



# Modeling cost-effective monitoring schemes for food safety contaminants: Case study for dioxins in the dairy supply chain

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## ABSTRACT

Food safety monitoring is essential for hazard identification in food chain, but its application may be limited due to costly analytical methods and (inefficient) sampling procedures. The objective of this study was to design cost-effective monitoring schemes for food safety contaminants along the food production chain, given restricted monitoring budgets. As a case study, we focused on dioxins in the dairy supply chain with feed mills, dairy farms, dairy trucks and storage silos in dairy plants as possible control points. The cost-effectiveness of monitoring schemes was assessed using a model consisting of a simulation module and an optimization module. In the simulation module, the probability to collect at least one contaminated sample was computed for different sampling strategies (simple random sampling, stratified random sampling and systematic sampling) at each control point. The optimization module maximized the effectiveness of a monitoring scheme to identify the contaminated sample by determining the optimal sampling strategies, the optimal number of incremental samples collected, and the pooling rate (number of collected samples mixed into one aggregated sample) at each control point. The modelling approach was applied to two cases with different types of contamination. Results of these cases showed that, to identify the same contaminated sample, monitoring schemes with systematic sampling were more cost-effective at feed mills and dairy farms. The combination of simulation and optimization methods showed to be useful for developing cost-effective food safety monitoring schemes along the food supply chain.

## 1. Introduction

Food safety incidents can have serious adverse impacts on the (inter) national economy and pose a threat to public health (Lascano-Alcoseer et al., 2011; Hoogenboom, Traag, Fernandes, & Rose, 2015; Knutsen et al., 2018). In order to safeguard animal and human health, the European Commission has set legal maximum limits (ML) and, in some cases, action levels (AL) for the maximal presence of contaminants in certain foods and animal feed brought on the European market (European Commission, 2014, 2019, 2020). In addition, official procedures stipulate sample collection and analysis methods for contaminants in feed and food products. The sampling and analysis procedure is a major part of food and feed safety monitoring, and is defined as a three-stage process, including sample collection, sample preparation, and contaminant analysis (European Commission, 2009, 2017). While feed and food safety is monitored across the globe, monitoring programs vary, even

between various EU Member States, because of financial constraints of analytical methods and sampling procedures (Bouzembrak & van der Fels-Klerx, 2017; European Food Safety Authority, 2012; Powell, 2014). Given the often restricted budgets available for monitoring, it is of utmost importance to determine which food safety monitoring schemes are most cost effective.

The economic optimum of sampling design has been studied in the past years, for example to find the balance between sampling costs and economic losses due to imperfect decisions (Ferrell Jr. & Chhoker, 2002; Wetherill & Chiu, 1975). Several studies have addressed the issue of designing cost-effective sampling in food safety monitoring (Focker, Van der Fels-Klerx, & Oude Lansink, 2019). For instance, Lascano-Alcoseer et al. (2013) and Lascano-Alcoseer et al. (2014) developed a modeling approach to optimize number of samples in order to identify a dioxins incident in European food chains. Apart from the number of collected samples, the sampling strategy can also affect the performance of the

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monitoring scheme given the often heterogeneous distribution of contaminations (Bouzembrak & van der Fels-Klerx, 2017; Pantoja et al., 2012; Wang et al., 2012). In the sample collection step, the sampling strategy needs to be defined for collection of individual samples (Hoffman et al., 2013; Jongenburger et al., 2011; Pantoja et al., 2012). Information on the applied sampling strategy is often missing in monitoring results, and EU regulations do not clarify a specific benchmark sampling strategy for food safety monitoring (European Commission, 2017; European Food Safety Authority, 2012). Although residue control plans should apply targeted sampling, random sampling could be used if it is justified in the national monitoring program (European Commission, 1996, 2006a, 2006b). For example, targeted sampling was not implemented for identifying non-compliant samples in the Dutch national dioxin-monitoring scheme for both feed and food products (European Commission, 2006b; Schoss et al., 2012; Adamse et al., 2017). Apart from simple random sampling (SRS), two other commonly used methods in food safety monitoring are stratified random sampling (STRS) and systematic sampling (SS) (Bouzembrak & van der Fels-Klerx, 2017; Delmelle, 2014). The performance of different sampling strategies is influenced by the contamination source(s) and the spatial distribution of the contaminant; especially for locally or heterogeneously distributed contaminants (Bouzembrak & van der Fels-Klerx, 2017; Fotheringham & Rogerson, 2008; Jongenburger et al., 2011). Therefore, the cost-effectiveness of food safety monitoring schemes needs to be evaluated taking sampling strategy into account.

The aim of our study was to develop a modeling approach for the design of cost-effective food safety monitoring schemes at different control points along the food production chain. As a case study, we focused on dioxins along the dairy supply chain and used scenarios for two types of contamination. Since EC-prescribed procedures for dioxin monitoring require a lot of resources (European Commission, 2006c, 2017; Lascano-Alcoseer et al., 2013), improving the cost-effectiveness of such schemes along the dairy supply chain is essential.

