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**Combining fuzzy querying of imprecise data and predictive microbiology using category-based reasoning for prediction of the possible microbial spoilage in foods: application to [i]Listeria monocytogen[/i]es**

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1 **Combining fuzzy querying of imprecise data and predictive microbiology**  
2 **using category-based reasoning**  
3 **for prediction of the possible microbial spoilage in foods :**  
4 **application to *Listeria monocytogenes*.**

5  
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19 **Abstract**

20 Various predictive models of microbial behavior have been created and extensive data  
21 collection has been done by numerous private or public laboratories. However, significant  
22 differences between predicted and observed values in foods have been observed and need to  
23 be stressed, understood and explained as much as possible. In this paper, we present a  
24 software tool (currently at the level of a prototype) able : (i) to store in a database all relevant  
25 information expressed on one hand as qualitative or quantitative data and on the other hand as  
26 precise or imprecise data, (ii) to retrieve the more relevant information from the database  
27 using queries where criteria may be expressed as fuzzy values in order to enhance the  
28 flexibility of the search, (iii) to compute, in addition to the nearest data, an estimation of  
29 searched values using statistical models. The architecture of this software tool is structured as

30 a category-based reasoning system. Example queries about *Listeria monocytogenes* (*L.*  
31 *monocytogenes*) illustrate functionalities of this tool.

32 **Key words :** Predictive microbiology, *Listeria monocytogenes*, Fuzzy logic, Information  
33 retrieval system

## 34 **Introduction**

35 Numerous factors affect microbial growth in food systems and often synergistic or  
36 antagonist interactions are significant. Thus, microbial growth in foods can be enhanced or  
37 inhibited depending on multiple food ingredients and storage conditions (Eifert et al., 1996).  
38 This can explain why an understanding of microbial behavior usually requires large-scale  
39 experiments under a wide range of conditions and involving extensive data collection.

40 Since data collection can be very time-consuming and labor intensive, numerous  
41 laboratories have developed predictive growth models, especially in Australia, the U.K., the  
42 U.S.A. and France with particular reference to *L. monocytogenes*.

43 *L. monocytogenes* has been associated in the last 15 years with several food-borne illness  
44 outbreaks involving a large range of foods such as raw milk, cheeses (particularly soft-ripened  
45 varieties), raw vegetables, fermented raw-meat sausages, raw or cooked meats. Microbial  
46 safety of many food products depends on refrigeration after commercialization, as most  
47 microorganisms do not grow at refrigeration temperatures. However this is not the case for *L.*  
48 *monocytogenes* because of its ability to grow at temperatures as low as 3°C (even 0.1°C and –  
49 0.4°C (Bajard et al., 1996).

50 In order to evaluate food safety relating to the *Listeria* growth hazard in "chilled prepared  
51 food products", temperature, pH and water activity are the main factors that must be taken into  
52 account in predictive models (Bajard et al., 1996). Various models are able to predict lag  
53 times and growth rates of *L. monocytogenes* (or other microorganisms) in many food matrices

54 at constant temperatures (Ratkowsky et al., 1983; Zwietering et al., 1991; Duh and Schaffner,  
55 1993; Rosso et al., 1993; Baranyi et al., 1993) and a small number of models also do so in a  
56 dynamic temperature environment (Baranyi et al., 1995; Van Impe et al., 1995; Alavi et  
57 al.,1999). Most of them have improved their predictions by including other environmental  
58 factors such as the presence of organic acids, the nature of packaging atmosphere (Buchanan  
59 and Phillips, 1990; Murphy et al., 1996; Fernandez et al., 1997) or some other biological  
60 factors such as the physiological state of inoculum cells and inoculum size (Mc Kellar et al.,  
61 1997).

62 However, some authors have observed significant differences between predicted values and  
63 observed values in foods and suggest that these differences are due to factors not taken into  
64 account in existing models (Brouillaud-Delattre et al., 1997; Dalgaard and Jorgensen, 1998).  
65 For example, the growth response of *L. monocytogenes* can be modified by the strain  
66 considered (Siswanto and Richard, 1992; Begot et al., 1997), the accumulation of inhibiting  
67 substances (Guinot-Thomas et al., 1995), initial contamination level (Gay et al. 1996),  
68 competitive interactions (Farrag and Marth, 1989) or microstructural texture (Guerzoni et al.,  
69 1994; Brouillaud-Delattre et al., 1997).

70 In some cases, failure of predictive models is due to insufficient knowledge of bacterial  
71 behavior in complex environments such as food matrices. However, particularly over the last  
72 few years, a lot of studies have provided better knowledge of new factors that may  
73 significantly influence the growth of bacteria. The main problem concerns the quality of these  
74 data : they might be imprecise and incomplete. On the one hand, experimental results are  
75 often synthesized as intervals of values obtained with or without statistical methods, in order  
76 to represent variability, then the data are imprecise. On the other hand, experimental results  
77 exist only for a limited amount of substrates, then the data are incomplete, in comparison to  
78 the set of substrates on which users may query. The use of an computerized logical reasoning

79 may help to manage this incomplete and potentially imprecise information (Dubois and Prade,  
80 1995).

81 The object of this study is to develop a "logical tool" to include the incomplete and  
82 imprecise information provided by the literature in the database of a "decision support system  
83 for prediction of microbial risk". Previous works have already proposed such a kind of system.  
84 Zwietering et al., (1992) takes only into account the fact that information is incomplete for  
85 food products. He does not propose any solution to represent and manage imprecise  
86 information. Estimation is only proposed for growth phenomena using a universal model.  
87 Adair and Briggs (1993) presents only the concept and main stages of a dedicated expert  
88 system.

89 Our logical approach suggests a new kind of predictive response. First, we propose a  
90 unified framework based on fuzzy logic and theory of possibility which permits to : (i) express  
91 the user's query preferences (and therefore to control the possible enlargement process of  
92 database scanning) (ii) represent and manage the imprecise information. Second, the system  
93 presents the ability of delivering several hierarchical responses (experimental results obtained  
94 from bibliography, unpublished experimental results, ...) brought by the database with an  
95 indication of the respective degree of matching for each response. Third, the system is able to  
96 propose a fuzzified estimated response using predictive models stored in its knowledge base.  
97 Fourth, a case based reasoning system identifies the category of queried data. This support  
98 system is part of a national project on predictive microbiology in food systems.

99 The originality of our approach is demonstrated using as an example to *L. monocytogenes*  
100 in this paper. But, our method and our tool are completely independent to any particular  
101 bacterium and can be used whatever studied bacterium.

## 102 **Materials and methods**

103 In this paper, we are concerned on one hand with the storage and handling of imprecise  
104 information and on the other hand with the expression of querying using fuzzy values to  
105 retrieve the more relevant information available in the database. In the first section, we  
106 introduce the relational model chosen to structure the information in the database. In the  
107 second section, we present the unique framework selected to represent on one hand query  
108 preferences and on the other hand precise or imprecise values. In the third section, we present  
109 statistical models we use to compute estimated values delivered to the user in addition to the  
110 closest information found in the database. In the fourth section, we introduce resemblance  
111 relations used to retrieve the closest information stored in the database in addition to query  
112 preferences. Finally, in the fifth section, we present the main concepts of the information  
113 retrieval system we have designed.

