The complex system science for optimal strategy of management of a food system: the camembert cheese ripening

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ABSTRACT

Significant advances are needed for food systems in terms of real-time prognosis capability developments, incorporating large scale modelling, distributed simulation and optimisation, and complete integration of the methods and algorithms. The goal is to be able to develop new paradigms at the frontier of life science and computing science for the management of systems like food systems. In parallel, just in the process of emerging and linked to these same questions is the science of complex systems, that proposes ways to understand systems located in turbulent, instable and changing environments. This paper points out and illustrates the interest to develop an approach adapting and coupling some fundamental tools of the complex system science. It combines viability and robustness analysis, multi-objective optimisation calculus and high computational performance using a computing grid. Adapted to the camembert cheese ripening, it has led to propose new strategies for control the process. One solution of the calculated pareto front, is compared to two trajectories tested during experiments led on a pilot, one standard and another optimized one. The total mass loss deviation for the calculated trajectory by comparison to the standard one is 0.04 kg in the same time and for identical microorganisms behaviour.

Keywords: cheese ripening; viability study; optimal strategy of management; computing grid; multiobjective optimisation

INTRODUCTION
Significant advances are needed for food systems in terms of real-time prognosis capability developments, incorporating large scale modelling, distributed simulation and optimisation, and complete integration of the methods and algorithms. In parallel, just in the process of emerging and linked to these same questions is the science of complex systems, that proposes ways to understand systems located in turbulent, instable and changing environments. This paper point out and illustrate an approach developed in link with this computing science on a camembert cheese ripening process. The cheese ripening process, such as the one used for Camembert, is considered to be a complex system. Numerous interactions take place at different levels of scale, from microscopic to macroscopic level, over time. To enhance camembert ripening control, numerous studies have been carried out in the food sciences, but there is still lack of knowledge. Despite the number of experimental databases collected, they remain incomplete, and it is obviously impossible to carry out all of the variable combinations through experimental trials because of the time necessary (41 days per trial). In this context, we propose an approach adapting and coupling some fundamental tools of the complex system science. It combines viability and robustness analysis, multi-objective optimisation calculus and high computational performance using a computing grid.

MATERIALS & METHODS

On the basis of a well-representative mechanistic model of the cheese ripening process [1], a theoretical framework coupling a viability-robustness analysis [2] and an optimal viable path search using a multi-objective EA achieved using parallel computing on a grid is proposed (figure 1).
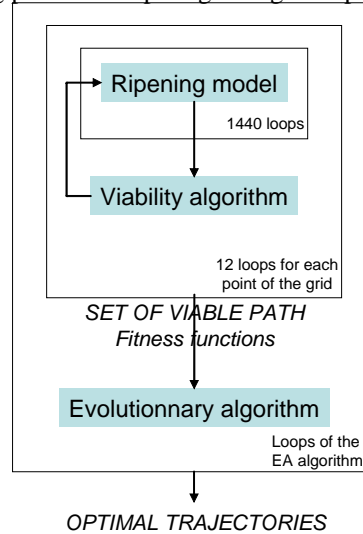

Figure 1. Coupling of a viability algorithm and an evolutionary algorithm as to calculate optimal viable path for a cheese ripening process

The cheese ripening process an model
Industrial cheesemaking of camembert is based on the use of pasteurized milk, and on a ripening process conducted in controlled chambers, in order to obtain a product at a given (safety and quality) target. For modeling purpose, we consider here a critical phenomenon for industrials which is the cheese mass loss during the ripening process. It is linked in a complex way to evaporation and to carbon consumption due respiration of micro-organisms in the ripening chamber [1], for instance:
- Low relative humidity and high temperature on the cheese surface increases evaporation.
- Cheese surface temperature decreases when evaporation occurs.
- Respiration increases the cheese surface temperature as heat is produced during the substrate degradation.

