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Decision support system design using the operator skill to control cheese ripening—application of the fuzzy symbolic approach

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Abstract

In food industries, managing sensory properties from the fabrication stage in an automatic framework constitutes a key issue for companies but is no easy task. It is an open field of research in which few studies have been carried out. Therefore, we propose to integrate the operator skill using a fuzzy symbolic approach. More precisely, the aim of our study is to present an application of such an approach to the development of a support system dedicated to help the operator on-line during cheese ripening. The information delivered by the support system, on the basis of sensory instantaneous measurements, is the global change in the cheese at each time step in comparison to a standard trajectory of ripening. The results are relevant to the control of the sensory properties of the products at the fabrication stage. Thus, the model follows the sensory trajectory of the cheese during ripening and helps the operator to diagnose and control it. It is validated on a data set of 106 points at a level of 97% and 80% for respectively a sensitivity of 3.5 and 1.75 days for a response time of the process of at mean 2 days. It opens an interesting road of cooperation between operators and food process control systems.

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Keywords: Cheese ripening; Fuzzy logic; Decision support system; Food process; Expert system; Operator; Sensory perception

1. Introduction

In the food industry, end-products are a compromise between several properties. Among the latter, sensory properties are essential because they condition the choice and preferences of consumers. Managing sensory properties right from the fabrication stage with the aim of controlling them is no easy task. Indeed, on the one hand, few sensors are available to carry out such measurements (Trystram, 1996). On the other hand, it is difficult to develop a classical automated approach due in part to (1) the many dimensions that must be taken into account in parallel and (2) the non linearity and coupling between the variables involved in the system. A recent study (Iiyukhin, Haley, & Singh, 2001) shows that 59% of food manufacturing plants are not fully auto-

mated for those reasons and involved operators interventions.

Indeed, in this context, operators often play an important role and, in practice, interact with automatic systems so as to, (1) evaluate on line the sensory properties of the product and/or (2) adjust on line the process.

The integration of the operator skill in a control frame is a relevant direction especially for traditional processes (Davidson, 1996; Goyache et al., 2001; Linko, 1998; Perrot, Trystram, Le Gennec, & Guely, 1996; Trystram, 1996). Nevertheless, it induces the design of mathematical tools that should integrate: (i) a reasoning based on the use of linguistic symbols like “over coated”, “good color”, etc. expressed not on a numerical scale but on an discontinuous graduated scale and refers to a deviation evaluation from a set point; (ii) an uncertainty on those symbols which is translated after fusion in a precise action; (iii) an action which is the result of an implicit or explicit interpolation between specific states registered by the operator over time.

Although many mathematical approaches can be developed to treat this problem (Fig. 1) from linear

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Nomenclature

EA, EB	the two experts of the ripening process involved in our experiments	IS ₃	sensory indicator humidity on a line structures scale with anchors graduated in 0.5
L	set of word	IS ₄	sensory indicator color on a line structures scale with anchors
N	numerical set	t	time of ripening
$F(N)$	fuzzy numerical subset	MF	fuzzy meanings
$F(L)$	fuzzy symbolic subset	DF	fuzzy description
RF	fuzzy relation	μ	membership degree
DR	degree of cheese ripening in weeks, the output of the decision support system expressed on a line structured scale with five anchors “standard state A, B, C, D and E” graduated in 1.75 days	$\mu_x(y)$	membership degree of y to x
IS _{i}	Sensory indicator i , input of decision support system	$\mu_{RF}(a, x)$	fuzzy relation between a and x
IS ₁	sensory indicator cheese consistency on a line structure scaled with anchors graduated in 0.5	μ_{D_j}	membership degree to a symbolic deviation j
IS ₂	sensory indicator Gc coat on a line structures scale with anchors graduated in 0.5	μ_{R_i}	activation grade of rule i
		LX, LY, LZ	sets of linguistic terms
		E, F, G	fuzzy subsets
		t_1, t_2	triangular norms
		$\alpha, \beta, \delta, \varepsilon$	result at t time of the symbolic calculus of the deviation of each sensory indicator (IS _{i}) to its value in standard conditions—answer in symbols

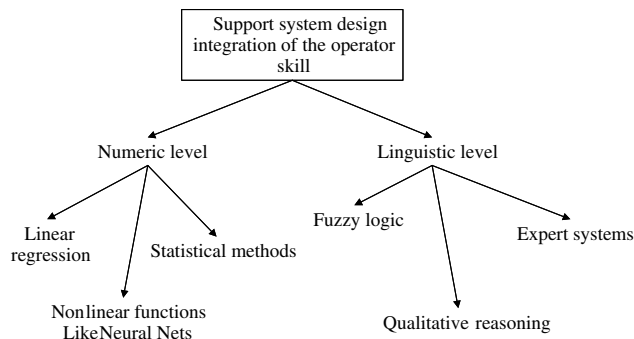


Fig. 1. Mathematical approaches to treat the integration of the operators skill in an industrial support system.

regression to more elaborated ones such as statistical methods (Bayesian for example), neural networks, fuzzy logic (theory of fuzzy sets and theory of possibility), few are adapted to processing the data at the linguistic level used by the experts. Working at a linguistic level can be relevant for several reasons. Firstly, the work achieved in the operator's reasoning space can be directly used by the manufacturing plant as a skill formalized procedure. Secondly, it gives the opportunity to develop quickly decision support systems which are well accepted by the operators. Finally, the symbols manipulated by the operators not only incorporate a qualification of the state of the product at time t , but they also provide a major indication of the imprecision and graduality of the operator's evaluation. This is linked to his future action on the process which risk being neglected in the former approach.

The purpose of this study is to apply a particular mathematical framework: the fuzzy symbolic approach, coming from the theory of fuzzy subsets (Dubois, Foulloy, Galichet, & Prade, 1999; Zadeh, 1971) to design a decision support system incorporating the operator skill at a linguistic level. It is applied to cheese ripening.

Cheese ripening still remains a process where the operators evaluation and reasoning play a major role (Lemoine, 2001). It is in part due to a lack of knowledge on (i) the complex interactions taking place between the whole microorganisms of the cheese and (ii) the link between those interactions and the kinetics of the sensory changes taking place in the cheese during ripening. To cope with this lack of knowledge, some studies have developed methods to (1) monitor on-line certain sensory properties of the product such as texture using sensors (O'Callaghan, O'Donnell, & Payne, 1999) and (2) characterize the sensory properties of a cheese in laboratory (Lesage, Sauvageot, Voilley, & Lorient, 1992; Martin et al., 1999). Few studies have focused on the prediction of the sensory changes of a real cheese during ripening versus time, due to a lack of biophysicochemical models of the behavior of a real cheese during ripening and the associated impact on the cheese quality. Nevertheless, it is a key issue to help the ripening expert to control the process and as a consequence improve the cheese quality and yield. In parallel, the ripening expert is able to explain at a symbolic level which is not the numeric one, a part of the complex reactions that are taking place in the real cheese through

his perception of the quality changes. Based on this symbolic understanding of the process he generally makes his control decisions. We have tried to structure and formalize this other level of knowledge using the concept of the fuzzy symbolic approach.

