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Towards a holistic approach for multi-objective optimization of food processes: a critical review

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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.

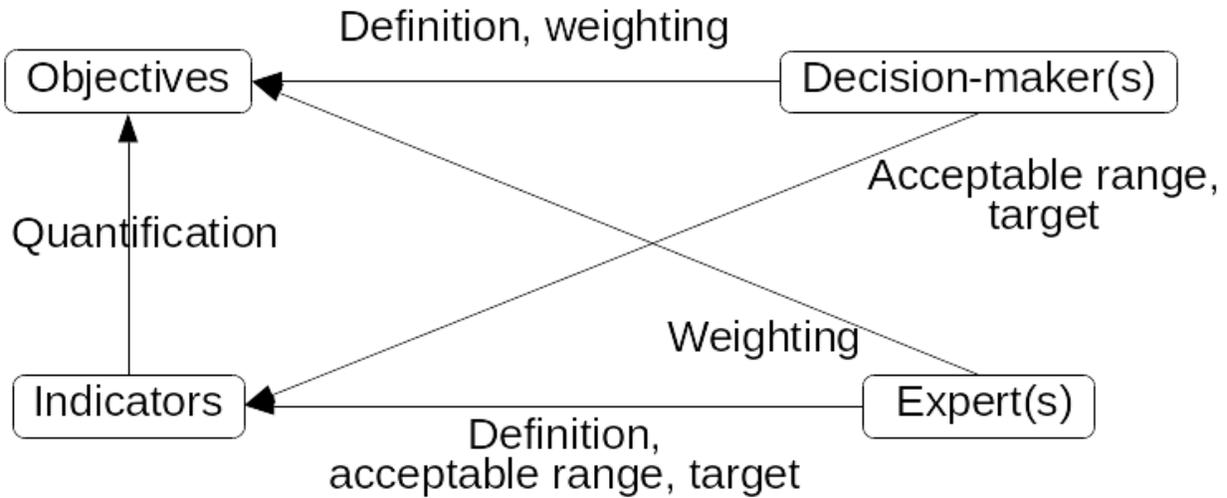
To solve multi-objective design problems, different kinds of methods have been

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

43
44 MOO is a general methodology aimed at identifying the best trade-off(s) between
45 several conflicting objectives. Numerous applications in engineering can be found, from
46 the design of a single mechanical part (Collignan et al., 2012) to the optimization of a
47 worldwide supply chain (Wang et al., 2011). MOO consists in a) a multi-objective
48 processing method, to transform the original multi-objective problem into a solvable
49 problem, and b) an **optimization algorithm**, to search for trade-off solutions to the
50 multi-objective problem (Collette and Siarry, 2013).

51
52 A multi-objective processing method requires the following elements, in the food
53 processes framework:

- 54 1) Optimization objectives and associated indicators. The decision maker defines
55 **objectives**, i.e. changes that the decision-maker(s) wish(es) to cause in the
56 process (profit increase, productivity increase, environmental impact decrease...),
57 and these changes are quantified or described by suitable performance
58 **indicators** (margin, yield, carbon dioxide emissions...) (Church and Rogers,
59 2006). Indicators are also called by the term “criteria”, which can itself be used as
60 an equivalent to “objectives” (Craheix et al., 2015). In this work, the terminologies
61 “objectives” and “indicators” will be used.
- 62 2) A **predictive food process model**: the effect of different values of the design
63 variables (input variables, i.e. operating conditions, equipment size, process
64 structure...) on the indicators is predicted by a process model. Thus, the different
65 design solutions available can be evaluated. The predictive model should provide
66 a satisfying level of prediction accuracy, while optimizing efficiently for reasonable
67 computation times.
- 68 3) A preference model, where the decision-maker **preferences and expert**
69 **knowledge** are integrated. Preferences may be specified at two different levels
70 (figure 1): i) objectives may be weighted according to their relative significance for
71 the decision-maker and/or qualified experts; ii) desirability functions may be used
72 to integrate satisfaction levels of experts according to indicator values. The
73 decision-maker may have sufficient knowledge to specify preferences at both
74 levels. However, it is considered in this work that the experts have more
75 qualifications to specify preferences on indicator values, based on a good
76 scientific and/or technical knowledge of the process and the installation context.



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

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- 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 consist in different approaches.

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

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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).

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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:

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- 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));

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

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

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

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

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

153 The different sections of this review match the aforementioned elements which

154 constitute a MOO method:

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

165 **2. Design indicators**

166 **2.1. Raw and integrative indicators**

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

- 180 • Raw indicators, i.e. variables of physical, chemical, biochemical or even biological
181 origin, calculated using the process model, such as the product treatment
182 temperature, its sensorial qualities (texture, colour...), steam consumption,
183 retention rate of a compound of interest, etc.
- 184 • Integrative indicators, which combine raw indicators referring to different (but
185 linked) phenomena into a unique variable, according to scientific and/or technical
186 or statistical principles, or even rule-like principles. They are constructed from
187 economic, environmental, social, or even product quality models. They
188 correspond to the definition of the composite indicators given by Von Shirdning
189 (2002).

190
191 In the case of raw indicators, interpretation i.e. the relationship between indicators and
192 objectives, is left to the decision-maker, which assumes a degree of expertise in the
193 process under study. A decision-maker not specializing in the process will be less
194 capable of analysing the solutions proposed, since the raw indicators may not be explicit
195 in terms of the objectives sought. Thus, the exergy proposed by Nishitani and Kunugita

196 (1983) requires an ability to understand this concept in terms of environmental impact;
197 the “head kernel” yield for optimizing rice drying by Olmos et al. (2002) cannot quantify
198 the economic implications of this indicator. Similarly, selecting a raw indicator could
199 partly conceal, or even bias, the information required for evaluating the objectives. Thus
200 Stefanis et al. (1997) opted to characterize the environmental impact in wastewater by
201 BOD (Biological Oxygen Demand), which represents a highly partial view of the
202 environmental impact that a process may have. In Nishitani and Kunugita (1979), the
203 exchange surface contributes only partially to the cost of the evaporator, and so appears
204 to be an incomplete indicator in terms of the defined economic objective.

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

213
214 On the other hand, integrative indicators can link the process physical variables to
215 variables of interest/which are meaningful for the decision-maker: a return on investment
216 time for example will be easier to interpret for an investor than an investment cost and
217 an operating cost taken separately. Sebastian et al. (2010) defined a total cost of
218 ownership, bringing together the operating cost (electricity and fluids consumption) and
219 an investment cost (purchasing and manufacturing costs), which can be used to quantify
220 what the equipment costs over a planned service life of twenty years.

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

232
233 The indicators encountered in the various articles studied in this work are rarely
234 integrative indicators. While aggregating raw indicators can produce an indicator which
235 is meaningful for the decision-maker, the way in which they are grouped induces a risk
236 of information loss. Thus, raw indicators of major significance in design choices may find
237 themselves concealed by the integrative indicator, as in the case of the SAIN-LIM
238 indicator which conceals the effect of certain nutrients on the overall score (Achir et al.,
239 2010). So the development of relevant indicators means finding a balance between an

240 excessive number of raw indicators, which is difficult to interpret and discuss, and an
241 integrative indicator, which would cause major information loss through aggregation.

242 **2.2. Relevance of indicators**

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

251
252 Economic evaluation of processes makes it possible to establish the cost that they
253 represent, and/or their profitability in the shorter or longer term. In the context of
254 optimization, it must be possible to predict their operating cost and the investment they
255 represent; there are correlations for predicting investment as a function of sizing
256 choices, the best known of which is from Guthrie (1969). Benchmark works provide
257 values for the parameters of this correlation (Maroulis and Saravacos, 2007; Turton et
258 al., 2008). Based on the economic and financial information on the process and the
259 company, it becomes possible to construct integrative economic indicators, the best
260 known of which are the internal profitability rate, return on investment time, discounted
261 income, net present value and net cumulative cash flow (Chauvel et al., 2001; Turton et
262 al., 2008). Other approaches are being developed, such as thermo-economics, which
263 associates a cost with exergy (a measure of energy quality to determine energy
264 degradation in the system), to evaluate economic feasibility and profitability (Rosen,
265 2008). In keeping with the “life cycle” approach, Life Cycle Costing (LCC), where the
266 financial, environmental and social costs are factored into the life cycle as a whole
267 (Norris, 2001), is another approach under development. Like thermo-economics, it still
268 requires construction of databases large enough for the economic indicators proposed to
269 evaluate the food engineering processes.

270
271 Food quality needs to be described through a holistic perspective which covers all
272 consumer requirements. Among several possible approaches, an attempt was made by
273 Windhab (2009) to provide such holistic perspective, known by the acronym PAN:
274 Preference (organoleptic and usage properties), Acceptance (religious, cultural,
275 GMO...), Need (health, nutrition...). However, the indicators used in the literature
276 primarily relate to the P and N dimensions. Only fragmentary elements of food quality
277 are dealt with, which were classified in three categories:

- 278 • Nutritional indicators are generally nutritional or anti-nutritional compound
279 degradation kinetics (Abakarov et al., 2009; Garcia-Moreno et al., 2014 ...) and
280 are thus raw indicators, although there are some integrative indicators in the form
281 of algebraic equations. Hence, among other approaches, the SAIN-LIM indicators
282 were developed in an attempt to classify foods by their nutritional value, by
283 quantifying their favourability or unfavourability for human health (Darmon et al.,

284 2007). However, they are ill-suited to optimization, as they are insufficiently
285 sensitive to the process control parameters (Achir et al., 2010; Bassama et al.,
286 2015).