#### 114 **Information structured using the relational model.**

115 The relational model is the most popular model used all over the world to represent  
116 information in databases. It was proposed by Codd (1970) in the early 70's and it has been  
117 available as a commercial product for 20 years. It manages large quantities of data using a  
118 DBMS - Database Management System- such as Oracle for instance as well as personal  
119 databases using a DBMS such as Microsoft Access. The basic concept is very simple :  
120 elementary information is gathered in *relations* which represent *objects* of the modeled world  
121 or *links* between these objects. The concept of relation is implemented as a table. For instance,  
122 a bacterium is an object of the world we want to model. Elementary information such as the  
123 name of the bacterium, the name of the strain, its identification (unique) number in the  
124 database are gathered in a table called *Bacterium* and represent the object Bacterium in the  
125 database. These 3 pieces of information are called attributes of the table. A domain of values  
126 is associated to each attribute. For instance, the attribute *BacteriumName* must be a string as

127 the attribute *BacteriumId* must be a positive integer. All the bacteria represented in the  
128 database are described by the values associated to these 3 attributes and are called tuples of  
129 the table *Bacterium*. Now, if we want to represent the fact that a bacterium produces a  
130 bacteriocin, we will add two new tables. The table called *Bacteriocin* will represent the object  
131 Bacteriocin. Another table will represent the semantic link between the bacterium and the  
132 bacteriocin ; this table will be called *IsProducedBy*.

133 The relational model is built on solid theoretical foundations and useful normalization rules  
134 have been provided to help the administrator of the database to define the table structures.  
135 But, an important drawback of the relational model is that the modeled world is split into a  
136 great number of tables and the database structure composed of a long list of tables is very  
137 complex to understand. This is the reason why the concept of view has been introduced. A  
138 view is a *virtual* table in which all the information needed by the user is brought together. For  
139 instance, we can define the view *BacteriocinProducedByBacterium* which brings together the  
140 information split into the 3 tables *Bacterium*, *Bacteriocin* and *IsProducedBy*. Only the  
141 administrator of the database needs to know the real and entire structure of the database. A  
142 user only knows the view designed by the administrator to access the data he needs.

### 143 **Query preferences and imprecision representation.**

144 The fuzzy logic theory base approach presented in Zadeh (1965) has been largely used to  
145 represent values associated to selection attributes in order to enhance query flexibility (Cox,  
146 1995; Bosc et al., 1999). More precisely, fuzzy sets are mathematical objects here used with a  
147 semantic of preferences. For example, if one queries a database with the selection attribute  
148 Duration associated to the fuzzy value *HighDuration* (presented in fig. 1), the database engine  
149 will first retrieve information corresponding to Duration value in the interval [50, 70] and

150 second, with a decreasing degree of preference, information corresponding to duration in the  
151 interval [20, 50[ or ]70, 100].

152 Formally, for each element in a fuzzy set, there is a grade of membership score that represents  
153 the degree to which the element belongs to the set. These scores are assumed to vary between  
154 0 and 1 inclusive. A 0 indicates that the element has no membership in the set and a 1  
155 indicates that the element has complete, or crisp, membership in the set.

156 It is a common think to find imprecise data in the bibliography, expressed as intervals of  
157 value, without any reference to the manner it has been obtained. The reason why we have  
158 chosen the possibility theory is that we want to represent imprecision that is characterized by  
159 an inherent vagueness (as *high duration*) and not uncertainty which occurs when one can  
160 accurately predict the behavior of many similar experiments (Laviolette et al., 1995). The  
161 framework of fuzzy logic restated in the possibility theory base approach presented in Zadeh  
162 (1978) has been used to represent precise or imprecise values of data and to realize fuzzy  
163 pattern matching. A lot of works have focussed on the management of this kind of data in  
164 databases (Dubois and Prade, 1995; Bosc and Pivert, 1997; Bosc and Pivert, 1998; Galindo et  
165 al., 1998).

166 Representation of precise or imprecise values on continuous or discrete domain are illustrated  
167 here with 3 examples. In Figure 1, the fuzzy set *HighDuration* represents an imprecise value :  
168 the duration is completely possible in the interval 50-70 seconds, but it is still possible with a  
169 decreasing degree of possibility until the interval 20-100 seconds. Figure 2 illustrates the  
170 imprecise value *SterilizedMilk* which can be whole sterilized milk with a degree of possibility  
171 of 1 and which may be also skimmed sterilized milk with a degree of possibility of 0.5. The  
172 figure 3 shows that the same framework may also represent a precise value (here the precise  
173 value 80 seconds for the attribute Duration), it may be used to represent both kinds of  
174 information (precise or imprecise).



175 More formally, the value associated to an attribute  $A$  for a tuple  $t$  is defined as a possibility  
176 distribution  $\pi_{A(t)}$  on the underlying domain  $D$ . The possibility distribution  $\pi_{A(t)}$  can be viewed  
177 as a fuzzy restriction of the possible value of  $A(t)$  by a fuzzy subset  $F$ . Given  $\chi$  the  
178 membership function associated to  $F$  :

$$\begin{cases} \forall d \in D, \chi_F(d) \in [0,1] \\ \pi_{A(t)}(d) = \chi_F(d). \end{cases} \quad (1)$$

179 For instance, the information « *thermisation  $t$  has a high duration* » will be represented by:

180  $\pi_{Duration(t)}(d) = \chi_{HighDuration}(d)$ . Here,  $\chi_{HighDuration}$  is a membership function which represents  
181 the vague predicate *HighDuration* defined as a fuzzy subset. We consider two kinds of  
182 membership functions depending on the domain : (i) on an ordered and continuous underlying  
183 domain, a trapezoidal fuzzy subset is associated to each value (see fig. 1), (ii) on a discrete  
184 and non ordered domain, a standard fuzzy subset is associated to each value (see fig. 2).

### 185 **Statistical models**

186 Two types of models are used in order to give an estimation of the data sought. The first one  
187 concerns growth model and the second one inactivation model.

188 The growth model comes from a bacterial growth simulation model with two levels (Rosso et  
189 al., 1993). Primary level model F (adaptive model) describes how microbial density  $x$  changes  
190 with time  $t$  in a specified environment  $x(t)=F(p_i, t)$  where  $p_i$  are at most 6 characteristic  
191 parameters (maximum growth rate  $\mu_{max}$  or generation time  $t_g=ln2/\mu_{max}$ , lag phase duration  $\lambda$ ,  
192 inoculum  $x_0$ , maximal density  $x_{max}$ , and eventually initial growth rate  $\mu_0$ , adaptation rate  $\rho_a$ ).

