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Abstract

While Multi-objective Optimization (MOO) has provided many methods and tools for solving design problems, food processes have benefitted little from them. MOO encompasses the identification of performance indicators, process modelling, preference integration, trade-off assessment, and finding the best trade-offs. In this review, the use of these five elements in the design of food processes through MOO is analysed. A number of studies dealing with food processes MOO have been identified. Even though these studies improve the design process, they often approach MOO in a simplified and insufficiently rationalized way. Based on this review, several research issues are identified, related to the improvement of the different models and methods, and to the development of more holistic MOO methods for food processes.

Key words

Multi-objective optimization; food process design; multi-criteria decision aids

1. Introduction

In food process engineering, most design problems are aimed at several objectives, which can often be contradictory. Thus, maximizing food product quality (texture, nutrients concentration, flavour…) is often in conflict with process performance objectives, such as minimizing energy consumption, maximizing profit, or ensuring safety in the case of heat treatments. For the last two decades, solving multi-objective design problems has been a major concern as sustainable development practices also need to be integrated in the design process. Many kinds of objectives can be defined by the decision-maker, all with potential antagonistic effects, e.g. maximizing one has the effect of minimizing one or several others.

To solve multi-objective design problems, different kinds of methods have been developed, with the earliest being gradient-based methods and experiments-based methods. Gradient-based methods, such as the method of Lagrange multipliers, are based on the resolution of differentiable equation systems, and although they yield fast computation times, they converge toward local optima only, which may not be global optima. Experiments-based methods, and more specifically Response Surface Methodology, were and remain a common optimization approach in the food processing industry (Banga et al., 2008). Since then, new optimization methods for multi-objective problems have been developed, which are able to efficiently identify global optima. They have been grouped under the term “multi-objective optimization (MOO) methods”.

MOO is a general methodology aimed at identifying the best trade-off(s) between several conflicting objectives. Numerous applications in engineering can be found, from the design of a single mechanical part (Collignan et al., 2012) to the optimization of a worldwide supply chain (Wang et al., 2011). MOO consists in a) a multi-objective processing method, to transform the original multi-objective problem into a solvable problem, and b) an **optimization algorithm**, to search for trade-off solutions to the multi-objective problem (Collette and Siarry, 2013).

A multi-objective processing method requires the following elements, in the food processes framework:

1) Optimization objectives and associated indicators. The decision maker defines **objectives**, i.e. changes that the decision-maker(s) wish(es) to cause in the process (profit increase, productivity increase, environmental impact decrease…), and these changes are quantified or described by suitable performance **indicators** (margin, yield, carbon dioxide emissions…) (Church and Rogers, 2006). Indicators are also called by the term “criteria”, which can itself be used as an equivalent to “objectives” (Craheix et al., 2015). In this work, the terminologies “objectives” and “indicators” will be used.
2) A **predictive food process model**: the effect of different values of the design variables (input variables, i.e. operating conditions, equipment size, process structure...) on the indicators is predicted by a process model. Thus, the different design solutions available can be evaluated. The predictive model should provide a satisfying level of prediction accuracy, while optimizing efficiently for reasonable computation times.
3) A preference model, where the decision-maker **preferences and expert knowledge** are integrated. Preferences may be specified at two different levels (figure 1): i) objectives may be weighted according to their relative significance for the decision-maker and/or qualified experts; ii) desirability functions may be used to integrate satisfaction levels of experts according to indicator values. The decision-maker may have sufficient knowledge to specify preferences at both levels. However, it is considered in this work that the experts have more qualifications to specify preferences on indicator values, based on a good scientific and/or technical knowledge of the process and the installation context.

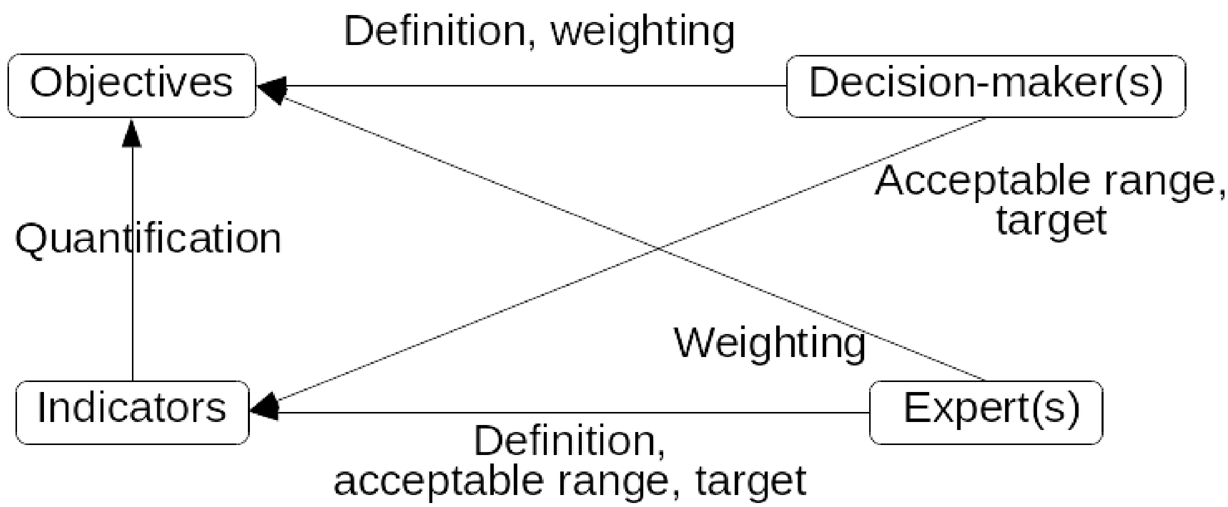

Figure 1: Relationships between objectives, indicators, and preference integration

4) A **selection method** to choose the "best trade-off" by sorting, ranking or scoring the design solutions available. The selection method generally consists in aggregating preferences and indicators to build an objective function for optimization, but may also in consist in different approaches.

Regarding the optimization algorithm, it integrates these four elements to search for trade-offs among possible design solutions.

Numerous methods and algorithms can be used to build a multi-objective processing method to be combined with an optimization algorithm. Detailed taxonomies and information on these methods can be found in reference books such as (Chen and Hwang, 1992; Collette and Siarry, 2013; Ehrgott, 2005; Miettinen, 1998). It is also noteworthy that predictive food process models and preferences models are used in single-objective (mono-objective) optimization, in order to obtain a single performance indicator. These elements are not specific to MOO, and a detailed comparison of single- and multi-objective optimization can be found in Rangaiah et al. (2015).

In this context, the application of MOO to food processing was studied, that is the transformation of biological raw materials by one or several unit operations to produce edible food products. The investigation field of this review was restricted to MOO for food process design, which excludes:

- process control (or closed loop optimal control, as defined in Banga et al. (2008) – see for example Trelea et al. (1997));
- product formulation (or mixture design - see for example Chen et al. (Chen et al., 2004));
- model parameter optimization.

The design problems included were:

- selection of fixed or variable operating conditions (i.e. open loop optimal control – Banga et al. (2008));

- equipment sizing;
- number and structure of unit operations in the process.

A number of articles have been reviewed to discuss the methods used by the authors to perform MOO. From these studies it was established that despite the advanced development of MOO as a generic design methodology, the tools and methods of MOO have not yet fully reached the area of food process design:

- MOO is infrequent in the design of food processes compared to chemical processes: around 40 articles on MOO application in food processing had been published in scientific journals before 2009 (Abakarov et al., 2009), whereas around 360 papers regarding MOO in chemical engineering applications had been published until mid-2012 (Rangaiah and Bonilla-Petriciolet, 2013). Several authors (Banga et al., 2003; Trystram, 2012) have identified two major hindrances: i) physical properties, and consequently quality parameters of food materials, are difficult to predict because of the complexity of food materials; ii) many food process models are unsuitable for optimization purposes, since they have been developed to understand the behaviour of food materials as biological reactors (with reaction kinetics and transfers), rather than predict its behaviour as a function of process control variables and size.
- Most studies focus on the optimization of operating conditions for design or process control; many of them concern heat treatment processes. In contrast only a few MOO studies concentrate on the integrated design of food processes, where both unit operations structure and equipment sizing are optimized (see for example Nishitani and Kunugita (1979)).
- Most MOO design studies published are limited to the production of the Pareto front, i.e. the set of trade-off solutions for the process design (Kiranoudis and Markatos, 2000; Kopsidas, 1995; Nishitani and Kunugita, 1979, 1983; Stefanis et al., 1997; Yuen et al., 2000 …). Multi-criteria decision making (MCDM) methods, which help to select the best trade-off amongst Pareto-efficient solutions, are seldom applied in these studies. MCDM methods can help include the preferences of the decision-maker in the design process, and rank the possible solutions to identify one (or a small set of) “best” trade-off(s) for process design.
- Very few design approaches are systemic: most optimization objectives are evaluated with “raw” indicators of process performance (nutrient retention, energy consumption, processing time…) and do not involve the interactions of the process with its environment (environmental impact based on LCA, overall economic profit, nutritional interest…).

Thus, the potential for developing more advanced MOO methods and associated tools for the design of food processes is high: most studies only partially use the constituent elements of MOO, while a variety of methods and tools are available to perform MOO. Hence it seemed relevant to study and review these methods and tools along with their use for food process design.