- 287 • Organoleptic quality is described either by denaturing kinetics (or conversely
288 development kinetics) of compounds relating to organoleptic appraisal of a
289 product (Gergely et al., 2003; Kahyaoglu, 2008; Yuen et al., 2000 ...), or by
290 sensory scores. These scores directly express the appraisal of product quality by
291 the consumer, but they are based on a posteriori evaluation (Abakarov et al.,
292 2013; Singh et al., 2010 ...). Sensory scores can be aggregated to produce
293 integrative indicators of overall appraisal, provided they have been evaluated on a
294 common scale (e.g. 1 to 9 from worse to best).
- 295 • Finally, sanitary quality, which is generally a feasibility constraint rather than an
296 indicator for optimization, is described by microorganism mortality kinetics, or
297 development kinetics of compounds hazardous to humans (Arias-Mendez et al.,
298 2013; Garcia-Moreno et al., 2014).

299
300 Quality indicators represent a particularly topical problem, with growing market demands
301 in terms of health, and consequently a research issue for modelling the links between
302 process, nutrition and health.

303
304 The issue of environmental impact indicators is particularly topical. While there are
305 numerous environmental impact approaches, they are all debatable in terms of
306 relevance regarding the process studied, and of over- or under-estimating the impact.
307 Three of the best known environmental impact evaluation methods are listed below:

- 308 • Life Cycle Analysis (LCA) is the most commonly used method, and most
309 comprehensive for evaluating the environmental impacts of a system (Azapagic et
310 al., 2011; Jacquemin et al., 2012; Manfredi et al., 2015). The indicators produced
311 are calculated based on the inventory of emissions and resources consumed
312 throughout the life cycle of the product in question, LCI (Life Cycle Inventory). An
313 LCI analysis methodology is employed to convert the emissions surveyed from
314 the entire system in question into environmental impact scores, using
315 characterization factors specific to the method used. LCA is a widely described
316 and analysed method (Jolliet et al., 2010), but rarely used in optimizing food
317 engineering processes: it was partially used in the study by Romdhana et al.
318 (Romdhana et al., 2016), where only the Global Warming Potential (GWP)
319 indicator, relating to climate change, was used, and in the works of Stefanis et al.
320 (1997), which defined several indicators comprising air pollution, water pollution,
321 solid wastes, photochemical oxidation, and stratospheric ozone depletion.
322 Although standardized and comprehensive, LCA contains possible biases caused
323 by the choice of inventory analysis method, functional unit, system and impact
324 allocation.
- 325 • Thermodynamic methods, based on the second law of thermodynamics, quantify
326 changes of thermodynamic state in the system under study, making it possible to
327 identify “degradations” caused by the process and thereby quantify the impact.
328 For example, the exergetic analysis, which quantifies quality loss of the energy
329 entering the system, i.e. destruction of exergy; this makes it possible to determine

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

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

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

349
350 Finally, the social dimension of sustainability is not represented in the literature studied
351 for this work, since it is hard to quantify at the process design stage. The concept of
352 social LCA is relatively recent (early 2000s), suffers among other things from a lack of
353 data (Norris, 2014), and has hitherto been applied to fields such as industrial
354 management and product development (Jørgensen et al., 2008); only a few works
355 (Schmidt et al., 2004) mention consideration of social objectives in the field of processes
356 for comparative studies. True, indicators such as job creation, safety and nuisance
357 generation have been proposed (Azapagic et al., 2011), but they often relate to the
358 operational phase, and are difficult to associate with indicators in the preliminary design
359 phase. Employment could be a relevant indicator for processes, for example via the
360 number of total local jobs (You et al., 2012), depending for example on the quantity of
361 labour required by each piece of equipment included in the process.

362
363 Thus, the choice from among all these indicators affects the meaning given to the
364 optimization, but also the results. Indeed, the results derived from the optimization of the
365 same process are dependent on the decision-maker’s objectives, and more generally on
366 the specific context of the optimization study. By way of example, the mass of the
367 equipment, used to quantify its transportability in Sebastian et al. (2010), would not be a
368 relevant indicator for a fixed process in a factory. Thus it is clear that the ranking of a
369 solution is closely linked to the mathematical construction of the indicators, hence the
370 usefulness of considering their relevance. Achir et al. (2010) for example showed that
371 the number of nutrients factored into the SAIN-LIM indicator affects the ranking of a
372 product by this indicator. Yet to our knowledge, no study has taken an in-depth look into
373 the subject, as the indicators are pre-selected, and not questioned thereafter. So
374 evaluation of the relevance of the indicators for optimization is a relevant research
375 question, but a difficult task.

376 **3. Models for multi-objective optimization**

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

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

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

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

417
418 White box models are often characterized by long calculation times, inherent in the
419 partial derivative equations which have to be solved. Although computing power aids
420 simulation, the most complex models are not necessarily the most appropriate for multi-
421 objective optimization. That is why model reduction techniques are proposed to create
422 quick tools, containing all the degrees of freedom with optimization at the core, and
423 which are sometimes broken down into hybrid (grey box) models - quick, efficient and
424 simple to employ.

425
426 Black box models are based on experimental or compiled data, and require approaches
427 which employ model parameter identification algorithms to be determined once the
428 mathematical structure has been chosen. There are countless examples of modelling
429 approaches in the literature; Response Surface Methodology (RSM) is the most
430 common in food processing, particularly for modelling osmotic dehydration (Abakarov et
431 al., 2013; Arballo et al., 2012; Corzo and Gomez, 2004; Eren and Kaymak-Ertekin, 2007;
432 Singh et al., 2010; Themelin et al., 1997; Yuan et al., 2018), in which the complex
433 mechanisms involved (transfer through vegetable cell membranes) are well-suited to the
434 black box approach. The field of possible modelling approaches is wide, also
435 encompassing Artificial Neural Networks (Asgari et al., 2017; Chen and Ramaswamy,
436 2002; Izadifar and Jahromi, 2007; Karimi et al., 2012), gene expression programming
437 (Kahyaoglu, 2008), fuzzy logic, pure algorithms, etc. The main advantage of these black

438 box models is probably the calculation speed, which enables use of a wide variety of
439 optimization algorithms. Nonetheless, these modelling approaches are often very data-
440 hungry (and demanding in terms of data quality), especially when a random dimension is
441 present in at least one of the indicators. In addition, black box models are limited by their
442 ability to cover all the influencing variables, and if one of the variables is not taken into
443 consideration, the whole work needs to be redone. Finally, due to the fact that the
444 modelling is based on incomplete or non-existing prior knowledge, extrapolation is
445 impossible or hazardous, and in this case confidence in the results obtained is generally
446 low.

447
448 Improvements to black box models are designed and applied when knowledge based on
449 expert opinion or experimental results is used. This knowledge makes it possible to
450 describe a priori a black box models structure, which entails at least some degree of
451 robustness after identification of the parameters. Numerous graph-based models enable
452 such approaches to be used (e.g. Bayesian graphs, dynamic or not, fuzzy graphs); see
453 for example Baudrit et al. (2010) and the review of Perrot et al. (2011). The modelling
454 approach used in Sicard et al. (2012) combines a mechanistic model with expert
455 knowledge to model the system dynamic. Thus in many cases, a compromise between a
456 first principle (white box) model based on explicit knowledge, and coupled black box
457 models is available, resulting in the creation of hybrid (grey box) models. For example in
458 Olmos et al. (2002), a mathematical model for transfer into a rice grain was combined
459 with empirical models of transfer coefficient and of quality deterioration. One of the
460 advantages of these models is their applicability on various scales, or ability to
461 contribute to multi-scale modelling, which is a major challenge for food engineering
462 processes.

463
464 There is a great variety of modelling approaches, which is why it is important to be able
465 to evaluate the model quality in terms of optimization, yet there are practically no
466 analysis methods that have been developed to this end. Vernat et al. (2010) proposed
467 rating the quality of a model by four aspects, united under the acronym "PEPS":

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

479 Two additional aspects could be added to the PEPS framework:

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

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

491
492 Once the indicators have been defined (section 2) and the process model is operational
493 (section 3), a method for selecting the best compromise must be chosen. This method
494 must be able to integrate the preferences of the decision-maker and/or experts in
495 evaluating the solutions. Multi-criteria analysis, which employs multiple criteria decision
496 analysis (MCDA) methods (also known as multi-criterion decision making – MCDM – or
497 multiple attribute decision making - MADM), refers to methods able to address this
498 issue. The following sections propose a review of methods of integrating preferences
499 and methods of identifying the best-performing solutions, used in the food engineering
500 literature.

501 **4. Integrating preferences**

502 Preferences apply to the indicator values and to the comparative significance of the
503 objectives. These preferences may be integrated before or after the optimization
504 process, or indeed during the process, i.e. interactively. Hence there are methods to
505 integrate these preferences in order to make the decision-making process more rational.
506 The articles reviewed in which the preferences are integrated via specific methods have
507 been classified in table 2, depending on whether the preferences are on the indicators,
508 the significance of the objectives, or whether they are integrated interactively.
509

Table 2: Preference integration methods

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

511

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

515 • Reducing the search space for possible solutions, by proposing desired values
516 (upper and lower) associated with each indicator. This may prove particularly
517 useful in the case of raw indicators, for which context-specific limitations may be
518 integrated; thus for example in Sebastian et al. (2010), the maximum acceptable
519 mass of the equipment makes it possible to evaluate the transportability objective
520 of the equipment.

