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Guest Editorial

Artificial intelligence in the field of drying: Revolution or evolution?

With the explosive launch of ChatGPT (Chat Generative Pre-trained Transformer) in November 2022, generative AI has since been recognized as a revolution that will reshape industries, societies and interactions between people. In fact, the concept of artificial intelligence is now new and was indeed raised even decades ago. For example, the paper of Minsk^[1] remains incredibly modern, where the concepts of pattern recognition, learning, language, grammar, inductive inference, “models of oneself” are already present.

What is considered a breakthrough today is the sudden availability of software capable of interacting in a manner very similar to that of a human being. With this spectacular leap forward, it is pertinent to question the contribution of artificial intelligence in the field of drying. In this Editorial, I propose a few answers that are as objective as possible, even if, with such an open question, the perception of the field of possibilities is necessarily partly subjective and dependent on individual experience.

For academics, these new tools are powerful and likely to change the way we will teach, acquire, and control knowledge in a near future.^[2] After a rejection phase (ChatGPT was banished from several universities), the importance of AI is now recognized everywhere and several universities are clearly engaging with it.

To test this new tool, I asked ChatGPT to answer some general questions on drying. For example, the question “*What is the best dryer technology to dry particles?*” gives an answer that would be considered as a good general answer from a student of chemical engineering. The content is correct and all technologies are listed, but without any element to help the choice. It ends by the following sentence “*Each technology has its advantages and limitations, so selecting the best one involves considering these specific requirements.*” With a more detailed case study (diameter, initial and final moisture contents, temperature limitation), the answer was reduced to 3 dryer technologies instead of 5, with fluid bed dryer as probably the best choice (good heat transfer, flexible with particle size and consistent with the given temperature level). In the last example, I inquired on the energetic yield of a particular dryer. ChatGPT gave basic energy balance, with values of latent heat of evaporation and some equations written in Latex, which is nice. I had to rephrase the question to obtain a quantified range: 1.5 to 4 kWh per kg of evaporated water for a timber kiln dryer. The answer is correct, but the range is too wide to be useful viz. for sizing of an equipment. The request for a full formulation of coupled heat and mass transfer was very poor. In terms of literature review, ChatGPT is useless as it generates realistic but false references. On the contrary, impressive feedback must be mentioned regarding the generation of simple computer codes or the translation of one existing code to another language.

To sum up these tests, it seems that the present version of ChatGPT is not mature enough in engineering. The level of answers is quite nice for a first screening of possibilities, playing a role of gateway to expertise (arrow 1 of Figure 1). At the same time, it is important to be aware that these powerful tools have serious drawbacks: plagiarism, superficial knowledge without appropriation, hallucinations, etc. For some months now, scientists submitting articles to scientific

journals have been required to declare whether or not they have used generative AI to prepare their manuscripts.

Getting back to the subject of this Editorial, it seems that, despite their impressive capabilities, the present tools of generative AI will not revolution drying, yet. But things are moving fast: generic tools such as ChatGPT are continually updating (version 4, for example, allows you to obtain exacted scientific references), and many specialized scientific and technical tools are emerging.

Nevertheless, we can expect spectacular improvements in drying, thanks to the tremendous progress made in complementary areas: high-performance computing (HPC), machine learning (ML), databases (DB), online sensors and soft sensors. In addition to the impressive progress made in each of these domains, the booming field of data science will enable these fields to work in synergy.

