

Modelling of the quality of food: optimisation of a cooling chain

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Abstract

The kinetics of food spoilage reactions are important for the optimization of food chains. It is shown that with a limited number of literature or experimental values, insight in the rate of spoilage can be acquired. A procedure to solve a simple optimization problem is given. Some possibilities for expanding modelling techniques into decision support systems are given. Predictive models, kinetic data, expertise, logistics, and simulation and optimization routines can be combined to support decisions in production, distribution and product development.

Introduction: Food Quality

Definition

Food quality can be defined as the sum of the characteristics of a food that determine the satisfaction of the consumer and compliance to legal standards. Food quality is a combination of numerous factors, such as organoleptic properties (e.g., texture, taste, flavour, smell, colour), nutritional value (e.g., caloric content, fatty acid composition), shelf life (e.g., microbial number), and safety conditions (e.g., presence of pathogens, toxins, hormones). Some of these (e.g., microbial numbers) can be relatively easily quantified, while others are very difficult to assess (e.g., taste). To determine total food quality, quality indicators are needed and must be weighted, since their relative importance depends on product, trends, producer, and market.

Significance

Food quality attracts ever more attention. Prediction of the rate of quality loss is important for the following reasons:

The food market is subject to saturation in most cases, therefore, quality becomes more important than quantity. There are new quality attributes which are highly appreciated by the modern consumer. Consumers show an increasing interest in convenience foods with the appearance and taste of fresh products and in food quality aspects such as flavour and (assumed) health aspects. Distribution routes have become longer due to more open borders in the EU, and therefore, there is a need for an increased shelf life. This increased shelf life is also desirable since consumers do less frequent shopping. In some areas there

is a rather rapid product development and formulation of products may be different in different countries or regions. Therefore, it would be useful to know the effect of different compositions on the shelf life, to avoid each formulation requiring a laborious shelf-life test.

New procedures are being developed to meet these quality demands, such as new technologies (e.g., microwave heating, ultrahigh temperature (UHT) processes, modified atmosphere packaging, supercooling, irradiation), and new strategies (e.g., logistics and modelling).

Quality loss along a chain

Quality loss can result from microbial, chemical, enzymatic, or physical reactions. Various factors influence quality loss, such as the composition of the product, and the processing and storage conditions (temperature, time, packaging material, gas atmosphere, machinery). From the past there are many dried, salted, frozen, sterilised products, while nowadays chilled and intermediate-moisture foods are becoming more important. Furthermore, there is a trend to use less additives, like preservatives. These trends largely increase possible bacterial deterioration of foods.

Quality is often assessed during production and distribution by taking samples of a product somewhere along the chain. This can give valuable information about long term quality changes and bottlenecks in the line. However, this gives only little information about the combined effect of all process steps in the production and distribution chain on the final quality. Therefore, it is important to get insight in the kinetics of spoilage in each step in the process.

Modelling can be a useful tool to get insights into the importance of factors in any part of the production and distribution chain, and is based on quantitative predictions of the rate of spoilage. Such modelling allows prediction of the quality or shelf life of products, detection of critical points in the production and distribution process, and optimization of production and distribution chains by combining cost models with the spoilage models.

Predictive modelling

Significance

Predictive modelling is a promising methodology in food research, to be used to optimize food chains. Models are used to describe deterioration under different physical or chemical conditions such as temperature, pH, and water activity (a_w). After the deterioration reactions have been modelled the models must be validated with quantitative data. The model parameters can then be estimated.

Firstly, sometimes deterioration reactions can be excluded. For example the micro-organism *Escherichia coli* can grow between pH 4.4 and 9.0. If the pH of a food product is 4.0, growth of *Escherichia coli* can be excluded. If the physical and chemical conditions of the product allow a specific deterioration reaction, an estimate can be made of the kinetics of the reaction. If the pH of a product is 4.6, *Escherichia coli* can grow in that product, but not very fast (and slower than at pH=5). This is all (important) qualitative reasoning.

