

Minimizing multi-pathogen risk and costs through control measures

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ArtiSaneFood: Biopreservation and Risk Modelling Approaches

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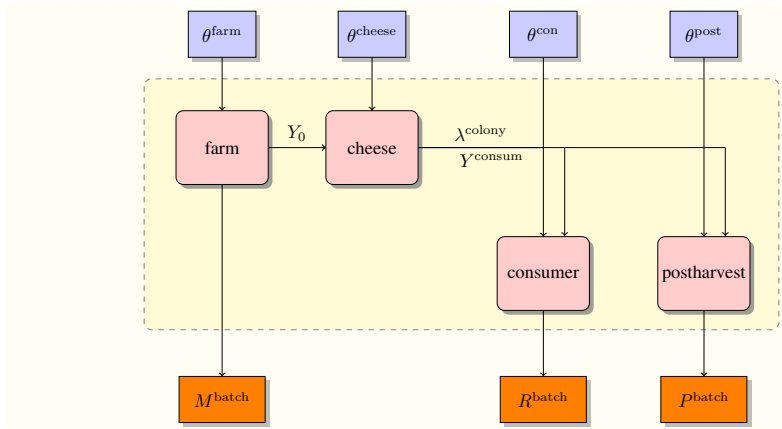
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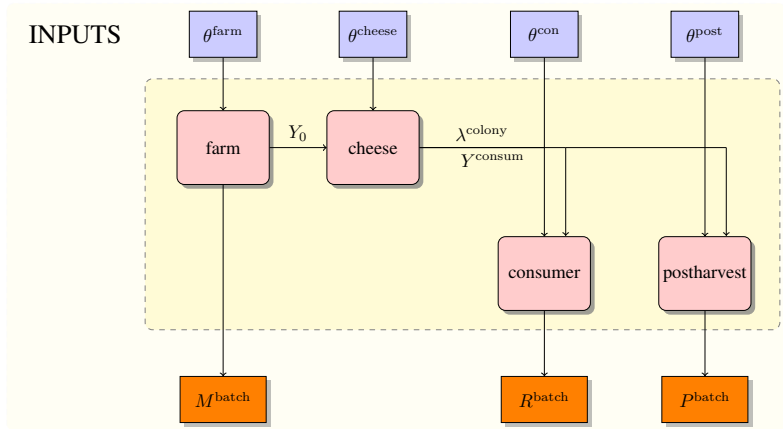
Motivation & application

- **Aim** : Control risk of illness from pathogens in raw milk cheese
 - **STEC** → Haemolytic Uremic Syndrome (HUS)
STEC & MPS STEC
 - **Salmonella** → Salmonellosis
High & Low Virulent Salmonella
- **Quantitative Risk Assessment (QRA)**
 - Based on *Perrin et al. (2014)* and *Basak et al. (in prep.)*
- **Optimization** : Find intervention parameters that minimize the objectives
 - Relative **risk** of illness & intervention **cost** (€)