521 • Favouring certain indicator values over others, by means of desirability functions.
522 Desirability functions convert the value of an indicator into a dimensionless variable of
523 between 0 and 1, known as “satisfaction index”, which quantifies the satisfaction of the
524 decision-maker on the performance of the indicator. They require the determination of a

525 high value for the indicator (associated with an upper or lower desirability value) and a
526 low value (associated with a lower or upper desirability value, respectively), in order to
527 demarcate the desirability domain. The most commonly used functions in the literature
528 (Arballo et al., 2012; Corzo and Gomez, 2004; Eren and Kaymak-Ertekin, 2007;
529 Lespinard et al., 2015) are those from Derringer (1980), one able to express increasing
530 or decreasing desirability (one-sided), and the other to express maximum desirability in
531 one domain, and decreasing when an indicator moves away from this domain (two-
532 sided). There are other forms of desirability function, in various mathematical forms,
533 such as from Harrington (1965), used in Sebastian et al. (2010), and the sigmoid
534 function (Raffray et al., 2015). All these functions lead to normalized indicators
535 (expressed on a common scale), which can facilitate ranking the solutions by
536 aggregating the scores. The choice between the different existing functions depends on
537 how the desirability values are seen, as a function of the values of the indicator under
538 study. Thus for example, the functions from Derringer (1980) strictly demarcate the
539 indicator's domain of variation, while the sigmoid function from Raffray et al. (2015)
540 remains discriminant in the vicinity of the domain under study.

541
542 The decision-maker may also formulate preferences over the relative significance of
543 their objectives, i.e. on the comparative significance of the indicators. This may involve
544 weighting the objectives, or ranking them in order of significance. If the decision-maker
545 is faced with a multitude of objectives, it may be difficult to rationally and consistently
546 attribute the weights. That is why there are methods to help the decision-maker to
547 prioritize the objectives: the AHP method (Analytic Hierarchy process – Saaty (1990)) for
548 example, which designates a method even capable of ranking the solutions, includes a
549 step of defining the weights by comparing the objectives (or indicators) in pairs, is used
550 in Abakarov et al. (2013). A score of between 1 and 9 is attributed to each objective
551 depending on its significance compared to every other objective, and the results are
552 aggregated using a given formula to provide a numerical value for the weight of each
553 objective. Other methods use pairwise comparison, a non-exhaustive list of which is
554 given in Siskos and Tsotsolas (2015). Ranking the objectives in order of significance
555 does not require prioritization methods. It has been used by Erdoğan and Balaban (2003)
556 and named “lexicographic ordering”. This approach seems uncommon, since most
557 decision-making aid and optimization methods require quantification of the significance
558 of the objectives for calculating the objective functions. Otherwise, lexicographic
559 ordering of the indicators must be implemented in the optimization algorithm, as is the
560 case in Erdoğan and Balaban (2003). Another possibility is to use a lexicographic
561 approach to produce a weighting (Sebastian et al., 2010): the objectives are ranked by
562 significance, and a mathematical function attributes a weight to each objective according
563 to its level of significance. This approach is similar to the SMARTER method (Edwards
564 and Barron, 1994), and to other hybrid approaches of this type, such as: the Simos
565 method (Figueira and Roy, 2002; Simos, 1990a, 1990b), where cards are used to order
566 the objectives and quantify their relative significance, and the SWING method, in which
567 the objectives are ranked based on solutions with the best possible value for one
568 indicator, and the worst possible value in all the others. Interested readers can find a
569 detailed review of weighting methods in Wang et al. (2009).

570
571 Finally, there are optimization methods in which the decision-maker formulates their

572 preferences through an iterative design process, in which solutions are presented to
573 them. These so-called interactive methods generally proceed in three phases (Coello,
574 2000):

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

579 The advantages of this type of method lie mainly in the low requirement for calculations
580 (few solutions calculated in each iteration), the absence of need for an overall
581 preferences diagram, and the possibility for the decision-maker to correct their
582 preferences and therefore learn through the optimization process (Taras and
583 Woinaroschy, 2012). Conversely, it is assumed that the decision-maker has the
584 necessary time and capacities to take part in the decision-making process, and that the
585 information supplied to the decision-maker is comprehensible and relevant (Miettinen,
586 1998). Although a substantial number of interactive optimization methods are available
587 (Collette and Siarry, 2013; Miettinen, 1998; Miettinen and Hakanen, 2009...), only
588 Hakanen et al. (2007) have used them, with the NIMBUS method (Miettinen and
589 Mäkelä, 1995, 2006). In NIMBUS, when a solution is presented to the decision-maker,
590 the latter specifies for each indicator how they would like it to evolve - for example if an
591 indicator needs to be improved, is satisfactory, or may be downgraded - and these
592 preferences are used to converge toward the most satisfactory possible solution for the
593 decision-maker.

594
595 If the optimization problem encountered has not been solved by an interactive method,
596 the preferences integration methods (desirability functions, weighting methods and
597 ranking methods for objective) prove useful in providing a framework for formulating the
598 preferences. To this end, the desirability function best suited to the objectives to be
599 optimized must be chosen, in particular preventing an indicator from adopting
600 undesirable values. The choice of weighting method meanwhile will depend primarily on
601 the user's affinity with one method or the other, and the ease with which they can
602 formulate their preferences.

603 **5. Selection methods**

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

- 611 • “No information” (Table 3): in the absence of information from the decision-maker,
612 it is possible to calculate a relevant set of solutions (“Sorting / Filtering”), which
613 can then be compared in a decision-making context, or to select a solution
614 anyway without reference to the decision-makers formulated preferences
615 (“Ranking with weight elicitation”);
 - 616 • “Preferences expressed” (Table 4): the decision-maker’s preferences are
617 expressed, so a solution acceptable under the decision-maker’s criteria can be
618 selected.
- 619

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

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

623
624

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

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

625

626 **5.1. No information**

627 If the decision-maker's preferences cannot be formulated, the approach most commonly
628 used in the literature is obtaining the Pareto front, i.e. a larger or smaller set of non-
629 dominated solutions. The concept of Pareto efficiency or dominance is illustrated in
630 figure 2, where the Pareto front covers all the solutions which are not inferior to any
631 solution at any point (i.e. for each indicator). Thus many authors have opted for this
632 approach (Abakarov et al., 2009; Kiranoudis and Markatos, 2000; Kopsidas, 1995;
633 Massebeuf et al., 1999; Nishitani and Kunugita, 1979...) for the purpose of providing
634 Pareto efficient design solutions uncoupled from any context, on which a decision-maker
635 can formulate their preferences. So there is no bias, hence it is possible to optimize
636 without *a priori* knowledge of the decision-maker's preferences (Massebeuf et al., 1999),
637 since an initial sort is carried out by eliminating the dominated solutions. However, this
638 method entails the risk of generating a large number of Pareto-efficient solutions
639 (Raffray et al., 2015), or even absurd solutions for the decision-maker, due to the low
640 solution filtering capacity (Scott and Antonsson, 1998). Indeed, a solution which is
641 extremely poor under one of the indicators may be among the non-dominated solutions,
642 but could be useless as a design solution. In addition, as identified by several authors
643 (Hadiyanto et al., 2009; Hakanen et al., 2007; Subramani et al., 2003), Pareto efficient
644 solutions may be presented to the decision-maker in graphic form for two or three
645 indicators, but interpretation becomes difficult after three.
646

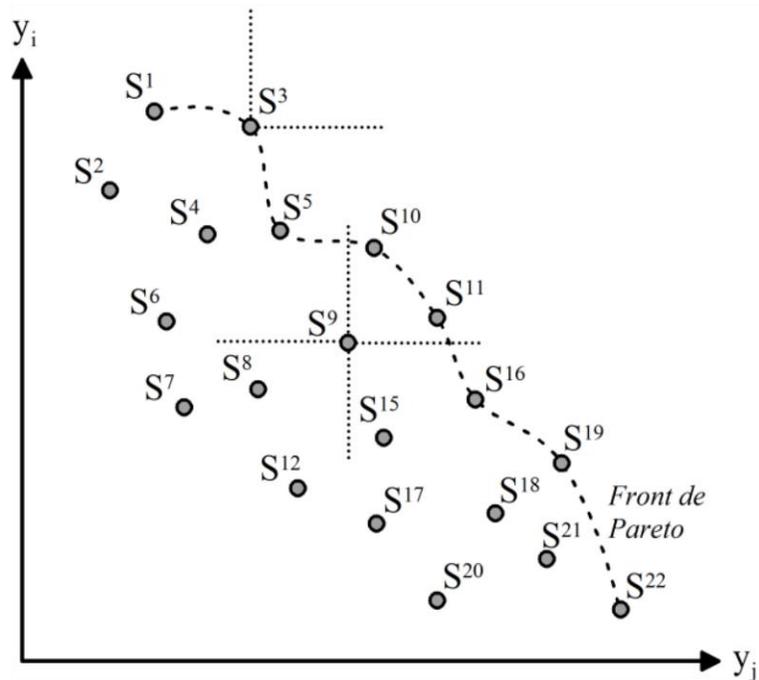


Figure 2: Graphic representation of a Pareto front for two indicators (y_i and y_j). The solutions are designated by the symbols S^i (Collignan, 2011)

