient. Cohesive separation occurs when the hydrodynamic loads encountered exceed the cohesive binding forces of the soil. As a result, pieces of the soil are dislodged. However, in near-surface areas, the transport mechanism is similar to diffusive dissolution because only very small pieces of the soil are detached. For this reason, the two cleaning mechanisms diffusive dissolution and cohesive separation were combined in the diploma thesis under the name of cohesive separation. In contrast, adhesive detachment occurs when the hydrodynamic loads exceed the adhesion between the soil and the substrate. Large areas of soil detach at once. In viscous shifting, the soil itself is or becomes flowable. This is caused by physical processes, such as heating, or chemical reactions.

Until now, model development has been based on the use of prototypical model soils, which have been selected so that they ideally detach according to a particular cleaning mechanism. However, real soils often have mixed forms or change their cleaning mechanism when the operating parameters are changed. To address this problem, this thesis has developed an AI-based approach to objectively identify the cleaning mechanism of a soil. This was done based on grey level video footage from previously conducted cleaning experiments. The development of the machine learning (ML) algorithm was based on the prototypical model soils. The algorithm was then also applied to more realistic soils that also exhibit mixed forms of cleaning mechanisms.

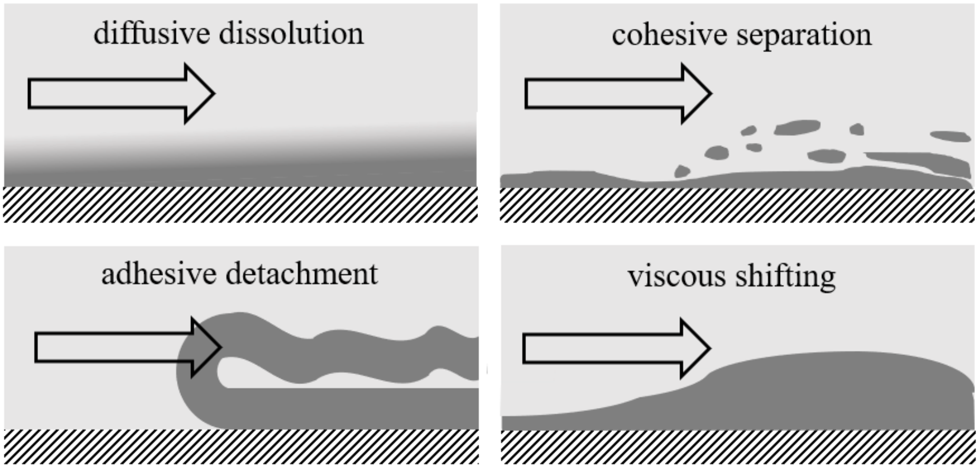

Figure 1: Overview of cleaning mechanisms for which a classification method was developed in this work.

The introduction discussed the general motivation for the topic, as well as the basics of cleaning and cleaning mechanisms.

In the second chapter, the relevant foundations of ML were developed and compiled. On the one hand, knowledge was gathered about how ML algorithms need to be structured in order to solve the underlying problem. On the other hand, methods were explored to better understand and interpret ML algorithms. They also discussed how best to prepare the data for the algorithm. It was decided to use neural networks (NNs) for classification, as they are suitable for solving image processing tasks. Due to their large number of hyperparameters, NNs can be optimised for the task at hand. The influence of the hyperparameters has also been discussed. In this work, special attention should also be paid to the comprehensibility of the algorithms. Therefore, test procedures such as Analysis of Variance (ANOVA) and Mutual Information (MI) were chosen in order to later understand which input values have a particular influence on the output of the NNs. Principal Component Analysis was also used as a basis for interpretation.