193 Secondary level models indicate how parameters  $\mu_{max}$  and  $\lambda$  of primary model change with  
194 respect to cardinal values (maximum, minimum and optimal) of temperature  $T$  and of pH and  
195 a fourth parameter  $\mu_{opt}$  (value of  $\mu$  at optimal temperature and optimal pH). With this model we

196 are able to give a fuzzy estimation of the parameter  $\mu_{max}$  (or the generation time  $t_g$ ) using fuzzy  
197 arithmetic (Pedrycz and Gomide, 1998, pp129-150).

198 Inactivation models (Augustin, 1996) used are linear models : primary modeling is a linear  
199 relation between  $\log_{10}$ (cell population  $N$ ) and time  $t$  :  $\log_{10}(N)=at+b$ , allowing us to define  
200  $D=1/a$ , time of decimal reduction. Then a linear regression of  $\log_{10}(D)$  on the temperature  $T$  :  
201  $\log_{10}(D)=cT+d$ , is calculated from numerous data found in the literature. This model allows us  
202 to calculate the estimation of the duration  $D$  for a given temperature value and moreover to  
203 calculate a fuzzy estimation of it. This calculus takes into account two kinds of variability :  
204 the limits of the fuzzy subset representing the user's preferences and the confidence interval  
205 on the coefficients of the regression model (Buche and Dervin, 1999).

206 Two conditions must be fulfilled to obtain a fuzzy estimation using those both models : (i)  
207 values for each model parameter must be expressed in the selection attributes (for example,  
208 temperature and pH for the selected growth model and temperature for the selected  
209 inactivation model) ; (ii) values associated to each attribute expressed as fuzzy subset must be  
210 included in the limits of the model. If the second condition is not fulfilled, we deliver a precise  
211 estimation using precise values for model parameters (defined as the center of the core of the  
212 trapezoidal fuzzy subsets).

213 However, our method is not dependent on those previous models because : first, our system  
214 incorporates in its knowledge base predictive models which can be replaced or enhanced if  
215 necessary; second, different models may be used for different categories of data (see section  
216 The Information Retrieval System for more details).

## 217 **Resemblance relations**

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<sup>1</sup> Defined as the set of values where the membership function is equal to 1

218 If no information stored in the database corresponds to the values specified for the selection  
 219 attributes, it is still possible to retrieve the closest information if resemblance relations have  
 220 been defined. Resemblance relations  $res_i$  are defined on the domain  $D_i$  of an attribute  $i$  which  
 221 belongs to the query. Given a distance  $d_i$  on the domain  $D_i$ , the resemblance relations between  
 222  $x$  and  $y$  are defined as follows:

$$\begin{cases} res_i: D_i \times D_i \rightarrow [0,1] \\ \forall (x, y) \in D_i \times D_i, res_i(x, y) = \frac{1}{1 + d_i(x, y)}. \end{cases} \quad (2)$$

223 We have defined two kinds of distance  $d_i$ :

224 (i) for biological qualitative information (e.g., substrates or serotypes), called concepts in  
 225 the following, we have defined a semantic distance  $d_i$  computed in  
 226 generalization/specialization trees, called *GS* trees. A *GS* tree is defined as follows : concept  
 227  $C_1$  is the father of  $C_2$  (i.e.  $C_1$  is above  $C_2$  in the tree) if  $C_1$  is more general than  $C_2$  ( $C_2$  is more  
 228 specific than  $C_1$ ). An example of *GS* tree is given in Fig. 4, representing the distance  
 229 associated to the attribute Substrate. We drew upon the work of (Foo et al., 1989) to build a  
 230 semantic distance function on *GS* trees. Given two concepts  $C_1$  and  $C_2$ , we consider  $C_3$ , the  
 231 more specific concept which generalizes  $C_1$  and  $C_2$ ; then the semantic distance  $d_i(C_1, C_2)$  is  
 232 equal to  $d_i(C_1, C_3) + d_i(C_2, C_3)$ . By example, in the fig.4, the distance between concepts  
 233 *Skimmed milk* and *Whole milk* is 2 ( $d_i(\text{Skimmed milk}, \text{Sterilized Milk}) + d_i(\text{Whole Milk},$   
 234  $\text{Sterilized Milk}) = 1 + 1 = 2$ ) and the distance between *Skimmed milk* and *Raw milk* is 4 ( $d_i$   
 235  $(\text{Skimmed milk}, \text{Milk}) + d_i(\text{Raw Milk}, \text{Milk}) = 3 + 1 = 4$ ).

236 (ii) for information defined on an ordered domain, we have defined a distance  $d_i$  between  
 237 two values  $x$  and  $y$  of an attribute  $i$ , as follows : given an increasing ordered series of values  
 238  $\Delta_n$  ( $\Delta_n < \Delta_{n+1}$ ) on the domain  $D_i$  associated to increasing numerical values  $\alpha_n$ ,  $d_i(x, y) = \alpha_n$   
 239 where  $\alpha_n$  is the value associated to  $\Delta_n$  such as  $\Delta_n \leq |x-y| < \Delta_{n+1}$

240 By example, the following values  $\alpha_n$  may be associated to the values  $\Delta_n$  on the domain  $D_i$  of  
 241 the attribute Temperature

<b>n</b>	1	2	3	4	...
<b><math>\Delta_n</math></b>	0	1	3	5	...
<b><math>\alpha_n</math></b>	0	1	2	3	...

242 Then for values 2,3,7 of attribute Temperature

243  $d_{\text{température}}(2, 3) = 1$  because  $\Delta_2 \leq |2-3| < \Delta_3$

244  $d_{\text{température}}(3, 7) = 2$  because  $\Delta_3 \leq |3-7| < \Delta_4$

### 245 **The information retrieval system**

246 Using a graphical user interface called GUI in the following (see fig 7), the user queries the  
 247 database specifying selection criteria using the form attribute/value. The value associated to  
 248 each selection attribute is a fuzzy subset. It represents the user's preferences. Result attributes  
 249 are the closest values retrieved from the database for the selection attributes and specific  
 250 attributes depending on the view through which the query is executed.

