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ABSTRACT

Optimizing 0.1 μm microfiltration (MF) of skim milk requires formulating optimization of a food processing problem with conflicting objectives that consider product composition, process variables and operating conditions. Formulating the MF optimization problem requires knowledge from experts about food processing, dairy product production and equipment manufacturing. This study formulated the MF optimization problem in an innovative manner: as a multiobjective optimization problem that considered the entire MF process. Eleven experts were interviewed to identify the knowledge domains necessary, which required 36 interviews over a total of 14 h. Formulation was achieved from the MF process to the compositions of the permeate and retentate fractions. Five conflicting optimization objectives, influenced by 36 variables, were set up to formulate the problem. Five of the variables were decision variables used to control the MF, and the other 31 were intermediate calculation variables. This approach opens new perspectives for optimization of food processes that integrate expert knowledge.

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1. Introduction

Crossflow microfiltration of skim milk with a pore size of 0.1 μm (MF) is commonly used in the dairy industry to separate the two main groups of proteins: native casein micelles (retentate), used to make cheese, and serum protein (permeate), used mainly to formulate food for specific populations (e.g. elderly people, infants). Milk protein can be fractionated either with ceramic or polymeric spiral wound membranes. In order to overcome fouling and avoid retrofiltration, skim milk microfiltration operating with ceramic membranes is never operated in conventional filtration system (Gésan et al., 1993; Gésan-Guiziou, 2010). Microfiltration is operated with either uniform transmembrane pressure system (UTP system) which consists in the circulation of the permeate co-current to the retentate in order to get a pressure drop in the permeate side similar to the one obtained in the retentate side and then an homogeneous TMP along the filtering path (Sandblöm, 1974), or ceramic membranes with a hydraulic resistance gradient (such as GP® and Isoflux® membranes) (Garcera and Toujas, 1998; Skrzypek and Burger, 2010). Comparatively, microfiltration with polymeric SW membranes is performed in conventional mode with TMP high enough to avoid retrofiltration at the outlet of the membrane. Each technology (further called UTP, GP and SW) has its own benefits and drawbacks, which leads to conflicting objectives. For instance, ceramic membranes have higher permeation flux (ca. 75–80 L h^{-1} m^{-2} in industrial conditions) than polymeric membranes (ca. 25 L h^{-1} m^{-2}), while polymeric membranes have lower investment costs than ceramic membranes. Despite the dairy sector's interest in MF, this operation is not completely optimized.

In the dairy sector, two main approaches have been used to compare or optimize processes in the dairy sector. The first approach focuses on the definition of the best process options either by optimizing production scheduling (i.e. time management) (Sel et al., 2017) or

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Nomenclature

C	concentration (g kg^{-1})
CD	concentration on a dry-matter basis (g kg DM^{-1})
CI	investment cost (€)
CO	cost (€)
CPR	production cost (€)
DM	dry matter (g kg^{-1})
GP	membrane with gradient of permeability (-)
Jp	permeation flux (L h^{-1} m^{-2})
MF	skim milk crossflow microfiltration with 0.1 μm pore size (-)
MT	membrane technology (-)
NM	number of modules (-)
P	pressure (Pa)
q	quantity (g)
Q_{feed}	feed flowrate (m^3 h^{-1})
Q_{rec}	recirculation flow (m^3 h^{-1})
R	score given by experts (-)
SW	polymeric spiral wound membrane (-) specific weighted average (-)
T	filtration temperature (°C)
t	filtration time (min)
TMP	transmembrane pressure (Pa)
Tr	transmission rate (%)
UTP	uniform transmembrane pressure (-)
V	volume (m^3)
VRR	volume reduction ratio (-)
w	weighting factor (-)
η	recovery yield (-)

Subscripts

CN	casein
i	ith line in parallel in one stage of the microfiltration plant
in	inlet
j	jth microfiltration module on line i
k	issue
m	number of issues per criterion
n	number of stages of the microfiltration plant
o	outlet
p	permeate
r	retentate
SP	serum protein

by comparing multiple process scenarios on the basis of several criteria (Gésan-Guiziou et al., 2019; Depping et al., 2017, 2020). In these studies, the operating conditions and process design of each unit operations, combined in the overall process, have been considered as constant. The second approach consists in including the choice of operating conditions and process design in an optimization process. This is the case for instance for the optimization of the evaporator (Madoumier et al., 2020) or heat exchanger (Deka and Datta, 2017) in the dairy field. In this last approach, operating parameters and design parameters are optimized to define the optimal mode of operation and design of the process in order to meet specific requirements. This approach requires to know the relations between variables and variables and optimization objectives. Nowadays in skim milk microfiltration, these relations are not explicitly defined.

The lack of knowledge in microfiltration about mechanisms that limit process performances is a real obstacle for the definition of the relations between variables and variables and optimization objectives (Jimenez-Lopez et al., 2008; Tolkach and Kulozik, 2006; Trystram, 2012). At the industrial level, the choice of membrane technology as well as processing design and conditions are based on the know-how of operators and available expert knowledge, which are closely related to the history and experience of each equipment manufacturer. They do not have enough data to compare the three filtration technologies defined in this study in terms of fractions compositions, operating variables and design of the plant. This lack of data makes the optimisation of given specifications impossible regarding the choices of the optimal membrane technology, operating variables and process design. In the scientific literature, optimal operating conditions are often identified empirically in experiments that reveal the influence of one variable on a group of chosen variables (Adams et al., 2015; Gésan-Guiziou et al., 1999, 2000; Jørgensen et al., 2016; Tremblay-Marchand et al., 2016; Zulewska and Barbano, 2013, 2014). Other studies, such as that of Astudillo-Castro (2015), modelled the MF process. Each of these experiments and models assessed only one membrane technology to determine processing conditions that increase the yield of serum protein recovery in the permeate and/or improve permeation flux. To our knowledge, only one study (Zulewska et al., 2009) compared the performance (i.e. serum protein recovery yield and permeation flux) of all three membrane technologies. This study highlighted strong differences in these performances among the membrane technologies. Its authors suggested that to achieve a serum protein recovery yield with SW technology similar to those obtained with the UTP and GP technologies, the membrane area would have to be increased, which increases the costs of the SW plant. Although microfiltration studies are useful because they identified influential operating variables and helped understand membrane fouling, they did not optimize operating variables, process design and economic costs responding to given conflicting objective specifications. They generally consider a single optimization objective and when they consider several, the optimization of all the objectives is not achieved simultaneously. While optimizing microfiltration must address several conflicting objectives, such as maximizing product recovery while minimizing costs. As it is not possible to solve a multiobjective problem by merging incremental optimizations, it is necessary to optimize the whole unit operation of microfiltration.

To address the challenge of optimizing an entire process with conflicting objectives, we formulated MF optimization as a multiobjective optimization problem that considered conflicting objectives simultaneously. Multiobjective optimization has three main challenges: formulating the multiobjective problem, modelling the optimization objectives and solving the problem. Problem formulation consists of identifying the decision problem through its objectives, decision variables and constraints. Modelling the optimization objectives consists of formulating them as mathematical functions or computational algorithms of decision variables (i.e. "objective functions"). Modelling the objective functions requires establishing the "influence relations" between decision variables and optimization objectives, but also good understanding of the phenomena that connect them. Problem solving consists of exploring the solution space to find Pareto optimal solutions (i.e. non-dominated solutions) (Reyes-Sierra and Coello Coello, 2006). This last challenge is addressed by wide variety of efficient metaheuristic algorithms such as NSGA2, MOPSO and Ant Colony (Collette and Siarry, 2002). However, the relevance of the results of these algorithms depends on the quality of problem formulation. This study focused on formulating MF optimization as a multiobjective optimization problem.