To predict the kinetics of the various deterioration processes more quantitatively, models describing the effects of different conditions are essential. Several models are known

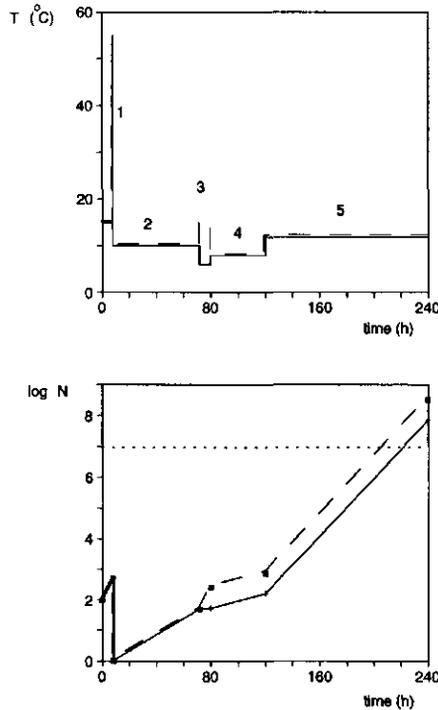


Figure 1. Temperature history (example) and calculated development of the number of organisms (N) with different temperature conditions during distribution (1= production and pasteurising; 2=storage; 3=distribution (chilled and unchilled); 4=retail; 5=consumer storage). Solid line: chilled transport; dashed line: unchilled transport; dotted line: spoilage level.

to predict deterioration reactions. Examples are given by Ratkowsky et al. (1983) and Zwietering et al. (1991) to describe the effect of temperature on microbial growth. The resulting quantitative estimation can be used to predict the shelf life.

With a model for the effect of temperature on bacterial growth, microbial spoilage in a product can be predicted if the temperature in a production and distribution chain is known (Figure 1). Moreover, an estimate can be made of the effect of changes in the process, for example of unchilled transport. The difference in product quality, and the difference in the shelf life can be calculated easily (Figure 1). Furthermore, it can be seen easily that quality is mainly lost in this case during storage by the consumer. This insight into kinetics is a great advantage of the modelling procedure compared to fragmentary sampling for quality control.

Types of models

In order to build and/or validate models, large amounts of experimental data must be gathered. In Figure 2 an example shows how a model can be derived for the effect of tem-

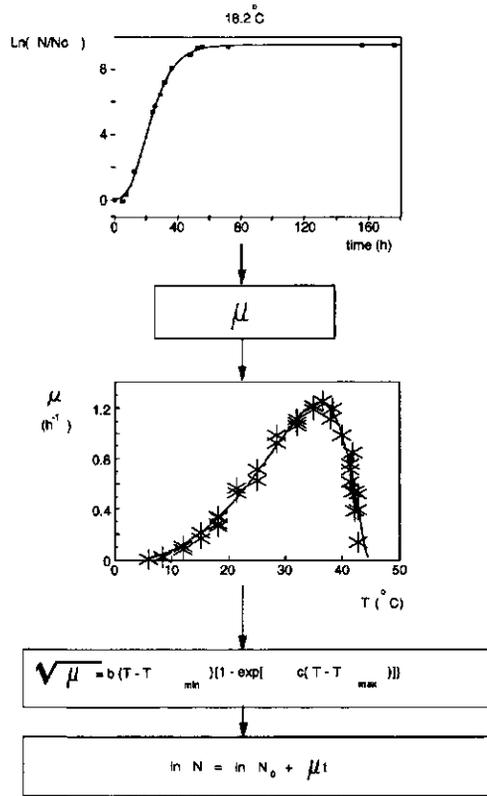


Figure 2. Pathway of model building for bacterial growth as function of temperature (N =number of organisms; μ =growth rate; b, c, T_{min}, T_{max} are Ratkowsky parameters).

perature on microbial growth. First a number of growth curves has to be measured at different temperatures. Then these growth data are analyzed using a growth model. In doing so, the values of the kinetic parameters (e.g., the growth rate (μ)) are estimated. Then these parameters of the growth curves at different temperatures can be used to select a model that describes the effect of temperature on these parameters. In Figure 2 the Ratkowsky model (1983) is given as an example. This model then can be used to predict growth rates at any temperature, and graphs such as Figure 1 can be calculated. The same procedure can also be used for other variables like pH and a_w . In this way a total model can be developed for microbial spoilage.