In this paper, a critical review of multi-objective optimization methods which have been used in food process design studies is developed. The main purpose is to demonstrate how design methods engineering can solve design problems in food processing, which however requires a choice among existing MOO methods.

The different sections of this review match the aforementioned elements which constitute a MOO method:

- Section 2 is a critical analysis of **indicators** which describe design objectives;
- Section 3 briefly reviews **process models** used for MOO of food processes;
- Section 4 deals with the integration of **preferences** in decision-making;
- Section 5 handles the methods used in the literature to **select the best solutions**;
- Section 6 explores **optimization algorithms** for MOO from the perspective of methods engineering;
- Section 7 describes some holistic MOO methods, which include all elements for MOO (process indicators and model, preference model, ranking method, optimization algorithm) and discusses research issues.

2. Design indicators

2.1. Raw and integrative indicators

The indicators required for optimization are produced by a set of more or less complex models, based on knowledge of the process. The indicators are mostly quantitative, but may possibly be qualitative (one product more appreciated than another, soft or hard texture, sanitary risk present or absent, etc.); the latter case is not considered in this work. A quantitative indicator may be an integer variable, but is more generally a real variable in the field of food processing. Process sizing parameters, such as a number of effects of an evaporator or number of cleaning cycles, may be represented by an variable integer, which is common in the field of chemical processing (see for example Morandin et al. (2011) and Rangaiah and Bonilla-Petriciolet (2013)). Quantitative indicators can be constructed simply using the physical variables (or chemical, biochemical, biological variables) of the process, or be generated by an economic model or environmental impact model, making it possible to quantify global objectives (especially sustainability). In this work, the indicators are categorized in two families:

- Raw indicators, i.e. variables of physical, chemical, biochemical or even biological origin, calculated using the process model, such as the product treatment temperature, its sensorial qualities (texture, colour…), steam consumption, retention rate of a compound of interest, etc.
- Integrative indicators, which combine raw indicators referring to different (but linked) phenomena into a unique variable, according to scientific and/or technical or statistical principles, or even rule-like principles. They are constructed from economic, environmental, social, or even product quality models. They correspond to the definition of the composite indicators given by Von Shirdning (2002).

In the case of raw indicators, interpretation i.e. the relationship between indicators and objectives, is left to the decision-maker, which assumes a degree of expertise in the process under study. A decision-maker not specializing in the process will be less capable of analysing the solutions proposed, since the raw indicators may not be explicit in terms of the objectives sought. Thus, the exergy proposed by Nishitani and Kunugita

(1983) requires an ability to understand this concept in terms of environmental impact; the “head kernel” yield for optimizing rice drying by Olmos et al. (2002) cannot quantify the economic implications of this indicator. Similarly, selecting a raw indicator could partly conceal, or even bias, the information required for evaluating the objectives. Thus Stefanis et al. (1997) opted to characterize the environmental impact in wastewater by BOD (Biological Oxygen Demand), which represents a highly partial view of the environmental impact that a process may have. In Nishitani and Kunugita (1979), the exchange surface contributes only partially to the cost of the evaporator, and so appears to be an incomplete indicator in terms of the defined economic objective.

Conversely, raw indicators can be tailored to specific contexts, where the process objectives can be expressed directly by physical variables derived from the process model: in Yuen et al. (2000), the objective is to remove alcohol from beer while minimizing loss of chemicals associated with taste, which is explicitly expressed by an “alcohol removal” indicator and an “extract removal” indicator. In particular in the case of explicitly known product quality objectives, they can be expressed by selecting certain nutritional compounds, such as in Tarafdar et al. (2017), where the indicators are contents of nutritional compounds of interest.

On ther other hand, integrative indicators can link the process physical variables to variables of interest/which are meaningful for the decision-maker: a return on investment time for example will be easier to interpret for an investor than an investment cost and an operating cost taken separately. Sebastian et al. (2010) defined a total cost of ownership, bringing together the operating cost (electricity and fluids consumption) and an investment cost (purchasing and manufacturing costs), which can be used to quantify what the equipment costs over a planned service life of twenty years.

However, due to the construction of the associated functions, integrative indicators entail a risk of bias in the interpretation. Firstly, the models used may be subject to debate; in the case of impact scores based on Life Cycle Analysis (LCA) for example, modelling of the environmental impacts varies according to the impact calculation methodologies, and there is not always an established consensus on these models (Hauschild et al., 2008). Then, the weighting of different kinds of indicators (greenhouse effect and eutrophication, texture and colour…) for the purpose of aggregating them in an integrative indicator may also entail a bias. Finally, constructing integrative indicators assumes use of data which is sometimes uncertain; thus it is not always possible, at the scale of a process situated in a larger system (e.g. factory), to predict its profitability or maintenance cost.

The indicators encountered in the various articles studied in this work are rarely integrative indicators. While aggregating raw indicators can produce an indicator which is meaningful for the decision-maker, the way in which they are grouped induces a risk of information loss. Thus, raw indicators of major significance in design choices may find themselves concealed by the integrative indicator, as in the case of the SAIN-LIM indicator which conceals the effect of certain nutrients on the overall score (Achir et al., 2010). So the development of relevant indicators means finding a balance between an excessive number of raw indicators, which is difficult to interpret and discuss, and an integrative indicator, which would cause major information loss through aggregation.

2.2. Relevance of indicators

Besides the advantages and shortcomings of raw and integrative indicators, the question of choice of indicators is an issue of interest, firstly in terms of the meaning given to the indicators. There are numerous approaches for constructing more or less integrative indicators which are meaningful for the decision-maker in view of their objectives. An overview of some of these approaches is proposed here, via the four dimensions of sustainability of food engineering processes: economic sustainability and product quality, which are the most frequently encountered dimensions, plus environmental and social sustainability.

Economic evaluation of processes makes it possible to establish the cost that they represent, and/or their profitability in the shorter or longer term. In the context of optimization, it must be possible to predict their operating cost and the investment they represent; there are correlations for predicting investment as a function of sizing choices, the best known of which is from Guthrie (1969). Benchmark works provide values for the parameters of this correlation (Maroulis and Saravacos, 2007; Turton et al., 2008). Based on the economic and financial information on the process and the company, it becomes possible to construct integrative economic indicators, the best known of which are the internal profitability rate, return on investment time, discounted income, net present value and net cumulative cash flow (Chauvel et al., 2001; Turton et al., 2008). Other approaches are being developed, such as thermo-economics, which associates a cost with exergy (a measure of energy quality to determine energy degradation in the system), to evaluate economic feasibility and profitability (Rosen, 2008). In keeping with the “life cycle” approach, Life Cycle Costing (LCC), where the financial, environmental and social costs are factored into the life cycle as a whole (Norris, 2001), is another approach under development. Like thermo-economics, it still requires construction of databases large enough for the economic indicators proposed to evaluate the food engineering processes.

Food quality needs to be described through a holistic perspective which covers all consumer requirements. Among several possible approaches, an attempt was made by Windhab (2009) to provide such holistic perspective, known by the acronym PAN: Preference (organoleptic and usage properties), Acceptance (religious, cultural, GMO…), Need (health, nutrition...). However, the indicators used in the literature primarily relate to the P and N dimensions. Only fragmentary elements of food quality are dealt with, which were classified in three categories:

- Nutritional indicators are generally nutritional or anti-nutritional compound degradation kinetics (Abakarov et al., 2009; Garcia-Moreno et al., 2014 …) and are thus raw indicators, although there are some integrative indicators in the form of algebraic equations. Hence, among other approaches, the SAIN-LIM indicators were developed in an attempt to classify foods by their nutritional value, by quantifying their favourability or unfavourability for human health (Darmon et al., 2007). However, they are ill-suited to optimization, as they are insufficiently sensitive to the process control parameters (Achir et al., 2010; Bassama et al., 2015).

- Organoleptic quality is described either by denaturing kinetics (or conversely development kinetics) of compounds relating to organoleptic appraisal of a product (Gergely et al., 2003; Kahyaoglu, 2008; Yuen et al., 2000 …), or by sensory scores. These scores directly express the appraisal of product quality by the consumer, but they are based on a posteriori evaluation (Abakarov et al., 2013; Singh et al., 2010 …). Sensory scores can be aggregated to produce integrative indicators of overall appraisal, provided they have been evaluated on a common scale (e.g. 1 to 9 from worse to best).
- Finally, sanitary quality, which is generally a feasibility constraint rather than an indicator for optimization, is described by microorganism mortality kinetics, or development kinetics of compounds hazardous to humans (Arias-Mendez et al., 2013; Garcia-Moreno et al., 2014).

Quality indicators represent a particularly topical problem, with growing market demands in terms of health, and consequently a research issue for modelling the links between process, nutrition and health.