The state variables that have then been chosen to build the viability kernel are:
- The cheese mass, with a range from 250g to 310g with steps of 1g,
- the cheese temperature from 8°C to 16°C (step1°C),
- the respiration rate of micro-organisms from 0 to 50 g=m2=day (step 1g=m2=day.

Additionally, the control variables are
- The ripening room temperature (from 8°C to 16°C, step 1°C),
- the relative humidity (from 84% to 98%, step 2%).

Calculus of the viability kernel and associated robustness trajectories
On the basis of this model, a viability kernel has been calculated [2]. It aims at providing all the possible path in the state space, linked to the control space, that ensure the process to reach a target at the end of the process. It is defined in accordance with the experts of the process. This target can include the different requirements needed as sensory, ecological, energy consumption or process yield characteristics, etc...The principle of the viability approach (VA) is that the variables and constraints are characterized by the geometry that its generates in the state space of the model, then the space is classified to identify, for example, the viability kernel: the subset of the space where almost one evolution starting in the subset remains indefinitely inside of the domain of some (viability) constraints. A fundamental difference between

VA and classic control engineering is that VA represents a deep comprehension of the behavioral space, replacing the update procedure from single-valued maps to set-valued maps. For the end user, its knowledge offer a freedom of choice to incorporate new criteria in the decision process. For the decision support system, VA offers an unique opportunity to connect the set structure of the model with an evolutionary optimization mechanism.

The general definition of the basis of the viability theory is the viability kernel, referred to as Viab $_{f,U}$(K), which contains all states from which at least one control function u(t) exists so that the state of the system remains in K for t in [0,T]. It is defined for a system that evolves over time x(.): t $\rightarrow$ x(t) for t∈R_+:=[0,∞], and which evolution depends on the state of the system and as well as controls. It is supposed to be governed by a control dynamical system where available controls u(t) belong to the set U(x(t)) with $U(t) \subset R^p$ and Sf,U(x) the set of all trajectories governed by the control dynamical system. The viability kernel is then defined as equation (1).

$$V \, iab_{f,U} \, (K) := \left\{ x \in K \middle| \exists x(.) \in S_{f,U}(x), \forall t \in [0,T], x(t) \in K \right\} \quad (1)$$

This viability kernel also determines the set of controls that would prevent the system from violating the state constraints. The particular case of the capture basin is to find trajectories remaining in the constraint domain that reach a target C within a finite time. This also aims at selecting robust process actions from among the set of viable controls for decision help purposes. The viability kernel is defined by the following constraints:
- The ripened cheese should have at the end of the process a mass between 250g to 270g,
- a temperature between 8°C and 10°C,
- a respiration between 23 and 50g/m^2/day.

The (CO2, O2) gas rate evolution should follow a specified profile along the process, in order to fully exploit the micro-organisms capabilities. This constraint is set by experts. The respiration rate should begin at level 0 on day 1 (microbial growth latency), reaches a maximum between day3 and day 8 and decreases slowly during the last days of ripening (see [2] for more details).

Coupled to this calculus, a geometric analysis of the shape of the viability kernel, and of all the viable paths to the target (also named the viability tube), provides useful information about the robustness and uncertainties of the system. This analysis is based on the computation of the boundaries of the viability tube, and for each point of the tube, on its distance to the nearest boundary. Optimal algorithms for the Euclidean distance transform (EDT) in arbitrary dimension have been developed for morphological mathematics and image analysis purpose [3] adapted one of these algorithms [4] for the analysis of viability tube data.