Use of models (an example)

If we are interested in the deterioration of chicken, we have to determine the main spoilage reaction. Chicken is mainly spoiled by *Pseudomonas*, therefore the growth rate (μ) of these bacteria is of importance. If the product should remain unchanged, i.e. pH, water content, antimicrobial agents etc. are fixed, the temperature is the variable left to control

the spoilage. The square-root model of Ratkowsky et al. (1983) can be used to describe the effect of temperature (T) on the growth rate (μ):

$$\sqrt{\mu} = b \cdot (T - T_{\min}) \cdot (1 - \exp[\alpha(T - T_{\max})]) \quad (1)$$

Since the product will be stored at low temperatures, the second part of the equation can be neglected, resulting in (Ratkowsky et al. 1982):

$$\sqrt{\mu} = b \cdot (T - T_{\min}) \quad (2)$$

Now the growth rate of *Pseudomonas* at various temperatures has to be determined, and the parameters T_{\min} (minimum temperature of growth) and b (regression parameter) can be calculated by linear regression. Specific growth rates at different temperatures were taken from literature data and from own data. The square-root of the specific growth rate is plotted versus temperature, and the data are very well described by a straight line (Figure 3). This is very promising for the use of predictive models, since these data were from different laboratories, with different strains, on different media, and they all agree very well. The Ratkowsky parameters of this curve are given in Table 1.

Table 1. Ratkowsky parameters of *Pseudomonas* on chicken.

b ($C^{-1} \cdot h^{-0.5}$)	T_{\min} (C)
0.030	-6.0

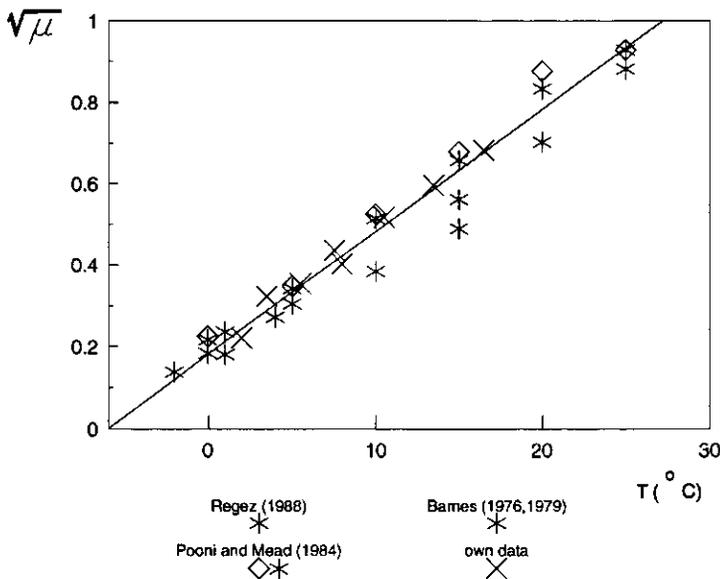


Figure 3. Ratkowsky plot for *Pseudomonas* on chicken.

For simplicity exponential growth of the micro-organisms is assumed:

$$\ln\left(\frac{N}{N_0}\right) = \mu \cdot t = 0.0009 \cdot (T+6)^2 \cdot t \quad (3)$$

Equation 3 gives the microbial load (N) at any temperature between 0°C and 25°C, at any time during storage, if the initial spoilage level (N_0) is known. Furthermore, the shelf life (Θ) can now be calculated at any temperature, if the maximum allowed spoilage level (N) is known:

$$\Theta = \frac{\ln\left(\frac{N_\Theta}{N_0}\right)}{\mu} = \frac{\ln\left(\frac{N_\Theta}{N_0}\right)}{0.0009 \cdot (T+6)^2} \quad (4)$$