Formulating the multiobjective optimization problem of MF is complex due to the large number and heterogeneity of the variables involved (e.g. ordinal, cardinal, discrete, continuous) and the lack of knowledge about the physical laws involved. Description of influence relations among the variables themselves and between the variables and optimization objectives can be based on expert knowledge, especially when relations are not scientifically established. Two studies on integrating expert knowledge when representing a food process have been performed in the past several years. The first combined expert and rheological knowledge about French bread to predict the state of dough and bread from raw materials and processing conditions (Ndiaye et al., 2009). The second predicted cheese ripening from biochemical measurements and sensory observations (Baudrit et al., 2010). To our knowledge, only one study (Hobballah et al., 2018) developed a method to integrate expert knowledge into the formulation of a multiobjective optimization problem. This method was applied to formulate a preliminary design of wood-based insulating materials (Hobballah et al., 2018). In this study, the optimization objectives, initially defined by partners, concerned only the product for a given predefined process, and scientific knowledge was sufficient to formulate the optimization problem successfully. To use the Hobballah et al. (2018) method to formulate the optimization of MF, it was necessary to add to it i) establishment of optimization objectives, ii) consideration of process design and operating conditions and iii) knowledge of industrial experts.

The objective of the present study was thus to formulate the multiobjective optimization problem of microfiltration in a holistic way. Due to the lack of scientific knowledge on the different implied process/phenomena, and in order to integrate objectives that are rarely found in the literature, it requires to use knowledge from both scientific and industrial knowledge. This paper focuses on knowledge acquisition and modelling in order to be able to perform the multiobjective optimization. The issue is not only to define the objectives but also to graphically represent knowledge about milk microfiltration from scientific and industrial information in order to ultimately enable decision-makers to make more rational decisions, coupling scientific and expert knowledge. It is certain that nowadays, decision-makers in microfiltration process design include several criteria in their decision, but they do so in an unformalized, non-reproducible way, at the same time limiting their ability to “rationally” justify their choices and to explain them. This first formalization work is a step to provide computerized decision support. The formulation of MF was performed using the method of Hobballah et al. (2018) in which the choice of optimization objectives and experts was added as an initial step. The Hobballah et al. (2018) method is robust, because it can consider both MF products and processes, which involves many variables.

The present study was performed as part of the “Optimal” project, whose main objective is to study and develop a method to optimize crossflow microfiltration of skim milk with a pore size of 0.1 μm to support the design and performance of filtration. This study brought together dairy product producers, an equipment manufacturer and researchers from several scientific domains into a “project group”.

2. Materials and methods

2.1. Description of the process system

In this first approach of the formulation of the multiobjective problem of microfiltration, the assumptions were made in order to specify the framework of the study while considering industrial constraints. These assumptions imply to set several variables as constants. Not considering the assumptions would imply to keep the same methodology but to modify the knowledge model by adding the relations between the new variables (previously set as constants) with the variables and objectives of the microfiltration optimization model.

In this study, bovine milk was assumed to be stored at 4 °C for 48 h, skimmed, thermized (68 °C for 30 s) and then bactofuged to decrease the bacterial count of the processed milk. Skim milk was then maintained at the filtration temperature for 20 min to reach mineral equilibria prior to MF. Characteristics of milk history (pre-treatments, storage conditions) were set as constants.

MF can be performed using three main membrane technologies (Table 1). The membranes considered in this study were those usually used in the dairy industry: a 0.1 μm UTP ceramic tubular membrane, Pall 7P1940 UTP (19 channels, 4 mm diameter, 1.68 m^2 filtration area); a 0.1 μm GP ceramic tubular membrane, Pall 7P1940 GP (19 channels, 4 mm diameter, 1.68 m^2 filtration area); and a polymeric spiral wound membrane 800 kDa SW, Synder FR 3A 6338 (41 mils spacers, 15.9 m^2 filtration area). The temperature was set to the usual MF temperature: 12 °C for SW and 50 °C for GP and UTP. To be consistent with industrial constraints, MF was assumed to be performed at constant permeation flux, which ensures continuous feeding of the next steps in the process. The MF plant was described with *n* the number of stages (2–5), *i* the ith line in parallel in one stage and *j* the jth module on line *i*. In a given stage, each line *i* had the same number of modules.

In this study, the following configurations are considered: UTP microfiltration system performed at 50 °C in continuous mode without diafiltration, GP membrane performed at 50 °C in continuous mode without diafiltration and SW polymeric membrane performed at 12 °C in continuous mode with or without diafiltration. The diafiltration solvent is reverse osmosis water. Diafiltration increases the performance of the separation by adding a solvent, which increases the recovery of serum protein in the permeate but in a more diluted form. Increasing the volume of the MF permeate fraction strongly influences the design of the ultrafiltration and reverse-osmosis plants which follow the MF, but their design lay outside the scope of the study. In addition, cleaning and disinfection steps were considered in this study but not optimized. All effluents were sent to the wastewater treatment plant, and effluent treatment was considered to lie outside the scope of the study.

Although researchers continue to study optimization of cleaning procedures, the cleaning procedures chosen in this study were assumed to be effective and reproducible. Cleaning and disinfection procedures for each type of membrane were defined according to industrial standards. Membranes were assumed to be chemically and bacteriologically cleaned, the water flux was assumed to be constant, and degradation of membranes due to chemicals was assumed to be negligible throughout their lifetime.

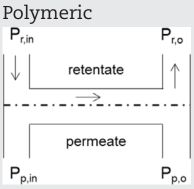
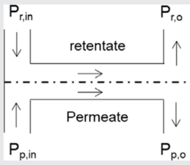
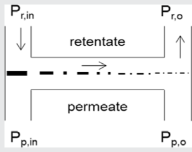
We made certain assumptions about the composition of retentate and permeate fractions. In the retentate fraction, we considered the caseins as a whole, without distinguishing casein micelles and free caseins (ca. 85% and 15% of caseins, respectively). In this study and as a first attempt, casein permeation is not considered in the optimization approach. It is known that casein permeation depends on filtration temperature, concentration factor, membrane type and diafiltration mode (ratio and solvent). However, there is few data on casein permeation as function of these parameters in the literature (Zulewska et Barbano, 2014; Zulewska et al., 2009; Beckman and Barbano, 2013; Hartinger and Kulozik, 2020) and none of them are relevant for the three filtration technologies considered in the study. Including casein permeation in the optimisation approach would have required acquisition of data, which lay beyond the scope of this study.

Investment cost was estimated from the cost of equipment (i.e. tanks, pumps, heat-exchangers, membranes, modules, sensors, plant automation and cleaning plant) and labour (i.e. engineering department, project follow-up, installation and commissioning, automation programming). Production cost was estimated from consumption of utilities (i.e. water, energy and chemical products), maintenance costs and the operator’s salary.