Optimal path search using a multi-objective EA for help in the conception of strategies of process management

Table 1. Parameters of the multi-objective algorithm

Population size		10000
Crossover rate	UX	0.1
	AX	0.1
Mutation rate	Inversion	0.7
	random	0.1
Stopping criterion	Max number of evaluations	10000000
	Max number of evaluations without improvement	10000
Number of replication		1000

The aim is to find an optimal strategy, i.e. an optimal and real path, among each possible viable path to the target. Convenient algorithms for that purpose are thus multiobjective Convenient algorithms for that purpose are thus multiobjective optimisation ones. Multi-objective optimisation problems are often NP-hard, complex and CPU time consuming. Exact methods can be used to find the exact Pareto front (or a subset of the front),

but usually it is impossible to compute exact solutions for large problems, as they are time and memory consuming. For instance, for the cheese ripening case, there exists 10^{24} possible trajectories in the viability kernel we defined.We rely in this work on the use of multi-objective Evolutionary Algorithm (EA) to approximate Pareto fronts within a reasonable computation time. Additionnally, as the cheese mass loss modeling is actually a large sized problem, the algorithms have been implemented on a parallel and distributed computation grid. Our problem corresponds to a search for an optimal path in a graph, where each node represents the state of the cheese (mass and breath) and each edge represents a control (relative humidity and chamber temperature). The graph is organised as a succession of slices, each representing a day, it is therefore not complete. An adaptation of the encoding was proposed as to be able to take into account this drawback. We have chosen to use the multiobjective approach proposed by [5] and [6]: Nondominated sorting genetic algorithm (NGSA). For selection and elitism we choose a tournament selection due to its parcimonious mechanism that only considers a small random subsample of the population. Additionaly comparison are based on both domination and crowding criteria [7]. For mutation we used a basic random mutation. Simple crossover are used as the uniform one (UX) and order crossover (AX). Parameters selected are presented in table 1.

For fitness function and pareto optimality, each trajectory in the viability tube can be evaluated according to four goals :

- Loss mass minimisation
- number of control changes to be minimized,
- trajectory robustness to be maximized,
- number of days to get the maximum of respiration linked to optimal breath and to minimize.

It is a classical mulitobjective optimisation usually defined as in equation (2) with x=(x1, x2,..., xn) €X an n-dimensional vector and X the search space, fi are partial evaluation of the solution, usually corresponding to contradictory aims. The optimal solutions correspond thus to a set of compromise between the m various partial evaluations. In other words, the Pareto optimal set X* is made of all non-dominated points, i.e. points for which it is impossible to improve any objective without simultaneously worsening another.

$$"min/max" z = f(x) = (f_1(x), f_2(x),......, f_m(x)) \in R^m \qquad (2)$$

Parallel implementation
In this paper, we deal with a grid of computers (multicomputers architecture), a multiple-population (or multiple-deme) structure is more convenient. These algorithms maintain several subpopulations that occasionally exchange individuals (during a migration step). Our implementation is based on the OpenMOLE platform of "workflow" [8]. The development of OpenMOLE was organized under the form of a community of free software programs that is today very active. OpenMOLE is a framework providing distributed computing facilities. It takes advantage of generic interface of JSAGA (http://grid.in2p3.fr/jsaga/) and provides on top of that. OpenMOLE has been designed to work out of the box on the user desktop with the idea of completely hiding the fact that computation may be carried out on distributed environments.

RESULTS & DISCUSSION

The Pareto front that has been estimated is made of 142937 trajectories, however, with respect to the objectives, they correspond to only 329 combinations . A principal component analysis (PCA) was performed on the Pareto front obtained using our implementation. The PCA was based on the four variables associated to the objective: mass loss, control changes, trajectory robustness and optimal breath. The first two eigenvectors represent 45.35% and 28% of the total variance, respectively. The variable projection and the distribution of the Pareto front solutions are represented figure 2. We can notice that the objective space is diversified: several solutions are associated to each objective.
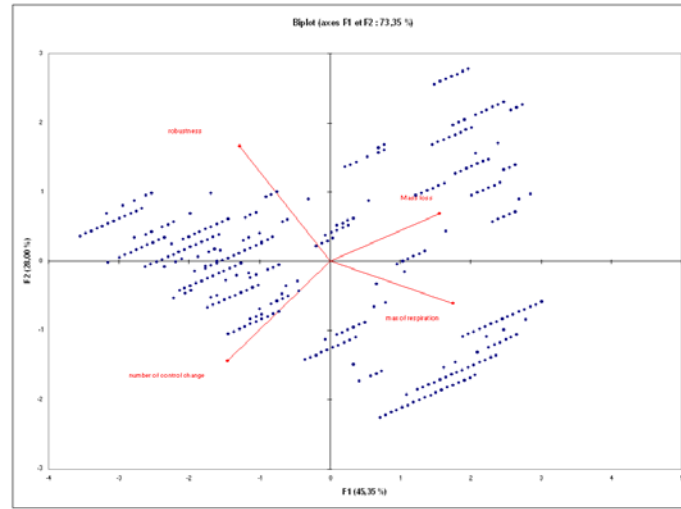
Figure2. Projection, using the PCA, of the Pareto front solutions for the cheese ripening problem.