The issue of environmental impact indicators is particularly topical. While there are numerous environmental impact approaches, they are all debatable in terms of relevance regarding the process studied, and of over- or under-estimating the impact. Three of the best known environmental impact evaluation methods are listed below:

- Life Cycle Analysis (LCA) is the most commonly used method, and most comprehensive for evaluating the environmental impacts of a system (Azapagic et al., 2011; Jacquemin et al., 2012; Manfredi et al., 2015). The indicators produced are calculated based on the inventory of emissions and resources consumed throughout the life cycle of the product in question, LCI (Life Cycle Inventory). An LCI analysis methodology is employed to convert the emissions surveyed from the entire system in question into environmental impact scores, using characterization factors specific to the method used. LCA is a widely described and analysed method (Jolliet et al., 2010), but rarely used in optimizing food engineering processes: it was partially used in the study by Romdhana et al. (Romdhana et al., 2016), where only the Global Warming Potential (GWP) indicator, relating to climate change, was used, and in the works of Stefanis et al. (1997), which defined several indicators comprising air pollution, water pollution, solid wastes, photochemical oxidation, and stratospheric ozone depletion. Although standardized and comprehensive, LCA contains possible biases caused by the choice of inventory analysis method, functional unit, system and impact allocation.
- Thermodynamic methods, based on the second law of thermodynamics, quantify changes of thermodynamic state in the system under study, making it possible to identify “degradations” caused by the process and thereby quantify the impact. For example, the exergetic analysis, which quantifies quality loss of the energy entering the system, i.e. destruction of exergy; this makes it possible to determine

the “available energy” in outgoing currents in the form of “exergetic efficiency”, which is used as an environmental impact indicator (Ouattara et al., 2012). Used in Nishitani and Kunugita (1983), this seems to be the most developed thermodynamic method, though there are still insufficient thermodynamic data to be able to generalize its application.

- The Sustainable Process Index (SPI) is an indicator measuring the environmental impact in terms of surface of the planet used to provide goods or services (Steffens et al., 1999). Assuming that the sole external input into the system is solar energy, any process occupies a more or less large fraction of the Earth’s surface for its workings “from cradle to grave” (raw materials, energy, personnel, environmental emissions...). Thus, a low SPI will indicate an efficient process. This approach provides a sole indicator, independent of modelling environmental damage, but it lacks data for the area attributed to each substance or process, and there are inconsistencies when the use of fossil or mineral resources is analysed (Hertwich et al., 1997).

Mention may be made of other methods, such as the WAR (Waste Reduction) algorithm, and the IChemE indicators, which are both (like LCA) based on using impact factors, and the AIChE metrics developed for petrochemical processes, though these cannot be used to evaluate the potential damage.

Finally, the social dimension of sustainability is not represented in the literature studied for this work, since it is hard to quantify at the process design stage. The concept of social LCA is relatively recent (early 2000s), suffers among other things from a lack of data (Norris, 2014), and has hitherto been applied to fields such as industrial management and product development (Jørgensen et al., 2008); only a few works (Schmidt et al., 2004) mention consideration of social objectives in the field of processes for comparative studies. True, indicators such as job creation, safety and nuisance generation have been proposed (Azapagic et al., 2011), but they often relate to the operational phase, and are difficult to associate with indicators in the preliminary design phase. Employment could be a relevant indicator for processes, for example via the number of total local jobs (You et al., 2012), depending for example on the quantity of labour required by each piece of equipment included in the process.

Thus, the choice from among all these indicators affects the meaning given to the optimization, but also the results. Indeed, the results derived from the optimization of the same process are dependent on the decision-maker’s objectives, and more generally on the specific context of the optimization study. By way of example, the mass of the equipment, used to quantify its transportability in Sebastian et al. (2010), would not be a relevant indicator for a fixed process in a factory. Thus it is clear that the ranking of a solution is closely linked to the mathematical construction of the indicators, hence the usefulness of considering their relevance. Achir et al. (2010) for example showed that the number of nutrients factored into the SAIN-LIM indicator affects the ranking of a product by this indicator. Yet to our knowledge, no study has taken an in-depth look into the subject, as the indicators are pre-selected, and not questioned thereafter. So evaluation of the relevance of the indicators for optimization is a relevant research question, but a difficult task.

3. Models for multi-objective optimization

Although there are optimization approaches without models (especially sequential experimental strategies such as the simplex method), the exploration of various scenarios, and the need to rank them to identify the best (especially if the question is to find a compromise between several objectives), it would seem that optimization definitely requires numerical models.

For food and biological processes, there are numerous long-standing modelling approaches. Table 1 presents and categorizes the approaches listed in the literature. These process model construction and validation methods present various characteristics, and may be classified in three categories (Banga et al., 2003; Perrot et al., 2011; Roupas, 2008): knowledge-driven models (“white box” type), which are derived from the physical laws governing the behaviour of the process; data-driven models (“black box” type), which are solely based on empirical data; and hybrid models (“grey box” type), which are a combination of the two.

Table 1: Process model types

Model type	Categories	References	Comments
Data-driven models ("Black box")	Response surface methodology (RSM)	Abakarov et al. (2013); Annor et al. (2010); Collignan and Raoult-Wack (1994); Corzo and Gomez (2004); Eren and Kaymak-Ertekin (2007); Garcia-Moreno et al. (2014); Gergely et al. (2003); Kahyaoglu (2008); Karimi et al. (2012); Kowalski and Ganjya (2018) ; Lespinard et al. (2015); Noshad et al. (2012); Singh et al. (2010); Tarafdar et al. (2017); Themelin et al. (1997); Yuan et al. (2018)	Provides insight into process behaviour without knowledge of intrinsic mechanisms; minimizes the number of experiments to model the process; it is risky to use the process models out of their validity domain.
	Artificial neural networks (ANN)	Asgari et al. (2017); Chen and Ramaswamy (2002); Izadifar and Jahromi (2007); Karimi et al. (2012); Taheri-Garavand et al. (2018); Winiczenko et al., (2018a-c)	Require no a priori knowledge of relationships between input and output variables; however a high amount of experimental data is needed.
	Gene expression programming	Kahyaoglu (2008)	
Knowledge-driven models ("White box")	Batch thermal treatment	Abakarov et al. (2009); Erdoğdu and Balaban (2003); Sendín et al. (2010)	Mainly mechanistic approach; provide robust and resilient models which account for involved mechanisms; however the models may take into account a limited number of variables; precision in prediction may also be low in a given domain compared to data-driven models.
	Fermentation	Rodman and Gerogiorgis (2017)	
	Continuous heat treatment	De Jong (1996); Sidaway and Kok, (1982)	
	Evaporation	Nishitani and Kunugita (1979, 1983); Sebastian et al. (2010); Sharma et al. (2012)	
	Filtration	Yuen et al. (2000)	
Hybrid models ("Grey box")	-	Arias-Mendez et al. (2013); Ferrández et al. (2018a,b); Goñi and Salvadori (2012); Hadiyanto et al. (2009); Kiranoudis and Markatos (2000); Olmos et al. (2002); Romdhana et al. (2016); Sicard et al. (2012)	Combine mechanistic models (heat & mass transfer, chemical reactions) with empirical equations, and even expert knowledge; trade-off between precision in prediction and range of validity domain.

White box models, also known as “mechanistic” models, are now capable of addressing various scales (from molecular to macroscopic), making it possible to produce just as great a variety of indicators. Purely mechanistic models are uncommon, since the links between molecular and macroscopic scales are still difficult to establish. Various approaches have been proposed which take into account prediction of phase changes in food matrices with the SAFES methodology (Systematic Approach for Food Engineering Systems; Fito et al. (2007)), but in which information requirements on the systems to be modelled go beyond current knowledge (Trystram, 2012). The models considered in this work as knowledge-driven use well-known laws, within specific domains:

- Some white box models relate to heat treatment in a container. The classic equations of diffusion and convection of mass and heat, as well as the degradation kinetics of compounds of interest, are used to describe the phenomena occurring in the container.
- The works of Rodman and Gerogiorgis (2017) consider only part of the chemical reactions occurring during fermentation, which makes it possible to use generic kinetic parameters.
- Modelling of heat exchangers, with or without phase change, is abundantly covered in the literature, especially in chemical engineering. This means that it can be applied to food engineering processes, but using empirical correlations for the exchange coefficients specific to the food products. Thus Sharma et al. (2012) designed an evaporator treating milk, while Sidaway and Kok (1982) developed a heat exchanger sizing program for heat treatment.
- Yuen et al. (2000) modelled the performance of a beer dialysis module, including the molecular scale in the solute transfer rate calculation. Although simplified, this is the closest model to a purely mechanistic model.

White box models are often characterized by long calculation times, inherent in the partial derivative equations which have to be solved. Although computing power aids simulation, the most complex models are not necessarily the most appropriate for multi-objective optimization. That is why model reduction techniques are proposed to create quick tools, containing all the degrees of freedom with optimization at the core, and which are sometimes broken down into hybrid (grey box) models - quick, efficient and simple to employ.

Black box models are based on experimental or compiled data, and require approaches which employ model parameter identification algorithms to be determined once the mathematical structure has been chosen. There are countless examples of modelling approaches in the literature; Response Surface Methodology (RSM) is the most common in food processing, particularly for modelling osmotic dehydration (Abakarov et al., 2013; Arballo et al., 2012; Corzo and Gomez, 2004; Eren and Kaymak-Ertekin, 2007; Singh et al., 2010; Themelin et al., 1997; Yuan et al., 2018), in which the complex mechanisms involved (transfer through vegetable cell membranes) are well-suited to the black box approach. The field of possible modelling approaches is wide, also encompassing Artificial Neural Networks (Asgari et al., 2017; Chen and Ramaswamy, 2002; Izadifar and Jahromi, 2007; Karimi et al., 2012), gene expression programming (Kahyaoglu, 2008), fuzzy logic, pure algorithms, etc. The main advantage of these black box models is probably the calculation speed, which enables use of a wide variety of optimization algorithms. Nonetheless, these modelling approaches are often very data-hungry (and demanding in terms of data quality), especially when a random dimension is present in at least one of the indicators. In addition, black box models are limited by their ability to cover all the influencing variables, and if one of the variables is not taken into consideration, the whole work needs to be redone. Finally, due to the fact that the modelling is based on incomplete or non-existing prior knowledge, extrapolation is impossible or hazardous, and in this case confidence in the results obtained is generally low.