2.2. Problem formulation approach

In adapting the Hobballah et al. (2018) method, formulation of the multiobjective optimization problem was divided into four iterative steps (Fig. 1): i) choose optimization objectives and experts, ii) rate the relative importance of knowledge

Table 1 – Description of the three membrane technologies considered in this study. P is the pressure (in Pa), and p, r, in and o are subscripts for permeate, retentate, inlet and outlet, respectively.

Membrane technology	Spiral wound (SW)	Uniform transmembrane pressure (UTP)	Gradient of permeability (GP)
Type of membrane	Polymeric	Ceramic	Ceramic
Mechanism of membrane technology			
Details	Permeate under pressure ($P_{p,in} = P_{p,o} > 0$ Pa)	Circulation of permeate co-current to that of the retentate.	Permeate under pressure ($P_{p,in} = P_{p,o} > 0$ Pa). Membrane with a gradient of permeability that increases between the inlet and the outlet.

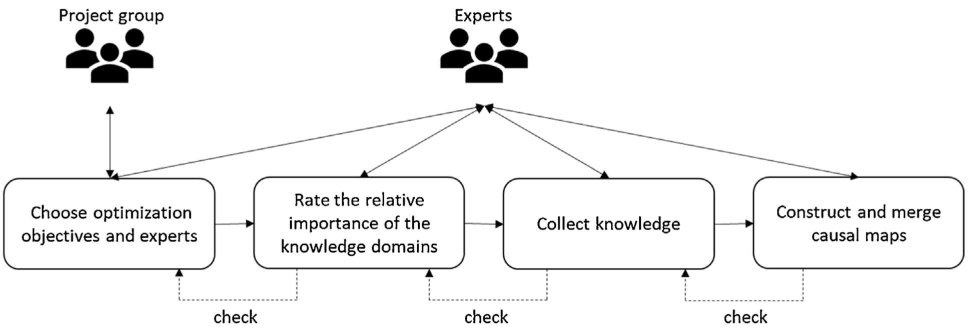


Fig. 1 – The formulation method applied to the microfiltration multiobjective optimization problem (adapted from Hobballah et al. (2018)).

domains, iii) collect knowledge and iv) construct and merge causal maps.

2.2.1. *Choose optimization objectives and experts*

In the first step, the project group determined the optimization objectives, guided by scientific interests and industrial practices obtained from a question e-mailed to the chosen experts in the project group. The survey asked, “In your opinion, what relevant criteria need to be considered to optimize the separation of casein micelles and serum protein by microfiltration?”. The project group aggregated similar responses into sets and discussed each set to determine if it was an optimization objective (i.e. a goal to optimize) or a decision criterion (i.e. a preference within the optimized solutions). Based on the list of optimization objectives, the project group chose relevant and available experts. These experts were asked to identify their expertise domain(s) (i.e. “knowledge domains”) within the entire MF knowledge domain. Experts were chosen in an iterative process that was closely related to the identification of knowledge domains in order to ensure that the available expertise covered the MF knowledge domain.

Knowledge about MF came from a variety of knowledge domains, such as process design, dairy technology and food biochemistry, all of which were shared by several experts. The experts first defined boundaries of the MF scope to drive knowledge acquisition, as is usually done for life cycle assessment (Tillman et al., 1994) or software development (Paetsch et al., 2003). As recommended by Milton (2007), experts divided the entire domain of MF into more specific manageable knowledge domains: the chosen experts were asked via survey about the knowledge domains necessary to describe MF. Responses from these experts were merged, discussed and validated by the entire group of experts (i.e. project group and chosen).

2.2.2. *Rate the relative importance of knowledge domains*

Once the experts had covered the entire MF knowledge domain, they were asked to rate the relative importance of knowledge domains to each other to organize the knowledge elicitation (Milton, 2007). Each knowledge domain was rated according to two criteria. The first was the relative importance of capturing the knowledge domain, which was assessed according to four issues: ability to achieve the project objective, closeness to the subject, novelty of the knowledge to the subject and ability to increase the quality of knowledge. Each issue of this criterion was scored on a scale from 1 (slightly important) to 4 (very important). The second criterion was the ease of capturing the knowledge domain, which was assessed according to three issues: explicitness, existence of documents and availability of experts (Hobballah et al., 2018). Each issue of this criterion was scored on a scale from 1 (easy) to 3 (difficult).

The relative importance of the knowledge domains was rated as follows. First, each expert scored each issue of each criterion for the knowledge domains. From the issue scores, we calculated a mean score per issue. A specific weighted average (SWA) was then calculated for each criterion of each knowledge domain from the mean scores per issue:

$$\mathrm{SWA} = \frac{\left(\sum_{k=1}^{m} R_k \times w_k\right)}{m} \tag{1}$$

with k the subscript of the issue, m the number of issues per criterion (4 or 3), R the mean score of the issue and w the weighting factor of the issue, which was the same as those of Hobballah et al. (2018).

For the importance of capturing the knowledge domain, the SWA was divided into thirds: "high", "medium" and "low". For the ease of capturing the knowledge domain, the SWA was divided into "easy", "moderate" and "difficult". Finally, a scoping matrix was built that combined both the importance and ease of capturing the knowledge domains. The knowledge domains selected for the next step were those of high or medium importance.

2.2.3. *Collect knowledge*

For each knowledge domain selected, experts were interviewed to identify pertinent variables and their relations (Cooke, 1994). The semi-structured interviews, which consisted of a set of open-ended questions, were used mainly to capture experts' knowledge and know-how (Brinkmann, 2013). Structured and unstructured interviews were also used when necessary (Bonneau de Beaufort et al., 2015; Elsawah et al., 2015). The types of questions used were inspired by those of Kvale (2007): i) "introduction" questions to identify pertinent variables, ii) "following" questions to identify influence relations between the variables identified, iii) "clarifying" questions to obtain more details about key points and iv) "probing" questions to validate the understanding of the concepts used. With experts' permission, interviews were audio recorded and transcribed.

2.2.4. *Construct and merge knowledge*

The knowledge collected from the interviews was used to identify the influence relations between variables and objectives. The influence relations were extracted from interview transcripts and formalized as causal maps. A causal map is a graphical representation that formalizes variables as nodes and relations between them as edges (Montibeller and Belton, 2006). In this context, a causal map represented the influences of decision variables on optimization objectives. For each expert, we created one causal map for each knowledge domain, which the expert then validated. Next, for each knowledge domain, we merged the causal maps of all experts, which the group of experts involved in that domain then discussed and validated as the knowledge domain's causal map. Next, we merged the causal maps of all knowledge domains, which all experts then discussed and validated as the overall causal map. Finally, to obtain the causal map for optimization objectives, we trimmed the overall causal map to show only those decision variables (and their associated intermediate variables, used in calculations) that influenced optimization objectives, which could conflict with one another. In a hypothetical example (Fig. 2), variables A, B, C, D and E are involved in formulating optimization objective 1, and variables B, C and E in formulating optimization objective 2. Variables A, B and C are decision variables, and D and E are intermediate variables calculated from decision variables. At the same time, variable E influences objectives 1 and 2. Causal maps can also be expressed as generic equations that contain minimization and/or maximization objectives.

3. Results

3.1. *Choose optimization objectives and experts*

The project group initially suggested nine objectives, but only five of them were chosen as optimization objectives: to maximize casein concentration in retentate, to maximize serum protein concentration in permeate, to maximize serum protein recovery yield in permeate, to minimize investment cost and to minimize production cost (Table 2).