647
648

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

676 **5.2. Preferences expressed**

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

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

697
698 To obtain a ranking of solutions or select the best compromise, the decision-maker's
699 preferences may be integrated into the aforementioned aggregation functions, in the
700 form of weighting. The most classic are the weighted sum, used in Asgari et al. (2017),
701 Hadiyanto et al. (2008a; 2008b) and Sidaway and Kok (1982), and the weighted
702 geometric mean (or weighted product) used in four studies (Arballo et al., 2012; Eren
703 and Kaymak-Ertekin, 2007; Lespinard et al., 2015; Sebastian et al., 2010). Proposed by
704 Derringer (1994), the geometric mean is used in the four studies to aggregate
705 normalized indicators by means of desirability functions. A potential shortcoming of the
706 weighted geometric mean is that the meaning given to the weights is less intuitive than
707 in a weighted sum, since the indicators between them have an exponential relative
708 significance instead of a proportional relative significance (Collignan, 2011). However, it
709 makes it possible to eliminate solutions where an indicator adopts a very low value or
710 zero, under an "aggressive" strategy as mentioned above. Besides these "primary"
711 aggregation functions (as per Marler and Arora (2004)), it is possible to adopt more
712 complex aggregation strategies, at least two of which have been identified within this
713 work:

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

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

Equation 1

723
724
725
726
727
728 The aggregation functions mentioned above belong to full aggregation approaches,
729 characterized by the synthesis of several indicators into a single score, which can be
730 distinguished from so-called partial aggregation approaches or outranking approaches
731 (Brans and Vincke, 1985). The latter are based on construction of binary relationships
732 between solutions, based on the decision-maker's preferences (Wang et al., 2009).
733 Hence it is possible to do without an overall aggregation function, but it is also
734 necessary to be able to compare the solutions in twos. This means that partial
735 aggregation methods are applicable only when a sufficiently small set of solutions has
736 been generated. Thus in Massebeuf et al. (1999), the best solution is selected after
737 obtaining Pareto efficient solutions. The partial aggregation method employed in
738 Massebeuf et al. (1999) is constructed from methods such as ELECTRE (Elimination
739 and choice translating reality) and PROMETHEE (Preference ranking organization
740 method for enrichment evaluation); these two terms represent method families suited to

741 various types of issue (sorting for Electre-Tri, choice for ELECTRE I and PROMETHEE
742 I, ranking for ELECTRE III and PROMETHEE II, ...), the general principles of which are
743 in brief:

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

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

758

759 **5.3. Normalization**

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

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

Equation 2

770
771

772 **5.4. Difficulty of choosing a selection method**

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

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

791 **6. Multi-objective optimization algorithms**

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

- 799 • Exhaustive search;
- 800 • Graphic optimization;
- 801 • Deterministic indirect search and direct search methods;
- 802 • Methods using stochastic metaheuristics;
- 803 • Interactive methods.

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

808
809 It should be noted that in the literature, a considerable number of authors do not
810 explicitly give the algorithm employed for optimization purposes, if at all. Thus it appears
811 that the question of the optimization algorithm is often neglected, due to a probable lack
812 of knowledge and command of the subject (highly mathematical approach). This leads to
813 papers which are not reproducible by other researchers. One easy solution consists in
814 using software equipped with dedicated optimization functions.

Table 5: Optimization approaches and methods without optimization engines

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

Table 6: Optimization approaches and methods with optimization engines

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

818 **6.1. Exhaustive search and graphic methods**

819 It is possible to do without optimization engines, generally when the problem is simple,
820 i.e. when it comprises a small number of design variables and objective functions, and
821 when the calculation time of a solution is sufficiently short. In this case, all possible
822 solutions are generated, and an MADM can be applied to rank them and/or select the
823 best. In Lespinard et al. (2015), the total desirability is calculated over the entire
824 feasibility domain based on polynomial regression models. In Nishitani and Kunugita
825 (1979), the number of possible solutions is limited to 6 in the first optimization study (6
826 possible flow patterns), and in the second optimization study, the 6 solutions are
827 recalculated for various temperature levels of the incoming product. Finally, in Sidaway
828 and Kok (1982), the indicators are evaluated for all temperature and holding time
829 combinations which comply with a given sterility constraint.

830

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

841 **6.2. Optimization engines**

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

846

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

862 Biegler (2006), Nishitani and Kunugita (1983) and Olmos et al. (2002) use the ϵ -
863 constraint method, the formulation of which is to optimize one indicator at a time,
864 considering the other indicators as constraints limited by a given value ϵ (Seng and
865 Rangaiah, 2008). So the gradient-based method makes it possible to solve every single-
866 objective problem, which entails solving several optimization problems, and requires the
867 values ϵ to be defined, which may prove difficult without a priori knowledge of the
868 possible optimal value of the indicators. Furthermore, varying only one design variable in
869 the search space (with the others fixed) does not necessarily make it possible to
870 converge toward an optimum due to failure to factor in interactions between variables
871 (Myers et al., 2016). Another example is use of the weighted sum with variable weights
872 to generate the Pareto front by Hadiyanto et al. (2009). In order to identify overall optima
873 and not only local ones, some deterministic methods have been developed. These
874 methods, known as direct search methods, evaluate the objective functions without
875 calculating their derivative. For example, the Hooke-Jeeves method used by De Jong
876 (1996) and Gergely et al. (2003), consists in evaluating the objective function around a
877 start point, and shifting the search zone in the direction that improves the objective
878 function until a stop criterion is obtained (Benasla et al., 2008). Certain authors
879 (Azarpazhooh and Ramaswamy, 2012; Corzo and Gomez, 2004; Eren and Kaymak-
880 Ertekin, 2007; Kahyaoglu, 2008; Noshad et al., 2012; Vieira et al., 2012; Yadav et al.,
881 2012) have used a direct search method implemented in the Design-expert software,
882 dedicated to RSM (Myers et al., 2016). Direct search methods have the major
883 shortcoming of converging less and less quickly as the size of the problem to solve
884 increases (number of design variables and of objective functions) (Banga et al., 2003).
885 In addition, just like indirect search methods, they require an objective function in
886 algebraic form.

887
888 Due to the fact that deterministic optimization methods are not always suitable, methods
889 based on random draws and iterative procedures have been developed. These
890 methods, known as stochastic methods, or using stochastic metaheuristics, are
891 generally inspired by natural phenomena or everyday life, and have been developed in
892 order to solve problems for which conventional deterministic methods proved ineffective
893 (Collette and Siarry, 2013). They make it possible to couple the optimization algorithm to
894 the problem without having to formulate it in an algebraic form, by directly optimizing
895 based on indicator values returned by the process model. In addition, stochastic
896 methods are able to converge more quickly than deterministic methods in the case of
897 complex problems, but with no guarantee of obtaining an overall optimum (Banga et al.,
898 2003). Recently, a literature review of the application of metaheuristics in food
899 engineering (in the broad sense, including formulation of foods and production of
900 pharmaceutical products) was conducted by Wari and Zhu (2016); it emerged that
901 stochastic methods, despite their complexity, are seeing increasing use with the
902 development of computer calculation capacities. The three major common points of
903 stochastic methods are: i) seeking an overall optimum for the entire feasibility domain of
904 the design solutions; ii) the stochastic (random) nature of the calculation of new
905 solutions in each iteration; iii) they authorize downgrading of the indicators to explore the
906 search space more widely. In the literature, the genetic algorithms are by far the most
907 popular, with no fewer than 12 studies (Table 5). Genetic algorithms imitate the process
908 of genetic evolution: an initial “population” of solutions undergoes “genetic modifications”

909 by crossover, mutation, and selection of elements of its DNA (its “genes” correspond to
910 the values adopted by the indicators) according to the performances of each initial
911 individual (i.e. solution) to form new individuals, i.e. potentially better-performing
912 solutions for the multi-objective problem (Hugget et al., 1999; Wari and Zhu, 2016).
913 Several optimization methods employ genetic algorithms, such as MOGA (Multiple
914 Objective Genetic Algorithms) or NSGA (Non-dominated Sorting Genetic Algorithms),
915 the differences between which reside in the Pareto efficiency calculation for the
916 individuals. It is possible to couple together stochastic methods, as in Romdhana et al.
917 (2016), where a genetic algorithm was coupled to a particle swarm algorithm. Wari and
918 Zhu (2016) provided some guidelines on selecting a metaheuristic tailored to the design
919 problem encountered.
920

921 **6.3. Interactive methods**

922 Interactive methods, presented in section 4, are not optimization engines in themselves,
923 but rather “interaction principles” (Collette and Siarry, 2013). They may require use of an
924 optimization engine to generate a small number of solutions to present to the decision-
925 maker in each iteration. In the NIMBUS method for example, used in Hakanen et al.
926 (2007), several single-objective sub-problems are defined according to the decision-
927 maker’s preferences, and a gradient-based method is used to optimize each of the sub-
928 problems. It should be noted that there are a host of heuristics, including the one known
929 as “simplex”, which do not require an optimization engine to progress in the interactive
930 search process.

931 **7. Toward holistic design approaches**

932 Hitherto, optimization frameworks have been constructed primarily either with a view to
933 generating the Pareto front, or by partially employing MADMs. Various functions coupled
934 to optimization algorithms have been used to generate a Pareto front, leaving
935 expression of decision-maker preferences outside of the field of study. Use of partial
936 aggregation methods and interactive methods, which provide a framework for
937 preference integration, has been encountered once for each of these types of method
938 (Massebeuf et al. (1999) and Hakanen et al. (2007) respectively). Highly diverse solution
939 selection methods have been employed, such as weighted sum, which is among the
940 best known, or weighted geometric mean recommended by Derringer (1994).
941 Conversely, certain aspects of MOO are often neglected; for example, use of methods
942 able to help the decision-maker weigh the objectives remains restricted.
943

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

951 This approach, used in Sebastian et al. (2010) and Raffray et al. (2015), combines
952 process modelling to link design variables and indicators (Observation), integrating
953 preferences on the indicators using desirability functions (Interpretation), and
954 constructing an objective function with an aggregation function (Aggregation). A
955 stochastic optimization algorithm may then be integrated into the design framework to
956 obtain the best solutions. This is a general methodology, which must be tailored to the
957 specific context of the study, i.e. the type of problem and field of application (Miettinen,
958 1998).

