Merging digitalization tools for training the new generation of bio-chemical engineers: challenges and perspectives

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Abstract

Digitalization is reshaping the qualifications required for a growing industry 4.0. Efforts are necessary to introduce those skills into the biochemical engineers’ competences. Future engineers need to feel comfortable designing and using digitalization tools to drive developments in biomanufacturing. In this contribution, we discuss the challenges of building digital objects for novel pilot units, to be used for student exercises and research towards more digital assisted operation within the context of digital twins. Besides, relevant topics for digitalization strategy are discussed as planning, team assembly, and infrastructure upgrades. For illustration, obstacles of digitalization of novel membrane technologies with time-variant nature and limited process understanding are discussed, focusing on the modelling approaches from whiter hybrid models to pure data-driven representations. Perspectives on the future needs and potential implications are presented.

**Keywords**: Digitalization, digital object, dynamic ultrafiltration

* 1. Introduction

Activities in Digitalization strategies are increasing at an outstanding rate in both Academia and Industry. Academic publications in Digital twins for Chemical Engineering have grown almost exponentially in the last 10 years (Source: Scopus). Besides, the Digital twins market is reported between 10 - 13 billion USD (2022-2023), with a CAGR of up to 61 % for 2027 (Markets and Markets, 2023). The current picture of software development for digital twins has grown by 71 % between 2020 and 2022, and from a survey, 29 % of worldwide manufacturing companies are implementing their digitalization strategies and 63 % are developing them. An important driver for digitalization lies in the less capex-intensive upgrades required, where disruptive technologies are not necessarily linked to high investments and it is expected that only 40 % to 50 % of the cases require equipment replacement (McKinsey Digital, 2015). It is known that biomanufacturing processes are still operated relying on recipes and workers’ experience with limited monitoring and automation (Bähner et al., 2021). Therefore, digitalization has great potential to propel the next generation of bioprocesses, where interactive communication between the real-plant, high-fidelity digital objects (core of digital twins) and users becomes a powerful decision-support tool useful from enhanced process/product development, up to partially automated or self-optimizing operation. However, biomanufacturing is progressing in digitalization at a slower pace compared to telecommunications and finances, due to the complex monitoring which limits process understanding, lack of confidence in digital technologies and it is not entirely clear the cost of implementation (Deloitte, 2017). As the foundation for building the required understanding and transforming biomanufacturing through digitalization, a key step is to assemble a skilled and empowered team on digital competencies to set up governance and steering into designing quick-release digitalization strategies. Biochemical engineers are important players in digitalizing biomanufacturing. Nevertheless, it has been pointed out that there is a big gap between available technologies and harnessing them for PSE teaching/training practices (Lewin *et al.,* 2023). Also, in a time of graduates considered digital natives, this does not mean they are competent in technologies required in digitization of the manufacturing sector areas such as big data, internet of things, cloud technology, data analytics/intelligence, artificial intelligence, and physical-to-digital conversion. Then, there is a call to narrow the skills gap in future biochemical engineers for an industry going through a digital transformation.

The Department of Chemical and Biochemical Engineering at DTU has been maturing a Digitalization strategy. This includes the transformation of the pilot units hall for both teaching and research (Jones et al., 2022). In this contribution, a discussion is made around challenges encountered in constructing digital objects aiming for future digital twins to assist students to develop the skills for dealing with digital tools/infrastructures, explore the potential of hybrid modelling combining data and first principles; and ultimately enhance their capabilities for problem solving designing or using dockable digital entities. As illustrating cases, experiences with two novel dynamic membrane technologies are presented, where different approaches have been investigated to develop digital objects capable of predicting best operation scenarios (so-called critical flux), membrane rejection, fault detection, and forecast fouling rate under uncertain operation. Finally, some perspectives are presented on the digital objects’ deployment and impact.