The other four objectives — environmental impacts (water and energy consumption), return on investment, ease of implementing the process and area of the process floor space — which are not used in the multi objective optimization may be used as criteria in the multi criteria decision support allowing to choose among the optimized solutions resulting from the multi objective optimization. The ease of implementation combined maintenance accessibility and membrane storage requirements (if needed), as ceramic membranes can be stored in the open air, while polymeric membranes must be stored in water with bacteriostatic additive. The area of the process floor space depended on the compactness of the membrane (SW is more compact than UTP and GP for a given filtration area).

Eleven experts were identified from a variety of sectors: scientists, dairy product producers (both permeate- and retentate-fraction end-users) and an equipment manufacturer. Each knowledge domain (except for one) was covered by at least two experts (Fig. 3), which could generate differences in opinion that would lead to rewarding discussions.

The experts identified 11 knowledge domains. Few domains were related to product characteristics: "Permeate fraction", "Retentate fraction", "Cheese", "Physico-chemical analysis". The two "Retentate and permeate fractions" knowledge domains referred to the expert's expectations on the two fraction characteristics (such as composition) and how these expectations can be influenced by the microfiltration process (such as TMP). The "cheese" knowledge domain focused on how retentate fraction properties can affect the manufacturing of cheese. The "physico-chemical analysis" knowledge domain focused on how the choice of the analysis technique and the operating mode can influence the measured characteristics of the obtained fractions.

Others were characteristics of the design and performance of the MF itself: "Membrane properties", "Operating variables", "Hydraulic performance of the filtration", "Process design", "Scale-up". "Membrane properties" knowledge domain referred to the membrane material chemical properties and hydrophobicity and how they can affect the filtration in time (with ageing for example). As we focused on three filtration technologies in this study, there is no choice in membrane material and this knowledge domain was considered as not relevant regarding the defined scope for our optimization problem. "Operating variables" and "hydraulic performance of the filtration" knowledge domains were closely related to each other but focused on two different aspects of the filtration. "Hydraulic performance of the filtration" focused on variables related to the circulation of the retentate (crossflow velocity, retentate pressure drop etc.) while "operating variables" focused on all the variables allowing to control the filtration process. "Process design" knowledge domain focused on the design variables of the microfiltration (such as number of stage or filtration area) and how these variables impacted the microfiltration performances. The "scale-up" knowledge domain was closely related to the process design but focused on how to transfer design rules and experimental data from pilot scale to industrial scale.

Two knowledge domains represented non-technical performances: "Environmental impacts" and "Economic costs". Experts agreed that these knowledge domains covered the entire MF knowledge domain.

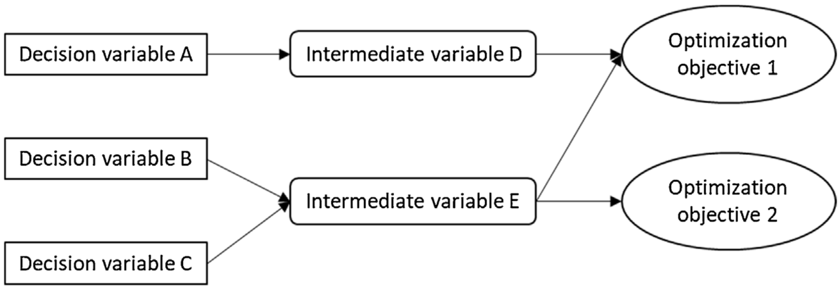


Fig. 2 – Example of a hypothetical causal map with three decision variables, two intermediate variables and two optimization objectives.

Table 2 – Optimization objectives.

Criterion	Symbol (unit)	Objective	Observation
Casein concentration in retentate	$CD_{CN,r}$ (g kg^{-1} DM)	Maximize $CD_{CN,r}$	Estimated from retentate dry matter
Serum protein concentration in permeate	$CD_{SP,p}$ (g kg^{-1} DM)	Maximize $CD_{SP,p}$	Estimated from permeate dry matter
Serum protein recovery yield permeate	η_P (-)	Maximize η	Estimated from the initial amount of serum protein in milk
Investment cost	CI (€)	Minimize CI	Sum of equipment, engineering design and installation costs
Production cost	CPR (€)	Minimize CPR	Sum of consumption of utilities, maintenance costs and the operator's salary

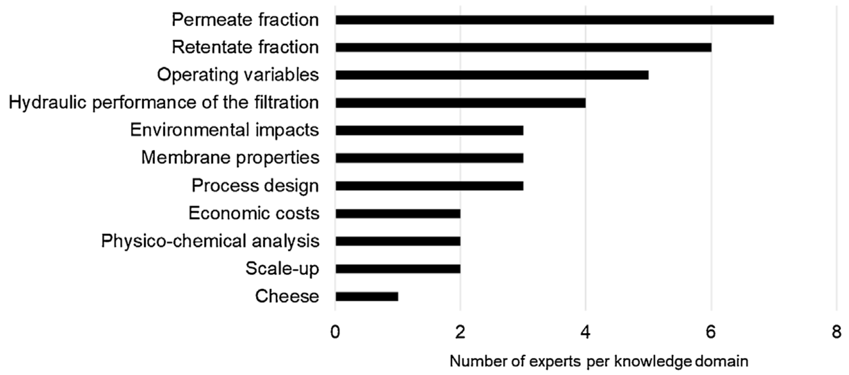


Fig. 3 – Number of experts per knowledge domain of microfiltration.

3.2. *Rate the relative importance of knowledge domains*

The thresholds of SWA used to divide the knowledge domains into thirds were 4.50 and 3.70 for the importance of capture and 3.30 and 3.10 for the ease of capture. Based on the thresholds, the most important knowledge domains were "Hydraulic performance of the filtration", "Permeate fraction", "Retentate fraction" and "Process design" (Table 3), while the easiest to capture were "Hydraulic performance of the filtration", "Permeate fraction" and "Operating variables" (Table 4).

The knowledge domains of high and medium importance chosen in the scoping matrix (Table 5) were "Hydraulic performance of the filtration", "Permeate fraction", "Process design", "Retentate fraction", "Operating variables", "Environmental impacts", "Scale-up" and "Economic costs". The scoping matrix helped collect knowledge by prioritizing the knowledge domains that had the highest importance and were the easiest to capture. The experts also used the scoping matrix to discuss the relevance of considering certain knowledge domains. After additional discussion, they decided to reject "Scale-up" because they considered it redundant with "Process design". They also decided to add "Membrane properties" to improve understanding about how membrane properties can influence MF. The final 8 knowledge domains considered for knowledge collection were "Hydraulic performance of the filtration", "Permeate fraction", "Process design", "Retentate fraction", "Operating variables", "Environmental impacts", "Economic costs" and "Membrane properties".

3.3. *Collect knowledge*

Knowledge was collected by interviewing the 11 experts about their knowledge domains. Doing so required 36 interviews and 14.5 h of audio recording. Experts were interviewed in two steps: capturing knowledge and then, if necessary, clarifying it.

3.4. *Construct and merge causal maps*

From the knowledge collected, 33 causal maps were initially created. Each map represented the knowledge of the

Table 3 – Mean scores and weights used to determine the relative importance of capturing each knowledge domain identified (w = weight, H = high, M = medium, L = Low).