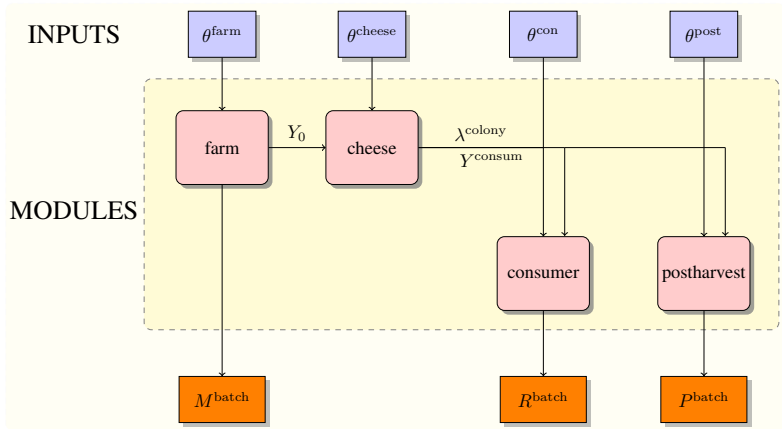
QRA model – Raw milk cheese



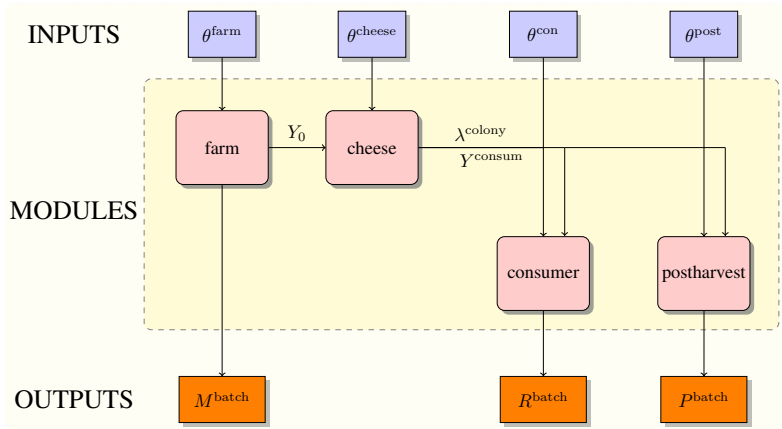
QRA model – Raw milk cheese



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QRA model – Raw milk cheese



Farm module : Milk collection

- **Milk sorting:** **Reject** farm if E.coli conc. ($Y_{\text{milk}}^{\text{Ecoli}}$) > threshold

$Y_{\text{milk}}^{\text{Ecoli}} \sim \text{Lognormal}$ with parameters based on *CNIEL + ACTALIA* data

- **Concentrations** are computed indirectly due to limit of detection

$$Y_{\text{milk}}^{\text{X}} = Y_{\text{milk}}^{\text{Ecoli}} \cdot (Y_{\text{feces}}^{\text{X}} / Y_{\text{feces}}^{\text{Ecoli}})$$

– $X \in \{\text{STEC}, \text{Salmonella}\}$

– $Y_{\text{feces}}^{\text{Salmo}} \sim \text{Lognormal}$, $Y_{\text{feces}}^{\text{STEC}} \sim \text{Weibull}$, $Y_{\text{feces}}^{\text{Ecoli}} \sim \text{Lognormal}$

- **Prevalence** rates and distribution parameters:

– (*Perrin et al., 2014*) & (*Bonifait et al., 2021*)

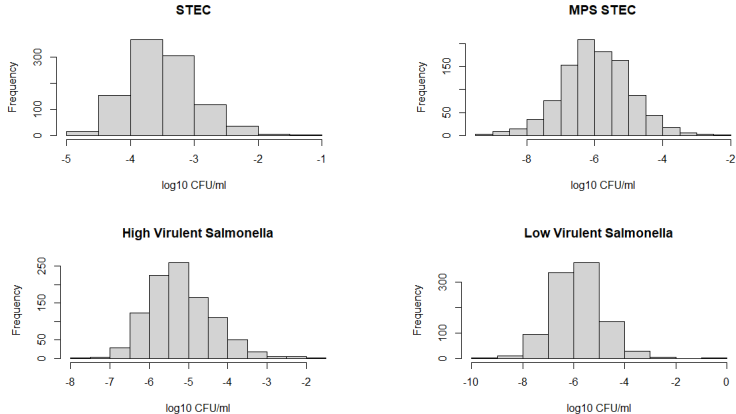


Figure 1: Simulated concentration of bacterias in milk in production
Farm module outputs

Cheese module

- Growth ↗ phase

$$\frac{dy}{dt} = \mu_X^{\max}(t) \cdot y(t) \cdot \left(1 - \frac{y(t)}{y^{\max}}\right)$$

Milk storage → Molding → *Colony formation* → Draining → Salting

- Decline ↘ phase

$$\text{STEC} : Y_{\text{STEC}}^{\text{consume}} = Y_{\text{STEC}}^{\text{salting}} \cdot 10^{-\rho \cdot t}$$

$$\text{Salmonella} : Y_{\text{Salmo}}^{\text{consume}} = Y_{\text{Salmo}}^{\text{salting}} \cdot 10^{-(t/\delta)^p}$$

Ripening → Cheese storage → Consumption

→ Decline rates based on *ACTALIA* report

Cheese module : Pre-molding stages

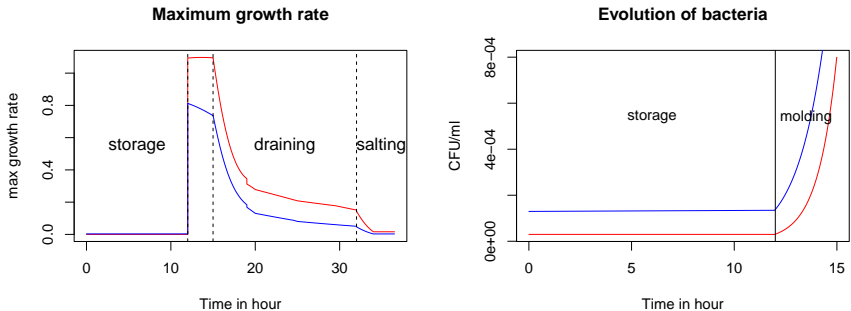


Figure 2: Growth rate $\mu^{\max}(t)$ and evolution $y(t)$ of **STEC** and **Salmonella**

