

ML Unit 12 Seminar Preparation:

Diez-Olivan et al. (2019) discuss the impact that Industry 4.0, i.e., the interconnectivity of devices, has on the ability to analyse system failures in, e.g., industrial manufacturing.

Following their argumentation, in the context of Industry 4.0, data science can especially create value by predicting abnormal behaviour of machines and, e.g., anticipating machine failures which typically come with major economic and technical costs. They differentiate between descriptive, predictive and prescriptive prognostic machine learning models which are applied in industry 4.0. Descriptive models solely find the cause of a failure. Going a step further, predictive models evaluate when a monitored asset, e.g., an industrial machine, will fail. Prescriptive models go even an additional step further, evaluating which mitigation steps are necessary to minimise the impact of a failure on the industry at hand.

I choose to focus on why predictive models provide a value at the example of a company that is active in chemical manufacturing. Predictive models, as explained above, are used to tell when a machine will fail. This is achieved by using, e.g., time series analyses to analyse sensor data or machines as well as contextual data such as temperature and humidity levels. These data sources get combined and all flow in the analysis of the risk at which the machine operates. From a mixture of recent and historical data, the company can then plan when to change their machinery whenever it is at a too high risk of failing. This is a highly beneficial process for the manufacturer if carried out optimally and thus I decide to analyse it in more detail at the example of chemical manufacturing.

Automation.com (2021) estimate that machine failures cause economic losses of about 1 Trillion Dollars per year for the world's largest manufacturers, among which are many chemical manufacturers. Thus, reducing this number is of highest importance for them. However, it is also important not just to change the machinery before it fails but also to change at the right time. Changing it too early would also cause unnecessarily high economic and technical costs. Thus, analysing all available sources provides a high value for chemical manufacturers. Using this technology, they can react to alerts raised by the system after an individually set threshold for a too high probability of a machine failure is reached. While this will typically not prevent all machine failures from happening, it still is a strong mitigation strategy. Furthermore, chemical manufacturing is inherently high-risk due to the involvement of hazardous substances and reactions. Predictive models can identify conditions leading to

unsafe scenarios, such as leaks, pressure build-ups, or thermal runaways. This allows for proactive measures, reducing the likelihood of accidents and protecting workers and the environment.

However, using predictive models also has some limitations. Ensuring high-quality, relevant data for training predictive models remains a challenge. Predictive ML models rely on large volumes of high-quality data from diverse sources, such as sensors, production systems, and historical maintenance logs. Inconsistent, incomplete, or noisy data can compromise model training, leading to inaccurate predictions. Data silos within organisations may limit the integration of datasets from different departments, such as production, quality control, and logistics. Here, data sharing within an organisation is especially important. Furthermore, machine learning models often are seen as black boxes where chemical manufacturers could face difficulties to understand how the system derived its solution and calculated the failure probability of a given machine. However, this could be improved via the emergence of systems that feature explainable AI which ensures better understanding of the model's outcomes. Also, the usage of such a predictive model could be hindered by its costs. Especially small to medium size chemical manufacturers could face problems to put up the infrastructure and pay for the operation of such a machine learning system, especially since a significant investment up front would be necessary before the reduced costs of machine failures outweigh the costs of implementing the machine learning system. Here, government support or partnerships with technology providers could make sense to support the smaller chemical manufacturers with the upfront investment needed for this predictive approach to machine safety.

Concluding, the challenges associated with implementing predictive prognostic machine learning models in chemical manufacturing are significant but surmountable. By adopting a structured approach - prioritizing data quality, ensuring interpretability and managing costs - manufacturers can overcome these barriers. Addressing these challenges not only accelerates the transition to Industry 4.0 but also establishes a more efficient, sustainable, and competitive chemical manufacturing industry.

References:

Automation.com (2021) World's Largest Manufacturers Lose Almost \$1 Trillion a Year to Machine Failures. Available from: <https://www.automation.com/en-us/articles/june-2021/world-largest-manufacturers-lose-almost-1-trillion> [Accessed 20.01.2025]

Diez-Olivan, A., Del Ser, J., Galar, D. and Sierra, B. (2019) Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0. *Information Fusion* 50: 92-111.