Knowledge domain	Ability to achieve the project (w = 3)	Closeness to the subject (w = 2)	Novelty of the knowledge to the subject (w = 1)	Ability to increase the quality of knowledge (w = 1)	Specific weighted average	Importance
Hydraulic performance of the filtration	3.00	3.00	2.25	3.00	5.06	H
Permeate fraction	2.86	2.86	2.00	2.57	4.71	H
Retentate fraction	2.83	2.83	2.17	2.33	4.67	H
Process design	2.50	3.00	2.00	2.50	4.50	H
Scale-up	2.50	2.50	2.50	2.50	4.38	M
Economic costs	2.50	3.00	2.50	1.50	4.38	M
Operating variables	2.40	2.80	1.60	2.80	4.30	M
Environmental impact	2.33	2.00	2.67	2.00	3.92	M
Membrane properties	2.00	2.00	2.33	2.33	3.67	L
Cheese	2.00	2.33	2.33	1.67	3.67	L
Physico-chemical analysis	1.67	1.67	2.33	2.33	3.25	L

Table 4 – Mean scores and weights used to determine the ease of capturing the knowledge domains identified (w = weight, E = easy, M = moderate, D = difficult).

Knowledge domain	Explicitness (w = 2)	Existence of documents (w = 2)	Availabilityof experts (w = 1)	Specific weightedaverage	Ease
Hydraulic performance of the filtration	1.75	1.50	1.75	2.75	E
Operating variables	1.80	1.60	2.00	2.93	E
Permeate fraction	1.86	1.71	2.00	3.05	E
Physico-chemical analysis	1.67	2.33	1.33	3.11	M
Membrane properties	1.67	2.00	2.00	3.11	M
Process design	1.50	2.50	1.50	3.17	M
Cheese	2.00	1.67	2.67	3.33	D
Retentate fraction	2.17	1.83	2.00	3.33	D
Environmental impact	2.00	2.33	1.67	3.44	D
Economic costs	1.50	3.00	1.50	3.50	D
Scale-up	3.00	3.00	2.00	4.67	D

Table 5 – Scoping matrix of the relative importance and ease of capture of the knowledge domains identified.

Importance	Ease of capture		
	Easy	Moderate	Difficult
High	Hydraulic performance of the filtration Permeate fraction	Process design	Retentate fraction
Medium	Operating variables	–	Environmental impactsScale-up Economic costs
Low	–	Membrane properties Physico-chemical analysis	Cheese

Table 6 – Decision variables for optimization objectives.

Symbol	Description	Type	Unit	Value domain
MT	Membrane technology	nominal	–	[SW, UTP, GP]
Q_{feed}	Feed flow	continuous	$m^3\ h^{-1}$	[5, 20]
$Q_{rec,n}$	Recirculation flow n[a]	continuous	$m^3\ h^{-1}$	[10, 50]
Jp_n	Permeation flux n[a]	continuous	$L\ h^{-1}\ m^{-2}$	[5, 100]
VRR_n	Volume reduction ratio n[a]	continuous	–	[1, 3.5]

[a] n is the number of stages of the microfiltration plant.

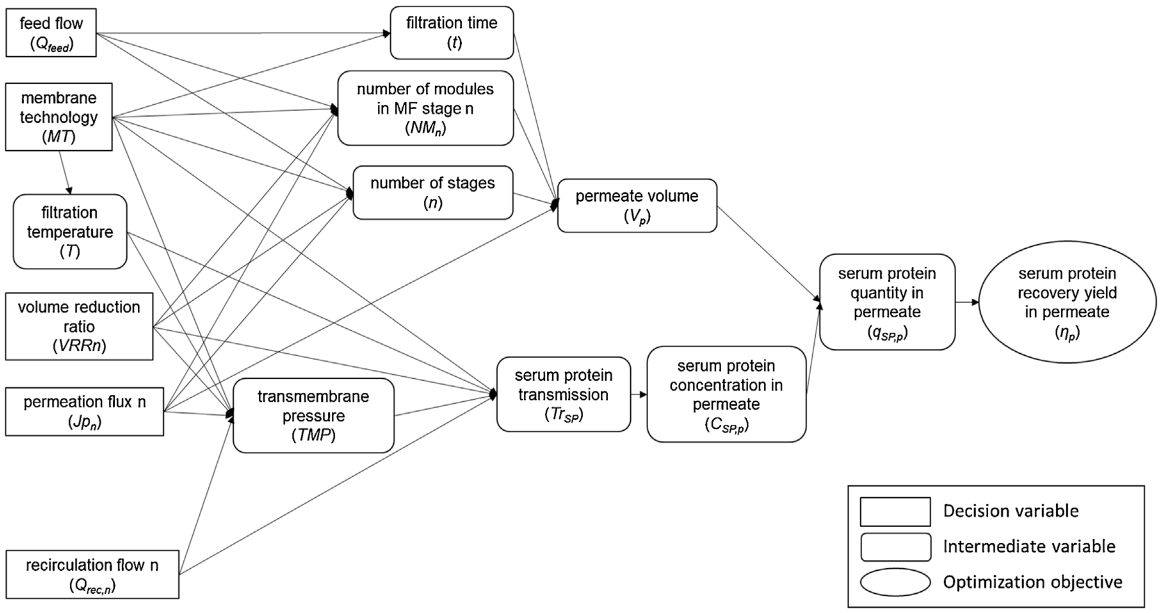


Fig. 4 – Causal map of the serum protein recovery yield in permeate.

Table 7 – Intermediate variables used to calculate optimization objectives. All variables are continuous unless identified as discrete (*).

Symbol	Description
$C_{SP,p}$	Serum protein concentration in permeate
$C_{CN,r}$	Casein concentration in retentate
$q_{SP,p}$	Serum protein quantity in permeate
Tr_{SP}	Serum protein transmission rate
DM_p	Permeate dry matter
DM_r	Retentate dry matter
TMP	Transmembrane pressure
t	Filtration time
T	Filtration temperature*
V	Volume of the microfiltration plant
V_p	Permeate volume
n	Number of stages*
NM_n	Number of modules in microfiltration stage n*
$CO_{heating}$	Heating consumption cost
$CO_{chemical}$	Chemical consumption cost
$CO_{electricity}$	Electricity consumption cost
CO_{energy}	Energy consumption cost
$CO_{equipment}$	Equipment cost including membranes, modules, tanks, pumps, sensors, heat exchangers, pipes and plant automation
$CO_{cooling}$	Cooling consumption cost
$CO_{human\ time}$	Total cost of human time
$CO_{insta\&com}$	Installation and commissioning cost
$CO_{maintenance}$	Maintenance cost (including membrane replacement)
$CO_{office\ work}$	Cost of time for work on engineering, project follow-up and automation programming
$CO_{operator's\ costs}$	Operator's costs
$CO_{utility}$	Utility consumption cost
CO_{water}	Water consumption cost

1–7 experts for one of the 11 knowledge domains initially identified. Once merged and trimmed, the causal maps for optimization objectives (serum protein recovery yield in permeate in Fig. 4; the others in the Supplementary material) contained a total of 5 decision variables (Table 6) and 31 intermediate variables (Table 7).