In this paper, we first present the context of our approach by giving an overview of applications of fuzzy logic to food processes, followed by a more detailed description of the fuzzy symbolic approach. The second part presents the materials and methods used in the application. Part three describes the support system developed, and finally part four is dedicated to the results obtained with the associated discussions.

2. The fuzzy symbolic approach

The fuzzy subsets theory was introduced by Zadeh in 1965 as an extension of the set theory by the replacement of the characteristic function of a set by a membership function whose values range from 0 to 1 (Zadeh, 1965). Soft transitions between sets are thus obtained and allow the representation of gradual concepts as well as the representation and the inference of linguistic rules stemming from expertise. It is now a wide field of study with different tools developed over the past 10 years. It is particularly adapted for taking human linguistic and reasoning processing into account (Dubois et al., 1999; Linko, 1998; Mauris, Benoît, & Foulloy, 1996; Perrot et al., 2000). Among the papers focused on the application of fuzzy logic to different domains, about 30 are dedicated to food processes. Two specific research fields are well represented in those papers: (i) modeling of a sensory evaluation of an operator or a consumer (Davidson, Ryks, & Chu, 2001; De Silva, Gamage, & Gosine, 1996; Harris, 1998; Shahin, Verma, & Tollner, 2000); (ii) fuzzy control of food processes (O'Connor et al., 2002) to control the brewing process and (Curt, Hossenlopp, Perrot, & Trystram, 2002) to control sausage ripening.

More recent studies results concentrated on the semantic scope of fuzzy logic or theory of possibilities and the ability of such a methodology to capture the operator's reasoning and its uncertainty. In this way, Davidson, Brown, and Landman (1999) used a fuzzy arithmetic that estimates peanut eating time and browning to control peanut roasting. Perrot et al. (2000) have developed three modules dedicated to each function of control: evaluation, diagnosis and action at a linguistic level to control biscuit quality during baking. Wide (1999) used aggregated sensor measurements to help operators to optimize the dough mixing process. These latter authors underline the relevance of this open field of research in the context of food processes and the interest of fuzzy symbolic representation of the expert reasoning.

In this paper we propose the description of a fuzzy mathematical frame that enhances this fuzzy symbolic aspect. It is based on the concept of the fuzzy symbolic sensor proposed by Mauris, Benoit, and Foulloy (1994) which was initially developed to process instrumental and operator data at a symbolic level understandable by operators and at the same time provide a control system.

2.1. The mathematical frame of the fuzzy symbolic approach

The mathematical frame of the fuzzy symbolic approach embed two specific tools:

- A tool to build the link between numeric and linguistic sets so as to treat all the data at a linguistic level.
- A tool to build the fusion between symbols.

2.2. The symbolic approach and the link between numeric and linguistic sets

Since 1971, Zadeh and later Dubois and Prade (1980) have shown the relevance of fuzzy sets to establish a link between a set of words and a universe of "discourse".

Applied to the measurement of perceptive "magnitudes", the fuzzy subset theory led to the development of a new concept proposed by Mauris et al. (1994): the fuzzy symbolic sensor. Fuzzy techniques are used to define a language such as a relation between a set of words (L) and a numerical set (N). This relation is characterized by a membership function, μRF , which represents the degree or the strength of the link between the symbols and numbers. This fuzzy relation can be described by two projections that take their values from the set of fuzzy numerical subsets $F(N)$ and from the set of the fuzzy symbolic subsets

$F(L)$: meanings and descriptions.

Meanings (MF) and descriptions (DF) can be defined as follows (Eqs. (1) and (2)):

$$\text{MF} : \begin{array}{l} L \rightarrow F(N), \\ \forall a \in L, \forall x \in N, \quad \mu M(a)(x) = \mu RF(a, x). \end{array} \quad (1)$$

Fuzzy meaning allows the representation of the symbols manipulated by operators in the form of words. For example this notion can be used to represent, after expert handling, a projection in a numeric space of the symbolic way used by operators to qualify their cheese in terms of moisture content of their product: "dry, normal, humid" (Fig. 2).

$$\text{DF} : \begin{array}{l} N \rightarrow F(L), \\ \forall x \in N, \forall a \in L, \quad \mu D(x)(a) = \mu RF(a, x). \end{array} \quad (2)$$

The fuzzy description is a simple way of describing a measurement with words. For example, in Fig. 2 a

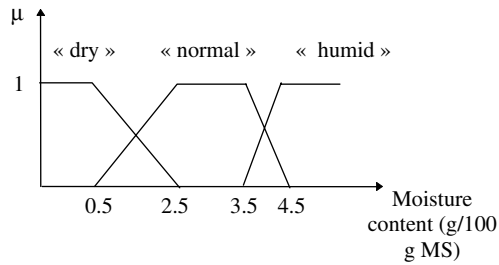


Fig. 2. Example of a fuzzy meaning vis-a-vis the moisture content of a cheese.

moisture content of 4 g/100 g MS can be described like this:

$$\begin{aligned}\mu D(4)(\text{“dry”}) &= 0, & \mu D(4)(\text{“normal”}) &= 0.5, \\ \mu D(4)(\text{“humid”}) &= 0.5.\end{aligned}$$

We can also note:

$$D(4) = 0/\text{dry} + 0.5/\text{normal} + 0.5/\text{humid}.$$

To conclude, the symbolic sensor approach provides a tool for processing the different symbolism used to represent a physical entity like operator's measurement on a linguistic scale or on an ordinated scale and sensor measurements expressed on a numerical scale.

2.3. The symbolic approach and fusion between symbols at a linguistic level

To complete the latter tool, it is necessary to build approaches able to aggregate several symbols together. This is the case in a control framework where decisions for actions are based on a diagnosis of the combined deviations of the different dimensions of the quality of the product and the state of the process. For example, four main sensory characteristics are required on-line by the operator to evaluate the changes in the cheese during ripening and to initiate his control: color, coat, consistency, humidity.

The fuzzy function used for fusion are created on the basis of an expert explanation of the logical links between the symbols. These links between the symbols, incorporate the global aim of the merging. The inference is made by Zadeh's compositional rule of inference, applied to the fuzzy symbolic descriptions of the inputs, which is explained below.