251 The system scans the database through the different views available in its knowledge base and  
 252 retrieves the results associating an adequation degree to each of them. More precisely, the GUI  
 253 translates and submits to the engine the user's preferences as a set of queries  $Q_V$ . For each  
 254 available view  $V$ , the syntax of  $Q_V$  is a set  $\{V, a_1, \dots, a_n, \langle a_{n+1}, v_{n+1}, r_{n+1}, ft_{n+1} \rangle, \dots, \langle a_m, v_m,$   
 255  $r_m, ft_m \rangle, nb, t\}$  where  $V$  is the name of the view through which the query is executed;  $a_1, \dots, a_n$   
 256 are the expected attributes (limited to 1 in the examples),  $\langle a_{n+1}, v_{n+1}, r_{n+1}, ft_{n+1} \rangle, \dots, \langle a_m, v_m,$   
 257  $r_m, ft_m \rangle$  are quadruplets defining the selection criteria,  $nb$  and  $t$  define respectively the  
 258 maximum number of tuples and the minimum degree of matching of each tuple in the result ( $t$   
 259 in  $[0, 1]$ ). The quadruplets defining the selection criteria have the following meaning:

260 For all  $i$  in  $[n+1, m]$  :

- 261 •  $a_i$  is a selection attribute and  $v_i$  is a fuzzy set defining the value associated with  $a_i$ . We
- 262 distinguish two kinds of labels depending on the underlying domain of the attribute :  
263 discrete or continuous. Two examples of fuzzy sets are given in fig 1 and fig 2.
- 264 •  $r_i$  is a boolean value specifying to the engine whether the resemblance relations
- 265 available in the engine knowledge base may be used or not.
- 266 •  $ft_i$  is a boolean value specifying to the engine whether the users' preferences expressed
- 267 in the fuzzy sets may be enlarged or not.

268 For instance, we consider the following query  $Q_{ex}$ :

269  $V=HeatResistance$

270  $a_1 = DecimalReductionTime,$

271  $\langle a_2=Substrate, v_2=MyEggProductPreferences, r_2= true, ft_2= false \rangle,$

272  $\langle a_3= DecimalReductionTime, v_3=HighDuration, r_3= false, ft_3= true \rangle$

273  $nb = 40, t = 0.3$

274 The value represented by the fuzzy subset  $MyEggProductPreferences = \{(egg\ yolk, 1),$   
275  $(whole\ egg, 0.5)\}$  indicates that the user is first interested by information about egg yolk and  
276 second by whole egg. The definition of the fuzzy set is made by the user using the GUI. This  
277 is the first way to enlarge the query , completely controlled by the user. The second way of  
278 enlargement is also controlled by the user : he may activate or deactivate the automatic  
279 enlargement based on the set of resemblance relations defined in the previous section and  
280 stored in the knowledge base of the engine. The boolean value  $r_i$  , specified in the above  
281 quadruplet definition, permits to control this mechanism. In the above example  $Q_{ex}, (r_2= true)$   
282 the engine is authorized to realize enlargement using the resemblance relation defined on the  
283 domain of values of the attribute  $Substrate$ . The third way of enlargement is also controlled  
284 by the user : he may activate or deactivate the automatic enlargement of his preferences based  
285 on fuzzy tolerance coefficients defined in the knowledge base of the engine for each category

286 of data. The boolean value  $ft_i$ , specified in the above quadruplet definition, permits to control  
287 this mechanism. In the above example  $Q_{ex}$ , ( $ft_3 = true$ ) the engine is authorized to realize  
288 enlargement on the user's preferences represented by the fuzzy set *HighDuration* for the  
289 attribute *DecimalReductionTime*.

290 In the running version of the system prototype, the selection attributes available for each  
291 view are substrate, conditions of the process step (temperature and pH) and bacterium. For the  
292 moment, views available concern growth, heat resistance (inactivation) and bacteriocin  
293 interaction. In this information retrieval system, we have introduced the new concept of  
294 category-based fuzzy view (Buche and Loiseau, 1999; Buche and Dervin, 1999). This notion  
295 is an extension of the classical view concept in databases, e.g. a virtual table in which all the  
296 information needed by the user is brought together. This view is fuzzy because the selection  
297 attributes are expressed as fuzzy predicates as in (Galindo et al., 1998; Zadrozny and  
298 Kacprzyk, 1998). This view is category-based because the system identifies the category of  
299 queried information (defined in the information retrieval system knowledge base). Three  
300 advantages are provided by this category-based reasoning system implemented in the  
301 category-based fuzzy view. First, if the user authorized it, the view engine enlarges user's  
302 preferences expressed in his query if they are too restrictive due to the real content of the  
303 database: it provides an additional degree of flexibility not available in the previous systems.  
304 Second, the view engine is able to propose, in addition to the nearest information retrieved  
305 from the database, an estimation of the data sought. For this purpose, statistical models well-  
306 adapted to each category of data (choice of the model and associated parameters) are  
307 incorporated into the knowledge base of the engine. Third, the view engine optimizes the  
308 fuzzy matching processing because the user's preferences are only compared to the  
309 information associated to the category selected : in the previous systems, all the information  
310 stored in the queried tables are compared to the user's preferences.

311 Adequation between, on one hand, sought values and their category definition and, on the  
312 other hand, sought values and values from the database are computed using pattern matching  
313 techniques presented in (Dubois and Prade, 1995) and fuzzy object comparison measures  
314 proposed in (Bosc and Pivert, 1997). A detailed description of the engine processing can be  
315 find in (Buche and Loiseau, 1999).

316 We have implemented the concept of category-based fuzzy view in a prototype called CFQ  
317 (for Category-based Fuzzy Querying). This software is written in Java language. Thus, CFQ is  
318 available on the Web. The information is stored in an Oracle DBMS using the imprecision  
319 representation model of FSQ (Galindo et al., 1998). A CFQ query is executed using a three  
320 tier process architecture (see fig 8): (i) the CFQ Java client applet running under a usual Web  
321 browser, (ii) a database connectivity middleware (running on the Web server due to security  
322 checking on applet execution), (iii) an Oracle/FSQ database server. First, the user loads the  
323 CFQ engine applet from the Web server on his Web browser. Second, he expresses his  
324 preferences using the GUI of CFQ and asks for information scanning. Third, the GUI transfers  
325 the user's query to the CFQ engine. The engine identifies the queried category of data and  
326 builds the fuzzy filter. To retrieve the closest tuples stored in the database, the engine submits  
327 SQL queries to the Oracle database server through the Web server.

## 328 **Results**

329 In this section, we present four results provided by our system CFQ corresponding to four  
330 different examples of queries. Each query illustrates functionalities provided by the system :  
331 in example 1, automatic category-based enlargement of data sought by the user to take into  
332 account variability of data values stored in the database ; in the second and third examples,  
333 comparison between estimated values and closest experimental values retrieved from the  
334 database may provide on one hand a validation of the estimation or on the other hand

335 important differences which need to be explained by a sound bibliographical analysis ; in the  
 336 fourth example, proposal of values unknown by the user but essential to obtain an estimation.  
 337 The first example is about the behavior of *L. monocytogenes* in egg products under  
 338 inactivation conditions. It is a sort of process validation query. The user specifies as querying  
 339 attributes, substrate, temperature conditions and decimal reduction time of his process and  
 340 wants to compare it to the decimal reduction time values stored in the database. Values sought  
 341 for decimal reduction time are represented by the fuzzy set *HighDuration* (see fig 1). Values  
 342 sought for temperature are in the interval [60, 64]. Values sought for substrates are  
 343 represented by the following fuzzy set called *MyEggProductPreferences*={ (egg yolk, 1),  
 344 (whole egg, 0.5)}. It means that the user is first interested by information about egg yolk and  
 345 second by information about whole egg. The 3 views available in the system are executed and  
 346 only the view *HeatResistance* provides results (with a adequation degree superior to a  
 347 threshold, set arbitrarily to 0.3). The syntax of the query *Q* generated by the GUI  
 348 corresponding to the view *HeatResistance* is the following :