Four of the five decision variables — membrane technology, volume reduction ration, recirculation flow and permeation flux — influenced all optimization objectives, which highlights their conflicting nature. Among the five decision variables, three (membrane technology, feed flow and volume reduction ratio) described the entire MF plant, while the other two (recirculation flow and permeation flux) had values that depended on the stage of the MF plant. Thus, 2 + 3n decision variables were ultimately considered, with n the number of stages of the MF plant.

The overall causal map led to the following equations for optimization objectives:

$$\max CD_{CN,\,r} = f(C_{CN,r}(VRR_n),\, DM_r(C_{CN,r},\, Tr_{SP})) \quad (2)$$

$$\max CD_{SP,p} = f(C_{SP,p}(Tr_{SP}),\, DM_p\left(C_{SP,p}\right)) \quad (3)$$

$$\max \eta_p = f(q_{SP,p}(C_{SP,p}(Tr_{SP}),\, V_p(t(Q_{feed},\, MT),\, n,\, NM_n)) \quad (4)$$

$$\min CI = f(CO_{equipment},\, CO_{human\,time}(CO_{insta\&com}(n),\, CO_{office\,work}(n)) \quad (5)$$

$$\min CPR = f(CO_{operator's\,salary}(n),\, CO_{maintenance}(n,\, MT,\, NM_n),\, CO_{utility}) \quad (6)$$

Subject to:

$$T = \begin{cases} 12\ if\ MT = SW \\ 50\ otherwise \end{cases} \quad (7)$$

with

$$Tr_{SP} = f\,(TMP,\, MT,\, T,\, Q_{rec,n},\, VRR_n) \quad (8)$$

$$TMP = f\left(MT,\, VRR_n,\, T,\, Q_{rec,n},\, J_{p,n}\right) \quad (9)$$

$$n = f\left(MT,\, Q_{feed},\, J_{p,n},\, VRR_n\right) \quad (10)$$

$$NM_n = f\left(MT,\, Q_{feed},\, J_{p,n},\, VRR_n\right) \quad (11)$$

$$CO_{equipment} = f\,(NM_n,\ n,\ MT,\ T,\ Q_{rec,n}) \tag{12}$$

$$CO_{utility} = f\,(CO_{water}(V\,(n,\ NM_n,\ MT)),\ CO_{chemical}\,(V\,(n,\ NM_n,\ MT)),\ CO_{energy}) \tag{13}$$

$$CO_{energy} = f\left(CO_{electricity}\,(n,\ MT,\ Q_{rec,n}),\ CO_{heating}\,(n,\ T,\ Q_{rec,n}),\ CO_{cooling}(n,\ T,\ Q_{rec,n})\right) \tag{14}$$

See Tables 2,6 and 7 for the symbols used in the equations for the optimization objectives, decision variables and intermediate variables, respectively.

4. Discussion

The design of a food process is an essential and complex step in implementing it at an industrial scale. This study addressed the first design step by developing a method to formulate the multiobjective optimization problem of a food process. It also showed how applying the method to skim milk MF can help new knowledge and research insights emergence.

4.1. *Method to formulate the multiobjective optimization problem of a food process*

The method developed in this study allows a group of scientific and industrial experts to discuss, formalize and share knowledge about the food products and MF process. Because the experts had different backgrounds, the method of Hobballah et al. (2018) was adapted by adding an initial step to identify the optimization objectives and the relevant experts who covered different but complementary backgrounds. Their differences in culture and perspective made mutual understanding more difficult.

The first major challenge was differences in vocabulary. When collecting knowledge, an expert's background could strongly influence his/her understanding of certain terms, which sometimes caused misunderstandings in the group of experts. For instance, there was confusion between "concentration factor" and "volume reduction ratio", both of which are key parameters in membrane separation. "Concentration factor" is the concentration of a given component in the retentate compared to the concentration of the same given component in the feed (Eq. 15). It is calculated from concentrations of the component (e.g. casein) measured in both the retentate and the fluid to be treated (milk).

$$FC = \frac{C_r}{C_{Feed}} \tag{15}$$

"Volume reduction ratio" is the ratio of feed flowrate to retentate extraction flowrate (Eq. 16) and is used in industry to adjust the retentate extraction flowrate to obtain a targeted concentration of the component (casein) in the retentate (concentration factor).

$$VRR = \frac{Q_{Feed}}{Q_r} \tag{16}$$

In industry, the volume reduction ratio is commonly called the "volume concentration ratio" (although the concentration of a volume remains unclear), which leads to confusion. The volume reduction ratio equals the concentration factor only if the membrane retains all casein.

Another misunderstanding arose over "transmembrane pressure", a parameter used by the scientists but rarely by the industrial partners. Although all experts agreed that "transmembrane pressure" meant the "driving force through the membrane", industrial MF plants are generally not equipped with pressure sensors that can estimate it accurately. In them, transmembrane pressure is calculated from the difference between mean retentate pressure and mean permeate pressure. In laboratory pilots, pressure sensors are installed both in the retentate and permeate compartments, and as close as possible to each module to calculate its transmembrane pressure (Fig. 5). At the industrial scale, few pressure sensors are installed, and they lie far from modules, which provides only a rough estimate of each module's transmembrane pressure. These calculations required making two assumptions. First, pressure loss between a sensor and the inlet or outlet of a module was ignored regardless of the distance to the sensor (length of pipes, bends and change of cross section). Second, the retentate outlet pressure was considered similar to the feed pressure because each stage's retentate outlet was placed close to its feed. For example, the transmembrane pressure for module 111 in stage 1 (Fig. 5) could be calculated for the industrial plant (Eq. 15) and the experimental pilot (Eq. 16).

$$TMP = \left(\frac{P_{r,in,1} + \left(P_{r,in,1} - \frac{1}{2}\left(P_{r,in,1} - P_{feed}\right)\right)}{2}\right) - P_{p,1} \tag{15}$$
$$TMP = \frac{1}{4}\left(3\,P_{r,in,1} + P_{feed}\right) - P_{p,1}$$

$$TMP = \left(\frac{P_{r,\,in,1} + \left(P_{r,in,1} - \frac{1}{2}\left(P_{r,in,1} - P_{r,ou,1}\right)\right)}{2}\right) - P_{p,111} \tag{16}$$
$$TMP = \frac{1}{4}\left(3\,P_{r,in,1} + P_{r,ou,1}\right) - P_{p,111}$$

Besides differences in vocabulary, experts also had different, albeit complementary, visions of how to operate the MF plant. The scientists wanted to study the influence of specific parameters on MF performance and thus obtain as much information as possible. Conversely, the dairy product producers wanted a simple and robust plant that would ensure the desired quantity and quality of dairy products. These different visions resulted in differences in the process control of filtration.