959

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

987

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

995

996 In this regard, some research questions have been identified:

997 • Evaluation of the relevance of the indicators has been identified as a difficult

998 search question. Thus the definition of the indicators can have a crucial impact on
999 the optimization results, and few authors have looked into this subject. The
1000 question of relevance of the sustainability indicators is particularly topical,
1001 especially with regard to the social dimension, which remains hard to integrate
1002 into the process. The challenge is the integration of all the sustainability
1003 dimensions using appropriate indicators.

- 1004 • The development of food engineering process simulators suitable for design
1005 purposes. To develop these simulators, it should be defined what is expected of a
1006 model tailored to optimization, especially in terms of compromise between
1007 calculation speed and accuracy of results. The development of evaluation
1008 frameworks based for example on the PEPS framework (Vernat et al., 2010)
1009 would make it possible to select the models best suited to a given context.
- 1010 • Although there are some weight definition aid tools (AHP, SMARTER, Simos,
1011 SWING...), decision-maker weighting of the objectives remains a difficult task, for
1012 example if it involves weighting economic objectives against environmental
1013 objectives. Knowledge derived from psychology and social sciences could
1014 develop weighting methods best meeting the decision-maker's preferences, while
1015 avoiding as far as possible cognitive biases, and integrating data such as opinion
1016 surveys.
- 1017 • A huge amount of research has been carried out in stochastic metaheuristics
1018 since the 90's. However, they find limited applications, in particular in food
1019 process engineering, which brings many opportunities to researchers in
1020 metaheuristics. We identified two search fronts in particular: simplifying the
1021 search space to limit the number of calculations, and integrating robustness
1022 criteria in the selection of the best solutions, in order to directly eliminate the
1023 solutions most sensitive to small variations in the design variables. Thus,
1024 collaborations between researchers in metaheuristics and researchers in food
1025 process design could produce better-suited algorithms for food process design.
- 1026 • Finally, in the more general framework of food systems sustainability, how can
1027 processing design be integrated into a more global system? In fact, design of
1028 sustainable industries actually entails factoring in food production as well as
1029 processing. Consequently, the performances of processing must be evaluable on
1030 a larger scale, and models must be tailored to optimization of the industry as a
1031 whole.

1032 **8. Conclusion**

1033 This review has identified various MOO methods employed in the design of food
1034 engineering processes, which are mostly fragmentary. Indeed, the possibilities offered
1035 by design engineering and decision-making aid are still under-exploited in the food
1036 engineering field. The associated methods facilitate the design process, by clearly
1037 defining the preferences of the experts and/or decision-maker, and by optimizing the
1038 process depending on the type of problem encountered.

1039
1040 The lack of development of holistic methods can be explained by several factors. First,
1041 the difficulty in selecting suitable indicators, which can give meaning to the decision-

1042 making variables, in particular for certain sustainability dimensions. Then, while it is
1043 sometimes possible to find the desired balance between calculation time and accuracy
1044 of the results, on the other hand gaps in the modelling of food engineering processes
1045 have been observed, as well as a need for simulators tailored to optimization. Also,
1046 weighting of the objectives is difficult, and the optimization algorithms require further
1047 improvements to be able to rapidly converge toward high-performance solutions.

1048
1049 Hence it would seem pertinent to develop an overall methodological framework which
1050 could guide the designer step-by-step in handling a design problem. This framework
1051 would greatly facilitate integration of the various decision-making aid and optimization
1052 tools. In this way it could rationalize the methodological choices and simplifications
1053 necessary for optimization.

1054 REFERENCES

- 1055 Abakarov, A., Suhkov, Y., & Mascheroni, R. H. (2013). A multi-criteria optimization and
1056 decision-making approach for improvement of food engineering processes.
1057 *International Journal of Food Studies*, 2(1), 1–21.
- 1058 Abakarov, A., Sushkov, Y., Almonacid, S., & Simpson, R. (2009). Multiobjective
1059 optimization approach: thermal food processing. *Journal of food science*, 74(9),
1060 E471–E487.
- 1061 Achir, N., Kindossi, J., Bohuon, P., Collignan, A., & Trystram, G. (2010). Ability of some
1062 food preservation processes to modify the overall nutritional value of food.
1063 *Journal of food engineering*, 100(4), 613–621.
- 1064 Alam, M. S., Amarjit, S., & Sawhney, B. (2010). Response surface optimization of
1065 osmotic dehydration process for aonla slices. *Journal of food science and
1066 technology*, 47(1), 47–54.
- 1067 Andersson, J. (2000). A survey of multiobjective optimization in engineering design.
1068 *Department of Mechanical Engineering, Linköping University. Sweden.*
- 1069 Annor, G. A., Sakyi-Dawson, E., Saalia, F. K., Sefa-Dedeh, S., Afoakwa, E. O., Tano-
1070 Debrah, K., & Budu, A. S. (2010). Response surface methodology for studying
1071 the quality characteristics of cowpea (*vigna unguiculata*)-based tempeh. *Journal
1072 of food process engineering*, 33(4), 606–625.
- 1073 Arballo, J. R., Bambicha, R. R., Campañone, L. A., Agnelli, M. E., & Mascheroni, R. H.
1074 (2012). Mass transfer kinetics and regressional-desirability optimisation during
1075 osmotic dehydration of pumpkin, kiwi and pear. *International Journal of Food
1076 Science & Technology*, 47(2), 306–314.
- 1077 Arias-Mendez, A., Warning, A., Datta, A. K., & Balsa-Canto, E. (2013). Quality and
1078 safety driven optimal operation of deep-fat frying of potato chips. *Journal of Food
1079 Engineering*, 119(1), 125–134.
- 1080 Asgari, S., Sahari, M. A., & Barzegar, M. (2017). Practical modeling and optimization of
1081 ultrasound-assisted bleaching of olive oil using hybrid artificial neural network-
1082 genetic algorithm technique. *Computers and Electronics in Agriculture*, 140, 422–
1083 432.
- 1084 Azapagic, A., Perdan, S., & Clift, R. (2011). *Sustainable development in practice: Case
1085 Studies for Engineers and Scientists* (2nd éd.). Wiley Online Library.

- 1086 Azarpazhooh, E., & Ramaswamy, H. S. (2012). Modeling and optimization of microwave
1087 osmotic dehydration of apple cylinders under continuous-flow spray mode
1088 processing conditions. *Food and Bioprocess Technology*, 5(5), 1486–1501.
- 1089 Banga, J. R., Balsa-Canto, E., & Alonso, A. A. (2008). Quality and Safety Models and
1090 Optimization as Part of Computer-Integrated Manufacturing. *Comprehensive*
1091 *Reviews in Food Science and Food Safety*, 7(1), 168–174.
- 1092 Banga, J. R., Balsa-Canto, E., Moles, C. G., & Alonso, A. A. (2003). Improving food
1093 processing using modern optimization methods. *Trends in Food Science and*
1094 *Technology*, 14(4), 131 – 144.
- 1095 Bassama, J., Achir, N., Trystram, G., Collignan, A., & Bohuon, P. (2015). Deep-fat frying
1096 process induces nutritional composition diversity of fried products assessed by
1097 SAIN/LIM scores. *Journal of Food Engineering*, 149, 204–213.
- 1098 Baudrit, C., Sicard, M., Wuillemin, P.-H., & Perrot, N. (2010). Towards a global modelling
1099 of the Camembert-type cheese ripening process by coupling heterogeneous
1100 knowledge with dynamic Bayesian networks. *Journal of Food Engineering*, 98(3),
1101 283–293.
- 1102 Benasla, L., Belmadani, A., & Rahli, M. (2008). Hooke-Jeeves' Method Applied to a New
1103 Economic Dispatch Problem Formulation. *Journal of Information Science &*
1104 *Engineering*, 24(3).
- 1105 Brans, J. P., & Vincke, P. (1985). A Preference Ranking Organisation Method.
1106 *Management Science*, 31(6), 647-656.
- 1107 Chauvel, A., Fournier, G., & Raimbault, C. (2001). *Manuel d'évaluation économique des*
1108 *procédés*. Editions TECHNIP.
- 1109 Chen, C. R., & Ramaswamy, H. S. (2002). Modeling and optimization of variable retort
1110 temperature (VRT) thermal processing using coupled neural networks and
1111 genetic algorithms. *Journal of Food Engineering*, 53(3), 209-220.
- 1112 Chen, M.-J., Chen, K.-N., & Lin, C.-W. (2004). Sequential Quadratic Programming for
1113 Development of a New Probiotic Dairy Tofu with Glucono- δ -Lactone. *Journal of*
1114 *Food Science*, 69(7), 344–350.
- 1115 Chen, S.-J., & Hwang, C.-L. (1992). *Fuzzy Multiple Attribute Decision Making Methods:*
1116 *Methods and Applications*. Berlin, Heidelberg: Springer Berlin Heidelberg.
- 1117 Church, C., & Rogers, M. M. (2006). *Designing for results: Integrating monitoring and*
1118 *evaluation in conflict transformation programs*. Search for Common Ground.
- 1119 Coello, C. A. C. (2000). Handling preferences in evolutionary multiobjective optimization:
1120 a survey. In *Proceedings of the 2000 Congress on Evolutionary Computation*.
1121 (Vol. 1, p. 30-37 vol.1).
- 1122 Collette, Y., & Siarry, P. (2013). *Multiobjective optimization: principles and case studies*.
1123 Springer Science & Business Media.
- 1124 Collignan, A. (2011). *Méthode d'optimisation et d'aide à la décision en conception*
1125 *mécanique: application à une structure aéronautique (Doctoral thesis)*. Université
1126 Sciences et Technologies – Bordeaux 1.
- 1127 Collignan, A., & Raoult-Wack, A.-L. (1994). Dewatering and salting of cod by immersion
1128 in concentrated sugar/salt solutions. *LWT-Food Science and Technology*, 27(3),
1129 259–264.
- 1130 Collignan, A., Sebastian, P., Pailhes, J., & Ledoux, Y. (2012). Arc-elasticity and
1131 hierarchical exploration of the neighborhood of solutions in mechanical design.
1132 *Advanced Engineering Informatics*, 26(3), 603–617.