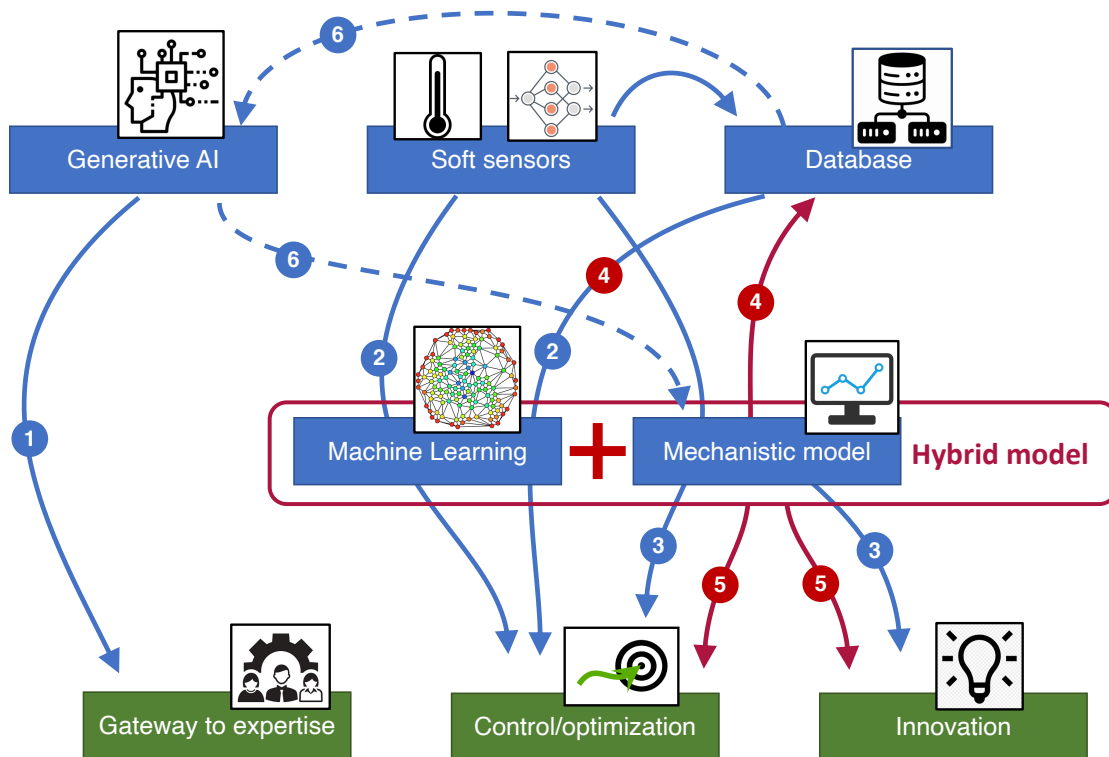


Figure 1 Synoptic diagram of the benefits of AI in the domain of drying for three fields of interest: gateway to a first expertise, control/optimization of an existing process and innovation.

Over the past decades, thanks to its ability to tackle non-linear and dynamics problems, machine learning, namely artificial neural networks (ANN), has demonstrated amazing success in several fields such as autonomous cars, face recognition and weather forecasting without solving any equation. The tools have also been disseminated in the drying field to study drying kinetics, materials characteristics, product microstructure and energy consumption. In this sense, ML is capable of coping with complex situations even better than mechanistic modelling.^[3,4] ML-based

models are easily operational and can be used in process control, based on an existing database or real-time sensors, or both (arrows 2 of Figure 1). However, one must keep in mind that these black-box approaches are trained on a database. As the main drawback, the predictive capability of pure ML-based models is limited to situations than have been observed many times before.

On the contrary, even if they remain complex as operational tools, mechanistic models can simulate situations that have never been encountered before: they can be used both for control/command and innovation (arrows 3 of Figure 1). Drying is a process for which the product quality depends on the whole process history and is therefore difficult to predict different scenarios without a mechanistic approach. Rather than using ML instead of mechanistic modeling, we believe that both areas should work together.^[5] For example, the concern on energy is likely to increase in the future. Drying control will have to account for the availability of energy, in terms of cost and quantity. These ever-changing situations could be handled by hybrid models, combining mechanistic modeling and ML. The mechanistic core will allow several scenarios to be predicted and tested *in silico* by ML algorithms to choose the best one, dynamically. The quality of real-time information is crucial here, whether for gathering information on the process itself or for obtaining information and forecasts on energy availability/costs. Again, the interpretation of complex information such as spectral information, computer vision or combination of several variables, known as soft sensors, are fields in which ML excels. Applied to drying, ML can extract real-time information such as drying time, temperature, moisture content, color, deformation or product quality.

The combination of mechanistic modelling and ML can be organized in different ways:

- 1) **A fully coupled method (hybrid model):** ML exploits real-time information for online tuning of the mechanistic model. The model becomes more and more accurate with time (arrows 5 of Figure 1) and can be used to test several strategies regarding energy demand, drying time and product quality and select the best condition based on multi-objective optimization.
- 2) **A fully decoupled method** (arrows 4 of Figure 1): The prediction capability of the mechanistic model is used to generate a database by numerous simulations covering a wide range of conditions. The final approach is a black box, but a black box trained on a mechanistic database. The generation of the database can be very CPU-intensive but, once done, the ML model trained on this database is very fast.
- 3) **A cascade coupling:** The mechanistic model is “augmented” by ML used to extend the outputs of the mechanistic model. For example, the prediction of product quality by a mechanistic model (drying stress, thermal degradation, product shape, stress reversal, color change, biological activity, etc.) is by far more challenging than that of moisture content or temperature. Yet, the prediction of the final product quality by ML is likely to be more relevant if inferred from the evolution of temperature and moisture content fields over time than directly from the drying conditions.

To conclude, one can try to predict the future of generative AI in our domain. In the not too far horizon, we could imagine generative AI being powerful enough to revolutionize this complex coupling between mechanistic modeling and data science. We could dream of a tool capable of deriving a set of partial differential equations governing the problem from a large database, then

generating the code capable of solving it in a predictive way and using this simulation tool in a dynamic loop, considering real-time information and the forecast of exogenous parameters (arrows 6 or Figure 1). Then, the initial database would be dynamically populated by further real observations or simulated configurations.

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