As to select among this Pareto front solutions, an efficient optimized trajectory, an expert was consulted. The new control applied for the optimal trajectory found (PT) has been compared to a viable trajectory (TVA) computed in a 8-day viability kernel and already applied a pilot [2], and to a standard one (SRT) running in 12-day and used in dairy industry. This TP trajectory differs from the TVA trajectory and from the classical one. The relative humidity is not constant like in TVA (94%) or in the standard SRT trajectory (92%) (figure 3). However, like in TVA (figure 3) the temperature control varies whereas in the standard trajectory it remains constant. To analyse the consequences of these PT trajectory control changes, we compare its cheese mass loss evolution and respiration rate to those of TVA and standard trajectories.
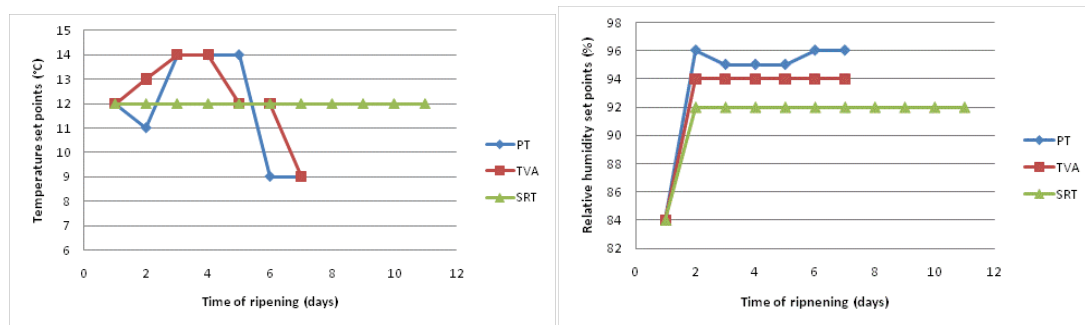

Figure 3. Control values applied during time for the optimal trajectory selected using our algorithm (PT) in comparison to other trajectories tested in previous studies (TVA and SRT).

Figure 4 shows the expected mass loss during the PT trajectory compared to the mass loss during the TVA and SRT trajectories. The quantities that are displayed are computed for PT, and measured during experiments led in a ripening chamber for TVA and SRT. The mass loss is 0.013 kg for the PT trajectory, while it is of 0:034 kg for the TVA trajectory and of 0:054 kg for the standard ripening. This result is significative, as a minimisation of mass loss is a very challenging issue for the dairy industry. This small mass loss can be explained by the high values of relative humidity of the PT trajectory and as a consequence the low moisture gradient taking place during the cheese ripening. The cheese mass at the end of the robust ripening remains within the desired target range (0:25 kg to 0:27 kg). If Mass loss is a very sensitive parameter for the industry, it should also be evaluated as regard to the other optimality criteria (see below) as

