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ABSTRACT

Although standardized, food processing is subject to many sources of variability resulting from compositional and structural variabilities of raw materials and/or ingredients, human perception and intervention in the process, capabilities of processing tools and their wear and tear, *etc*. Altogether, they affect the reproducibility of final product characteristics representing deviations to standard, the production yield impacting the economic performance of the food manufacturing process, and many other performance indicators. They are grossly classified as economic, quality and environmental indicators and their simultaneous consideration can be used to define the overall performance of a manufacturing process. Optimizing the overall performance of food processing requires the use of multi-objective optimization methods. Multi-objective optimization methods include five steps: defining the objectives, modelling performance indicators, formulating the problem and constraints, solving the multi-objective problem, and finally identifying an ideal solution. The integration of data-driven approach, particularly machine learning, into the multi-objective optimization offers new perspectives for optimizing and controlling food processes. The potential of this approach is still underestimated by the food industry sector.

1. Introduction: industrial performance in the food industry

By 2050, the world's population is projected to reach approximately 9.7 billion inhabitants, posing a sustainability challenge for the food industry which needs to optimize the use of agriculture raw materials, as well as water and energy while maintaining an absolute priority for food safety and food quality (Erdogdu, 2023; Karunakaran et al., 2021). Globally, the food industry generates several social and economic benefits for society but also causes significant environmental impacts (greenhouse gas emission, energy consumption, etc.). Given the projected population growth, food demand should continue to rise, consequently leading to even more adverse effects on the environment if the way food is produced remains unchanged.

For these reasons, it is necessary to redefine the overall performance of industries to address current societal and industrial challenges. Economic, environmental, and product quality dimensions can be considered altogether as key when considering the overall performance of industry (Drofenik et al., 2023; Madoumier et al., 2019). The successful integration of these three dimensions will not only enhance the competitiveness of companies in the sector but will also contribute to their long-term sustainability. The challenge lies in integrating all these performance dimensions in an overall performance function using appropriate indicators. Fig. 1 illustrates these performance dimensions and some examples of associated indicators. The definition of this overall performance cannot be limited to a single dimension. Indeed, considering only one aspect of performance or neglecting the other aspects potentially compromise the scope of the optimization. A holistic view of performance would enable finding a balance between these aspects.

Moreover, in the food industry, performance objectives are often contradictory, and their simultaneous optimization seems difficult to achieve (for example, increasing product shelf-life while reducing the heat load for microbial destruction or the amounts of chemical additives and preservatives). The integration of multiple performance aspects to steer and optimize food processes is a real challenge for the future (Drofenik et al., 2023; Feil et al., 2023; Feliciano et al., 2022). In this context, optimizing a single performance objective while neglecting the others seems inappropriate and less relevant. Finding a compromise between conflicting objectives is not a straightforward task, and the implementation of these optimization methods requires precise process

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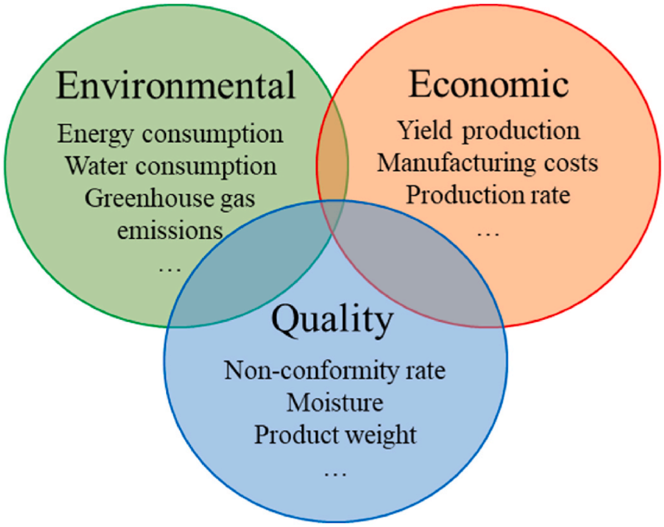

Fig. 1. Example of indicators defining the three dimensions of performance.