349  $Q = \{V=HeatResistance, a_1 = DecimalReductionTime,$   
 350  $\langle a_2=Substrate, v_2=MyEggProductPreferences, r_2= true, ft_2= false \rangle,$   
 351  $\langle a_3= DecimalReductionTime, v_3=HighDuration, r_3= true, ft_3= true \rangle$   
 352  $, nb = 40, t = 0.3\}$

353 In this view, the system has determined that the category of queried data is *Egg Product*. For  
 354 this category, the system has found in its knowledge base an enlargement coefficient (called  
 355 fuzzy tolerance coefficient) for the selection attribute *DecimalReductionTime*. Fig. 5 shows  
 356 user's preferences enlargement for this selection attribute. The values sought for decimal  
 357 reduction time are compared to the values stored in the database which are represented as  
 358 imprecise values defined by the interval given by the two attributes *Duration Min* and  
 359 *Duration Max*. Table 2 shows results obtained without or with enlargement of preferences



360 computed for the decimal reduction time attribute. The first five tuples appear in the two  
 361 query results. An additional tuple is provided in the second result set thanks to the  
 362 enlargement mechanism even if the threshold set on the adequation degree is the same for the  
 363 two queries (set arbitrarily to 0.3 as said previously). This additional datum concerns a  
 364 substrate which does not belong to the user's preferences expressed by  
 365 *MyEggProductPreferences*. Therefore, it has been retrieved thanks to the fuzzy resemblance  
 366 relation defined on the domain of values associated to the attribute Substrate and thanks to the  
 367 category-based enlargement mechanism adapted to the category *EggProduct*. In the context of  
 368 this example, it may be a relevant piece of information which indicates that the addition of salt  
 369 or sugar to eggs provides a high increase in the decimal reduction time.

370 The second example is about the behavior of *L. monocytogenes* in dairy products under  
 371 growth conditions. The user wants to retrieve the generation time and queries on substrate,  
 372 temperature and pH attributes. Values sought are the following : for substrate, the fuzzy set  
 373 *MyDairyProductPreferences* is {(Sterilized milk, 1)} which means that user queries sterilized  
 374 milk only; for temperature, the fuzzy set *MyTemperaturePreferences* is the interval [2.2, 2.8]  
 375 ; for the pH, the fuzzy set *MypHPreferences* is the precise value 6.6. The 3 views available in  
 376 the system are executed and only the view *Growth* provides results. The syntax of the query  
 377  $Q$  generated by the GUI corresponding to the view *Growth* is the following :

378  $Q = \{V = \textit{Growth}, a_1 = \textit{GenerationTime},$   
 379  $\langle a_2 = \textit{Substrate}, v_2 = \textit{MyDairyProductPreferences}, r_2 = \textit{true}, ft_2 = \textit{false} \rangle,$   
 380  $\langle a_3 = \textit{Temperature}, v_3 = \textit{MyTemperaturePreferences}, r_3 = \textit{true}, ft_3 = \textit{false} \rangle,$   
 381  $\langle a_4 = \textit{pH}, v_4 = \textit{MypHPreferences}, r_4 = \textit{true}, ft_4 = \textit{false} \rangle$   
 382  $, nb = 40, t = 0.3\}$

383 In this case, the system CFQ is able to compute a fuzzified estimation thanks to the statistical  
 384 growth model stored in the system knowledge base for the queried category *Dairy Product*.

385 The generation time estimation (in hours) computed with the sought values is the interval  
386 [66.18, 105.27]. Simultaneously, CFQ system retrieves the closest experimental data stored in  
387 the database (see table 3). The closest experimental value retrieved from the database  
388 (identified by number 33) is out of the estimated interval of values (duration = 28.5 hours).  
389 This value has been published in Walker et al. (1990), this bibliographical reference may also  
390 be provided by the querying system. In this case, this experimental value tends to invalidate  
391 the estimation.

392 The third example is about the behavior of *L. monocytogenes* in dairy products under  
393 inactivation conditions. The user queries using substrate and temperature as selection  
394 attributes. Values sought are the following : for substrate, the fuzzy set  
395 *MyDairyProductPreferences* is {(Raw milk, 1)} ; for temperature, the value is defined by the  
396 fuzzy set *ImpreciseTemperature* (see fig. 6). The 3 views available in the system are executed  
397 and only the view *HeatResistance* (due essentially to the temperature values) provides results.  
398 The syntax of the query *Q* generated by the GUI corresponding to the view *HeatResistance* is  
399 the following :

400  $Q = \{V=HeatResistance, a_1 = DecimalReductionTime,$   
401  $\langle a_2=Substrate, v_2= MyDairyProductPreferences, r_2= true, ft_2= false \rangle,$   
402  $\langle a_3= Temperature, v_3= ImpreciseTemperature, r_3= true, ft_3= false \rangle$   
403  $, nb = 40, t = 0.3\}$

404 As in the previous example, the CFQ system is also able to compute a fuzzified estimation  
405 thanks to the statistical inactivation model stored in its knowledge base for the category of  
406 queried data, here Dairy Products. The fuzzy kernel (values with a membership degree equal  
407 to 1) of the estimated decimal reduction time (expressed in seconds) is the interval [4.83,  
408 287.18]. The fuzzy support (values with a membership degree > 0) of the estimated decimal  
409 reduction time is the interval [1.99, 697.99]. Most experimental values retrieved from the

410 database (see table 4) are included in the fuzzy estimation support. Only one experimental  
411 value (ID = 8 in table 4) is far from the kernel (but still belongs to the support). Therefore, the  
412 great majority of experimental values confirm the estimation.

413 The fourth example is about the behavior of *L. monocytogenes* in meat products under growth  
414 conditions. In this case, we suppose that the user only knows the values for the substrate and  
415 the temperature. He has no idea about the value of the pH. It is then possible to use the CFQ  
416 system to perform an initial screening to retrieve possible values for the unknown parameter  
417 (here the pH) and a second scan to obtain simultaneously an estimated value of the growth  
418 (which can be computed only if temperature and pH are simultaneously provided in the query)  
419 and a comparison with the closest experimental values.