Let us consider that $LX = \{A_1, \dots, A_i, \dots, A_l\}$, $LY = \{B_1, \dots, B_j, \dots, B_m\}$ and $LZ = \{C_1, \dots, C_k, \dots, C_n\}$ three sets of linguistic terms and let us consider a set of rules with the generic form:

If X is A_i and Y is B_j .

Then C is $g_{i,j,1}/C_1 + \dots + g_{i,j,k}/C_k + \dots + g_{i,j,n}/C_n$.

This set of rules defines a fuzzy relation RF on the Cartesian product $LX \times LY \times LZ$, with a membership

degree μR . The generic rule provides the membership degrees

$$\begin{aligned}\mu R(A_i, B_j, C_1) &= g_{i,j,1}, \dots, \mu R(A_i, B_j, C_k) \\ &= g_{i,j,k}, \dots, \mu R(A_i, B_j, C_n) = g_{i,j,n}.\end{aligned}$$

Obviously, this relation is crisp if no weighting is used (i.e. $g_{i,j,k}$ is equal to 0 or 1).

Let us consider E to be a fuzzy subset of LX and F a fuzzy subset of LY , defined by:

$$E = a_1/A_1 + \dots + a_i/A_i + \dots + a_l/A_l$$

and

$$F = b_1/B_1 + \dots + b_j/B_j + \dots + b_m/B_m.$$

The image of $E \times F$ from the fuzzy relation R is a fuzzy subset G of LZ whose membership degrees are presented:

$$\begin{aligned}\forall k \in \mu G(C_k) &= \sup \min(\mu E \times F(A_i, B_j), \mu R(A_i, B_j, C_k)) \\ &= \sup(i, j) \min(\mu E \times F(A_i, B_j), g_{i,j,k}),\end{aligned}\quad (3)$$

with $i = \{1, \dots, l\}$, $j = \{1, \dots, m\}$ and $k = \{1, \dots, n\}$.

According to the definition of the fuzzy Cartesian product:

$$\begin{aligned}\mu E \times F(A_i, B_j) &= \min(\mu E(A_i), \mu F(B_j)) \\ &= \min(a_i, b_j).\end{aligned}\quad (4)$$

The equation giving G is the direct application of Zadeh's compositional rule of inference. It can be generalized by replacing the min operator by a triangular norm. In other respects, since the sets are finite, the optimum can be replaced by the maximum, and even generalized by a triangular co-norm. The generalized equation thus becomes:

$$\forall k \in K \mu G(C_k) = s(i, j) \in I \times J t_1(t_2(a_i, b_j), g_{i,j,k}),\quad (5)$$

with t_1 and t_2 being two triangular norms, often similar while and s is a triangular co-norm.

3. Materials and methods

3.1. Equipment and product

3.1.1. Ripening cellar

For the purpose of this work, we have worked at two levels: (i) an industrial level (a traditional ripening cellar) and (ii) a pilotplant level.

The *pilotplant* was used to create a dataset of changes in cheese ripening under different process conditions (humidity and temperature of the air). The size of this cellar is $(0.5 \times 0.45 \times 1.5 \text{ m}^3)$. It is an experimental pilotplant, which can contained 100 cheeses and allows the control, in an uncoupled way, of air temperature and relative humidity. To control temperature, the cellar is

placed in a cold room. And the temperature in the cellar is controlled by the temperature in the cold room. To control humidity, air is treated to humidify or dry it with a regulation column. Air is pumped in at the top of the cellar with an air pump (KNF Neuberger) ($0.66 \text{ m}^3 \text{ h}^{-1}$). Then, it is diffused through a regulation column. This column ($0.05^2 \times \pi \times 1 \text{ m}^3$) is insulated and filled with water. A cryothermostat (Huber) controls the water temperature via a heat exchanger. Ambient air is injected at the bottom of the column through four porous tubular ceramic elements 10 mm for diameter and 100 mm for length. In contact with water, air bubbles decrease or increase the relative humidity of air according to the water temperature (Baucour & Daudin, 2000). Then, air is injected at the bottom of the cellar.

A traditional ripening cellar was used to validate the approach on line, in the factory. The size of the cellar was around 15 m^3 regulated at a mean temperature of $12 \text{ }^\circ\text{C}$ and adjusted empirically in humidity at around 95%.

3.1.2. Product

The example dealt with focuses on the ripening of a soft mould cheese known as “rogeret”. It is manufactured at an industrial plant, according to a confidential process. These cheeses are manufactured from pasteurized ($72 \text{ }^\circ\text{C}$ for 20 s) cow milk and the principal micro-organism on the surface is *Geotrichum candidum* (Gc). They are round with a diameter of 10 cm and 2 cm in thickness. The time of ripening is usually 30 days (about 4 weeks) in industrial cellars at a temperature of $10\text{--}12 \text{ }^\circ\text{C}$ and a relative humidity of 95–98%. For the study in the pilotplant, batches of cheeses (100 cheeses per batch) were transferred from the plant to the research laboratory, the day following their manufacturing to be matured for 30 days in the experimental cellar.

3.2. Method

Our aim was to develop a decision support system able to (i) represent the knowledge of the ripening expert in a given symbolic structure and (ii) help the expert in his daily task of estimation of the potential changes in of a cheese under given process conditions of air humidity and temperature.

3.2.1. Decision support system design

The decision support system has been designed in three steps (Fig. 3):

- (1) handling the expertise,
- (2) building the fuzzy algorithm,
- (3) validation of the approach (1) on a data basis acquired using the pilotplant and (2) on-line at the factory.

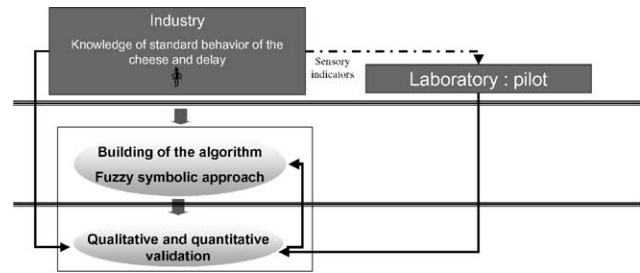


Fig. 3. Decision support system design IS₂ (Gc coat) versus the ripening time for an experiment in the pilotplant at a temperature of $9 \text{ }^\circ\text{C}$ and RH of 92%.

3.2.2. Handling the expertise on the manufacturing plant and programming

The first part was dedicated to work on the manufacturing plant. Skill about (1) sensory measurements achieved by the experts (2) standard changes in the sensory indicators and standard global degree of ripening, both explained in word by the experts and (3) deductive reasoning applied to estimate the changes in a cheese was handled and formalized using the fuzzy symbolic approach. It was achieved in one month.