knowledge. Recently, multi-objective optimization has gained popularity due to its capacity to evaluate problems from diverse perspectives by concurrently addressing multiple objectives (Cerda-Flores et al., 2022; Wari & Zhu, 2016). Multi-objective optimization is a mathematical approach used to solve problems involving multiple objectives that need to be achieved simultaneously. Multi-objective problems are numerous and can be found in various areas of human life. Along with this, there are many methods in solving the multi-objective optimization problem. The choice of the appropriate method depends on the nature of the problem to be solved (Ehrgott, 2005; Gunantara, 2018). In the chemical industry, multi-objective optimization method is widely used to optimize processes. The implementation of this method has improved the industries performance objectives (Wang et al., 2022; Xu et al., 2024). Despite significant advances in the application of virtualization and process optimization in many technological sectors, the food industry has not fully exploited the advantages of these methods that remain largely underutilized. Multi-objective optimization tools and methods slowly entered the field of food processes (Li & Wu, 2022; Madoumier et al., 2019; Wang et al., 2022) whereas food industry can benefit from these advantages thanks to the large amount of measurements collected all along the process. The advent of Industry 4.0 and the abundance of sensors that measure process parameters for providing more precise monitoring constitutes a powerful lever for optimizing real-time food production (Ding et al., 2023). Despite extensive data collection, their analysis remains often imperfect and incomplete up to now.

Based on these observations, it seems that the transposition of this systemic methodology, which encompasses the whole process and associated collected data, could be very beneficial and offers a holistic asset to the food industry sector.

2. Methodology for implementing the multi-objective approach

An optimization problem can be defined as the search for a minimum or maximum of a given function within a predefined space. A distinction can be made between single-objective optimization and multi-objective optimization. The goal of mono-objective optimizations is to search for the optimal value of the objective function (Li & Wu, 2022). However, it is well known that the majority of real optimization problems have several objectives and requiring the calculation of more than one optimal solution (Abakarov et al., 2009). Consequently, the aim of multi-objective optimization is to optimize several objectives simultaneously, even if they appear conflicting. This multi-objective method aims to identify the best compromise between these contradictory objectives and to obtain a set of acceptable solutions called Pareto optimal solutions (Alaya et al., 2007; Houam, 2013; Konak et al., 2006).

The multi-objective approach can be divided into five steps as summarized in Fig. 2.

Step 1: definition of objectives

The first step involves the definition of the performance objectives that describe the industry's overall performance. Their definition requires collaboration with experts of the manufacturing process in order to gather various perspectives, identify needs and collect convictions. These objectives are characterized by key indicators measured all along the manufacturing process and must be in the form of minimising or maximising indicators. For example, the objective could be "minimization of production cost" with the indicator "production cost".

Step 2: modelling objectives

The second step involves modelling performance indicators with the measured process parameters. Three types of models can be distinguished: knowledge-driven models, data-driven models and hybrid models (Madoumier et al., 2019). Knowledge-driven models, also known as mechanistic models, are based on the knowledge of one or more mathematical equations that simulate the performance indicators using data representative of the process. Data-driven models are empirical and based on experimental data. The concept is to learn from the data and establish relationships between them. This approach makes it possible to model complex systems that do not have known mathematical equations. Finally, hybrid models combine the two previous approaches; they combine one or more mechanistic and data-driven models in one hybrid model (Erdogdu, 2023; Madoumier et al., 2019). Hybrid models enable the integration of all available information about a process, encompassing both collected data and known equations. The aim is to compile all the knowledge available on a system and create synergies to improve the accuracy of the final model's predictions (Sansana et al., 2021; Zhou et al., 2023)

This step will produce predictive models for each performance indicator. These models will then be used in the optimization step. The quality of the models and their prediction are therefore important.