Improvements to black box models are designed and applied when knowledge based on expert opinion or experimental results is used. This knowledge makes it possible to describe a priori a black box models structure, which entails at least some degree of robustness after identification of the parameters. Numerous graph-based models enable such approaches to be used (e.g. Bayesian graphs, dynamic or not, fuzzy graphs); see for example Baudrit et al. (2010) and the review of Perrot et al. (2011). The modelling approach used in Sicard et al. (2012) combines a mechanistic model with expert knowledge to model the system dynamic. Thus in many cases, a compromise between a first principle (white box) model based on explicit knowledge, and coupled black box models is available, resulting in the creation of hybrid (grey box) models. For example in Olmos et al. (2002), a mathematical model for transfer into a rice grain was combined with empirical models of transfer coefficient and of quality deterioration. One of the advantages of these models is their applicability on various scales, or ability to contribute to multi-scale modelling, which is a major challenge for food engineering processes.

There is a great variety of modelling approaches, which is why it is important to be able to evaluate the model quality in terms of optimization, yet there are practically no analysis methods that have been developed to this end. Vernat et al. (2010) proposed rating the quality of a model by four aspects, united under the acronym “PEPS”:

- Parsimony: a model must be as simple as possible, which is quantified by the number of variables and mathematical relationships. This aspect could be supplemented by an execution time indicator for compatibility with optimization;
- Exactitude (accuracy): the distance between the results derived from the model and the experimental measurements/observations must be as low as possible. This aspect touches on the concept of physical (or chemical, biological) robustness, which means that whatever the simplification employed, the physical laws and the consequent behaviour of the model are still conserved;
- Precision: the uncertainty over the results derived from the model must be as low as possible;
- Specialization: the restriction of the model’s field of application must be minimal.

Two additional aspects could be added to the PEPS framework:

- The identifiability of unknown model parameter values (transfer coefficient, activation energy of a reaction...) is validated.
- Sensitivity is established (and quantified) between the degrees of freedom for optimization and the key variables.

Model quality analyses are often limited to exactitude (accuracy), by comparison with experimental results, and to the sensitivity of the model's responses to the operating or sizing parameters. Hence the process models used are often developed specifically for a unit operation or a process (Diefes et al., 2000), which means a high degree of specialization. The development of more generic food engineering process models, using IT tools able to easily evaluate model performances, would make it possible to establish a logic of model quality compliance for optimization.

Once the indicators have been defined (section 2) and the process model is operational (section 3), a method for selecting the best compromise must be chosen. This method must be able to integrate the preferences of the decision-maker and/or experts in evaluating the solutions. Multi-criteria analysis, which employs multiple criteria decision analysis (MCDA) methods (also known as multi-criterion decision making – MCDM – or multiple attribute decision making - MADM), refers to methods able to address this issue. The following sections propose a review of methods of integrating preferences and methods of identifying the best-performing solutions, used in the food engineering literature.

4. Integrating preferences

Preferences apply to the indicator values and to the comparative significance of the objectives. These preferences may be integrated before or after the optimization process, or indeed during the process, i.e. interactively. Hence there are methods to integrate these preferences in order to make the decision-making process more rational. The articles reviewed in which the preferences are integrated via specific methods have been classified in table 2, depending on whether the preferences are on the indicators, the significance of the objectives, or whether they are integrated interactively.

Table 2: Preference integration methods

Preference level	**Methods**	**References [*Product & process type*]**
Preferences on indicator values	Desirability function: Harrington	Sebastian et al. (2010) [*Wine evaporation*]
	Desirability function: Derringer	Arballo et al. (2012) [*Pumpkin, kiwi, pear osmotic dehydration*]; Corzo and Gomez (2004) [*Sweet melon osmotic dehydration*]; Eren and Kaymak-Ertekin (2007) [*Potato osmotic dehydration*]; Kowalski and Ganjya (2018) [*Pea extrusion*]; Lespinard et al. (2015) [*Pumpkin pasteurization*]; Karimi et al. (2012) [*Wormwood leaves drying*]; Taheri-Garavand et al. (2018) [*Banana convective drying*]
	Sigmoid desirability function	Raffray et al. (2015) [*Fish hot-smoking*]
	Desirability function not given (use of software)	Alam et al. (2010) [*Indian gooseberry osmotic dehydration*]; Azarpazhooh et al. (2012) [*Apple osmotic dehydration*]; Kahyaoglu (2008) [*Pistachio nut roasting*]; Noshad et al. (2012) [*Quince dehydration process*]; Vieira et al. (2012) [*Guava osmotic dehydration*]; Yadav et al. (2012) [*Peach osmotic dehydration*]
Preferences on objectives	AHP weighting	Abakarov et al. (2013) |*Carrot osmotic dehydration*]
	Ordinal ranking: lexicographic ordering	Erdoğdu and Balaban (2003) [*Food product thermal processing*]
Interactive methods	NIMBUS	Hakanen et al. (2007) [*Glucose-fructose separation*]

The preferences may relate to the values adopted by the indicators. They originate from expert knowledge, functional analysis of the process to be designed, data mining, market studies... Their usefulness is based on:

- Reducing the search space for possible solutions, by proposing desired valves (upper and lower) associated with each indicator. This may prove particularly useful in the case of raw indicators, for which context-specific limitations may be integrated; thus for example in Sebastian et al. (2010), the maximum acceptable mass of the equipment makes it possible to evaluate the transportability objective of the equipment.
- Favouring certain indicator values over others, by means of desirability functions.

Desirability functions convert the value of an indicator into a dimensionless variable of between 0 and 1, known as “satisfaction index”, which quantifies the satisfaction of the decision-maker on the performance of the indicator. They require the determination of a high value for the indicator (associated with an upper or lower desirability value) and a low value (associated with a lower or upper desirability value, respectively), in order to demarcate the desirability domain. The most commonly used functions in the literature (Arballo et al., 2012; Corzo and Gomez, 2004; Eren and Kaymak-Ertekin, 2007; Lespinard et al., 2015) are those from Derringer (1980), one able to express increasing or decreasing desirability (one-sided), and the other to express maximum desirability in one domain, and decreasing when an indicator moves away from this domain (two-sided). There are other forms of desirability function, in various mathematical forms, such as from Harrington (1965), used in Sebastian et al. (2010), and the sigmoid function (Raffray et al., 2015). All these functions lead to normalized indicators (expressed on a common scale), which can facilitate ranking the solutions by aggregating the scores. The choice between the different existing functions depends on how the desirability values are seen, as a function of the values of the indicator under study. Thus for example, the functions from Derringer (1980) strictly demarcate the indicator's domain of variation, while the sigmoid function from Raffray et al. (2015) remains discriminant in the vicinity of the domain under study.

The decision-maker may also formulate preferences over the relative significance of their objectives, i.e. on the comparative significance of the indicators. This may involve weighting the objectives, or ranking them in order of significance. If the decision-maker is faced with a multitude of objectives, it may be difficult to rationally and consistently attribute the weights. That is why there are methods to help the decision-maker to prioritize the objectives: the AHP method (Analytic Hierarchy process – Saaty (1990)) for example, which designates a method even capable of ranking the solutions, includes a step of defining the weights by comparing the objectives (or indicators) in pairs, is used in Abakarov et al. (2013). A score of between 1 and 9 is attributed to each objective depending on its significance compared to every other objective, and the results are aggregated using a given formula to provide a numerical value for the weight of each objective. Other methods use pairwise comparison, a non-exhaustive list of which is given in Siskos and Tsotsolas (2015). Ranking the objectives in order of significance does not require priorization methods. It has been used by Erdoğdu and Balaban (2003) and named "lexicographic ordering". This approach seems uncommon, since most decision-making aid and optimization methods require quantification of the significance of the objectives for calculating the objective functions. Otherwise, lexicographic ordering of the indicators must be implemented in the optimization algorithm, as is the case in Erdoğdu and Balaban (2003). Another possibility is to use a lexicographic approach to produce a weighting (Sebastian et al., 2010): the objectives are ranked by significance, and a mathematical function attributes a weight to each objective according to its level of significance. This approach is similar to the SMARTER method (Edwards and Barron, 1994), and to other hybrid approaches of this type, such as: the Simos method (Figueira and Roy, 2002; Simos, 1990a, 1990b), where cards are used to order the objectives and quantify their relative significance, and the SWING method, in which the objectives are ranked based on solutions with the best possible value for one indicator, and the worst possible value in all the others. Interested readers can find a detailed review of weighting methods in Wang et al. (2009).