Sensory measurements was carried out by two experts on the ripening process. For each sensory variable, two methods of evaluation were used. The first was the traditional one used in the factory, that is an evaluation in words like the cheese is “few coated” with a “high humidity” on the surface. The second method was a more descriptive way according to the concept of sensory indicators developed by Curt, Trystram, and Hos-senlopp (2001). Thus experts have been trained as a sensory to measure properties on a line structured scale with anchors and minimum graduations of 0.5. For example “cheese coat = 1.5 and humidity = 6”. Modeling of the link between those two sets of measurement was achieved using the concept of fuzzy meanings.

Standard changes in the cheese and standard degree of ripening was expressed by both experts in words. The deductive reasoning of the experts was handled upon the methodology presented Fig. 4 in three steps: (i) understand the hierarchy between variables implicitly manipulated by experts; (ii) formalize the strategy of

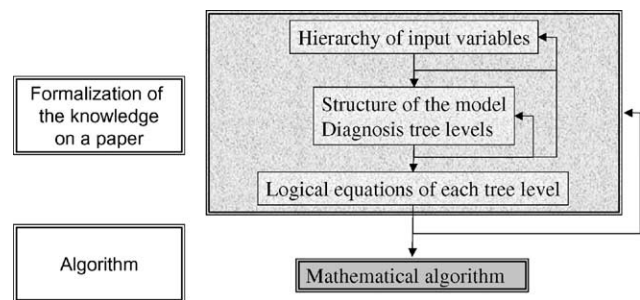


Fig. 4. Methodology to build the decision support system applied to cheese ripening.

diagnosis based on a diagnosis tree; (iii) formalized the logical equations at each tree level. Programming of this structured knowledge was achieved using Matlab v 6.5.

3.2.3. Validation

3.2.3.1. Validation of the fuzzy meanings of the sensory indicators. The fuzzy mathematical links, using fuzzy meanings, established about the sensory quality of the cheese between the scale in words and the line structured scale was validated. For the four main sensory measurements 30 observations were tested during two sets of ripening kinetics. Symbols given on those points, by the two industrial experts, were compared to the description processed by the fuzzy functions of the measurements made by the experts on the indicator scale. Descriptions were expressed in terms of membership degrees to each symbol.

For each point of the data validation set, a compatibility measurement was calculated based on the definition of Bouchon-Meunier, Rifqui, and Bothorel (1996) as follows. Suppose a given sensory variable like humidity was evaluated (i) by the expert in the form of a description (A) and (ii) by a calculation using the fuzzy function in the form of a description (B):

$$A : \mu AT_1/T_1 + \mu AT_2/T_2 + \dots + \mu AT_i/T_i,$$

$$B : \mu BT_1/T_1 + \mu BT_2/T_2 + \dots + \mu BT_i/T_i,$$

with T_i being the i words used to described the variable like “high” for the variable humidity and μAT_i , μBT_i the membership degree of A or B to T_i .

The compatibility measurement represents the mean of the standard deviation between both descriptions:

$$C = \sum_{i=1,2,\dots,j} |(\mu AT_i - \mu BT_i)|/j, \quad (6)$$

with j being the number of membership functions activated at the same time ($j = 2$ in our application) for one linguistic variable.

This measurement C for each point of the test data set was compared in our application to the experts measurements on the indicator scale (0.25). For a point, expert measurements and fuzzy algorithm measurements are considered compatible if $C \leq \text{level}(0.25)$.

3.2.3.2. Validation of the decision support system. Validation of the decision support system was achieved in two steps: (i) validation, without any parametric optimization of the model, on a data set acquired during experiments on the pilotplant; (ii) validation during two experiments conducted on-line directly at the manufacturing plant. For those validations, two experts of the ripening process, EA and EB, were involved to carry out the sensory evaluation of the cheese.

- In the pilotplant, experiments at six combinations of air humidity and temperature (Table 1) were used in

Table 1

Constitution of the whole data set through an experimental plan, T : ripening temperature ($^{\circ}\text{C}$) and RH: air relative humidity (%)

Experiments	Experimental conditions	Number of observations
1	$T = 9^{\circ}\text{C}$, RH = 96%	16
2	$T = 9^{\circ}\text{C}$, RH = 94%	20
3	$T = 9^{\circ}\text{C}$, RH = 92%	19
4	$T = 15^{\circ}\text{C}$, RH = 98%	15
5	$T = 15^{\circ}\text{C}$, RH = 94%	18
6	$T = 12^{\circ}\text{C}$, RH = 94%	18
Total set		106

the experimental cellar with 80 cheese followed during 20–27 days. It globally covers the categories of behavior of the cheese (standard, delayed, advanced) encountered in the factory. Sensory measurements were carried out by EA and EB every day during the first 15 days of ripening and every 2 days thereafter. For each evaluation, three cheese among 80 were randomly selected and evaluated by the two experts EA and EB and the mean of those 2 (EA and EB) \times 3 measurements was kept. On the whole, the data set had a size of 107 observations.

- In the factory, the symbolic algorithm was validated on-line for two batch A and B of each one 100 cheeses, coming from two different manufacturing cycles of “rogeret”. On the whole it represents 29 observations for this validation. Sensory measurements were carried out by the experts EA and EB in accordance with the operator working in the factory (it was checked at 15 points homogeneously distributed over the two periods). Three cheeses were also randomly selected for the evaluation of the experts EA and EB and the mean of those 2 (EA and EB) \times 3 measurements was kept.

For both validations, the quality of the support system was evaluated using the compatibility measurement expressed in Eq. (6). For each data point, expert estimation and fuzzy algorithm estimation were considered similar if $C \leq \text{level}$. The level was defined upon the mean response time of the process.

4. Results and discussions

4.1. The decision support system applied to cheese ripening

The fuzzy symbolic approach was built to inform an operator of the potential drift of the sensory change of the cheese at a given time t in order to help him to control the process. The algorithm included the representation, at a symbolic level, of the expert macroscopic knowledge about the reactions that can take place in the

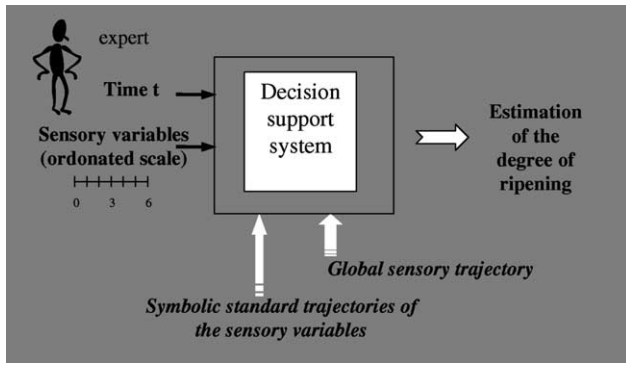


Fig. 5. Principle of the symbolic decision support system.

cheese during ripening. The principle of the symbolic approach is presented in Fig. 5. It is based on the expertise handled, formalized upon the fuzzy symbolic formalism.