- 1133 Corzo, O., & Gomez, E. R. (2004). Optimization of osmotic dehydration of cantaloupe
1134 using desired function methodology. *Journal of food engineering*, 64(2), 213–219.
- 1135 Craheix, D., Bergez, J.-E., Angevin, F., Bockstaller, C., Bohanec, M., Colomb, B., ...
1136 Sadok, W. (2015). Guidelines to design models assessing agricultural
1137 sustainability, based upon feedbacks from the DEXi decision support system.
1138 *Agronomy for Sustainable Development*, 35(4), 1431–1447.
- 1139 Darmon, N., Maillot, M., Darmon, M., & Martin, A. (2007). Le SAIN et le LIM. Un système
1140 de øg profilage nutritionnel \fg pour orienter favorablement les choix des
1141 consommateurs. In 3. *Journées annuelles INPES de la prévention. Du 29-03-
1142 2007 au 30-03-2007, Paris, France.*
- 1143 De Jong, P. (1996). *Modelling and optimization of thermal processes in the dairy
1144 industry (Doctoral thesis)*. Delft University of Technology. PhD Thesis.
- 1145 Derringer, G. (1980). Simultaneous optimization of several response variables. *Journal
1146 of quality technology*, 12(4), 214–219.
- 1147 Derringer, G. C. (1994). A balancing act-optimizing a products properties. *Quality
1148 progress*, 27(6), 51–58.
- 1149 Diefes, H. A., Okos, M. R., & Morgan, M. T. (2000). Computer-aided process design
1150 using Food Operations Oriented Design System Block Library. *Journal of Food
1151 Engineering*, 46(2), 99 – 108.
- 1152 Edwards, W., & Barron, F. H. (1994). SMARTS and SMARTER: Improved Simple
1153 Methods for Multiattribute Utility Measurement. *Organizational Behavior and
1154 Human Decision Processes*, 60(3), 306-325.
- 1155 Ehgott, M. (2005). *Multicriteria optimization*. Springer Science & Business Media.
- 1156 Erdoğan, F. (2008). *Optimization in food engineering*. CRC Press.
- 1157 Erdoğan, F., & Balaban, M. O. (2003). Complex method for nonlinear constrained multi-
1158 criteria (multi-objective function) optimization of thermal processing. *Journal of
1159 food process engineering*, 26(4), 357–375.
- 1160 Eren, İ., & Kaymak-Ertekin, F. (2007). Optimization of osmotic dehydration of potato
1161 using response surface methodology. *Journal of Food Engineering*, 79(1), 344–
1162 352.
- 1163 Ferrández, M. R., Puertas-Martín, S., Redondo, J. L., Ivorra, B., Ramos, A. M., &
1164 Ortigosa, P. M. (2018a). High-performance computing for the optimization of
1165 high-pressure thermal treatments in food industry. *The Journal of
1166 Supercomputing*.
- 1167 Ferrández, Miriam R., Redondo, J. L., Ivorra, B., Ramos, Á. M., & Ortigosa, P. M.
1168 (2018b). A Decision Tool based on a Multi-Objective Methodology for designing
1169 High-Pressure Thermal Treatments in Food Industry. *Preprint version*.
- 1170 Figueira, J., & Roy, B. (2002). Determining the weights of criteria in the ELECTRE type
1171 methods with a revised Simos' procedure. *European Journal of Operational
1172 Research*, 139(2), 317-326.
- 1173 Fito, P., LeMaguer, M., Betoret, N., & Fito, P. J. (2007). Advanced food process
1174 engineering to model real foods and processes: The « SAFES » methodology.
1175 *Journal of food engineering*, 83(2), 173–185.
- 1176 Garcia-Moreno, P. J., Morales-Medina, R., Perez-Galvez, R., Bandarra, N. M., Guadix,
1177 A., & Guadix, E. M. (2014). Optimisation of oil extraction from sardine (*Sardina
1178 pilchardus*) by hydraulic pressing. *International journal of food science and
1179 technology*, 49(10), 2167-2175.

- 1180 Gergely, S., Bekassy-Molnar, E., & Vatai, G. (2003). The use of multiobjective
1181 optimization to improve wine filtration. *Journal of Food Engineering*, 58(4),
1182 311-316.
- 1183 Gero, J. S., & Kannengiesser, U. (2007). A function–behavior–structure ontology of
1184 processes. *AI EDAM*, 21(4), 379-391.
- 1185 Goñi, S. M., & Salvadori, V. O. (2012). Model-based multi-objective optimization of beef
1186 roasting. *Journal of Food Engineering*, 111(1), 92-101.
- 1187 Guthrie, K. M. (1969). Data and techniques for preliminary capital cost estimating.
1188 *Chemical Engineering*, 76(6), 114.
- 1189 Hadiyanto, Boom, R. M., Van Straten, G., Van Boxtel, A. J. B., & Esveld, D. C. (2009).
1190 Multiobjective Optimization to Improve the Product Range of Baking Systems.
1191 *Journal of Food Process Engineering*, 32(5), 709–729.
- 1192 Hadiyanto, Esveld, D. C., Boom, R. M., van Straten, G., & van Boxtel, A. J. B. (2008a).
1193 Product quality driven design of bakery operations using dynamic optimization.
1194 *Journal of Food Engineering*, 86(3), 399-413.
- 1195 Hadiyanto, H., Esveld, D. C., Boom, R. M., van Straten, G., & van Boxtel, A. J. B.
1196 (2008b). Control vector parameterization with sensitivity based refinement applied
1197 to baking optimization. *Food and Bioproducts Processing*, 86(2), 130-141.
- 1198 Hakanen, J., Kawajiri, Y., Miettinen, K., & Biegler, L. T. (2007). Interactive multi-objective
1199 optimization for simulated moving bed processes. *Control and Cybernetics*, 36,
1200 283–302.
- 1201 Harrington, E. (1965). The desirability function. *Industrial quality control*, 21(10), 494–
1202 498.
- 1203 Hauschild, M. Z., Huijbregts, M., Jolliet, O., MacLeod, M., Margni, M., van de Meent, D.,
1204 ... McKone, T. E. (2008). Building a model based on scientific consensus for life
1205 cycle impact assessment of chemicals: the search for harmony and parsimony.
1206 *Environmental Science and Technology*, 42(19), 7032–7037.
- 1207 Hertwich, E. G., Pease, W. S., & Koshland, C. P. (1997). Evaluating the environmental
1208 impact of products and production processes: a comparison of six methods.
1209 *Science of the Total Environment*, 196(1), 13–29.
- 1210 Hugget, A., Sebastian, P., & Nadeau, J.-P. (1999). Global optimization of a dryer by
1211 using neural networks and genetic algorithms. *AIChE Journal*, 45(6), 1227–1238.
- 1212 Izadifar, M., & Jahromi, M. Z. (2007). Application of genetic algorithm for optimization of
1213 vegetable oil hydrogenation process. *Journal of Food Engineering*, 78(1), 1–8.
- 1214 Jacquemin, L., Pontalier, P.-Y., & Sablayrolles, C. (2012). Life cycle assessment (LCA)
1215 applied to the process industry: a review. *The International Journal of Life Cycle*
1216 *Assessment*, 17(8), 1028–1041.
- 1217 Jolliet, O., Saadé, M., & Crettaz, P. (2010). *Analyse du cycle de vie: Comprendre et*
1218 *réaliser un écobilan*. PPUR Presses polytechniques.
- 1219 Jørgensen, A., Le Bocq, A., Nazarkina, L., & Hauschild, M. (2008). Methodologies for
1220 social life cycle assessment. *The International Journal of Life Cycle Assessment*,
1221 13(2), 96–103.
- 1222 Kahyaoglu, T. (2008). Optimization of the pistachio nut roasting process using response
1223 surface methodology and gene expression programming. *LWT – Food Science*
1224 *and Technology*, 41, 26–33.
- 1225 Karimi, F., Rafiee, S., Taheri-Garavand, A., & Karimi, M. (2012). Optimization of an air
1226 drying process for *Artemisia absinthium* leaves using response surface and