Chapter 3 presented the methodology used. First, the experimental dataset was analysed in detail. The task of the NNs was specified in such a way that the NN receives as input the temporal evolution of the grey value of a 5x5 pixel region in a form to be defined and has to output the prevailing cleaning mechanism. It was decided to distinguish between two basic approaches, called the offline approach and the online approach. In the offline approach, the NN is given information about the whole evolution of the grey value over time and has to identify the dominant cleaning mechanism. In the online approach, the network had to determine the cleaning mechanism at each point in time. To do this, it has the information from the immediate past. Figure 2 shows a comparison of the two approaches. The next section describes how the image series were used to generate suitable data sets for the respective tasks. For this purpose, an additional application was developed in Python, which allowed an efficient labelling of the data. As input values for the NNs, also called features, different statistical parameters were determined from the respective grey value evolution over time. The strategy followed in this work was to first deliberately create too many features to capture all the information, and then to filter out the really relevant features using reduction and interpretation techniques.

The datasets generated contained 100,000 examples each. Of these, 60% were used for training and 20% for determining optimal hyperparameters. The last 20% were retained and used for the final evaluation of the fully trained NNs.

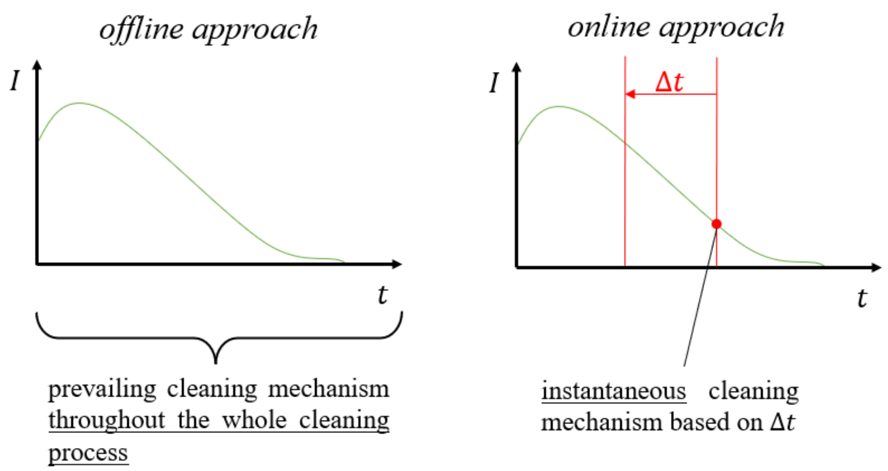

Figure 2: Comparison of the two approaches utilized in the diploma thesis.

In Chapter 4, the NNs from the offline approach were evaluated and interpreted. The NNs achieved accuracies of over 95% on the unseen training data. The interpretation techniques significantly improved the understanding of the workings of the NNs and resulted in reduced NNs requiring only 20% of the input data with almost no loss of accuracy.

The NNs for online classification were discussed similarly in Chapter 5. Here, the length of the time window from which the network receives the information is an additional parameter. A short segment of 12 images and a longer segment of 30 images were examined. A short time window is desirable for the best possible resolution of the cleaning mechanism, but it also makes the task more difficult. After improving the networks through interpretation techniques, 82% accuracy on unknown data was achieved for the NN with a short time window and 93% with a long time window.

In chapter 6, the limits of the NNs were tested. For this purpose, they were applied to data that differed from the training data. The best NN from the offline approach was applied to the leading edge of a soil. Here, viscous shifting is observed for both actually cohesively and adhesively detaching soils in the experiments. The offline NN was also able to detect this without doubt. Furthermore, the NNs from the online approach were applied to completely different soils with more complex detachment behaviour. For these soils, the cleaning mechanism varies in both in time and space. A comparison with subjective perception and spot checks show that a successful identification of the cleaning mechanisms is also possible here. In Figure 3 a sample result obtained with the online network is provided.

In summary, this work was the first to develop an AI-based approach to the physical classification of cleaning processes. The results of the work also underline the theory of cleaning mechanisms. The technology developed forms the basis for a tool that can be used to identify the cleaning mechanism of arbitrary soils and to select a suitable simulation model. This will pave the way for optimising inefficiently designed cleaning processes. In the last chapter of the thesis, the potential for follow-up work was evaluated. In particular, approaches were described on how online classification can be used to classify real soils.