If the spoilage level of chicken is $5 \cdot 10^7$ and the contamination after production is 10^3 and the temperature during storage is 0°C, the shelf life can be calculated with equation 4 to be 14 days. In the distribution chain it is difficult to retain a temperature of 0°C. If a producer has control over the distribution during the first 5 days and keeps the temperature at 0°C, the number of bacteria can be calculated with equation 3 to be $5 \cdot 10^4$. If the product is then kept at 4°C (e.g., during retail display) the remaining shelf life can be calculated to be 3 days. So the total shelf life is reduced from 14 days to 8 days and the shelf life during retail display is reduced from 9 days to 3 days. This can also be shown graphically (Figure 4). This kind of calculations can be used to show the importance of supercooling to all parties participating in the food chain. With these examples it is shown that with relatively little experimental effort, or even with literature data only, a simple model can be constructed which can be used for (preliminary) shelf life prediction and optimization.

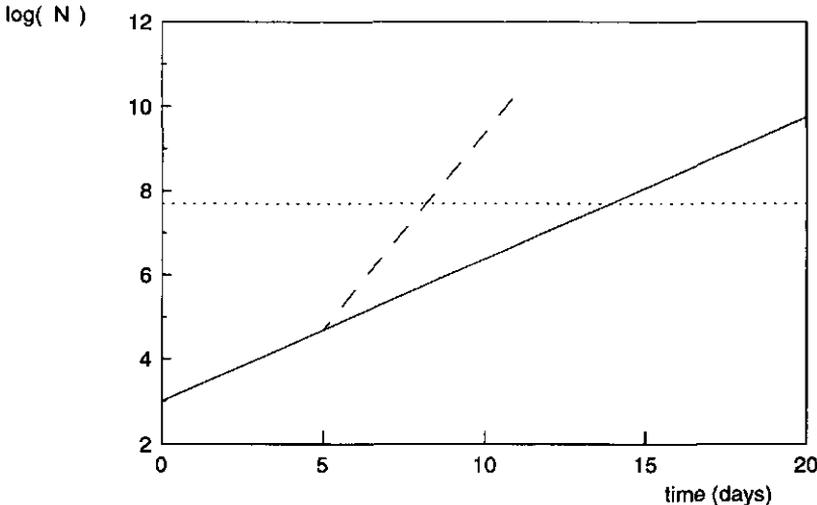


Figure 4. Spoilage of chicken at 0°C, and spoilage of chicken after 5 days at 0°C and the remainder at 4°C. Solid line: 0°C; dashed line: 5 days 0°C, then 4°C; dotted line: spoilage level.

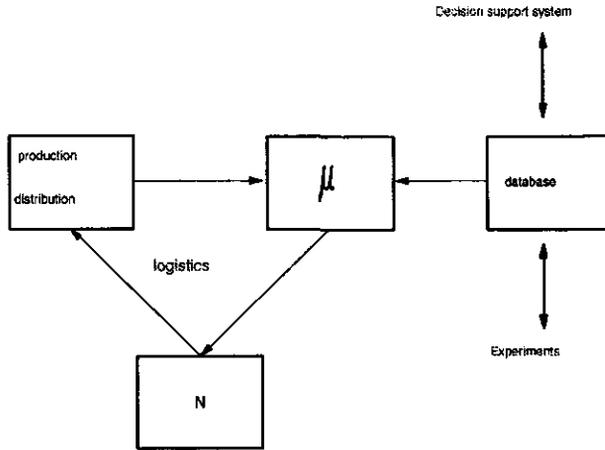


Figure 5. Optimization cycle of bacterial numbers.

Optimization of a cooling chain

From the process variables (e.g., temperature) in food production and distribution, the growth rate (μ) of the organisms can be predicted (see Figure 5). With these growth parameters the number of organisms over time can be predicted, and feedback can follow, resulting eventually in some changes in production or distribution (e.g., the temperature during distribution). This cycle of prediction and feedback can be repeated many times.