For instance, process control differed at the start of the production run. In an industrial plant, for sake of simplicity, permeate and retentate extraction valves are usually open during the initial flushing step, to a degree required by filtration operating parameters. In this step, the water initially present in the plant is flushed out and replaced by the milk to be treated. This step dilutes the permeate and retentate fractions, but the dilution can be limited by diverting the over-diluted fractions to the wastewater treatment plant for disposal. Over-dilution of the retentate can also be corrected by applying an over-estimated targeted volume reduction ratio. In a laboratory pilot, filtration is not usually started with diluted milk. Water is flushed with the permeate and retentate valves closed. The water is flushed through a specific valve connected to the sewer and, as soon as the retentate compartment is full of milk, the permeate valve is opened and filtration

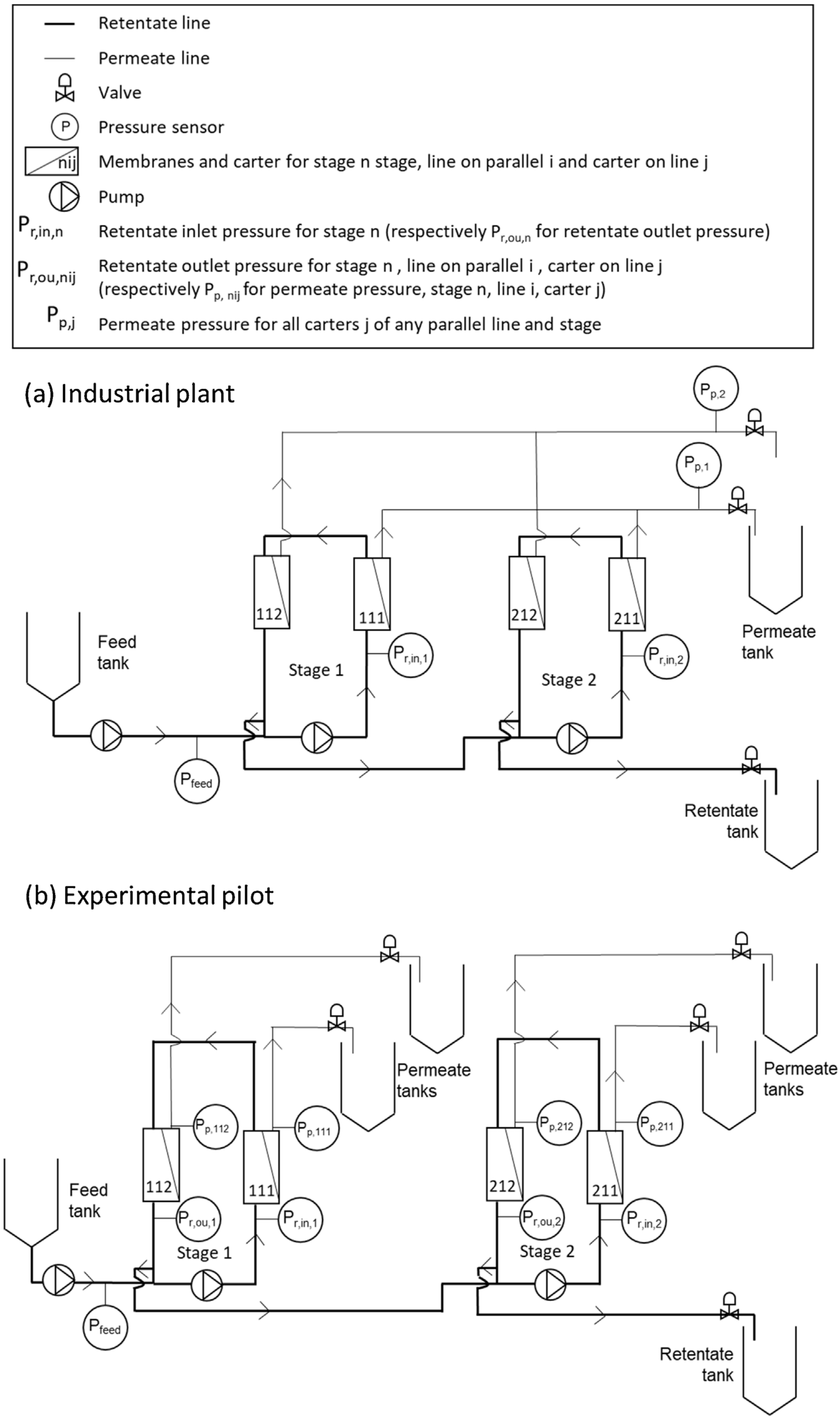


Fig. 5 – Locations of pressure sensors in (a) an industrial plant and (b) experimental pilot. Example of gradient of permeability membrane technology with two stages and one line in parallel, with two modules in series in each stage.

starts. The retentate extraction valve is thus open when the volume reduction ratio is reached.

Strong differences in regulation modes during filtration were also noted. In an industrial plant, there is no need to uncouple regulations of crossflow velocity and transmembrane pressure because the plant is designed to ensure targeted values of these two parameters. Conversely, in a laboratory pilot, their regulations need to be uncoupled to study the influence of each one (Daufin et al., 1993) (e.g. different crossflow velocities at a constant transmembrane pressure or vice versa) on permeation flux and transmission of serum proteins (e.g. Gésan-Guiziou et al., 1999). Regulating permeation flux is also challenging, especially with SW. Permeation flux is usually regulated by increasing transmembrane pressure by decreasing permeate pressure and opening the permeate valve (Daufin et al., 1993). However, no counter-pressure is generally applied to the permeate side of SW at the industrial scale because doing so could damage the membrane (back-filtration due to permeate pressure being higher than outlet retentate pressure), even though it can be applied at the laboratory scale. Industry thus regulates constant permeation flux with SW membranes using an overflow tank and a slightly oversized membrane area. This mode of operation is used with ultrafiltration polymeric membranes but has never been applied to MF as it may decrease the serum protein recovery yield.

To help scientific and industrial experts share and understand each other's vocabulary and visions better, their vocabulary was harmonized, and their visions of the design of MF were clarified, as recommended by Ndiaye et al. (2009). A list of variables, their symbols and their definitions were created to ensure that experts discussed the same concepts. Equivalences between industrial plants and laboratory pilots were established to be able to estimate transmembrane pressure in the industrial plant (Fig. 5). After sharing the different regulation modes used at industrial and laboratory scales, experts voted on which regulation modes of MF to use. It was stated to conduct microfiltration at constant permeation flux for the three membrane technologies. As a consequence, a valve has to be added on the permeate side of the polymeric spiral wound membrane to ensure a counter pressure. For the sake of clarity, the group established a production timeline to define MF production steps (provided with the supplementary materiel). This production timeline was also important to identify from which step the volumes of permeate and retentate fractions are collected and their associated concentrations. Managing experts' viewpoints can be challenging, but group synergy can occur if there are a variety of opinions.

4.2. New knowledge gained by formulating multiobjective optimization of MF

By requiring knowledge from scientist and industrialist experts, the approach developed obtained new knowledge from the optimization objectives, influence relations between variables and objectives and emerging knowledge domains. The optimization objectives and causal maps represented a combination of what is usually studied and known, what usually studied but not highlighted by experts and new insights.