- 1227 artificial neural network models. *Journal of the Taiwan Institute of Chemical*
1228 *Engineers*, 43(1), 29–39.
- 1229 Kawajiri, Y., & Biegler, L. T. (2006). Nonlinear Programming Superstructure for Optimal
1230 Dynamic Operations of Simulated Moving Bed Processes. *Industrial &*
1231 *Engineering Chemistry Research*, 45(25), 8503-8513.
- 1232 Khuri, A. I., & Mukhopadhyay, S. (2010). Response surface methodology. *Wiley*
1233 *Interdisciplinary Reviews: Computational Statistics*, 2(2), 128-149.
- 1234 Kiranoudis, C. T., & Markatos, N. C. (2000). Pareto design of conveyor-belt dryers.
1235 *Journal of Food Engineering*, 46(3), 145-155.
- 1236 Kopsidas, G. C. (1995). Multiobjective optimization of table olive preparation systems.
1237 *European Journal of Operational Research*, 85(2), 383-398.
- 1238 Kowalski, R. J., Li, C., & Ganjyal, G. M. (2018). Optimizing twin-screw food extrusion
1239 processing through regression modeling and genetic algorithms. *Journal of Food*
1240 *Engineering*, 234, 50–56.
- 1241 Kurup, A. S., Subramani, H. J., Hidajat, K., & Ray, A. K. (2005). Optimal design and
1242 operation of SMB bioreactor for sucrose inversion. *Chemical Engineering Journal*,
1243 108(1), 19-33.
- 1244 Lespinard, A. R., Arballo, J. R., Taus, F. J., & Mascheroni, R. H. (2015). Multi-Objective
1245 Optimization of the Pasteurization Process of Pumpkin Cubes Packaged in Glass
1246 Jars. *International Journal of Food Engineering*, 11(5), 679–689.
- 1247 Lind, E., Goldin, J., & Hickman, J. (1960). Fitting yield and cost response surfaces.
1248 *Chemical Engineering Progress*, 56(11), 62–68.
- 1249 Madoumier, M. (2016). *Modélisation et développement d'outils pour l'écoconception*
1250 *d'un procédé de concentration en industrie laitière: cas de l'évaporation du lait*
1251 *(Doctoral thesis)*. Agrocampus Ouest: Rennes.
- 1252 Manfredi, S., Allacker, K., Pelletier, N., Schau, E., Chomkham Sri, K., Pant, R., &
1253 Pennington, D. (2015). Comparing the European Commission product
1254 environmental footprint method with other environmental accounting methods.
1255 *The International Journal of Life Cycle Assessment*, 20(3), 389–404.
- 1256 Manivannan, P., & Rajasimman, M. (2008). Osmotic dehydration of beetroot in salt
1257 solution: optimization of parameters through statistical experimental design. *Int J*
1258 *Chem Biomol Eng*, 1(4), 215–222.
- 1259 Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for
1260 engineering. *Structural and Multidisciplinary Optimization*, 26(6), 369-395.
- 1261 Maroulis, Z. B., & Saravacos, G. D. (2007). *Food Plant Economics*. CRC Press.
- 1262 Massebeuf, S., Fonteix, C., Kiss, L. N., Marc, I., Pla, F., & Zaras, K. (1999). Multicriteria
1263 optimization and decision engineering of an extrusion process aided by a diploid
1264 genetic algorithm. In *Proceedings of the 1999 Congress on Evolutionary*
1265 *Computation* (Vol. 1, p. 21 Vol. 1).
- 1266 Miettinen, K. (1998). *Nonlinear multiobjective optimization*. Kluwer Academic Publishers,
1267 Dordrecht.
- 1268 Miettinen, K., & Hakanen, J. (2009). Why Use Interactive Multi-Objective Optimization in
1269 Chemical Process Design? *Multi-Objective Optimization: Techniques and*
1270 *Applications in Chemical Engineering*, 1, 153–188.
- 1271 Miettinen, K., & Mäkelä, M. M. (1995). Interactive bundle-based method for
1272 nondifferentiable multiobjective optimization: nimbus. *Optimization*, 34(3),
1273 231-246.

- 1274 Miettinen, K., & Mäkelä, M. M. (2006). Synchronous approach in interactive
1275 multiobjective optimization. *European Journal of Operational Research*, 170(3),
1276 909-922.
- 1277 Miri, T., Tsoukalas, A., Bakalis, S., Pistikopoulos, E. N., Rustem, B., & Fryer, P. J.
1278 (2008). Global optimization of process conditions in batch thermal sterilization of
1279 food. *Journal of Food Engineering*, 87(4), 485-494.
- 1280 Morandin, M., Toffolo, A., Lazzaretto, A., Maréchal, F., Ensinas, A. V., & Nebra, S. A.
1281 (2011). Synthesis and parameter optimization of a combined sugar and ethanol
1282 production process integrated with a CHP system. *Energy*, 36(6), 3675–3690.
- 1283 Myers, R. H., Montgomery, D. C., & Anderson-Cook, C. M. (2016). *Response Surface*
1284 *Methodology: Process and Product Optimization Using Designed Experiments*.
1285 John Wiley & Sons.
- 1286 Nishitani, H., & Kunugita, E. (1979). The optimal flow-pattern of multiple effect
1287 evaporator systems. *Computers & Chemical Engineering*, 3(1), 261–268.
- 1288 Nishitani, H., & Kunugita, E. (1983). Multi-objective analysis for energy and resource
1289 conservation in process systems. *Journal of Chemical Engineering of Japan*,
1290 16(3), 235–241.
- 1291 Norris, C. B. (2014). Data for social LCA. *The International Journal of Life Cycle*
1292 *Assessment*, 19(2), 261–265.
- 1293 Norris, G. A. (2001). Integrating life cycle cost analysis and LCA. *The international*
1294 *journal of life cycle assessment*, 6(2), 118–120.
- 1295 Noshad, M., Mohebbi, M., Shahidi, F., & Mortazavi, S. A. (2012). Multi-objective
1296 optimization of osmotic–ultrasonic pretreatments and hot-air drying of quince
1297 using response surface methodology. *Food and Bioprocess Technology*, 5(6),
1298 2098–2110.
- 1299 Olmos, A., Trelea, I. C., Courtois, F., Bonazzi, C., & Trystram, G. (2002). Dynamic
1300 optimal control of batch rice drying process. *Drying Technology*, 20(7),
1301 1319-1345.
- 1302 Otto, K. N., & Antonsson, E. K. (1991). Trade-off strategies in engineering design.
1303 *Research in Engineering Design*, 3(2), 87-103.
- 1304 Ouattara, A., Pibouleau, L., Azzaro-Pantel, C., Domenech, S., Baudet, P., & Yao, B.
1305 (2012). Economic and environmental strategies for process design. *Computers*
1306 *and Chemical Engineering*, 36, 174 – 188.
- 1307 Ozdemir, M., Ozen, B. F., Dock, L. L., & Floros, J. D. (2008). Optimization of osmotic
1308 dehydration of diced green peppers by response surface methodology. *LWT -*
1309 *Food Science and Technology*, 41(10), 2044-2050.
- 1310 Pailhès, J., Collignan, A., Sebastian, P., & Quirante, T. (2011). Modélisation et
1311 optimisation en conception multi-objectifs. In *20ème Congrès Français de*
1312 *Mécanique*. Besançon, France.
- 1313 Pavličić, D. (2001). Normalization affects the results of MADM methods. *Yugoslav*
1314 *journal of operations research*, 11(2), 251–265.
- 1315 Perrot, N., Trelea, I.-C., Baudrit, C., Trystram, G., & Bourguine, P. (2011). Modelling and
1316 analysis of complex food systems: state of the art and new trends. *Trends in*
1317 *Food Science & Technology*, 22(6), 304–314.
- 1318 Quirante, T. (2012, décembre 5). *Modelling and numerical optimization methods for*
1319 *decision support in robust embodiment design of products and processes*
1320 *(Doctoral thesis)*. Bordeaux 1.