420 For instance, in the first query, values sought are the following : for substrate, the fuzzy set  
421 *MyMeatProductPreferences* is {(Cuts of beef, 1)} ; for temperature, the fuzzy set  
422 *MyTemperaturePreferences* is the precise value 4°C. The 3 views available in the system are  
423 executed and only the view *Growth* provides results (due to the temperature values). The  
424 syntax of the query *Q* generated by the GUI corresponding to the view *Growth* is the  
425 following :

426  $Q = \{V = Growth, a_1 = pH, a_2 = GenerationTime$   
427  $\langle a_3 = Substrate, v_3 = MyMeatProductPreferences, r_3 = true, ft_3 = false \rangle,$   
428  $\langle a_4 = Temperature, v_4 = MyTemperaturePreferences, r_4 = true, ft_4 = false \rangle,$   
429  $, nb = 40, t = 0.3\}$

430 The results of the interrogation are given in table 5. In the entire set of experiments, the pH is  
431 included in the interval [5.5, 6.7]. In the second query, the user considers the same values for  
432 substrate and temperature and adds the first screening for the pH value, i.e. the fuzzy set

433 *MyHPPreferences* corresponding to the interval [5.5, 6.7]. ). The syntax of the query *Q*  
434 generated by the GUI corresponding to the view *Growth* is the following :

435  $Q = \{V = \textit{Growth}, a_1 = \textit{GenerationTime},$   
436  $\langle a_2 = \textit{Substrate}, v_2 = \textit{MyMeatProductPreferences}, r_2 = \textit{true}, ft_2 = \textit{false} \rangle,$   
437  $\langle a_3 = \textit{Temperature}, v_3 = \textit{MyTemperaturePreferences}, r_3 = \textit{true}, ft_3 = \textit{false} \rangle,$   
438  $\langle a_4 = \textit{pH}, v_4 = \textit{MyHPPreferences}, r_4 = \textit{true}, ft_4 = \textit{false} \rangle$   
439  $, nb = 40, t = 0.3\}$

440 The estimated generation time (expressed in hours) obtained during the second screening is  
441 the interval [6.38, 76.3]. The closest set of experimental values is identical to the one obtained  
442 in the first screening.

## 443 **Discussion**

444 One of the great difficulties in predicting microbial behavior in complex food matrix concerns  
445 the fact that we have to take into account the variability of biological systems (bacteria and  
446 food matrices) in a large range of environmental conditions (experimental or industrial  
447 conditions). Moreover, in most cases, we are not able to determine all of the factors that could  
448 interfere with the bacterial response. First, quantification cannot be done precisely (chemical  
449 or physical gradients are not easy to establish), second, we do not always know the influence  
450 of one factor (ingredient, other bacteria, physical conditions, etc.) on bacterial behavior. For  
451 example, the ability of *L. monocytogenes* to grow in many food products is mainly evaluated  
452 with regards to a small number of factors such as temperature, pH, etc. Nevertheless, other  
453 factors (physiological, biological or other physical factors) could significantly modify the  
454 growth response of *L. monocytogenes*. Because our knowledge in microbiology and  
455 particularly in microbial ecology is growing, predictive microbiology models will be able to  
456 take into account this new information in order to improve prediction. This new knowledge is  
457 incomplete and/or can be imprecise. Our information retrieval system allows us to take into

458 account these data that can (i) modulate or specify the prediction obtained with mathematical  
459 models or (ii) can propose a response when mathematical models have failed to calculate  
460 growth or inactivation parameters.

461 We have also to mention two main drawbacks the user will have to manage with this new  
462 querying approach. First, the adequation degree of a retrieved information may be the  
463 combining result of three different enlargement mechanisms (user's preferences expression,  
464 category-based enlargement of user's preferences, enlargement by resemblance relation  
465 definition on the domain of values). Then, it is not easy to explain to the user how it has been  
466 computed by the system. Second, the user has to be careful if he realizes comparisons between  
467 closest experimental data retrieved from the database and fuzzy estimation using statistical  
468 models. He has to check that retrieved experimental data are close enough compared to his  
469 selection criteria, knowing that the adequation degree only provides a relative ranking of  
470 retrieved information. For instance, in the result of the second query presented in the previous  
471 section, only the first closest information (ID 33) checks completely the selection criteria and  
472 can be really used to be compared to the fuzzified estimation.

## 473 **Conclusion**

474 In this paper, we have introduced the concept of category-based fuzzy view to design an  
475 information retrieval system adapted to microbial risk analysis of food products. In the query,  
476 the user has to specify his fuzzy preferences. Then the CFQ engine scans the database through  
477 the views available in its knowledge base. For each view, the engine builds a fuzzy filter with  
478 the user preferences *adapted to the category* of queried data - thanks to knowledge associated  
479 to each category. It brings three benefits : (i) The CFQ engine *optimizes* the processing time  
480 of the filtering because it only scans the data associated to the selected category ; (ii) the CFQ  
481 engine can deliver an *estimate* of the queried data if an estimation method has been defined  
482 for the selected category of data ; (iii) the CFQ engine can *enlarge* users' preferences to adapt

483 them to the real content of the database. The CFQ engine has been developed in Java  
484 language. Therefore, the information retrieval system is available through the WEB. It has  
485 been coupled to Oracle extended for fuzzy SQL (Buche and Loiseau, 1999; Buche and Dervin,  
486 1999). CFQ is complementary with classical simulation software because :

- 487 - It can be used when classical software does not work; for example when parameters are  
488 outside the limits of the model.
- 489 - It allows fuzzy expression of the parameters (selection attribute values) and takes into  
490 account this imprecision in the database scan and in the calculation of the estimated  
491 values.
- 492 - It allows comparison between estimated and experimental data, underlining possible  
493 contradictions and then acting as a basic tool to understand unknown phenomena.
- 494 - It may provide information on an original domain, such as interaction between bacteria.
- 495 - It produces synthesized information, and provides bibliographical references to the  
496 corresponding publications.
- 497 - It is a flexible tool able to evolve by incorporating new experimental results and/or new  
498 simulation models.

499 In order to improve this information retrieval system, it is now necessary to add data that  
500 come from more complete bibliography references. In the future, the database will have to  
501 integrate other pathogens in order to carry out a better microbial prediction of food products,  
502 predictive microbiology being an interesting tool for risk analysis..

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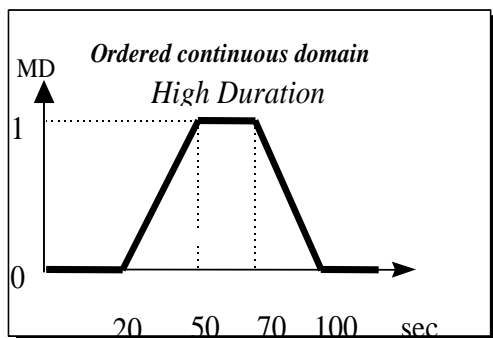
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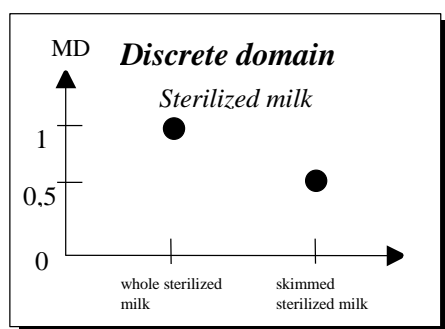
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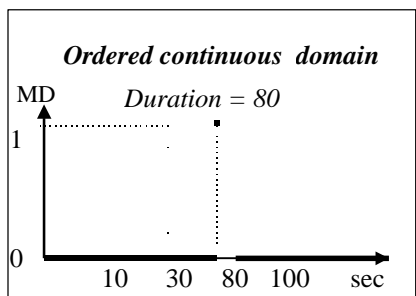
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**Figure 1. A trapezoidal fuzzy subset representing an imprecise value**  
(MD stands for Membership function)