The inputs were:

- Four visual sensory indicators “cheese consistency, Gc coat, humidity and color” evaluated by two experts of the ripening process, EA and EB (i) on a line structured scale with anchors and minimum graduations of 0.5 and (ii) on a symbolic scale (Table 2). The reproducibility of the expert measurement on those inputs was evaluated at 98% and 95% for respectively EA and EB.
- Time t of measurement.

The output: the degree of ripening (DR) expressed in weeks on a line structured scale from 0 to 4 with graduations of 0.25 weeks and 5 anchors: “4” for “state A”, “3.5” for “state B”, “3” for “state C”, “2” for “state D” and “0” for “state E”. The reproducibility of the expert measurement of DR was evaluated at 94.5% and 100% for respectively EA and EB. DR gives at each time:

- (1) Qualitative information on the potential sensory drift of the cheese. It is obtained by comparison with

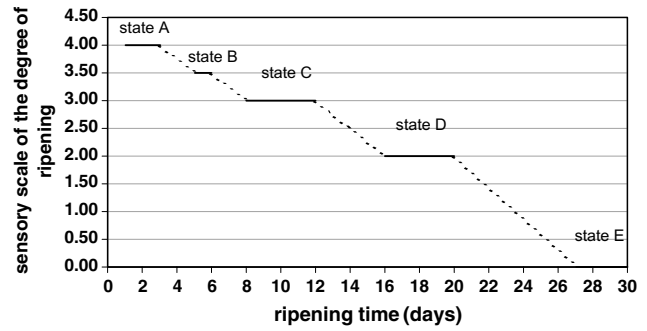


Fig. 6. Standard evolution of the degree of ripening versus ripening time memorized by the experts of the manufacturing plant.

the state at which the cheese should have been at the same time if it had followed the sensory change expected by the experts under average standard industrial conditions (Fig. 6).

- (2) Information, using Eq. (7), on the duration of ripening needed from t , at constant air conditions, to reach a final DR defined as optimum by the experts:

$$\begin{aligned}
 (t - t_{\text{final}}) &= [(DR_{\text{final}} - DR(t)) - \text{cst}(t)] / \text{slope}(t), \\
 &\text{with } \text{cst}(t) = \text{constant at } t \text{ of} \\
 DR &= f(t), \text{ slope}(t) = \text{slope at } t \text{ of} \\
 DR &= f(t). \tag{7}
 \end{aligned}$$

By hypothesis, the model was built without considering external disturbances such as contamination. The decision support system (Fig. 7), more precisely, was comprised of three specific mathematical modules:

Module 1 was dedicated to (1) the transfer of the 4 sensory indicators (IS₁ to IS₄) in symbols manipulated by the experts on the manufacturing plant and (2) the fuzzy description of the t time; *module 2* was dedicated to the mathematical calculation, at a symbolic level and at t time, of the deviation of each sensory indicator

Table 2
The four visual sensory characteristics taken into account by the support system as inputs and their indicator and symbolic scales

Sensory characteristics	Indicator scale manipulated by the experts of the laboratory	Symbolic linguistic scale manipulated by the experts coming from the industry			
		1	3	6	
Cheese consistency IS ₁	Line scale from 1 to 6 with 3 anchors: 1 (few), 3 (middle), 6 (high)	Few	Little	Middle	High
Gc coat IS ₂	Line scale from 1 to 6 with 3 anchors: 1 (few coated), 3 (coated), 6 (high coated)	Few coated	Little coated	Coated	High coated
Humidity IS ₃	Line scale from 1 to 6 with 3 anchors: 1 (dry), 3 (middle), 6 (humid)	Low		Middle	High
Color IS ₄	Line scale from 1 to 6 with 3 anchors: 1 (ivory), 3 (yellow), 6 (brown)	Ivory	Ivory-yellow	Yellow	Brown

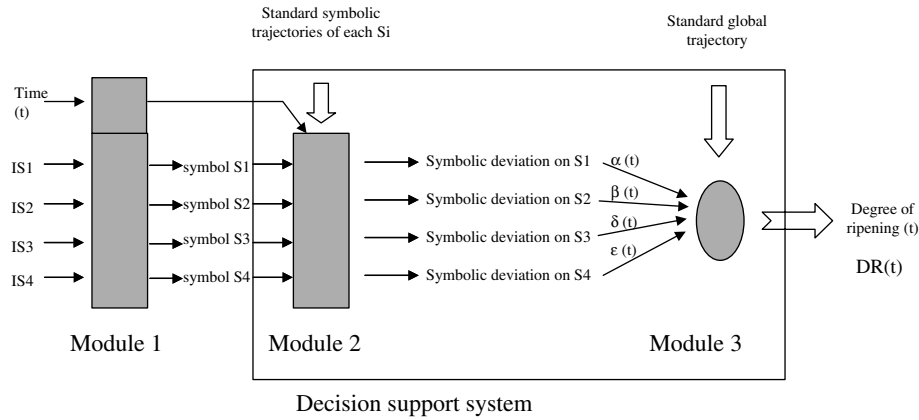


Fig. 7. Description of the decision support system.

translated into its symbolic value if it has followed its standard change pattern and, finally, *module 3* was dedicated to a fusion between the four symbolic deviations of the sensory indicators ($\alpha, \beta, \delta, \epsilon$) to evaluate the degree of ripening of the cheese and the potential drift of the cheese from its standard change pattern.