Finally, there are optimization methods in which the decision-maker formulates their preferences through an iterative design process, in which solutions are presented to them. These so-called interactive methods generally proceed in three phases (Coello, 2000):

1. Calculate a Pareto-efficient solution;
2. Put together the decision-maker's preferences on this solution, and its possible improvements;
3. Repeat steps 1 and 2 until the decision-maker is satisfied.

The advantages of this type of method lie mainly in the low requirement for calculations (few solutions calculated in each iteration), the absence of need for an overall preferences diagram, and the possibility for the decision-maker to correct their preferences and therefore learn through the optimization process (Taras and Woinaroschy, 2012). Conversely, it is assumed that the decision-maker has the necessary time and capacities to take part in the decision-making process, and that the information supplied to the decision-maker is comprehensible and relevant (Miettinen, 1998). Although a substantial number of interactive optimization methods are available (Collette and Siarry, 2013; Miettinen, 1998; Miettinen and Hakanen, 2009…), only Hakanen et al. (2007) have used them, with the NIMBUS method (Miettinen and Mäkelä, 1995, 2006). In NIMBUS, when a solution is presented to the decision-maker, the latter specifies for each indicator how they would like it to evolve - for example if an indicator needs to be improved, is satisfactory, or may be downgraded - and these preferences are used to converge toward the most satisfactory possible solution for the decision-maker.

If the optimization problem encountered has not been solved by an interactive method, the preferences integration methods (desirability functions, weighting methods and ranking methods for objective) prove useful in providing a framework for formulating the preferences. To this end, the desirability function best suited to the objectives to be optimized must be chosen, in particular preventing an indicator from adopting undesirable values. The choice of weighting method meanwhile will depend primarily on the user's affinity with one method or the other, and the ease with which they can formulate their preferences.

5. Selection methods

The quantified preferences of the decision-maker may then be used to select the most acceptable solution for the decision-maker. So in the case of an optimization problem, this involves constructing a function or a mathematical criterion able to evaluate the performances of the solutions generated by the process model. Yet it is also possible that the decision-maker will be unable to formulate preferences, or that they are not provided, in the absence of a decision-making context for example. That is why the reviewed articles are classified in two major categories:

- “No information” (Table 3): in the absence of information from the decision-maker, it is possible to calculate a relevant set of solutions (“Sorting / Filtering”), which can then be compared in a decision-making context, or to select a solution anyway without reference to the decision-makers formulated preferences (“Ranking with weight elicitation”);
- “Preferences expressed” (Table 4): the decision-maker’s preferences are expressed, so a solution acceptable under the decision-maker’s criteria can be selected.

Table 3: Selection methods – no information from the decision-maker

Optimization problem	**Methods**	**References [*Product & process type*]**
Filtering	Pareto front / Dominance	Abakarov et al. (2009) [*Pork puree sterilization*]; Arias-Mendez et al. (2013) [*Potato frying*]; Chen and Ramaswamy (2002) [*Food conduction heating*]; Ferrández et al. (2018a,b) [*High-pressure thermal treatment*]; Garcia-Moreno et al. (2014) [*Fish oil extraction*]; Goñi and Salvadori (2012) [*Beef roasting*]; Kawajiri and Biegler (2006) [*Glucose-fructose separation*]; Kiranoudis and Markatos (2000) [*Potato drying*]; Kopsidas (1995) [*Table olive preparation*]; Kurup et al. (2005) [*Glucose-fructose separation*]; Massebeuf et al. (1999) [*Food extrusion / granulation*]; Nishitani and Kunugita (1979, 1983) [*Milk evaporation*]; Sendín et al. (2010) [*Canned fish sterilization*]; Sharma et al. (2012) [*Milk evaporation*]; Subramani et al. (2003) [*Glucose-fructose separation*]; Stefanis et al. (1997) [*Cheese manufacturing*]; Winiczenko et al., (2018a-c) [*Apple convective drying*]; Yuen et al. (2000) [*Beer dialysis*]; Zhang et al. (2004) [*Fructose syrup production*]
Ranking with weight elicitation	Objective sum (weighted sum with equal weights)	Erdoğdu and Balaban (2003) [*Food product thermal processing*]; Rodman and Gerogiorgis (2017) [*Beer fermentation*]
	Geometric average	Corzo and Gomez (2004) [*Sweet melon osmotic dehydration*]; Kahyaoglu (2008) [*Pistachio nut roasting*]; Karimi et al. (2012) [*Wormwood leaves drying*]; Kowalski and Ganjya (2018) [*Pea extrusion*]; Taheri-Garavand et al. (2018) [*Banana convective drying*]; Vieira et al. (2012) [*Guavas osmotic dehydration*]
	TOPSIS	Madoumier (2016) [*Milk evaporation*]
	MaxiMin	Raffray et al. (2015) [*Fish hot-smoking*]

Table 4: Selection methods – preferences of the decision-maker(s) are expressed

Optimization problem	**Methods**	**References [*Product & process type*]**
Filtering	Superimposition of contour plots	Annor et al. (2010) [*Tempeh preparation process*]; Collignan and Raoult-Wack (1994) [*Fish dewatering and salting*]; Ozdemir et al. (2008) [*Pepper osmotic dehydration*]; Singh et al. (2010) [*Carrot osmotic dehydration*]
	Tabular method	Abakarov et al. (2013) [*Carrot osmotic dehydration*]; Winiczenko et al., (2018b) [*Apple convective drying*]
Ranking	Weighted sum	Asgari et al. (2017) [*Olive oil bleaching*]; De Jong (1996) [*Milk sterilization*]; Hadiyanto et al. (2008a ; 2008b) [*Bakery*]; Izadifar and Jahromi (2007) [*Oil hydrogenation*]; Sidaway and Kok (1982) [*Food continuous sterilization*]
	Weighted geometric mean / Derringer's desirability function	Arballo et al. (2012) [*Pumpkin, kiwi, pear osmotic dehydration*]; Eren and Kaymak-Ertekin (2007) [*Potato osmotic dehydration*]; Lespinard et al. (2015) [*Pumpkin pasteurization*]; Sebastian et al. (2010) [*Wine evaporation*]
	AHP	Abakarov et al. (2013) [*Carrot osmotic dehydration*]
	Loss-minimization function	Gergely et al. (2003) [*Wine membrane filtration*]
	Custom partial aggregation method based on ELECTRE and PROMETHEE	Massebeuf et al. (1999) [*Food extrusion / granulation*]

5.1. No information

If the decision-maker's preferences cannot be formulated, the approach most commonly used in the literature is obtaining the Pareto front, i.e. a larger or smaller set of non-dominated solutions. The concept of Pareto efficiency or dominance is illustrated in figure 2, where the Pareto front covers all the solutions which are not inferior to any solution at any point (i.e. for each indicator). Thus many authors have opted for this approach (Abakarov et al., 2009; Kiranoudis and Markatos, 2000; Kopsidas, 1995; Massebeuf et al., 1999; Nishitani and Kunugita, 1979…) for the purpose of providing Pareto efficient design solutions uncoupled from any context, on which a decision-maker can formulate their preferences. So there is no bias, hence it is possible to optimize without *a priori* knowledge of the decision-maker's preferences (Massebeuf et al., 1999), since an initial sort is carried out by eliminating the dominated solutions. However, this method entails the risk of generating a large number of Pareto-efficient solutions (Raffray et al., 2015), or even absurd solutions for the decision-maker, due to the low solution filtering capacity (Scott and Antonsson, 1998). Indeed, a solution which is extremely poor under one of the indicators may be among the non-dominated solutions, but could be useless as a design solution. In addition, as identified by several authors (Hadiyanto et al., 2009; Hakanen et al., 2007; Subramani et al., 2003), Pareto efficient solutions may be presented to the decision-maker in graphic form for two or three indicators, but interpretation becomes difficult after three.

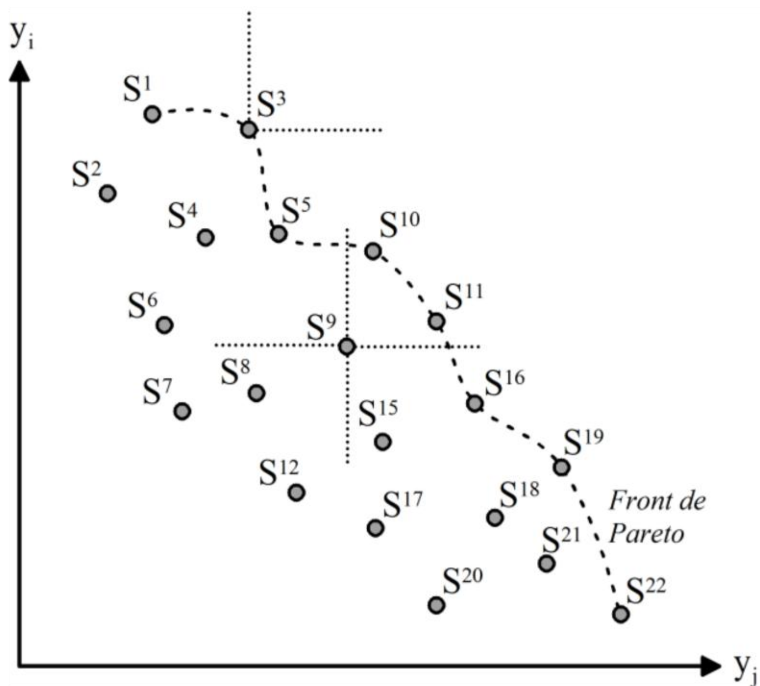

Figure 2: Graphic representation of a Pareto front for two indicators (y_i and y_j). The solutions are designated by the symbols S^i (Collignan, 2011)