Some of the optimization objectives were consistent with information in the literature, such as those for the composition of permeate and retentate fractions (Beckman et al., 2010; Zulewska and Barbano, 2013). Considering two optimization objectives for the permeate fraction revealed the dairy product producers' strong interest in processing the permeate fraction quantitatively (i.e. recovery yield) and qualitatively (i.e. serum protein concentration). Indeed, serum protein concentration is expressed as a function of the dry matter content and thus describes the purity of the fraction, which makes it possible to relate the objective of "maximizing serum protein concentration" to a qualitative feature of the permeate fraction. The experts did not choose certain optimization objectives, such as permeation flux or transmembrane pressure, which are related directly to membrane fouling. Permeation flux is usually considered as an optimization parameter, but the present study assumed that it remained constant. Regarding transmembrane pressure, the experts considered it as an intermediate variable that influenced three of the five optimization objectives: maximizing i) casein concentration in the retentate, ii) serum protein concentration in the permeate and iii) serum protein recovery yield in the permeate. This highlights the importance for experts to optimize not only the process but the product as well by setting objectives for the product properties which are influenced by process variables. As expected by the inclusion of experts from dairy product production and equipment manufacturing, economics objectives emerged as minimization of investment costs and of production costs. These economic objectives and that for serum protein recovery yield (i.e. three of the five objectives) highlighted the major influence of process design, which most scientific studies do not consider. In addition to classic economic indicators such as water, energy and chemical consumption, equipment maintenance and the operator's salary were included in the production cost. In the same way, investment costs were included in the installation and commissioning of the plant and the cost of office work for engineering, project follow-up and automation programming. These new objectives reflect the industrial reality of economic profitability. The approach developed combines this industrial knowledge with scientific knowledge related to MF in a homogenous format. It makes the interdependence of the variables in these domains explicit. In a decision-support perspective, these objectives are essential to rationalize trade-offs among economic, process and product issues.

Besides providing new insight into optimization objectives, the method developed can identify new knowledge domains needed to formulate a multidisciplinary optimization problem of a food process. The knowledge domains considered that had high and medium importance and were easy to capture are those usually studied in the literature, such the "Hydraulic performance of the filtration" (Astudillo-Castro, 2015; Gésan-Guiziou et al., 1999). It is easy to obtain knowledge about what is usually done, which is logical. The method highlighted two new important knowledge domains whose knowledge is difficult to capture and for which further studies are required. Although knowledge about the composition of the retentate fraction is relatively easy to capture, its ability to be transformed into cheese remain difficult to characterize for two main reasons: it is sometimes part of industrial recipes for cheese making that are considered trade secrets, and there is a lack of scientific knowledge about it. Identifying retentate functionality indicators and understanding the influence of operating parameters of upstream processes on them require further research. The second new knowledge domain highlighted by this method was the environmental impacts. In this study, only water and energy consumption were considered, but cleaning procedures and products, especially the complex detergent solutions applied to regenerate membranes, have high environmental impacts (Gésan-Guiziou et al., 2019). It is currently difficult to estimate environmental impacts of cleaning after MF because current life cycle analysis databases do not include these solutions. Further specific studies are thus needed.

4.3. Perspectives

The adapted method of Hobballah et al. (2018) was successfully applied to formulate the multiobjective optimization problem of skim milk 0.1 μm MF. However, two improvements could increase the reliability of its results: i) formulating the

MF multiobjective optimization problem in a more complex manner to approach the true functioning of MF and ii) integrating MF into the production line.

Considering uncertainties in influence relations also could improve the accuracy of the results. We assumed that each relation given by an expert was true without considering the expert's confidence level. In reality, experts may have high confidence about certain relations between variables but have doubts about others. This is important because certain influence relations were based only on expert knowledge, which has higher uncertainty than results of experiments. Discussions among experts decreased uncertainties in knowledge; however, setting the level of confidence in influence relations based on the source of or confidence in the knowledge would improve the reliability of results (Baudrit and Dubois, 2006). This approach would also help choose among opinions from experts who differ in their degrees of certainty. In this study, experts always managed to arrive at a consensus, but when is not possible, including a method to consider each expert's confidence level would be useful.

Knowing the protein composition of both retentate and permeate fractions more accurately would help dairy product producers perform MF better and then improve the quality of the fractions based on the final products desired. In particular, we assumed no free caseins in the permeate fraction, although some may pass through the membrane during MF, and their presence is detrimental for subsequent use of the serum protein concentrates. For instance, residual caseins precipitate when acidified (e.g. in some nutritional drinks for athletes) and cause undesirable turbidity.

The complexity of cleaning procedures should be considered in the optimization to guarantee effective cleaning regardless of the degree of fouling of the membrane. While cleaning procedures are still under investigation (Astudillo et al., 2010; Rabiller-Baudry et al., 2002; Regula et al., 2014) we assumed that they were effective and reproducible for each membrane technology according to industrial standards. Operating conditions determine how quickly the membrane fouls, and standard cleaning may not be effective for all fouling conditions. Optimized cleaning depending on the operating conditions would ensure effective cleaning of the membrane and consistent performances.

New insights that help to optimize the entire process including MF are also expected. Considering MF upstream stages makes it possible to represent differences in the milk pre-treatments used industrially. We assumed that milk was highly mixed and had a fixed composition. Industrially, milk is stored and pre-treated (e.g. skimmed, thermized and/or bactofuged) before MF. In a recent study, Granger-Delacroix et al. (2020) showed that milk storage and treatment conditions influence transmembrane pressure and recovery of serum protein during MF. Transmembrane pressure was influenced most by MF fouling, which depends mainly on the load of microorganisms, while recovery of serum protein was influenced mainly by the denaturation and/or aggregation of serum protein caused by the pre-treatment steps. More needs to be learned about how milk pre-treatment influences MF before including it in the formulation of the multiobjective optimization problem.

Including downstream processes in the overall vision of the MF process could modify the optimization objectives. In industry, ultrafiltration, nanofiltration and/or reverse osmosis are usually used to concentrate and purify the serum protein recovered in the permeate fraction, and the serum protein concentration determines how much membrane area will be required. As serum protein concentration increases, downstream processes need less membrane area and cost less; thus, an overall vision of the production line is necessary.

To complete the overall vision of the production line, considering dynamic aspects of the MF process during the lifetime of the membrane would increase reliability of the results. In any food process, even though variables that describe the process (e.g. transmembrane pressure) depend on time, their dependencies are not considered when formulating the problem. To simplify problem formulation in this study, we considered only steady-state process conditions, which we assumed already contained the main issues inherent in the MF process as a whole. In a comprehensive perspective, however, it would be useful to consider all dynamics of the MF process and to address new challenges. Influence relations among variables would vary over time, which would lead to considering multiple states of each variable and different knowledge structures. For simplicity, membrane ageing was excluded from the problem formulation, but the filtration efficiency of membranes does decrease over time. Consequently, as membranes age, fouling by skim milk increases, critical and limiting conditions of filtration are modified and cleanliness decreases (Rabiller-Baudry et al., 2019). Considering membrane ageing would require continuously adapting filtration and cleaning conditions throughout the lifetime of the membrane to ensure optimal operating conditions.

5. Conclusion

This study formulated the preliminary design of an optimal skim milk MF process as a multiobjective optimization problem. The method applied was adapted by adding steps to define optimization objectives and identify experts. It can consider product composition, process design and operating conditions. According to experts, it was important to consider both permeate and retentate compositions of fractions, the serum protein recovery yield in permeate and economic costs as optimization objectives. Eight knowledge domains were studied to describe which variables influenced the optimization objectives. Five decision variables and 31 intermediate variables were needed to represent influence relations among variables and between variables and objectives. This method identified optimization objectives and the variables that influenced each one. The next step before processing the optimization model is to model the objectives as mathematical functions or computational algorithms. Then, using an adapted optimization algorithm, optimal solutions for MF will be calculated and analysed. This approach opens new perspectives for optimizing MF and, more generally, food-processing processes that integrate expert knowledge.

Declaration of interests

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

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.fbp.2020.09.002.

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