Step 3: formulation of the multi-objective problem and constraints

The third step formulates the multi-objective problem, considering the indicator modelling and process constraints. The formulation step of the multi-objective problem is crucial to carry out the optimization and obtain realistic results. It involves identifying the problem's search space by defining all the constraints associated with the process. After defining the constraints, the decision-maker (person who will use the results after optimization) chooses the optimization strategy he/she wants to pursue. Multi-objective optimization methods can be classified into three categories. *A priori* optimization: the decision-maker intervenes upstream of the optimization process. He can assign a weight to each objective, transforming the multi-objective problem into a single-objective problem. *Interactive* optimization: the decision-maker expresses his preferences during the optimization problem-solving process. Integrating these preferences guides the search for optimal solutions through alternating calculation phases and dialogues with the decision-maker. This approach allows for a more dynamic and adaptable decision-making. *A posteriori* optimization: the decision-maker does not articulate preferences before optimization, and there is no distinction between objectives. The decision-maker will select his "best" solution from the set of optimal solutions. This method provides flexibility in decision-making but may require more effort in post-processing to make the final choice (Alaya et al., 2007; Konak et al., 2006).

Step 4: solving the multi-objective problem

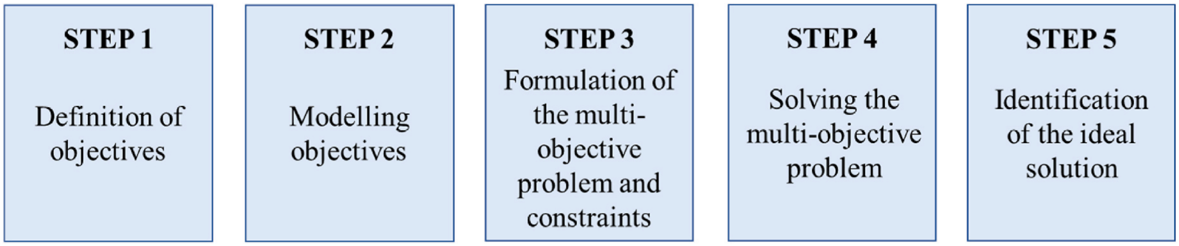

Fig. 2. Summary of the steps involved in multi-objective optimization.

The fourth step is dedicated to the solving of the multi-objective problem. Multi-objective optimization, unlike single-objective optimization, returns a set of acceptable solutions that meet the defined objectives. This set is also known as the Pareto front (Abakarov et al., 2009). There are two resolution methods for multi-objective optimization: approximate method and exact method. Approximate methods enable good quality solutions to be obtained in a reasonable amount of computing time, but without any guarantee of optimality. Exact methods, on the other hand, guarantee optimal solutions for problems of reasonable size, but generally run into difficulties with more complicated applications. When the problem becomes more complex (increased number of objectives, variable dependency, *etc*), approximate methods are recommended to speed up the resolution process (Ehrgott & Gandibleux, 2000). The set of acceptable solutions obtained after running the resolution algorithm is derived from the notion of dominance among solutions (Belna et al., 2022). This notion means that optimal solutions, for which it is impossible to improve one objective without degrading at least one other (Boix et al., 2012), will be retained. The other solutions are dominated. Only the non-dominated solutions (optimal solutions) are used to constitute the Pareto front (Abakarov et al., 2009). The set of optimal solutions or Pareto front is often preferred over singular solutions because the decision-maker can choose from among all acceptable solutions (Konak et al., 2006).

Step 5: identification of the ideal solution

The fifth step consists in identifying, from the set of optimal solutions, the ideal solution based on the decision-maker's preferences (Wang et al., 2022). To select an ideal solution on the Pareto front, several multicriteria decision-making methods are available. These methods formalize the decision-maker's preferences to identify an ideal solution within the set of optimal solution returned by the resolution algorithm. The goal of multi-objective optimization is to identify a set of acceptable solutions, in contrast to the objective of multicriteria decision-making methods, which is to rank acceptable solutions and recommend one for potential implementation in the factory (Belna et al., 2022; Wang et al., 2022).