Another possibility, making it possible to go beyond the Pareto front while maintaining as neutral an approach as possible, is to use an aggregation function which eliminates weighting of the objectives ("weight elicitation" - Wang et al. (2009)). Thus it is possible to calculate the weighted sum, definitely one of the simplest and most commonly used aggregation functions, with the normalized indicators, assuming equal weight for each indicator. In Erdoğdu and Balaban (2003), the weighted sum became a simple "objective sum" (Marler and Arora, 2004). Another neutral function, the geometric mean, is used in several works (Corzo and Gomez, 2004; Kahyaoglu, 2008; Vieira et al., 2012). Product aggregation functions, like the geometric mean, are said to be more "aggressive" than sum functions (Quirante, 2012), since a low value for one indicator will have a big impact on the total score, and consequently better discrimination of the compromise solutions. Another possible approach is calculating the distance (Euclidian distance, with two or more dimensions) from "utopian" or "ideal" solutions; in the TOPSIS method ("Technique for Order Preference by Similarity to Ideal Solution") used in Madoumier (2016), the solutions are ranked by a function which aggregates the distance of a given solution from the "ideal" solution (comprising the best values for each indicator) and from the "anti-ideal" solution (comprising the worst values for each indicator), with the best solutions evidently being the closest to the former and the furthest from the latter. A shortcoming of these aggregation functions is their compensatory logic, i.e. a high value for one indicator may counterbalance a low value for another indicator (Collignan, 2011). To offset this shortcoming, there are so-called "conservative" aggregation functions (Otto and Antonsson, 1991), such as minimum aggregation (Raffray et al., 2015): the score of a solution is represented by the lowest value among its indicators. So maximizing this score comes down to selecting the "least worst" of all the solutions. According to the same logic, maximum aggregation gives the score of a solution as being the best value among its indicators, but this logic is not suited to a design context (Scott and Antonsson, 1998).

5.2. Preferences expressed

If the decision-maker's preferences are expressed, they can be used to more finely filter a set of solutions. Within the framework of RSM modelling (Response Surface Methodology), a graphic method of filtering the response surfaces was developed by Lind et al. (1960): the overlaid contour plots method comprises overlaying the contour plots for the various indicators, the value of which is determined according to the decision-maker's preferences, in order to isolate a zone in which the indicator values are most satisfactory. Used with success by several authors (Annor et al., 2010; Collignan and Raoult-Wack, 1994; Ozdemir et al., 2008; Singh et al., 2010), this graphic method does however lose some efficiency when the number of design variables is greater than two (Khuri and Mukhopadhyay, 2010), and when the optimization requirements are more complex (Myers et al., 2016). Some authors (Alam et al., 2010; Arballo et al., 2012) use in addition an MADM based on desirability functions to select the best solution from those filtered. Another method, this time based on using tables (known as the "Tabular method"), is used in Abakarov et al. (2013). Its principle is to rank the values adopted by each indicator according to whether they must be maximized or minimized. Hence each row in the table no longer corresponds to one solution. This then enables the decision-maker's preferences to be applied to the indicators to eliminate the undesirable values.

If the remaining values correspond to proposed solutions, these are adopted. The risk with this type of approach is that if there is no solution corresponding to the preferences on the indicators, it forces the decision-maker to revise their requirements downward.

To obtain a ranking of solutions or select the best compromise, the decision-maker's preferences may be integrated into the aforementioned aggregation functions, in the form of weighting. The most classic are the weighted sum, used in Asgari et al. (2017), Hadiyanto et al. (2008a; 2008b) and Sidaway and Kok (1982), and the weighted geometric mean (or weighted product) used in four studies (Arballo et al., 2012; Eren and Kaymak-Ertekin, 2007; Lespinard et al., 2015; Sebastian et al., 2010). Proposed by Derringer (1994), the geometric mean is used in the four studies to aggregate normalized indicators by means of desirability functions. A potential shortcoming of the weighted geometric mean is that the meaning given to the weights is less intuitive than in a weighted sum, since the indicators between them have an exponential relative significance instead of a proportional relative significance (Collignan, 2011). However, it makes it possible to eliminate solutions where an indicator adopts a very low value or zero, under an "aggressive" strategy as mentioned above. Besides these "primary" aggregation functions (as per Marler and Arora (2004)), it is possible to adopt more complex aggregation strategies, at least two of which have been identified within this work:

- Integration strategy within a more complex decision-making aid framework, such as the AHP method employed in Abakarov et al. (2013): the steps for determining the weights, set out in section 4, lead to a weighted sum aggregation.
- "Mathematical" strategy, aimed at increasing the complexity of the aggregation functions. An example is the function derived from an optimization method known as "loss-minimization method" (Equation 1), corresponding to the weighted sum (weight w_i) of variables defined as the relative difference between an indicator (Q_i) and its optimal value (Q_i*) (Gergely et al., 2003). This function requires prior single-objective optimization of the indicators, to obtain their optimal value.

$$\Phi = \sum_{i=1}^{m} w_i \left[\frac{Q_i(x_1, x_2, \ldots, x_n) - Q_i^*}{Q_i^*} \right]^2$$

Equation 1

The aggregation functions mentioned above belong to full aggregation approaches, characterized by the synthesis of several indicators into a single score, which can be distinguished from so-called partial aggregation approaches or outranking approaches (Brans and Vincke, 1985). The latter are based on construction of binary relationships between solutions, based on the decision-maker's preferences (Wang et al., 2009). Hence it is possible to do without an overall aggregation function, but it is also necessary to be able to compare the solutions in twos. This means that partial aggregation methods are applicable only when a sufficiently small set of solutions has been generated. Thus in Massebeuf et al. (1999), the best solution is selected after obtaining Pareto efficient solutions. The partial aggregation method employed in Massebeuf et al. (1999) is constructed from methods such as ELECTRE (Elimination and choice translating reality) and PROMETHEE (Preference ranking organization method for enrichment evaluation); these two terms represent method families suited to various types of issue (sorting for Electre-Tri, choice for ELECTRE I and PROMETHEE I, ranking for ELECTRE III and PROMETHEE II, …), the general principles of which are in brief:

- ELECTRE (Roy, 1968) provides a ranking or preference relationships between solutions, without calculating a cardinal score, based on concordance & discordance indices, and threshold values (Wang et al., 2009). The relationships between solutions are obtained based on pair comparison under each of the decision-maker's objectives.
- PROMETHEE (Brans and Vincke, 1985) is based on quantified comparison of solutions, i.e. the relationship between solutions under a given indicator will be described by a preference function evaluating the intensity of this preference. This information is used to calculate the "incoming" and "outgoing" flows of a solution, i.e. the quantitative measurement of confidence and regret, respectively, relating to a solution (Wang et al., 2009).

For selection or ranking issues, methods such as PROMETHEE are deemed easier to use than methods such as ELECTRE (Velasquez and Hester, 2013), and were indeed designed as an improvement on the latter (Brans and Vincke, 1985).

5.3. Normalization

A question rarely addressed, concerning the application (or possible development) of selection methods, is that of normalization. Most of these methods require normalization of the indicators to enable their comparison on a common scale; if normalization is not applied by a desirability function, simple mathematical operators are applied, such as division by an optimum or a reference value. Yet the works of Pavličić (2001) indicate that the selection results may depend on the mathematical operation applied, and that use of vector type normalization (Equation 2 – x_{ij} is the value of the jth indicator for solution i, and $_{ij}$ is the corresponding normalized indicator) should be reconsidered. So it seems that the normalization operator must be wisely chosen for the applying the selection methods.

$$r_{ij}^{V} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^{2}}$$

Equation 2

5.4. Difficulty of choosing a selection method

In view of these technical considerations and noting the diversity of approaches, the question of choosing a selection method is potentially complex. Indeed, the diversity of solution selection methods, and more generally MADMs, is accentuated by possible combinations between methods. For example in Abakarov et al. (2013), the AHP method and tabular method are combined, and in Massebeuf et al. (1999), the Pareto front is filtered by a partial aggregation method, constructed with the elements of two well-known methods. While none of the methods appears to be the best, their respective advantages and shortcomings may make them incompatible with certain applications

(Velasquez and Hester, 2013). Thus partial aggregation methods may be incompatible with a decision-maker pressed for time, and so must be replaced by a full aggregation method requiring little interaction with the decision-maker. As with weighting methods (section 4), the choice will also be partly subjective, since it depends on the affinity with one method or another. Moreover, they can lead to different results, as observed by Wang and Rangaiah (2017): they compared 10 selection methods, obtained different results for the same problem, and discussed the relevance of these methods for dealing with an optimization problem. Considering a number of criteria (amount of user inputs, simplicity, and applicability), they even recommend 3 methods: TOPSIS, GRA (Gray relational Analysis) and SAW (Simple Additive Weighting).