4.1.1. Module 1

The fuzzy meanings of the indicator Gc coat and t , implemented in module 1, are presented in Fig. 8. For the 4 sensory indicators, through fuzzy meanings defined like in Fig. 8, a membership degree to each sensory

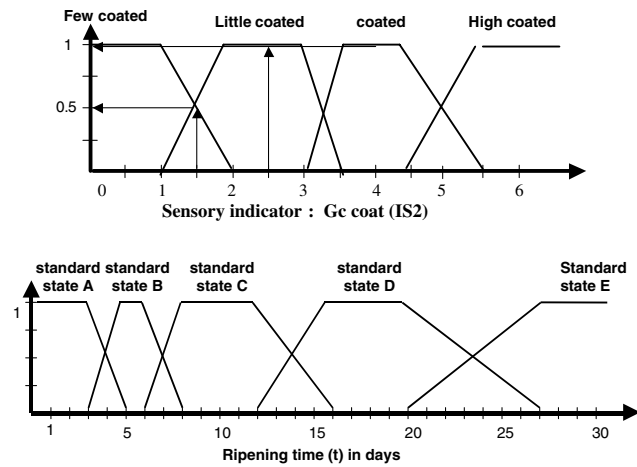


Fig. 8. Fuzzy meanings of the four indicators IS_1 to IS_4 and t , implemented in the module 1.

symbols manipulated by the expert, is extracted. For example if a cheese for IS_2 , Gc coat, is evaluated by the experts at 1.5, the answer from module 1 is that the cheese is between the symbols “few coated” and “little coated” with membership degrees of 0.5 (Table 3).

A description at time t is also achieved in this module (Fig. 8). It is related to a discretization by the experts in five imprecise characteristic periods of time. For example a cheese at 5 days is associated at the output of the module 1 to be in the state B with a membership grade to “state B” of 1. Those periods are linked to the biological activity taking place in the cheese during ripening. Indeed, at the beginning of the ripening process, the activity is important and the state of the cheese changes rapidly and inversely at the end of the ripening process. Linked to this phenomenon, the discretization of the time through fuzzy meanings is more narrow at the beginning than at the end of the ripening.

4.1.2. Module 2

On the basis of the fuzzy descriptions provided by each sensory indicator, IS_1 to IS_4 , and the period of time activated by the fuzzy description of t , the deviation of each sensory indicator description in this period to its value if it had followed its standard change pattern is calculated through a fuzzy symbolic description. Thus a membership degree for each symbolic deviation j (μD_j), with j expressed in symbols $-3, -2, -1, 0, +1, +2, +3$, is extracted by variable α, β, δ or ϵ . The symbolic change patterns of each sensory indicator under standard conditions are presented Table 4. We can see that all the

Table 3
Example of processing of the module 1 of the decision support system

Input: value of IS_2	Output module 1: fuzzy description of IS_2			
	Membership degree to “few coated”, $\mu_{fewcoated}(IS_2)$	Membership degree to “little coated”, $\mu_{littlecoated}(IS_2)$	Membership degree to “coated”, $\mu_{coated}(IS_2)$	Membership degree to “high coated”, $\mu_{highcoated}(IS_2)$
1.5	0.5	0.5	0	0

Table 4
Symbolic trajectories of each sensory indicator under standard conditions memorized by the experts of the manufacturing plant

	Standard state A	Standard state B	Standard state C	Standard state D	Standard state E
IS ₁ —Cheese consistency		Few	Little	Middle	High
IS ₂ —Gc coat	Few coated	Little coated	Coated	High coated	
IS ₃ —Humidity	High	Middle			
IS ₄ —Color					Brown

Table 5
Example of processing of module 2 of the decision support system

Input value IS ₂		Input value <i>t</i>	Output module 2: β on IS ₂	
$\mu_{fewcoated}$ (IS ₂)	$\mu_{littlecoated}$ (IS ₂)	Membership degree to “standard state B”	Deviation -1 symbol with a membership degree (μD_{-1})	Deviation 0 symbol with a membership degree (μD_0)
0.5	0.5	1	0.5	0.5

indicators are not activated at the same time and at the same standard period. Indeed, depending upon the period, the expert does not use the same indicators to establish a diagnosis of the product. For example, if we keep the example developed below (Table 3): A cheese of Gc coat equal to 1.5, at time 5 days, is evaluated by module 2 to be a bit late by comparison to its standard behavior on this indicator (Table 5 for details). Similar calculations are processed for the three other sensory indicators.

4.1.3. Module 3

On the basis of the fuzzy descriptions provided on the deviation of each sensory indicator from its standard behavior, $\alpha, \beta, \delta, \varepsilon$, a global deviation is calculated by the module 3 in the form of a membership degree μD_j to each deviation *j*. It is achieved through 30 symbolic equations of fusion represented in the form of 5 tables associated with each period of ripening (state A to E) defined by the time *t*. All equations are activated at the same time. An example of table of fusion is presented Table 6. More precisely, the calculations applied to

evaluate the degree of ripening (DR) on the basis of the global symbolic deviation deduced from those tables is presented in Eq. 8 as an application of Eq. (5) of the fuzzy symbolic fusion:

$$DR = DR \text{ standard} - \text{global deviation, with}$$

$$\text{global deviation} = \sum_{i=1}^{30} \mu R_i \times (\text{grade}(R_i)),$$

$$\mu R_i = \text{product}_{j,k}(\mu D_j^{\text{var}1} \mu D_j^{\text{var}2}). \tag{8}$$

With the example developed below (Table 5), and if we suppose a deviation of 0 with a grade of 1 for cheese consistency and a deviation of 0 with a grade of 1 for cheese humidity, the result is that the cheese is at a degree of ripening (DR): $DR = 3.5 + 0.125 = 3.6$ weeks (the detail of the calculation is presented Table 7). It means qualitatively that this cheese is a little late by comparison to its behavior under standard conditions at a period of “standard state B”.

Table 6
Part of the symbolic rules implemented in module 3 for a state B evaluated through the fuzzy meaning of *t*

State B	Rule number <i>i</i>	Gc coat IS ₂ symbolic deviation			
		-1	0	+1	+2
Humidity IS ₃ symbolic deviation	-1	Rule 4 delay grade (R_4) = -0.5 weeks	Rule 7 standard with drying default grade (R_7) = 0 weeks	Rule 9 Advance grade (R_9) = +0.5 weeks for a cheese consistency deviation +2	
	0	Rule 5 delay grade (R_5) = -0.25 weeks	Rule 8 standard behavior at state B grade (R_8) = 0	Rule 10 advance rade (R_{10}) = +0.5 weeks for a cheese consistency deviation +2	
	+1	Rule 6 delay grade (R_6) = -0.5 weeks			

Table 7
Example of processing of module 3 of the decision support system

Input				Output module 3 on R_7 2 rules R_5 and R_8 activated		
α on IS_1	β on IS_2	δ on IS_3	ε	μR_5	μR_8	Global deviation
$\mu D_0 = 1$	$\mu D_{-1} = 0.5,$ $\mu D_0 = 0.5$	$\mu D_0 = 1$	–	$\mu D_{-1}(IS_2) \times$ $\mu D_0(IS_3) = 0.5$	$\mu D_0(IS_2) \times$ $\mu D_0(IS_3) = 0.5$	$0.5 \times (-0.25) +$ $0.5 \times (0) = -0.125$

4.2. Results of validation of the decision support system

4.2.1. Validation of the module 1—the fuzzy meanings of the four sensory indicators

The first stage of our validation of the decision support system was to check if the fuzzy meanings implemented were able to represent with a good accuracy the symbols determined by the experts EA and EB during the ripening process. Descriptions, using fuzzy meanings, achieved by the module 1 for the four sensory indicators: cheese consistency, Gc coat, humidity and color were compared to the answers of the experts. Table 8 presents the results in terms of percentage of compatibility at 0.25. Globally results are coherent. The mean compatibility range was between 83% and 97%. It allows us to validate this module.