→ **Number of colonies:** $N_X^{\text{colony}} \sim \text{Poisson}(Y_X^{\text{molding}} \cdot c)$

Cheese module : Evolution of colonies

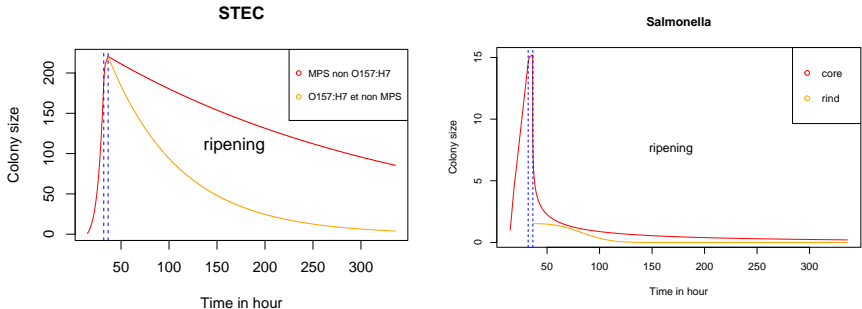


Figure 3: Evolution of colonies of different strains of STEC and Salmonella

→ **Size of colonies:** $Y_X^{\text{colony}} \sim \text{Lognormal with median } Y_X^{\text{consume}}$

Consumer module

- Dose in cheese serving:

$$\Gamma_X = \sum_{s \in \text{strains}} N_s^{\text{colony}} \cdot Y_s^{\text{colony}}$$

- Dose-response model:

$$P_{\text{STEC}}^{\text{illness}} = 1 - (1 - r_{\text{age}})^{\Gamma_{\text{STEC}}} \text{ (Perrin et al., 2014)}$$

$$P_{\text{Salmo}}^{\text{illness}} = 1 - \left(1 + \frac{\Gamma_{\text{Salmo}}}{\beta}\right)^{-\alpha} \text{ (Strickland et al., 2023)}$$

- Batch risk:

$$R_X^{\text{batch}} = \sum_{\text{age}=1}^{15} g(\text{age}) \cdot \mathbb{E}_{\Gamma_X}[P_X^{\text{illness}}]$$

→ Effect of Salmonella is independent of consumer age

Intervention steps

- Milk testing: Farm module

- Proportion of farm milk tested $\rightarrow p_{\text{milk}}$
- Threshold of E.coli test $\rightarrow l_{\text{milk}}$
 \rightarrow Computes M^{batch} milk rejected (in liters)

- Cheese testing: Postharvest module

- Proportion of cheese batch tested $\rightarrow p_{\text{cheese}}$
- Number of cheese samples tested $\rightarrow n_{\text{sample}}$
 \rightarrow Computes P_X^{batch} Probability of rejecting the batch

$$P_X^{\text{batch}} = 1 - (1 - P[\Gamma_X > 0])^{n_{\text{sample}}}$$

Quantities of interest (QoI)

- QoIs are computed using R_X^{batch} , P_X^{batch} and M^{batch}

$$R_X^{\text{illness}} = \frac{\mathbb{E}[R_X^{\text{batch}} \cdot (1 - P_X^{\text{batch}} \cdot p^{\text{cheese}})]}{\mathbb{E}[1 - P_X^{\text{batch}} \cdot p^{\text{cheese}}]}$$

$$C^{\text{avg}} = (c_1 + c_2 \cdot \mathbb{E}[M^{\text{batch}}]) + (c_3 + c_4 \cdot \mathbb{E}[P_X^{\text{batch}} \cdot p^{\text{cheese}}])$$

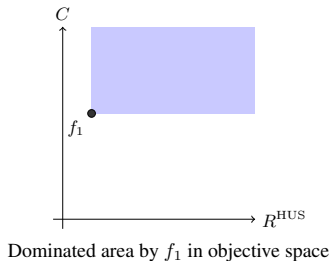
- Several **batches** are simulated to estimate
 → c_i 's denote cost values (*COPIL ArtiSaneFood, Caen, Normandie, 2022*)
- **DALY**: Disability-adjusted life year
 - Batch risk for HUS and Salmonellosis are computed
 - Overall risk was assessed by combining the burden of disease metrics

Multi-objective optimization $\rightarrow f = (R^{\text{HUS}}, C)$

- Consider an input: $x_1 = (p_{\text{milk}}, l_{\text{milk}}, p_{\text{cheese}}, n_{\text{sample}})$

$$p_{\text{milk}} = 30\%, l_{\text{milk}} = 50 \text{ CFU}, p_{\text{cheese}} = 50\%, n_{\text{sample}} = 5 \text{ units}$$