3. The multi-objective data-driven approach in the food industry

This section will detail the main challenges in implementing multi-objective optimization in the food industry. In the food sector, most multi-objective optimizations focus on specific processing step, such as thermal treatments, but few address the overall manufacturing process (Abakarov et al., 2009; Belna et al., 2022). The limited development of global multi-objective optimization methods can be explained by the complexity of the food processes (interactions between various parameters, interrelated sub-problems or steps, and non-comparable, contradictory objectives)(Wiecek & Gardenghi, 2009). The definition of the objectives, the modelling and the formulation of the multi-objective problem all depend on the field of application and the given problem (for example, making cheese is different from making crisps or canned soups). The implementation of steps 1, 2 and 3 given below is also challenging because of the consideration of variable raw materials, process constraints and the set of available data. Note that these latter must be of high quality in order to achieve a robust multi-objective optimization. The quality of the registered data can be checked using control charts, which ensure the manufacturing condition are stable. Automated sensors are preferred to human registration because of the risk of data reporting errors. When outliers are identified, thanks to mainly statistical methods and expert evaluation, they must be removed from the dataset before any other analysis. When data depend on human skills, the quality of the data is usually improved when staff is well trained and properly supervised and when the equipment is regularly checked and calibrated. These elements are generally part of quality management procedures.

3.1. Step 1: identifying indicators defining industrial performance

To determine the overall performance of the industry, it is essential to identify objectives that cover various performance dimensions. The challenge lies in simultaneously integrating all performance dimensions. To date, environmental indicators such as water or energy consumption are often included in performance targets, as factories may be regulated on these indicators. Their assessment and integration in optimization strategy have become major issues (Younsi & Louhab, 2017). The objectives covering all performance dimensions are subsequently defined by industry-measured indicators. For example, Drofenik et al. (2023) present the use of a process system engineering approach to improve the efficiency of the entire food supply chain at a national level, considering the three main criteria of sustainability, i.e. economic, environmental, and social criteria. For each criterion, the selected indicators are total profit as economic indicator; greenhouse gas emissions, food losses and waste, and amount of fertilizer used as environmental indicators; food self-sufficiency rate, percentage of land used for food and amount of kilocalories produced as social indicators. In their study, a compromise between the three performance aspects has been found through a multi-objective optimization method, integrating environmental indicators into performance considerations. Wang et al. (2022) propose a data-driven and multi-objective optimization approach to optimize complex processes in the chemical industry. For a combustion process in a power plant, turbine energy yield and total emissions of harmful pollutants were the two indicators to be optimized. Multi-objective optimization provides a set of solutions for increasing energy yield and reducing pollution.

While defining the full set of objectives is essential, it should be noted that a large number of objectives increases the complexity of the multi-objective problem, and consequently the time of resolving it. Optimization algorithms used to solve multi-objective problems evaluate a large number of plausible solutions, which can increase computation times if the number of objectives rises (Ehrgott & Gandibleux, 2000; Wari & Zhu, 2016).

To identify a representative subset of objectives that reflects the overall performance of the industry, a compromise among all these objectives is necessary. To define this performance, all industry stakeholders must engage in discussions to articulate their various needs and perspectives. Indeed, since stakeholders may hold differing opinions, gathering these views is crucial for establishing a comprehensive understanding of what performance is in each food industry.

In this step, multi-objective optimization in the food industry is challenging due to the necessity of simultaneously addressing multiple performance dimensions, to handle conflicting objectives and to select representative indicators defining performance objectives.

3.2. Step 2: modelling performance indicators with data-driven approach

Implementing an optimization strategy invariably requires a modelling step to define the relationships between manufacturing parameters and performance indicators (Madoumier et al., 2019). For systems such as food processing, it is challenging to define a mathematical equation describing all manufacturing steps (Belna et al., 2022; Li & Wu, 2022). There are some analytical equations to define some food transformation phenomena (heat transfer in heat exchangers, mass and heat transfers during drying, *etc*.) (Abakarov et al., 2009; Jeantet, Delaplace, & Brulé, 2011) but for most food processes there is no mechanistic model allowing its entire description. Thanks to the advent of Industry 4.0, data-driven modelling methods have emerged in the food industry offering unprecedented prospects (Shankarrao Patange & Bharatkumar Pandya, 2022). Most statistical methods rely on the assumption of linear relationships between variables and responses, which contrasts with the nonlinear relationships often observed in the real world (Ma et al., 2020). To overcome this limitation, some data-driven methods, like Machine Learning methods, have the ability to establish complex and non-linear relationships between measured parameters throughout the processes without the obligation to have an equation defining this process (Garre et al., 2020). Machine Learning enables the prediction of future or unobservable data by obtaining information on potential interactions between input and output parameters (Wan et al., 2022). However, Machine Learning models are often considered as "black-box" methods (Ma et al., 2020). These methods have strong predictive power, but their understanding and interpretation are tricky and limited (Münch et al., 2023). Moreover, the use of Machine Learning models requires optimization of hyperparameters to calibrate models, at the risk of obtaining non-exploitable results. Hyperparameters are settings in a Machine Learning model that are set before the training process and control the model's learning behavior and performance. This step is necessary for obtaining a realistic modelling but can be computationally expensive (Wan et al., 2022).