for example the microbial activities taking place during the ripening process. The microbial activities of optimized (PT), viable (TVA) and standard (SRT) ripening processes were then compared. The maximum respiration rate begins two days earlier in the PT ripening process than in the standard ripening process, and one day and a half earlier in the TVA ripening process.
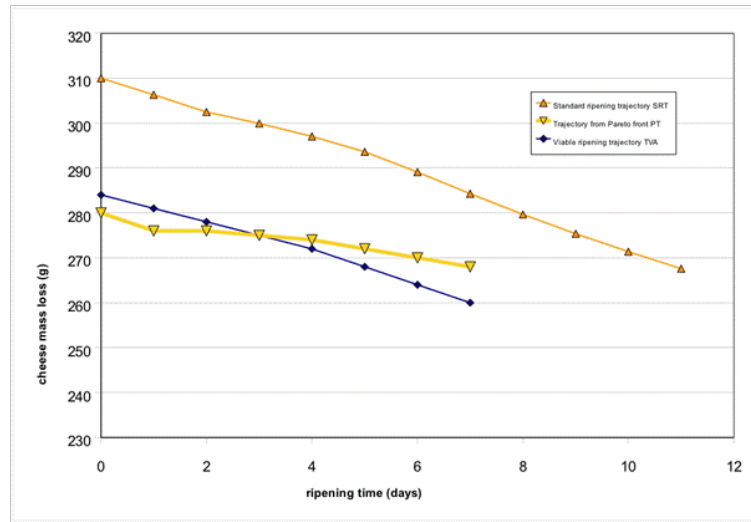

Figure 4. Comparison of cheese mass loss between PT trajectory (computed values), and TVA and SRT ones (measured values from real experiments in a ripening chamber).

CONCLUSION

In this work, we propose a new way, based on complex system science developments, to propose optimal strategies to manage the food systems. It is based on a coupling between viability principle, geometric robustness calculus, multiobjective evolutionary algorithm and parallel implementation on a grid calculus. Applied to the cheese ripening process, it has led to propose new strategies for control the process. Further studies will be focus on those promising results and developments.

REFERENCES

[1] Helias, A., Mirade, P. S. & Corrieu, G. 2007. Modeling of camembert-type cheese mass loss in a ripening chamber: Main biological and physical phenomena. Journal of Dairy Science, 90, 5324-5333.

[2] Sicard M., Perrot N., Baudrit C.,Reuillon R., Bourgine P., Alvarez I. & Martin S. 2009. The viability theory to control complex food processes. European Conference on Complex Systems 2009, University of Warwick (UK).

[3] Alvarez, I. & Martin., S. 2009. Explaining a result to the end-user: a geometric approach for classification problems. (2009), Twenty first International Joint Conference on Artificial Intelligence IJCAI - Workshop ExaCt.

[4] Coeurjolly, D. & Montanvert, A. 2007. Optimal separable algorithms to compute the reverse Euclidean distance transformation and discrete medial axis in arbitrary dimension. IEEE Trans. On pattern analysis and machine intelligence, 29(3), 437-448.

[5] Horn, J., Nafpliotis, N. & Goldberg, D.E. 1994. A niched pareto genetic algorithm for multiobjective optimization. In proceedings of the first IEEE conference on evolutionary computation, IEEE World congress on computational computation, Piscataway, NJ, IEEE Press, 1, 82-87.

[6] Deb, K., Agrawal, S., Pratap, A. & Meyarivan, T. 2000. A fast elitist non dominated sorting genetic algorithm for multi-objective optimization: Ngsa-ii. In M.S. et al. (Ed.) Parallel problem solving from nature PPSN VI, springer, 849-858.

[7] Tsai, C., Tsai, C. & Yang, T. 2002. A modied mulltiple searching method to genetic algorithms for solving traveling salesman problem. In IEEE Int. Conference systems, Man and Cybernetics, 3, 6-9.

[8] Reuillon, R., Chuffart, F., Leclaire, M., Faure, T. & Hill D. 2010, «Declarative Task Delegation in OpenMOLE», in proceedings of the IEEE International Conference on High Performance Computing &Simulation (HPCS 2010), Caen, France, June 2010, 7p.