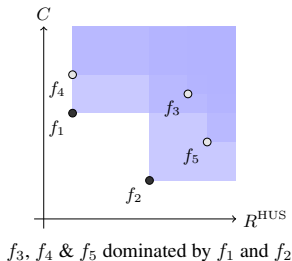
- Corresponding actual output: $f_1 = (R_1^{\text{HUS}} = 2.2, C_1 = 1000 \text{ EUR})$



Pareto optimal solutions

- **Example:** Inputs $\{x_i\}$ and outputs $\{f_i\}$, for $i = 1, \dots, 5$

Minimizing two **conflicting** functions: $\min_x f(x)$

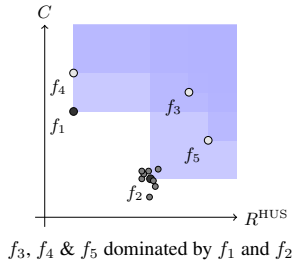


- **Goal:** Estimate the **Pareto set** $\mathcal{P} = \{x_1, x_2\}$ and **Pareto front** $\mathcal{F} = \{f_1, f_2\}$

Multi-objective **stochastic** optimization

- **Simulator:** Inputs $\{x_i\}$ and outputs $\{z_i = f_i + \text{noise}\}$, for $i = 1, \dots, 5$

Minimizing two **expensive** & **noisy** functions: $\min_x f(x)$

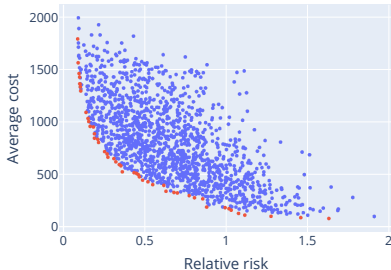


Naive approach Use Monte Carlo simulations → **computationally expensive**

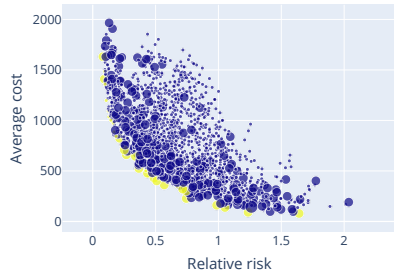
PALS (Barracosa et al., 2021) and (Basak et al., 2022)

- Input points: $(p_{\text{milk}}^i, l_{\text{milk}}^i, p_{\text{cheese}}^i, n_{\text{sample}}^i)_{i=1,2,\dots,1500}$

Monte Carlo: True Pareto front



PALS: Estimated Pareto front



(a) Samples ALL 1500 points $\times 5000$ (b) Samples only 300 points $\times 200$ (size)

- PALS has $\sim 4\%$ misclassification rate in estimating Pareto optimal points

Conclusions & Perspectives

- [QRA model](#) for STEC and Salmonella
- [Bayesian Optimization](#) for finding the optimal intervention parameters
 - Open sourcing (Github + FSKX) multipathogen QRA model
 - Optimization on DALY metrics
 - Propose a 3-pathogen model with Listeria

Thank you for your attention!



COPIL ArtiSaneFood 2022, Caen, Normandie

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A Bayesian Optimization (BO) framework

Expensive evaluations + Noisy observations

Algorithm 1 Using a Gaussian process regression (GPR) model ξ on f

Sample f at n_0 points ▷ initialization step

while budget > 0 **do**

 Update : GPR posterior ξ_n

 Compute : acquisition function $J_n(x)$

 Next point : $x_{n+1} = \arg \max_{x \in \mathbb{X}} J_n(x)$

 Sample : f at x_{n+1}

end while

Estimate $\hat{\mathcal{P}}$ and $\hat{\mathcal{F}}$ with GPR posterior mean ▷ Prediction step

Weighted Mean Square Error (W-MSE)

- **PALS** (*Barracosa et al., 2021*) + extension (*Basak et al., 2022*)
- MSE is used as a measure of uncertainty
- The new sample X_{n+1} corresponds to **highest uncertain** region of \mathbb{X}

$$X_{n+1} = \arg \max_{x \in \mathbb{X}} \left(w_n(x) \cdot \sum_{j=1}^q \frac{\sigma_{j,n}^2(x)}{R_{j,n}^2} \right)$$

- $R_{j,n}$ is a normalizing constant for $j = 1, 2, \dots, q$ -th objective
- $\sigma_{j,n}^2(x)$ is the GP posterior variance at $x \in \mathbb{X}$
- Non-zero weights are given to **"potentially Pareto optimal"** points