4.2.2. Validation of the decision support system

Two validations were carried out. The first one was based on the data acquired during the experiments in the pilotplant. The second one was based on the experiments on-line in the factory. As our support system is a model built on the knowledge of the experts and is not parametrically based on the data, all experiments on the pilotplant were used to validate our system.

4.2.2.1. Experimental validations. Fig. 9 shows an example of the results on 52 out of 106 observations achieved by using this approach on three experiments in the pilotplant (cf. Table 2) for respectively (a) experiment 3, (b) experiment 4, (c) experiment 6. A good adequacy between the results given by the operators and the result given by the fuzzy symbolic approach was reached in those results and moreover it is reached without any parameter identification using the data set. If we analyze the slope of each DR curve for each experiment, we can see that, based on the experimental conditions, the cheese was ripened in more or less time. For example at a temperature of 15 °C and a RH of 98%, a comparison of DR to the DR standard allows to

indicate to an operator, qualitatively at first, from the 10th day that the cheese is in advance of ripening and should reach its set point in less time than a standard

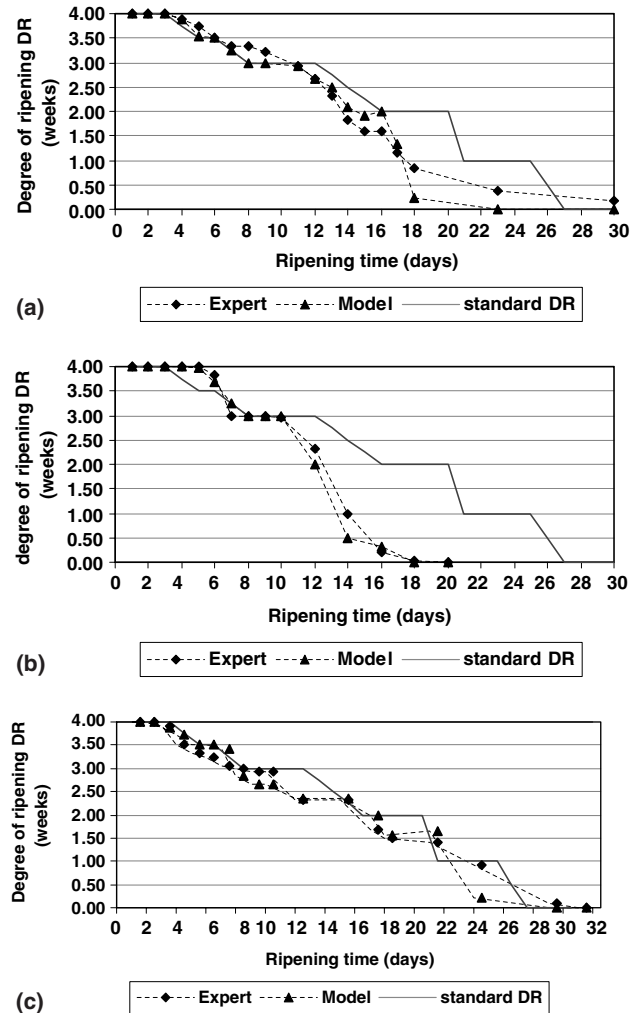


Fig. 9. Validation of the support system on 52 observations achieved on three experiments in the pilotplant for respectively (a) experiment 3, (b) experiment 4, (c) experiment 6. Degree of Ripening versus the ripening time.

Table 8
Results of validation of module 1 expressed as a percentage of compatibility at a sensitivity of 0.25

Percentage of compatibility	Cheese consistency IS_1	Gc coat IS_2	Humidity IS_3	Color IS_4
Industrial expert 1/fuzzy meanings	86	84	96	96
Industrial expert 2/fuzzy meanings	94	82	94	98
Mean	90	83	95	97

cheese. If we applied the calculation of Eq. (6), the quantitative estimation of $(t - t_{\text{final}})$ of the model compared to the reality of facts with a DR final fixed to 1 (the industrial set point) is validated with an error less than or equal to 2 days from the ninth day of ripening.

Same results are achieved with other observations (Fig. 10). Indeed on the whole data set of 106 observations, 97% of compatible results are reached at a grade of 0.5 weeks (3.5 days) and 80% of compatible results at a grade of 0.25 weeks (1.75 days) with a coefficient of correlation of 0.99. Moreover the capacity of quantitative prediction, based on Eq. (7), of time of ripening needed to reach an “optimum” cheese (setpoint: $DR_{\text{final}} = 1$) on those 6 experiments is confirmed from the ninth day of ripening. It means that from the ninth day of ripening, the decision support system anticipates the whole evolution of the cheese and is able, with a standard deviation of 3 days, to estimate when the cheese will be optimum.

4.2.2.2. Validation on the industrial plant. Validation in the industrial cellar was carried out on two batches A and B coming from two different manufacturing cycles of “rogeret”. Results are presented in Fig. 11: (a) for batch A and (b) for batch B. In both cases, without adaptation, results reached with the decision support system are coherent with those given by the experts. Nevertheless, from a quantitative point of view, the system is less precise than in the previous one, especially for batch B that is far from the manufacturing conditions of the cheeses during experiments in the pilotplant. Thus, for the batch A, at a grade of compatibility of 0.5 weeks, 15 points from 17 are compatible and at 0.25, 11 points from 17 are compatible. For batch B, at 0.5, 12 points from 12 are compatible and at 0.25 weeks, 7 points from 12 are compatible. Nevertheless, even (i) if the scale change (a pilotplant scale of 0.3 m³ to an industrial cell of 15 m³) and (ii) if the manufacturing steps applied to the milk before ripening change, it is interesting to notice that the system keeps robust globally without any parametric identification. It is in part due to our approach, that uses a global symbolic level of