6. Multi-objective optimization algorithms

An optimization algorithm refers to a more or less automated process, employed to seek combinations of design variables leading to the best solutions, according to the MADM used. Since the size of the space of the possible solutions varies exponentially with the number of design variables and the number of values that these variables may adopt, an "optimization engine" (as per Marler and Arora (2004)) is necessary to efficiently identify the best solutions (in a given context). There are many possible optimization strategies, and in the present work they have been grouped into five categories:

- Exhaustive search;
- Graphic optimization;
- Deterministic indirect search and direct search methods;
- Methods using stochastic metaheuristics;
- Interactive methods.

Exhaustive search and graphic optimization are considered as approaches without optimization engine, while the other three categories are considered as approaches using optimization engines. Thus, the reviewed articles are given in Tables 5 and 6, which correspond to the two groups respectively.

It should be noted that in the literature, a considerable number of authors do not explicitly give the algorithm employed for optimization purposes, if at all. Thus it appears that the question of the optimization algorithm is often neglected, due to a probable lack of knowledge and command of the subject (highly mathematical approach). his leads to papers which are not reproducible by other researchers. One easy solution consists in using software equipped with dedicated optimization functions.

Table 5: Optimization approaches and methods without optimization engines

Optimization approaches	**Optimization methods**	**References [*Product & process type*]**
Exhaustive search	-	Lespinard et al. (2015) [*Pumpkin pasteurization*]; Nishitani and Kunugita (1979) [*Milk evaporation*]; Sidaway and Kok (1982) [*Food continuous sterilization*]; Taheri-Garavand et al. (2018) [*Banana convective drying*]
Graphic	Overlaid contour plots	Alam et al. (2010) [*Indian gooseberry osmotic dehydration*]; Annor et al. (2010) [*Tempeh preparation*]; Arballo et al. (2012) [*Pumpkin, kiwi, pear osmotic dehydration*]; Collignan and Raoult-Wack (1994) [*Fish dewatering and salting*]; Ozdemir et al. (2008) [*Pepper osmotic dehydration*]; Singh et al. (2010) [*Carrot osmotic dehydration*]

Table 6: Optimization approaches and methods with optimization engines

Optimization approaches	**Optimization algorithms**	**References [*Product & process type*]**
Deterministic – indirect search	Custom gradient-based method	Hadiyanto et al. (2008a; 2009) [*Bakery*]
	Max-sensitive method	Nishitani and Kunugita (1983) [*Milk evaporation*]
	Newton-based method IPOPT	Kawajiri and Biegler (2006) [*Glucose-fructose separation*]
	Sequential quadratic programming (SQP)	Goñi and Salvadori (2012) [*Beef roasting*]; Manivannan and Rajasimman (2008) [*Beetroot osmotic dehydration*]; Olmos et al. (2002) [*Rice drying*]; Rodman and Gerogiorgis (2017) [*Beer fermentation*]
Deterministic – direct search	Complex method	Erdoğdu and Balaban (2003) [*Food product thermal processing*]
	Control vector parameterization	Hadiyanto et al. (2008a; 2008b) [*Bakery*]
	Direct method in Design-Expert software	Azarpazhooh and Ramaswamy (2012) [*Apple osmotic dehydration*]; Corzo and Gomez (2004) [*Sweet melon osmotic dehydration*]; Eren and Kaymak-Ertekin (2007) [*Potato osmotic dehydration*]; Kahyaoglu (2008) [*Pistachio nut roasting*]; Noshad et al. (2012) [*Quince dehydration process*]; Vieira et al. (2012) [*Guava osmotic dehydration*]; Yadav et al. (2012) [*Peach osmotic dehydration*]
	Hooke-Jeeves method	De Jong (1996) [*Milk sterilization*]; Gergely et al. (2003) [*Wine membrane filtration*]
Stochastic metaheuristics	Differential evolution	Sendín et al. (2010) [*Canned fish sterilization*]
	Genetic algorithms	Asgari et al. (2017) [*Olive oil bleaching*]; Chen and Ramaswamy (2002) [*Food conduction heating*]; Ferrández et al. (2018a,b) [*High-pressure thermal treatment*]; Izadifar and Jahromi (2007) [*Oil hydrogenation*]; Kowalski and Ganjya (2018) [*Pea extrusion*]; Kurup et al. (2005) [*Glucose-fructose separation*]; Massebeuf et al. (1999) [*Food extrusion / granulation*]; Raffray et al. (2015) [*Fish hot-smoking*]; Romdhana et al. (2016) [*Alfalfa and beet pulp dehydration*]; Sebastian et al. (2010) [*Wine evaporation*]; Sharma et al. (2012) [*Milk evaporation*]; Subramani et al. (2003) [*Glucose-fructose separation*]; Winiczenko et al., (2018a-c) [*Apple convective drying*]; Yuen et al. (2000) [*Beer dialysis*]; Zhang et al. (2004) [*Fructose syrup production*]
	Particle swarm	Romdhana et al. (2016) [*Alfalfa and beet pulp dehydration*]
	Scatter search	Arias-Mendez et al. (2013) [*Potato frying*]
	Adaptive random search	Abakarov et al. (2009) [*Pork puree sterilization*]; Abakarov et al. (2013) [*Carrot osmotic dehydration*]

6.1. Exhaustive search and graphic methods

It is possible to do without optimization engines, generally when the problem is simple, i.e. when it comprises a small number of design variables and objective functions, and when the calculation time of a solution is sufficiently short. In this case, all possible solutions are generated, and an MADM can be applied to rank them and/or select the best. In Lespinard et al. (2015), the total desirability is calculated over the entire feasibility domain based on polynomial regression models. In Nishitani and Kunugita (1979), the number of possible solutions is limited to 6 in the first optimization study (6 possible flow patterns), and in the second optimization study, the 6 solutions are recalculated for various temperature levels of the incoming product. Finally, in Sidaway and Kok (1982), the indicators are evaluated for all temperature and holding time combinations which comply with a given sterility constraint.

Under RSM, it is also possible to do without an optimization engine, using graphic optimization methods, such as overlaid contour plots, as mentioned above (section 5). So this method has both a filtering role according to the preferences, and search role in the solutions feasibility space. Indeed, overlaying certain surface response contours of various indicators makes it possible to reduce the search space without calculations, and thereby provide a smaller set of acceptable solutions. Use of this method has been found in six studies (Alam et al., 2010; Annor et al., 2010; Arballo et al., 2012; Collignan and Raoult-Wack, 1994; Ozdemir et al., 2008; Singh et al., 2010) as an optimization engine, and although its usefulness is recognized, it does have a number of shortcomings, mentioned in section 5.

6.2. Optimization engines

Conversely, when there are a high number of possible solutions and indicators, it becomes necessary to employ an optimization procedure enabling automated searches for the best solutions. The search methods may be divided into two categories: deterministic methods and stochastic methods.

Deterministic optimization methods guarantee that a solution representing an optimum will be obtained (Miri et al., 2008). However, depending on the method employed, the optimum found may only be local, i.e. the adopted solution is Pareto efficient in only a portion of the search space, but may be dominated by other solutions situated in other portions of the search space. There are two types of deterministic method, namely indirect search methods and direct search methods (Romdhana et al., 2016). Indirect, or gradient-based, search methods require derivable objective functions, which is seldom the case, since many variables are discrete and/or discontinuous (Pailhès et al., 2011). So gradient-based methods are applicable only to certain types of problem. Thus the algorithms implementing these methods converge toward an optimum, which achieves rapid convergence in the case of a single extremum. However, most multi-criteria problems involving several extrema (“multi-extremal” or “multimodal” problems), gradient-based methods are unable to converge unfailingly toward an overall optimum (Banga et al., 2003). When these methods are used to generate a Pareto front, they are coupled with aggregation functions. Thus, Goñi and Salvadori (2012), Kawajiri and

Biegler (2006), Nishitani and Kunugita (1983) and Olmos et al. (2002) use the ϵ-constraint method, the formulation of which is to optimize one indicator at a time, considering the other indicators as constraints limited by a given value ϵ (Seng and Rangaiah, 2008). So the gradient-based method makes it possible to solve every single-objective problem, which entails solving several optimization problems, and requires the values ϵ to be defined, which may prove difficult without a priori knowledge of the possible optimal value of the indicators. Furthermore, varying only one design variable in the search space (with the others fixed) does not necessarily make it possible to converge toward an optimum due to failure to factor in interactions between variables (Myers et al., 2016). Another example is use of the weighted sum with variable weights to generate the Pareto front by Hadiyanto et al. (2009). In order to identify overall optima and not only local ones, some deterministic methods have been developed. These methods, known as direct search methods, evaluate the objective functions without calculating their derivative. For example, the Hooke-Jeeves method used by De Jong (1996) and Gergely et al. (2003), consists in evaluating the objective function around a start point, and shifting the search zone in the direction that improves the objective function until a stop criterion is obtained (Benasla et al., 2008). Certain authors (Azarpazhooh and Ramaswamy, 2012; Corzo and Gomez, 2004; Eren and Kaymak-Ertekin, 2007; Kahyaoglu, 2008; Noshad et al., 2012; Vieira et al., 2012; Yadav et al., 2012) have used a direct search method implemented in the Design-expert software, dedicated to RSM (Myers et al., 2016). Direct search methods have the major shortcoming of converging less and less quickly as the size of the problem to solve increases (number of design variables and of objective functions) (Banga et al., 2003). In addition, just like indirect search methods, they require an objective function in algebraic form.