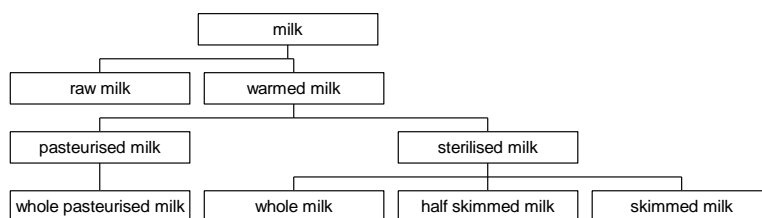
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**Figure 2. A fuzzy subset defined on a discrete domain**



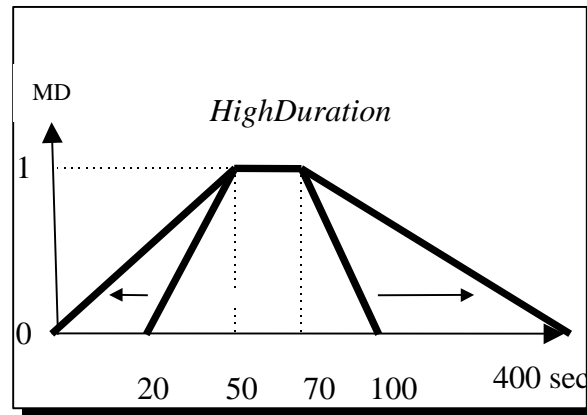
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**Figure 3. A fuzzy subset representing a crisp (precise) value**



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**Figure 4. Example of Generalization-Specialization (GS) tree for milk products**

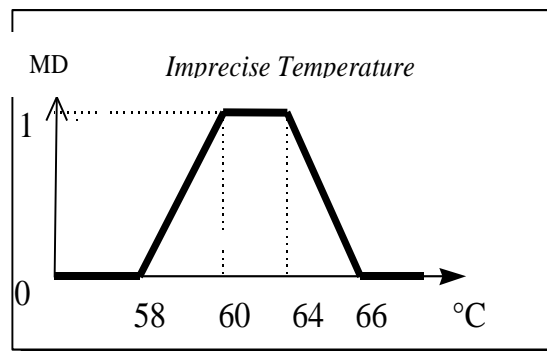


640 **Figure 5. Enlargement mechanism of the user's preferences using fuzzy tolerance coefficient**

641 **for the category EggProduct (first example of query)**

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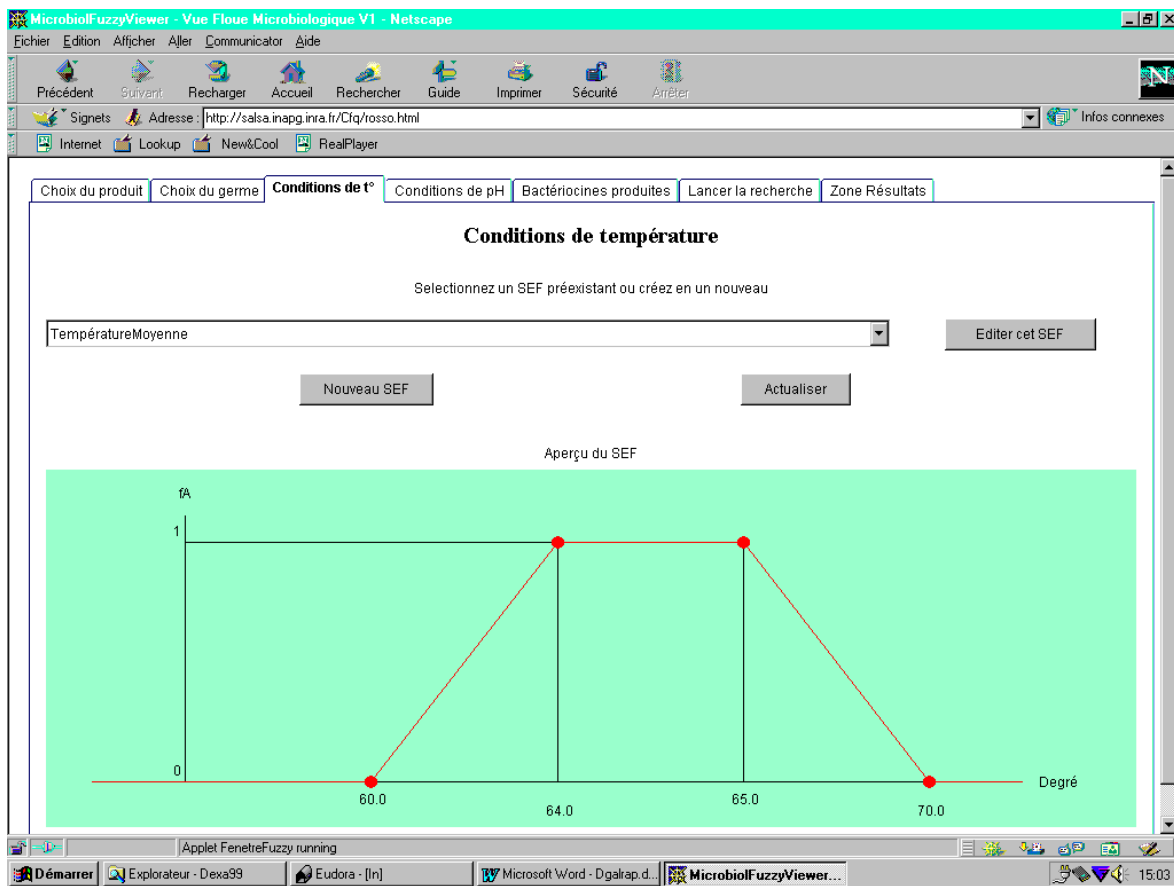
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**Figure 6. Temperature value for the third query**



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650 **Figure 7. The Graphical User Interface permits to express the selection criteria of a query and to**  
 651 **display the results. It is organized as a thumbnail formular. In the above example, the selected thumbnail**  
 652 **shows the value (expressed as a fuzzy set) associated by the user to the attribute temperature.**