* 1. Developing digital objects for novel membrane technologies

As part of the digitalization strategy, the department has defined a first project aiming to develop digitalization tools on the equipment available in the pilot hall. The target is to have a) a cloud-based system for data acquisition, storage, analysis and usage by digital objects, and b) Visualization tools for training. The project execution could lead to identifying future directions from technical, scientific, and even philosophical perspectives for education in the pilot hall. For illustration, we have investigated two novel membrane technologies referred to as high-frequency backshock/backwash and vibrating membranes. Those technologies impose challenges at different complexity levels that are common to other dynamic systems or under development intensified processes with limited process understanding. A sketch of how the technologies work is shown in Figure 1. In the high-frequency backshock/backwash system, two fouling mitigation strategies are applied at different frequencies. Both strategies involve reversing the transmembrane pressure to use permeate for cleaning. In the vibrating membrane, high-frequency membrane vibration creates a high shear rate at the membrane surface which mitigates fouling formation. Both technologies have shown remarkable performance for biomanufacturing, but their operation is not straightforward and could benefit from digitalization. Relevant to this contribution, the three main aspects of the strategy for the first goal are depicted in Figure 2; answering the questions Who (People), Through (Infrastructure), and What (Building digital objects). Those aspects are discussed in the following sections, focusing on the Digital Object implementation.

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| Backshock_diagram1.png  Backshock_diagram2.png |  |
| 1. High-frequency backshock/backwash | 1. Vibrating membrane system |

Figure 1. Illustration of the antifouling mechanisms in two dynamic ultrafiltration systems.

A diagram of software components

Description automatically generated

Figure 2. Approach for building digital objects for pilot units

* + 1. Setting-up the correct team

The team involved included the head of the department, faculty members with experience in relevant areas (i.e., process control, pilot unit operation, equipment maintenance), the University IT department and support researchers with projects in the area. In this manner, there was a combination of management capabilities and technical support to define specific activities and materialize them. Important topics where external consultancy is relevant are infrastructure, communication, and visualization. In an early stage, the main challenge is to establish a common reference language, due to the broad spectra of disciplines within the team. This difficulty was mitigated by performing workshops and regular meetings between key internal and external members. On the other end, the digital object developers must be trained or under training in digitalization tools complemented by experienced researchers in the technology of interest. This could be challenging with novel technologies where the process understanding should be built along the digital object development, therefore iteration is unavoidable. Also, it becomes a major endeavour accounting for the large number of units in a pilot laboratory. There, stepwise implementation is the most reasonable approach to build the required experience.

* + 1. Infrastructure upgrade

To build the cloud-based system, hardware and software infrastructure upgrades are required, this is capex-intensive. The pilot plants were evaluated to determine their instrumentation status and interconnectivity capabilities. The details of the infrastructure upgrade can be revised in previous contributions (Jones et al., 2022; Prado-Rubio et al., 2023). The hardware upgrade consisted mainly of sensors, PLCs, a system for connection (Cloud-connect) and a server for hosting. Software-wise, relevant acquisition consisted of SCADA (WinCC + Kubernetes), database (PostgreSQL) and IoT gateway. The key to the success was the appropriate people selection particularly the external consultancy, allowing to navigate the complexity of diverse available technologies, communication protocols and how to merge them into a scalable platform. The main bottleneck before implementation is budget. Secondly, it was complex to design a flexible cloud platform for students doing defined experiments as well as researchers developing digital objects. Sensitive topics addressed are the communication strategy, merging online measurements and metadata, space-efficient database design, SCADA design and objective-driven digital objects development.

* + 1. Digital Objects development

Having the end in mind, digital objects representing pilot units can use different modelling approaches depending on the ultimate purpose for the user (student/researcher) and information available. As a decision support tool, real-time system states forecasting plus prediction of unmeasured quantities provide the user better process understanding while running experiments. Then, it brings higher learning experience for students during the experimental phase and not when the report is written. For researchers, it can facilitate experimental design intervening the experiment ongoing and not when data are analysed.

Particularly, in the membrane filtration cases, predicting membrane rejection or fouling rate can alert the user the membrane is operating under not favourable conditions. Due to the benefits of digital objects, the new generation of engineering needs to become stronger in how to develop and utilize such tools. Here we would like to discuss the challenges of building digital objects for the mentioned novel membrane technologies.