Due to the fact that deterministic optimization methods are not always suitable, methods based on random draws and iterative procedures have been developed. These methods, known as stochastic methods, or using stochastic metaheuristics, are generally inspired by natural phenomena or everyday life, and have been developed in order to solve problems for which conventional deterministic methods proved ineffective (Collette and Siarry, 2013). They make it possible to couple the optimization algorithm to the problem without having to formulate it in an algebraic form, by directly optimizing based on indicator values returned by the process model. In addition, stochastic methods are able to converge more quickly than deterministic methods in the case of complex problems, but with no guarantee of obtaining an overall optimum (Banga et al., 2003). Recently, a literature review of the application of metaheuristics in food engineering (in the broad sense, including formulation of foods and production of pharmaceutical products) was conducted by Wari and Zhu (2016); it emerged that stochastic methods, despite their complexity, are seeing increasing use with the development of computer calculation capacities. The three major common points of stochastic methods are: i) seeking an overall optimum for the entire feasibility domain of the design solutions; ii) the stochastic (random) nature of the calculation of new solutions in each iteration; iii) they authorize downgrading of the indicators to explore the search space more widely. In the literature, the genetic algorithms are by far the most popular, with no fewer than 12 studies (Table 5). Genetic algorithms imitate the process of genetic evolution: an initial "population" of solutions undergoes "genetic modifications" by crossover, mutation, and selection of elements of its DNA (its “genes” correspond to the values adopted by the indicators) according to the performances of each initial individual (i.e. solution) to form new individuals, i.e. potentially better-performing solutions for the multi-objective problem (Hugget et al., 1999; Wari and Zhu, 2016). Several optimization methods employ genetic algorithms, such as MOGA (Multiple Objective Genetic Algorithms) or NSGA (Non-dominated Sorting Genetic Algorithms), the differences between which reside in the Pareto efficiency calculation for the individuals. It is possible to couple together stochastic methods, as in Romdhana et al. (2016), where a genetic algorithm was coupled to a particle swarm algorithm. Wari and Zhu (2016) provided some guidelines on selecting a metaheuristic tailored to the design problem encountered.

6.3. Interactive methods

Interactive methods, presented in section 4, are not optimization engines in themselves, but rather “interaction principles” (Collette and Siarry, 2013). They may require use of an optimization engine to generate a small number of solutions to present to the decision-maker in each iteration. In the NIMBUS method for example, used in Hakanen et al. (2007), several single-objective sub-problems are defined according to the decision-maker’s preferences, and a gradient-based method is used to optimize each of the sub-problems. It should be noted that there are a host of heuristics, including the one known as “simplex”, which do not require an optimization engine to progress in the interactive search process.

7. Toward holistic design approaches

Hitherto, optimization frameworks have been constructed primarily either with a view to generating the Pareto front, or by partially employing MADMs. Various functions coupled to optimization algorithms have been used to generate a Pareto front, leaving expression of decision-maker preferences outside of the field of study. Use of partial aggregation methods and interactive methods, which provide a framework for preference integration, has been encountered once for each of these types of method (Massebeuf et al. (1999) and Hakanen et al. (2007) respectively). Highly diverse solution selection methods have been employed, such as weighted sum, which is among the best known, or weighted geometric mean recommended by Derringer (1994). Conversely, certain aspects of MOO are often neglected; for example, use of methods able to help the decision-maker weigh the objectives remains restricted.

Yet the diversity of decision-making aid methods makes it possible to construct holistic design frameworks, i.e. frameworks which handle all aspects of MOO in a structured way. The constituent elements of the MOO associated with decision-making aid and optimization (preference integration methods, selection methods and optimization methods) may be defined under various approaches, the overview of which given in this work is far from exhaustive. Thus there are holistic approaches for handling a multi-objective problem, such as OIA design methodology (Gero and Kannengiesser, 2007).

This approach, used in Sebastian et al. (2010) and Raffray et al. (2015), combines process modelling to link design variables and indicators (Observation), integrating preferences on the indicators using desirability functions (Interpretation), and constructing an objective function with an aggregation function (Aggregation). A stochastic optimization algorithm may then be integrated into the design framework to obtain the best solutions. This is a general methodology, which must be tailored to the specific context of the study, i.e. the type of problem and field of application (Miettinen, 1998).

Once the study requirements have been identified, the methods to be employed need to be considered. This is a complex subject, into which the advantages and shortcomings of each method have to be factored, as well as the cognitive aspect of the decision-making process; thus, it is important to reduce the “cognitive load” on the decision-maker to facilitate the decision-making process (Hakanen et al., 2007). An initial avenue of consideration resides in the moment, in the design process, when the preferences of the decision-maker and/or expert are articulated. Thus optimization methods are often classified according to whether the preferences are articulated a priori, interactively (or progressively), or a posteriori (Collette and Siarry, 2013; Marler and Arora, 2004; Miettinen, 1998), or even in a fourth category with no preferences articulated (“no-preference”) (Andersson, 2000; Erdoğdu, 2008; Miettinen and Hakanen, 2009). Thus, if the preferences are formulated a priori, use of desirability functions, a weighting method and an aggregation function will make it possible to construct an objective function which will be incorporated into an optimization algorithm in order to generate the best solution. In the case of a posteriori formulation, obtaining a Pareto front is relevant, but it is easier for the decision-maker to select the best solution from a small set. Marler and Arora (2004) also postulated that it is important to define, prior to choosing a method, the type of preferences provided, as well as the quantity of information. Collette and Siarry (2013) provided clues to helping choose multi-objective optimization methods, based in particular on analysing the complexity of the problem and analysing the objective functions. Miettinen (1998) proposed an organization chart for the choice of multi-objective optimization methods, but it proved relatively complex to use. If no method is entirely suitable, various methods may be combined to combine the advantages and compensate for the shortcomings. Examples of these hybrid solving approaches can be found in Abakarov et al. (2013), which combined two solution selection methods, and in Romdhana et al. (2016), which combined two stochastic optimization methods.

The authors would like to emphasize that holistic approaches do not provide a guarantee of obtaining the best solution in terms of the decision-maker. Like any design approach, MOO approaches are part of an iterative decision-making process, which is only facilitated by using decision-making aid methods. Thus it is unlikely that a satisfactory solution will be found in the first iteration; that is why it is important to develop high-performance decision-making tools, which facilitate the optimization procedure.

In this regard, some research questions have been identified:

- Evaluation of the relevance of the indicators has been identified as a difficult search question. Thus the definition of the indicators can have a crucial impact on the optimization results, and few authors have looked into this subject. The question of relevance of the sustainability indicators is particularly topical, especially with regard to the social dimension, which remains hard to integrate into the process. The challenge is the integration of all the sustainability dimensions using appropriate indicators.

- The development of food engineering process simulators suitable for design purposes. To develop these simulators, it should be defined what is expected of a model tailored to optimization, especially in terms of compromise between calculation speed and accuracy of results. The development of evaluation frameworks based for example on the PEPS framework (Vernat et al., 2010) would make it possible to select the models best suited to a given context.
- Although there are some weight definition aid tools (AHP, SMARTER, Simos, SWING…), decision-maker weighting of the objectives remains a difficult task, for example if it involves weighting economic objectives against environmental objectives. Knowledge derived from psychology and social sciences could develop weighting methods best meeting the decision-maker’s preferences, while avoiding as far as possible cognitive biases, and integrating data such as opinion surveys.
- A huge amount of reasearch has been carried out in stochastic metaheuristics since the 90’s. However, they find limited applications, in particular in food process engineering, which brings many opportunities to researchers in metaheuristics. We identified two search fronts in particular: simplifying the search space to limit the number of calculations, and integrating robustness criteria in the selection of the best solutions, in order to directly eliminate the solutions most sensitive to small variations in the design variables. Thus, collaborations between researchers in metaheuristics and researchers in food process design could produce better-suited algorithms for food process design.
- Finally, in the more general framework of food systems sustainability, how can processing design be integrated into a more global system? In fact, design of sustainable industries actually entails factoring in food production as well as processing. Consequently, the performances of processing must be evaluable on a larger scale, and models must be tailored to optimization of the industry as a whole.

8. Conclusion

This review has identified various MOO methods employed in the design of food engineering processes, which are mostly fragmentary. Indeed, the possibilities offered by design engineering and decision-making aid are still under-exploited in the food engineering field. The associated methods facilitate the design process, by clearly defining the preferences of the experts and/or decision-maker, and by optimizing the process depending on the type of problem encountered.

The lack of development of holistic methods can be explained by several factors. First, the difficulty in selecting suitable indicators, which can give meaning to the decision-making variables, in particular for certain sustainability dimensions. Then, while it is sometimes possible to find the desired balance between calculation time and accuracy of the results, on the other hand gaps in the modelling of food engineering processes have been observed, as well as a need for simulators tailored to optimization. Also, weighting of the objectives is difficult, and the optimization algorithms require further improvements to be able to rapidly converge toward high-performance solutions.

Hence it would seem pertinent to develop an overall methodological framework which could guide the designer step-by-step in handling a design problem. This framework would greatly facilitate integration of the various decision-making aid and optimization tools. In this way it could rationalize the methodological choices and simplifications necessary for optimization.

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