- 1321 Raffray, G., Collignan, A., & Sebastian, P. (2015). Multiobjective optimization of the
1322 preliminary design of an innovative hot-smoking process. *Journal of Food*
1323 *Engineering*, 158, 94–103.
- 1324 Rangaiah, G. P., & Bonilla-Petriciolet, A. (2013). *Multi-objective optimization in chemical*
1325 *engineering: developments and applications*. John Wiley & Sons.
- 1326 Rangaiah, G., Sharma, S., & Sreepathi, B. K. (2015). Multi-objective optimization for the
1327 design and operation of energy efficient chemical processes and power
1328 generation. *Current Opinion in Chemical Engineering*, 10, 49–62.
- 1329 Rodman, A. D., & Gerogiorgis, D. I. (2017). Dynamic optimization of beer fermentation:
1330 Sensitivity analysis of attainable performance vs. product flavour constraints.
1331 *Computers & Chemical Engineering*, 106, 582–595.
- 1332 Romdhana, H., Bonazzi, C., & Esteban-Decloux, M. (2016). Computer-aided process
1333 engineering for environmental efficiency: Industrial drying of biomass. *Drying*
1334 *Technology*, 34(10), 1253–1269.
- 1335 Rosen, M. A. (2008). A concise review of energy-based economic methods. In
1336 *Proceedings of the 3rd IASME/WSEAS International Conference on Energy &*
1337 *Environment, Cambridge, UK* (Vol. 2325, p. 136142).
- 1338 Roupas, P. (2008). Predictive modelling of dairy manufacturing processes. *International*
1339 *Dairy Journal*, 18(7), 741 – 753.
- 1340 Roy, B. (1968). Classement et choix en présence de points de vue multiples. *Revue*
1341 *française d'informatique et de recherche opérationnelle*, 2(8), 57–75.
- 1342 Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. *European*
1343 *Journal of Operational Research*, 48(1), 9-26.
- 1344 Schmidt, I., Meurer, M., Saling, P., Kicherer, A., Reuter, W., & Gensch, C.-O. (2004).
1345 Managing sustainability of products and processes with the socio-eco-efficiency
1346 analysis by BASF. *Greener Management International*, 45, 79–94.
- 1347 Scott, M. J., & Antonsson, E. K. (1998). Aggregation functions for engineering design
1348 trade-offs. *Fuzzy Sets and Systems*, 99(3), 253-264.
- 1349 Sebastian, P., Quirante, T., Tiat, V. H. K., & Ledoux, Y. (2010). Multi-objective
1350 optimization of the design of two-stage flash evaporators: Part 2. Multi-objective
1351 optimization. *International Journal of Thermal Sciences*, 49(12), 2459–2466.
- 1352 Sendín, J. O. H., Alonso, A. A., & Banga, J. R. (2010). Efficient and robust multi-
1353 objective optimization of food processing: A novel approach with application to
1354 thermal sterilization. *Journal of Food Engineering*, 98(3), 317–324.
- 1355 Seng, C. K., & Rangaiah, G. P. (2008). Multi-objective optimization in food engineering.
1356 In *Optimization in Food Engineering*. CRC Press.
- 1357 Sharma, S., Rangaiah, G. P., & Cheah, K. S. (2012). Multi-objective optimization using
1358 MS Excel with an application to design of a falling-film evaporator system. *Food*
1359 *and Bioproducts Processing*, 90(2), 123 – 134.
- 1360 Sicard, M., Perrot, N., Reuillon, R., Mesmoudi, S., Alvarez, I., & Martin, S. (2012). A
1361 viability approach to control food processes: Application to a camembert cheese
1362 ripening process. *Food Control*, 23(2), 312–319.
- 1363 Sidaway, D., & Kok, R. (1982). The Optimization of Continuous Sterilization. *Canadian*
1364 *Institute of Food Science and Technology Journal*, 15(3), xxi.
- 1365 Simos, J. (1990a). *Evaluer l'impact sur l'environnement: une approche originale par*
1366 *l'analyse multicritère et la négociation*. Lausanne; Presses Polytechniques et
1367 Universitaires Romandes.

- 1368 Simos, J. (1990b). *L'évaluation environnementale: Un processus cognitif négocié*
1369 *(Doctoral thesis)*. École polytechnique fédérale de Lausanne.
- 1370 Singh, B., Panesar, P. S., Nanda, V., & Kennedy, J. F. (2010). Optimisation of osmotic
1371 dehydration process of carrot cubes in mixtures of sucrose and sodium chloride
1372 solutions. *Food Chemistry*, 123(3), 590–600.
- 1373 Siskos, E., & Tsotsolas, N. (2015). Elicitation of criteria importance weights through the
1374 Simos method: A robustness concern. *European Journal of Operational*
1375 *Research*, 246(2), 543-553.
- 1376 Stefanis, S., Livingston, A., & Pistikopoulos, E. (1997). Environmental impact
1377 considerations in the optimal design and scheduling of batch processes.
1378 *Computers & chemical engineering*, 21(10), 1073–1094.
- 1379 Steffens, M. A., Fraga, E. S., & Bogle, I. D. L. (1999). Multicriteria process synthesis for
1380 generating sustainable and economic bioprocesses. *Computers and Chemical*
1381 *Engineering*, 23(10), 1455 – 1467.
- 1382 Subramani, H. J., Hidajat, K., & Ray, A. K. (2003). Optimization of Simulated Moving
1383 Bed and Varicol Processes for Glucose–Fructose Separation. *Chemical*
1384 *Engineering Research and Design*, 81(5), 549-567.
- 1385 Taheri-Garavand, A., Karimi, F., Karimi, M., Lotfi, V., & Khoobakht, G. (2018). Hybrid
1386 response surface methodology–artificial neural network optimization of drying
1387 process of banana slices in a forced convective dryer. *Food Science and*
1388 *Technology International*, 24(4), 277–291.
- 1389 Tarafdar, A., Shahi, N. C., Singh, A., & Sirohi, R. (2017). Optimization of Freeze-Drying
1390 Process Parameters for Qualitative Evaluation of Button Mushroom (*Agaricus*
1391 *bisporus*) Using Response Surface Methodology. *Journal of Food Quality*, 2017.
- 1392 Taras, S., & Woinaroschy, A. (2012). An interactive multi-objective optimization
1393 framework for sustainable design of bioprocesses. *Computers and Chemical*
1394 *Engineering*, 43(0), 10 – 22.
- 1395 Themelin, A., Raoult-Wack, A., Lebert, A., & Danzart, M. (1997). Multicriteria
1396 optimization of food processing combining soaking prior to air drying. *Drying*
1397 *technology*, 15(9), 2263–2279.
- 1398 Trelea, I. C., Trystram, G., & Courtois, F. (1997). Optimal constrained non-linear control
1399 of batch processes: Application to corn drying. *Journal of Food Engineering*,
1400 31(4), 403–421.
- 1401 Trystram, G. (2012). Modelling of food and food processes. *Journal of Food*
1402 *Engineering*, 110(2), 269 – 277.
- 1403 Turton, R., Bailie, R. C., Whiting, W. B., & Shaeiwitz, J. A. (2008). *Analysis, synthesis*
1404 *and design of chemical processes*. Pearson Education.
- 1405 Velasquez, M., & Hester, P. T. (2013). An analysis of multi-criteria decision making
1406 methods. *International Journal of Operations Research*, 10(2), 56–66.
- 1407 Vernat, Y., Nadeau, J.-P., & Sébastien, P. (2010). Formalization and qualification of
1408 models adapted to preliminary design. *International Journal on Interactive Design*
1409 *and Manufacturing (IJIDeM)*, 4(1), 11–24.
- 1410 Vieira, G. S., Pereira, L. M., & Hubinger, M. D. (2012). Optimisation of osmotic
1411 dehydration process of guavas by response surface methodology and desirability
1412 function. *International journal of food science & technology*, 47(1), 132–140.
- 1413 Von Schirnding, Y. (2002). *Health in sustainable development planning: the role of*
1414 *indicators*. World Health Organization.

1415 Wang, F., Lai, X., & Shi, N. (2011). A multi-objective optimization for green supply chain
1416 network design. *Decision Support Systems*, 51(2), 262-269.

1417 Wang, J.-J., Jing, Y.-Y., Zhang, C.-F., & Zhao, J.-H. (2009). Review on multi-criteria
1418 decision analysis aid in sustainable energy decision-making. *Renewable and
1419 Sustainable Energy Reviews*, 13(9), 2263-2278.

1420 Wang, Z., & Rangaiah, G. P. (2017). Application and Analysis of Methods for Selecting
1421 an Optimal Solution from the Pareto-Optimal Front obtained by Multiobjective
1422 Optimization. *Industrial & Engineering Chemistry Research*, 56(2), 560-574.

1423 Wari, E., & Zhu, W. (2016). A survey on metaheuristics for optimization in food
1424 manufacturing industry. *Applied Soft Computing*, 46, 328-343.

1425 Windhab, E. (2009). Tailored food structure processing for personalized nutrition. In
1426 *Proceedings of the 5th International Symposium on Food Rheology and
1427 Structure—ISFRS* (p. 15–18).

1428 Winiczenko, R., Górnicki, K., Kaleta, A., Janaszek-Mańkowska, M., Choińska, A., &
1429 Trajer, J. (2018a). Apple Cubes Drying and Rehydration. Multiobjective
1430 Optimization of the Processes. *Sustainability*, 10(11), 4126.

1431 Winiczenko, R., Górnicki, K., Kaleta, A., Janaszek-Mańkowska, M., & Trajer, J. (2018b).
1432 Multi-objective optimization of the apple drying and rehydration processes
1433 parameters. *Emirates Journal of Food and Agriculture*, 30(1), 1-9.

1434 Winiczenko, R., Górnicki, K., Kaleta, A., Martynenko, A., Janaszek-Mańkowska, M., &
1435 Trajer, J. (2018c). Multi-objective optimization of convective drying of apple
1436 cubes. *Computers and Electronics in Agriculture*, 145, 341-348.

1437 Yadav, B. S., Yadav, R. B., & Jatani, M. (2012). Optimization of osmotic dehydration
1438 conditions of peach slices in sucrose solution using response surface
1439 methodology. *Journal of food science and technology*, 49(5), 547–555.

1440 You, F., Tao, L., Graziano, D. J., & Snyder, S. W. (2012). Optimal design of sustainable
1441 cellulosic biofuel supply chains: Multiobjective optimization coupled with life cycle
1442 assessment and input-output analysis. *AIChE Journal*, 58(4), 1157–1180.

1443 Yuan, Y., Tan, L., Xu, Y., Dong, J., Zhao, Y., & Yuan, Y. (2018). Optimization of
1444 Processing Parameters for Lettuce Vacuum Osmotic Dehydration Using
1445 Response Surface Methodology. *Polish Journal of Food and Nutrition Sciences*,
1446 68(1).

1447 Yuen, C. C., Aatmeeyata, Gupta, S. K., & Ray, A. K. (2000). Multi-objective optimization
1448 of membrane separation modules using genetic algorithm. *Journal of Membrane
1449 Science*, 176(2), 177-196.

1450 Zhang, Y., Hidajat, K., & Ray, A. K. (2004). Optimal design and operation of SMB
1451 bioreactor: production of high fructose syrup by isomerization of glucose.
1452 *Biochemical Engineering Journal*, 21(2), 111-121.