It can also be worthwhile to incorporate logistical sojourn times in this procedure, so that not only the effect of changes in physical parameters of the process can be evaluated but also the effect of changes in duration of the different stages. Furthermore, the effect of variation in several variables can be evaluated, such as variations in raw material contamination, storage time in the retail display, temperature, etc. Furthermore, these models can be combined with models for the costs of cooling in various stages, for purposes of investment decisions.

A procedure to minimise the cooling costs, with a certain lower bound for microbial quality as constraint, is developed. As an example a simplified chain is investigated, with three stages. In this chain three temperature variables can be chosen: the temperature at factory storage (T_1), during transportation (T_2) and at retail display (T_3). Several sets of temperature (T_1, T_2, T_3) can fulfil the same constraint (Figure 6).

The energy costs as function of the temperature in stage k ($k= 1,2,3$) can be estimated, taking into account the energy to cool the product (depending on T_k and T_{k-1}) and the energy losses in that phase (depending on T_k). In order to be able to estimate these energy losses numerous parameters are needed, like the dimensions of the cooling unit, thickness of the insulation, dimensions of the door, frequency of opening of the door, etc. The state of the system in stage k can be characterised by S :

$$S_k = \begin{pmatrix} N_k \\ T_k \end{pmatrix} \tag{5}$$

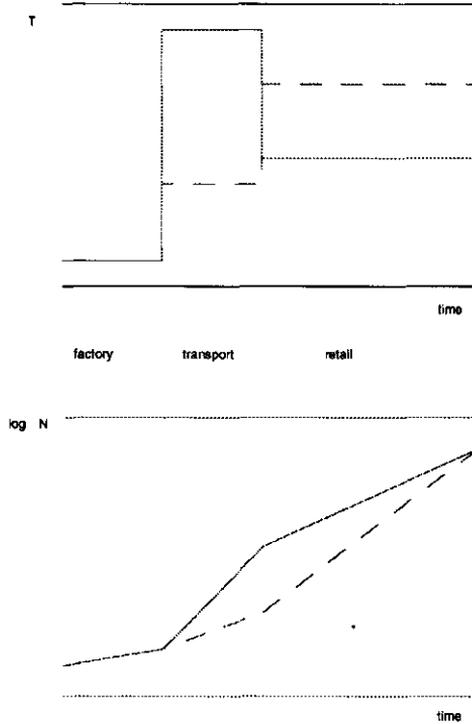


Figure 6. Different combinations of temperature that fulfil the same constraint.

The bacterial growth in phase k can be calculated:

$$\ln\left(\frac{N_k}{N_{k-1}}\right) = \mu_k \cdot t_k = b^2 \cdot (T_k - T_{min})^2 \cdot t_k \quad (6)$$

with t_k the sojourn time in phase k . Thus the state in phase k can be calculated from the former state ($k-1$):

$$S_k = \begin{pmatrix} N_k \\ T_k \end{pmatrix} = \begin{pmatrix} N_{k-1} \cdot \exp[b^2 \cdot (T_k - T_{min})^2 \cdot t_k] \\ T_k \end{pmatrix} \quad (7)$$

The costs G are depending on both the actual temperature and the temperature in the former phase: $G_k(T_k, S_{k-1})$, due to eventual cooling of the product. This results in a deterministic dynamic programming problem, which can be solved by the recurrent Bellman relation (Hendriks, Van Beek, 1991):

$$V_{k-1}(S_{k-1}) = \min_{T_k} [G_k(T_k, S_{k-1}) + V_k(S_k)] \quad (8)$$

To solve equation 8 the problem was discretised, in a finite number of temperature levels (0,5, and 10°C). Thereafter, the problem could be solved backwards.