In this step, implementing multi-objective optimization in the food industry is challenging due to the need to establish complex relationships between process parameters and performance indicators, while also considering the available datasets.

3.3. Step 3: formulation of constraints on the overall process

The constraint formulation step aims at restricting the algorithm's search space by considering the constraints of the process in order to facilitate the identification of feasible solutions. The feasible solutions are all the solutions calculated by the algorithm which respect the constraints, being optimal or not. Formulating constraints within the food industry represents a real challenge, primarily due to the need to accommodate variability in raw materials and accounts for human factors throughout the production process, *etc*. Raw materials in the food industry can vary significantly in quality, availability, and properties, requiring adaptive and flexible process management. Additionally, human factors such as operator skills, decision-making, and lab facilities play a crucial role in food production management. These elements, among others, make it essential to develop a robust set of constraints that can address the conditions of the food manufacturing environment. All these constraints must be identified and considered before beginning the optimization step.

The complete list of constraints associated with the process step should be compiled in collaboration with the industrial experts. It derives from practical knowledge about the specific conditions and limitations of the production environment that are critical for accurately defining the optimization space for the algorithm. Without this expertise, the optimization space cannot be restricted and computation times increase considerably during optimization. The quality of definition of the optimization space is decisive for the algorithms to return relevant results. A well-defined optimization space allows algorithms to operate more efficiently, navigating through the optimization space with precision and returning results that are both relevant and directly applicable to the process under study.

In this step, multi-objective optimization in the food industry presents some challenges, as it requires precise and realistic formulation of the problem with the definition of the constraints, considering the process and raw material variabilities.

Implementing a multi-objective approach in the food industry to optimize overall performance could be a real asset in understanding the origin of deviations from performance objectives and improving manufacturing processes. Its use would also provide industries with a powerful decision support tool.

4. Conclusion and perspectives

The implementation of a multi-objective and data-driven approach appears as an appropriate way for optimizing the overall performance of food industries. Indeed, the food processing is a complex system due to the lack of available equations describing the overall process, the variability of raw materials and equipment, the various relationships between manufacturing parameters and the performance objectives that are often conflicting and specific. Such complexity requires the use of appropriate methods, and for this, the multi-objective approach would be ideal as it integrates the diversity of industrial objectives and is able to find compromise between conflicting objectives. By providing an optimized response to the set of objectives, this approach offers a strategic response to the sector's challenges while paving the way for innovative and sustainable solutions.

The modelling of objectives is an essential step in the multi-objective approach. The emergence of data-driven modelling methods helps overcome the lack of mathematical equations defining the overall process. Data-driven modelling with Machine Learning methods provides a more reliable representation of complex systems, thus enabling more realistic optimizations.

Hence, this article highlights the relevance of the multi-objective approach coupled with data-driven modelling in a context where the complexity of food systems requires new adapted methods. By emphasizing the challenges of this approach in food industry, the article calls for a broader adoption of these methodologies in the food industry. The implementation of this approach promises not only a more efficient and balanced optimization of industrial performances and processes but also a significant contribution to the overall competitiveness and sustainability of the food sector.

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CRediT authorship contribution statement

Manon Perrignon: Conceptualization, Investigation, Writing – original draft. **Thomas Croguennec:** Supervision, Conceptualization, Writing – review & editing. **Romain Jeantet:** Supervision, Conceptualization, Project administration, Funding acquisition, Writing – review & editing. **Mathieu Emily:** Supervision, Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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