* + - 1. Monitoring and data pre-processing

Monitoring in biomanufacturing is complex. Normally, only regulatory variables (e.g., T, P, F, L, pH) are monitored at high frequency. On the contrary, supervisory variables (i.e., concentrations) if available, are monitored at a lower frequency especially if offline lab analysis is required. There are interesting developments in PAT for biomanufacturing and membrane technology, however, majorly are expensive or not massively available. In dynamic filtration, the first obstacle is to have the infrastructure to store the data at the required frequency to capture the systems’ fast dynamics (i.e., less than 1 second), thus being able to perform long experimental campaigns relevant at pilot scale. After significant experimentation performed with the high-frequency backshock/backwash system, modelling showed the selected sampling time (allowed by PLC memory) was insufficient (Prado-Rubio & von Stosch, 2017). This is corrected by having the cloud-based acquisition system as implemented for the vibrating membrane. Another challenge regarding the high-frequency backshock/backwash system is signal pre-processing. First, when information has not been recorded, then algorithms must be designed for signal reconstruction necessary for modelling (Prado-Rubio & von Stosch, 2017). Secondly, system information is hidden within complex signals and noise elimination might imply losing system information. To overcome this issue, wavelet feature extraction has shown to be handy (Zadkarami et al., 2023). This approach requires hyperparameters tuning, but it can be made based on historical data. Then, conventional signal preprocessing techniques can be used.

* + - 1. Modelling approaches for digital object development

The modelling challenge lies in process understanding (defines whiteness), information available for parameter estimation and tuning/solving procedures fast enough to be used in real-time. For the investigated novel membrane technologies, there are two extremes which define the modelling approach based on the available information. The spectra of modelling approaches investigated for the dynamic systems are shown in Figure 3.

A diagram of a model

Description automatically generated

Figure 3. Investigated modelling approaches for the novel dynamic membrane systems

First, information availability could not be a limitation in the case of well-understood processes (e.g., dextran filtration with no fouling) operated in controlled experiments (minimum uncertainty). In this scenario, digital objects can include a strong deterministic part (López-Murillo et al., 2021). Thus, online measurements and metadata are used to build a whiter hybrid model to describe membrane flux, dynamic concentration profiles and solute rejection. As a model backbone, there is a mass balance in the boundary layer (PDE) coupled with Darcy’s law to estimate the membrane flux. So, black box models are used to determine the osmotic pressure and membrane intrinsic rejection. In this way, knowledge of transport phenomena is harnessed and just complemented by data-driven models for model parameters. This hybrid model provides parameters interpretability and system insights very useful for design. As a drawback, due to the absence of fouling the system is time-invariant, and the challenge is considerably lower.

On the other hand, if the high-frequency backshock/backwash system is under uncertainty of real industrial application, the lack of concentration monitoring and dynamic operation forced the usage of darker hybrid approaches or fully data-driven model (Díaz et al., 2017; Prado-Rubio & von Stosch, 2017). The flux is modelled through Darcy’s law considering the osmotic pressure. Data-driven approaches are used to model the time-variant transport resistance. In that way, the fouling rate can be estimated in a wide range of operating conditions. Those approaches have shown high accuracy (>95%), comparable with machine learning results from the literature. Despite the performance, there are some drawbacks as a) there are still missing guidelines for model selection and how much data is required, b) models underperformance during validation, c) training time could be a problem in real-time applications, and d) it is uncertain when to perform a recalibration. To overcome the last issues, we have proposed to use online system identification which has shown comparable quality to machine learning techniques but it can be trained in real-time and perform fouling rate forecasting (Prado-Rubio et al., 2023).

* 1. Conclusions and Perspectives

The increasing interest in digitalization is driving advances in biomanufacturing. Then, education must cope with the future skills required in Industry 4.0, towards the development and usage of digital assisted tools. Relevant skills to be further developed for students are programming in different environments and numerical methods tuning for real-time applications. On the other hand, the implementation of digital objects becomes relevant for students’ training as a decision-support tool, where the forecasting capabilities of states and unmeasured KPIs can enable to obtain better experimental data and learning experience during the experiments. This is because the students can focus on the experience insights instead of dealing recipe-based tasks or solving by trial-and-error/intuition-based the experiment bottlenecks, accelerating their learning curve. As a take-home message, the digital objects could be the combination of approaches. From one side, hybrid models and data-hungry machine learning could be used for process design or to identify best operation scenarios (through determination of critical flux and faulty conditions), either for automatic operation or as decision support tool for users. As an alternative, the data inexpensive method as online system identification could be used for short horizon forecasting complementing results from hybrid approaches. Due to the emerging nature of this field, research projects involving the design of digital objects facilitate increasing the required understanding to massify their implementation.

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