For a cooling chain of milk, representative parameters (dimensions, sojourn times, etc.) were chosen. The optimum temperatures were calculated to be $T_1=0^\circ\text{C}$ ($t_1=24$ h), $T_2=0^\circ\text{C}$ ($t_2=26.5$ h), and $T_3=5^\circ\text{C}$ ($t_3=50.5$ h). The total costs of cooling were fl. $2\cdot 10^{-3}$ (dutch guilder) per kg of milk. It is shown that within a certain cooling chain the costs of cooling can be estimated in the various phases, which increases insight. Furthermore, the total costs can be minimised. It should be noted that the problem was simplified by taking only three temperature levels. Further fine-tuning is necessary in order to find a more realistic optimum.

In the future this project will focus on validation of these results, and on continuous solution of the problem (non-linear programming). Furthermore, the effect of statistical variations will be determined (stochastic dynamic programming).

Decision Support Systems

As can be expected a large number of parameter values are needed, such as the physical parameters of different foods, and the growth parameters of bacteria as function of the physical parameters. Therefore, a large number of data must be collected. There is an enormous number of different food products and micro-organisms, therefore, for practical purposes it is impossible to have a database with all necessary information. That is why it could be useful to incorporate also knowledge in the database.

A large amount of work is done on the modelling of deterioration of food. Yet, many cases are left without enough quantitative data. In other cases general qualitative knowledge is present, resulting from experience. In conclusion, there is a broad range of information, from qualitative to quantitative. Therefore, methods should be developed to combine quantitative and qualitative data with predictive models. When this is done in a structured manner it can be used to predict product quality in the best possible way. Possible deterioration reactions can be determined and a prediction of the kinetics can be made. Effects of different processing conditions, or product formulation can be evaluated. This can be an important tool for process optimization and product development.

A method has been developed to combine qualitative and quantitative information to predict possible growth of micro-organisms in foods (Zwietering et al. 1992). The pH, water activity, temperature and oxygen availability of foods are coupled to the growth requirements of micro-organisms. A database with characteristics of foods and a database of kinetic parameters of micro-organisms is built. A method is developed to make an estimation of the microbial growth kinetics on the basis of models. This is done by introducing a growth factor, which can be calculated on the basis of readily available data from literature. Finally, qualitative knowledge is added (Figure 7), in order to improve the predictions.

Conclusions

Modelling can be an important tool to predict the shelf life of products, to optimize production and distribution chains, and to gain insight about important variables that determine product deterioration. Predictive models, kinetic data, expertise, logistics, and simulation and optimization routines can be combined to support decisions in production and distribution, and product development. This can help to determine possible spoilage

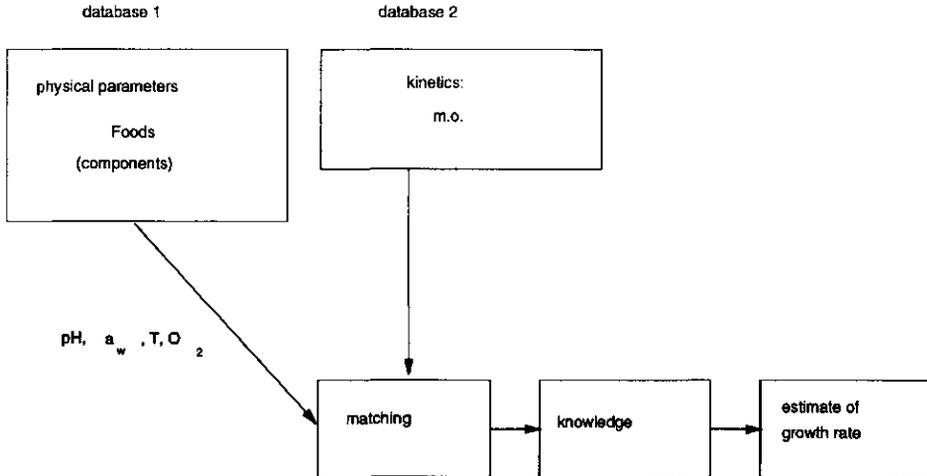


Figure 7. Structure of the decision support system

organisms, and changes in growth rates of organisms can be estimated, when the physical properties are changed.

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