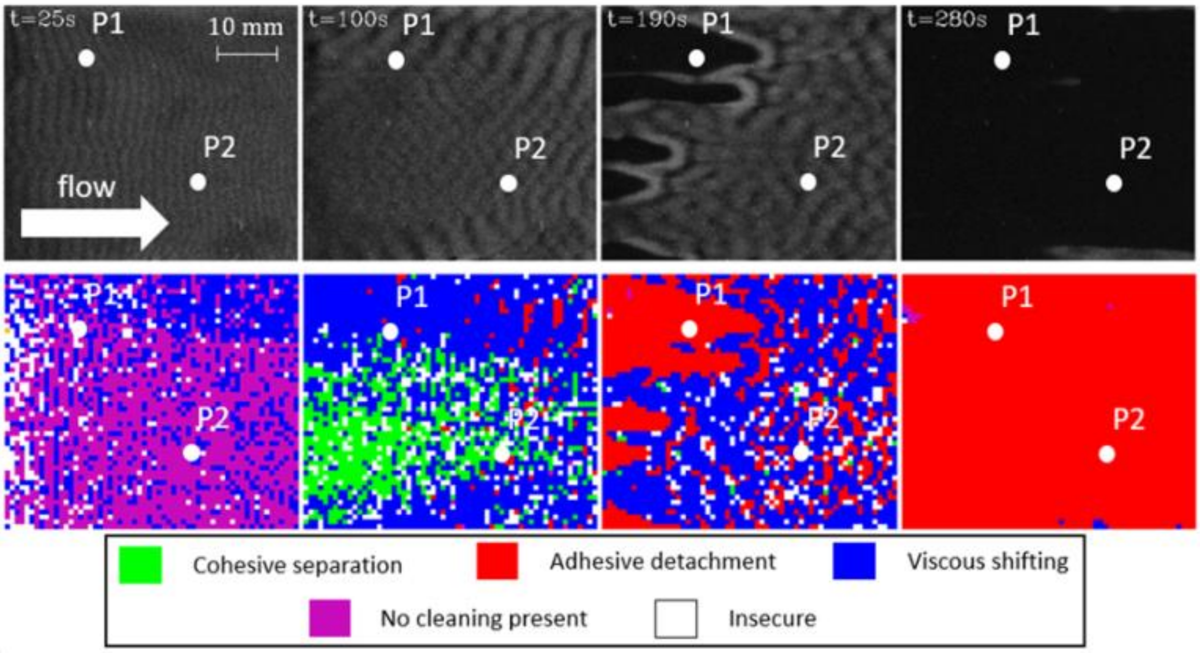

Figure 3: Sample classification result obtained with the online network on a soil not included in any dataset used for training.

Publications based on the diploma thesis

Some of the results of the work have already been published during the course of the work. A conference paper was presented at the "NAFEMS Seminar on ML and AI in Fluid Mechanics and Structural Analysis" [1]. The paper was subsequently selected for publication in the NAFEMS online magazine after a peer-review process [2]. Only four of the 16 conference papers were selected for publication.

Following the thesis, the full results were submitted and published in a comprehensive manuscript in the Journal for Food and Bioproducts Processing [3].

[1] Golla, C., Freiherr Marschall, W., Köhler, H., Rüdiger, F. and Fröhlich, J. (2022). Identification of cleaning mechanism by using machine learning methods. In *Machine Learning and Artificial Intelligence in CFD and Structural Analysis Conference Proceedings*, Wiesbaden, Germany

[2] Golla, C., Freiherr Marschall, W., Köhler, H., Rüdiger, F. and Fröhlich, J. (2022). Identifikation von Reinigungsmechanismen mit Hilfe von Methoden des maschinellen Lernens. *NAFEMS Mag.*, 63:54-66.

[3] Golla, C., Freiherr Marschall, W., Kricke, S., Rüdiger, F., Köhler, H. and Fröhlich, J. (2023). Identification of Cleaning Mechanism by using Neural Networks. *Food and Bioproducts Processing*, 138:86-102.