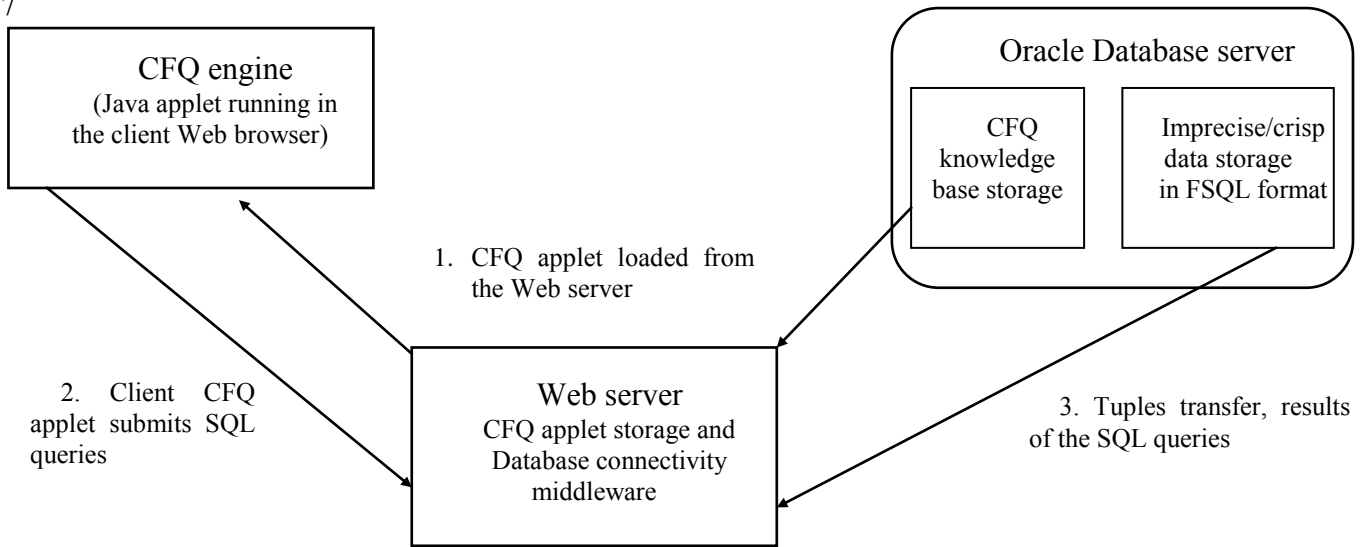
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659 **Figure 8. Category-based Fuzzy Querying engine is a software based on a three tier architecture : the**  
660 **Java applet is available on the Web server, the Java applet is loaded on the client to run in the Web**  
661 **browser, the CFQ engine running in the client applet queries the database through the Web server to**  
662 **retrieve the closest information**

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**Table 1. View BacteriocinProducedByBacterium**

BACTERIOCIN NAME	BACTERIUM NAME	STRAIN NAME
Pediocin ACH	Lactobacillus Plantarum	WHE92
Pediocin ACH	Pediococcus Acidilacti	H

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670 **Table 2. Closest data retrieved through the view *Heat Resistance* corresponding to the first query without**  
671 **enlargement of preferences (Adequation Degree (AD) > 0.3) are the first five tuples. With enlargement of**  
672 **preferences, same first five tuples are obtained plus the additional sixth tuple.**  
673

ID	AD	SUBSTRATE	TEMP (°C)	DURATION MIN (Sec)	DURATION MAX (Sec)
80	0.905	egg yolk	60	55.2	101.4
82	0.905	egg yolk	60	55.2	101.4
85	0.786	egg yolk	64.4	26.4	26.4
78	0.5	whole egg	60	78	84
81	0.5	whole egg	60	90	126
86	0.319	egg + salt or sugar	64.4	366.6	366.6

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**Table 3. Closest data retrieved through the view *Growth* corresponding to the second query**

678

**(AD means Adequation Degree)**

679

ID	AD	SUBSTRAT	TEMP	PH	GENERATION TIME (hours)
33	0.76	Sterilized_milk_(UHT)	2.5	6.6	28.5
4	0.35	Skimmed_milk	4	6.4	32.5
7	0.35	Skimmed_milk	4	6.4	30.6
10	0.35	Skimmed_milk	4	6.4	37.5
13	0.35	Skimmed_milk	4	6.4	38
16	0.35	Skimmed_milk	4	6.6	48.9
17	0.35	Skimmed_milk	4	6.6	53.5
20	0.35	Sterilized_whole_milk	4	6.4	30.6
23	0.35	Sterilized_whole_milk	4	6.4	30.5
26	0.35	Sterilized_whole_milk	4	6.4	36
29	0.35	Sterilized_whole_milk	4	6.4	36.5

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**Table 4. Closest experimental values for the third query**

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**(AD means Adequation Degree)**

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ID	AD	SUBSTRATE	TEMP	DURATION MIN (sec)	DURATION MAX (sec)
9	0.76	Raw_milk	63.3	19.8	19.8
8	0.5	Milk	61.7	570	570
11	0.2	Raw_milk	71.7	1.6	1.6
12	0.2	Raw_milk	71.7	1.9	1.9
13	0.2	Skimmed_milk	62.7	54	54
14	0.2	Sterilized_whole_milk	62.7	60	60
15	0.2	Half_skimmed_milk	62.7	54	54
16	0.2	Half_skimmed_milk	62	6	24
17	0.2	Half_skimmed_milk	62	6	24
18	0.2	Sterilized_whole_milk	63.3	19.8	34.8
19	0.2	Skimmed_milk	63.3	25.8	28.2
21	0.2	Sterilized_whole_milk	71.7	3.1	3.1
22	0.2	Sterilized_whole_milk	71.7	5	5
23	0.2	Half_skimmed_milk	72	0.05	1.5
24	0.2	Half_skimmed_milk	72	0.02	1.4
25	0.2	Sterilized_whole_milk	71.7	2.7	2.7
26	0.2	Sterilized_whole_milk	71.7	1.3	1.3
27	0.2	Sterilized_whole_milk	71.7	0.7	0.7
28	0.2	Sterilized_whole_milk	71.7	2	2
29	0.2	Sterilized_whole_milk	71.7	1.4	1.4
30	0.2	Sterilized_whole_milk	71.7	0.6	0.6
31	0.2	Sterilized_whole_milk	71.7	1.2	1.2
32	0.2	Pasteurized_whole_milk	57.8	138	138

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**Table 5. Closest experimental values for the fourth query**

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**(AD means Adequation Degree)**

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ID	AD	SUBSTRATE	TEMP	PH	GENERATION TIME (hours)
86	0.58	Cuts_of_fat_beef	4.7	5.6	11.9
81	0.5	Cuts_of_lean_beef	5	6.3	17.1
79	0.4	Cuts_of_lean_beef	5.5	5.5	22.1
77	0.38	Cuts_of_lean_beef	5.6	5.6	22.9
87	0.24	Cuts_of_fat_beef	7.5	5.6	7.1
85	0.21	Cuts_of_lean_beef	10	6.7	4.08
88	0.20	Cuts_of_fat_beef	10.1	5.6	4.62

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