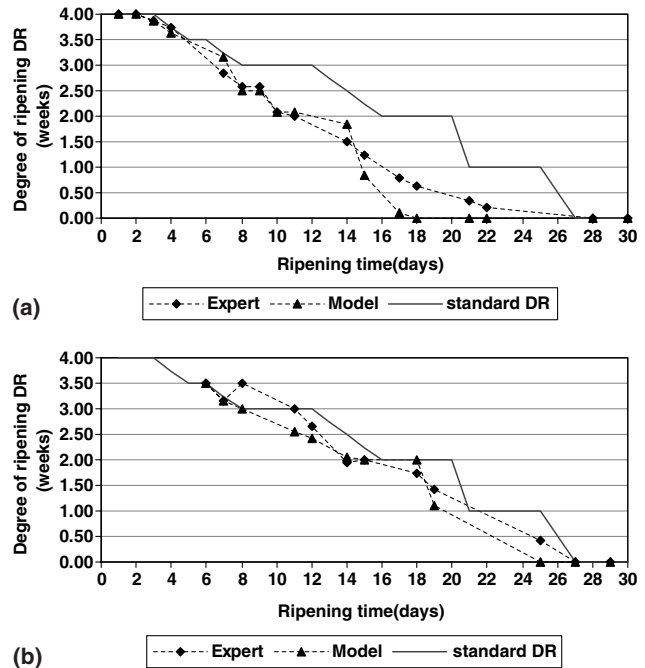


Fig. 11. Validation of the support system on the manufacturing plant on two batches A and B. Degree of ripening versus ripening time.

knowledge about the microbiological reactions taking place in the cheese during ripening.

To complete this study, we have tested the ability of our approach to deal with the imprecision of one of the key inputs of our decision support system: Gc coat (IS_2). Different analytical tests were achieved. The classical calculation of sensitivity of a model was applied at different input variations, from variation ΔIS_2 (IS_2 with imprecision to IS_2 without imprecision) of -1.5 to $+1.5$ of the input with a path of 0.25. An example of result is presented Fig. 12 for an imprecision varying from -1.5 to 1.5 with a path of 0.5 for a better visibility. Other inputs are fixed for this example to the symbol “few” for cheese consistency, the symbol “low” for humidity and the symbol “yellow” for color. The results on the degree of ripening with and without this imprecision are compared. Traditionally, in the studied manufacturing

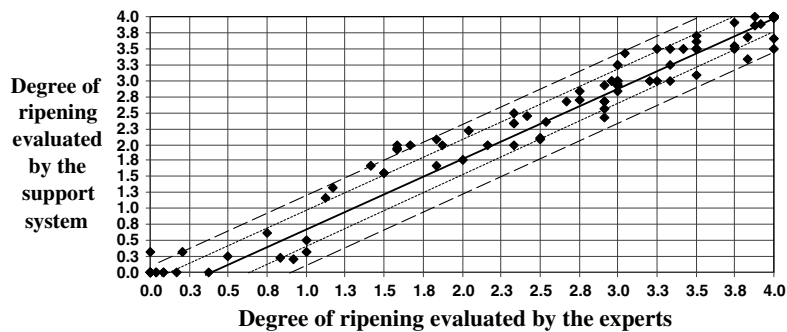


Fig. 10. Results using the decision support system on the degree of cheese ripening by comparison to the operator answer on the whole data set.

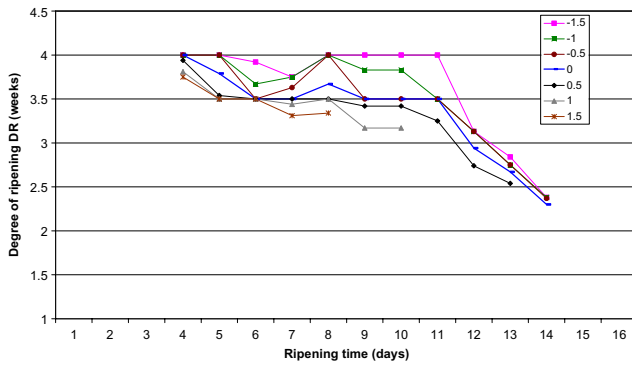


Fig. 12. Behavior of the support system in a context of imprecision on an input: the indicator “Gc coat” for imprecision from -1.5 to $+1.5$ with a path of 0.5 at fixed symbols “few” for cheese consistency, “low” for humidity and “yellow” for color. Degree of ripening versus ripening time for observations of the experiment 1.

plant, this indicator is given with a level of imprecision of 0.5 . It appears that the output of the support system after processing the imprecision on the input Gc coat is included in the imprecision of the answer of the operator. Similar results are reached for all the other simulations with the indicator Gc coat whatever the experiments used.

4.3. Discussions

Our approach to a decision support system applied to cheese ripening, developed using the operator skill of a manufacturing plant was validated in a pilotplant and at an industrial level with good results. Results are proposed in the symbolic space manipulated by the operators and can help them to guide their actions on the process.

Knowledge is extracted from expert handling and is expressed in the form of standard change patterns and drift to those standard trajectories using the fuzzy mathematical system. This method of treatment is easily understood by the operators and as a consequence easy to adapt in their space of symbolic knowledge of the process. It includes in some way at a macroscopic level, through a sensory operator perception of the cheese, a part of the complex microbiological reactions that are taking place in the cheese during ripening. While the approach is robust without adaptation for transposition to real experiments in an industrial plant, nevertheless it is less precise than an approach using a model of microbiological reactions and moreover properties of generalization of such a mathematical approach are still not proven. An integration of such a microbiological knowledge in our support system would be interesting.

Moreover the ability of the approach to deal with the imprecision brought by a key input “Gc coat”, if it is confirmed on the other input variables, opens an interesting road as regard to the robustness of such a support

system faced with uncertainty in its inputs whatever the origin of the uncertainty: operator or imprecision brought by a model developed to estimate the inputs of the support system.

5. Conclusions

The fuzzy symbolic approach has been implemented and validated for an application to a support system at a symbolic level to help the operators to evaluate the degree of cheese ripening during manufacturing on the basis of sensory measurements achieved on-line by the operators.

The results contribute to the control of the sensory properties of the products at the fabrication stage. This example is encouraging for several reasons:

- This approach is a simple way (few rules: only 30 symbolic equations, mathematical functions easy to implement) to integrate operator reasoning whenever the operator is involved in measurement, diagnosis or control of the process.
- It allows treatment of the data at a symbolic level that is easily accessible and usable by the operator.
- It introduces interpolation between symbols manipulated by the operators that provides robustness, but which should be quantified more precisely.

This work opens up an interesting direction and further studies will focus on (i) a generalization of the impact of such a symbolic approach on different examples and on (ii) a study to quantify more precisely the power of the approach faced to imprecision on the inputs.

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