## 2. Methods

Fig. 1 presents the modeling approach developed to maximize the effectiveness of dioxins monitoring along the dairy chain, given restricted budgets (only considering the costs for sampling and analytic activities). The monitoring effectiveness was defined as the probability of identifying at least one contaminated sample with a concentration above a pre-set decision limit<sup>1</sup> (estimated in Eq. (14)) for each control point, given a certain contamination scenario, during the monitoring period. Three sampling strategies (SRS, STRS, SS) were compared, and the optimal number of samples collected as well as the pooling rate (number of incremental samples mixed into one aggregated sample) were calculated for each control point. Sampling strategies and the spatial distribution of the contamination in case of flexible inputs and scenarios were computed via stochastic simulation. Then, mixed integer programming was used to find the optimal results.

### 2.1. Dioxins case study

Dioxins refer to a group of toxic chemicals, including polychlorinated dibenzo-p-dioxins (PCDDs) and polychlorinated dibenzofurans (PCDFs), which are persistently present in the environment. The contamination can easily spread through the entire dairy chain from the environment and feed, through transportation, primary milk production, dairy factories, wholesalers, and retailers to customers (Heres et al., 2010; Flores-Miyamoto, Reij, & Velthuis, 2014). The distribution of dioxins in different products varies among regions (Desiato et al., 2014), and the

original contamination can usually be traced back to certain geographic areas (Baars et al., 2004; Schoss et al., 2012). In the European Union, the legal maximum limit (ML) for dioxins in animal compound feed (with a moisture content 12%) and raw milk is set at 0.75 pg of TEQ/g feed<sup>2</sup> and 2.5 pg of TEQ/g fat<sup>2</sup> separately, and the action limit of dioxins (AL) in raw milk is set at 1.75 pg of TEQ/g fat (European Commission, 2014, 2019, 2020). The EC recommends an analysis method that consists of a screening method (e.g. CALUX assays (DR CALUX®)) and a confirmatory method (e.g. gas chromatography/high-resolution mass spectrometry (GC/HRMS)), which is both time and resource consuming (European Commission, 2017; Lascano-Alcoseer et al., 2014).

Our study uses a simplified, hypothetical West-European dairy supply chain (Fig. 2), starting with compound feed production, followed by raw milk production at the dairy farm, and further processing at a dairy processing plant (Asselt et al., 2017). The hypothetical dairy supply chain consists of 100 feed mills (FM), 20,000 dairy farms (DF), 5,000 dairy trucks (DT), and 100 processing plants (SP) in a target area divided in ten regions (Table 1). The feed mills receive new feed ingredients to produce compound feeds once every two weeks (Van der Fels-Klerx & Camenzuli, 2016), that are delivered to dairy farms in the Netherlands (i.e. each dairy farm receives new compound feeds every two weeks) (Lascano-Alcoseer et al., 2011). The milk from four dairy farms is collected and mixed into one milk truck, and subsequently sent to one processing plant. It was assumed that feed mills located in the same region receive feed ingredients from same sources, and dairy farm sends its raw milk to processing plants randomly localized in the ten regions. These four dairy chain stages were set as control points for the monitoring of dioxins. The monitoring period was set at two weeks, during which the monitoring of dioxins would be implemented once at each control point. Data about the hypothetical dairy supply chain are shown in Table 1. These data related to the hypothetical dairy chain were used in the simulation module of our modelling approach, to calculate the fraction of contaminated batches and the particular dioxins concentration in each stage of the chain, given predefined contamination scenarios.

### 2.2. Contamination scenarios

In our study, we defined the samples with an elevated dioxins concentration higher than the pre-set decision limits as the contaminated samples. The non-contaminated samples have a dioxin concentration equal to the average background level for each type of sample (Table 1), and this background level is the measured concentration of dioxins in samples due to the ubiquitous presence of dioxins as an environmental pollutant. To illustrate our modelling approach, we used two case studies related to contamination scenarios: the feed contamination case and the farm contamination case. The feed contamination case was based on two historical milk incidents in the Netherlands. In these incidents, elevated concentration of dioxins in milk were caused by the use of contaminated feed (Lascano-Alcoseer et al., 2011; Hoogenboom et al., 2015). The farm contamination case assumed a certain number of contaminated farms at certain dioxins concentrations, and used historical monitoring data from Dutch dairy farms for the number of samples collected and contaminated (details in the Section 2.6). In the feed contamination case, the contamination scenarios at FM were defined by the combination of the fraction of FM with contaminated compound feeds ( $F_{cf}$ , being 1%, 5%, or 10%) and the dioxins concentration in the contaminated compound feed ( $C_{fm}$ ) (Table 1). Dioxins concentrations in contaminated products were based on data from historical dioxins

<sup>1</sup> The decision limit represents the highest concentration of dioxins above the average background level. With a concentration below the decision limit, a sample (feed, milk) is considered not to be contaminated for dioxins.

<sup>2</sup> The unit of pg of TEQ/g feed and TEQ/g fat is based on the use of WHO-TEQ which is expressed as World Health Organization (WHO) toxic equivalent using the WHO-toxic equivalency factors (WHO-TEFs) from International Programme on Chemical Safety (IPCS) expert meeting which was held in Geneva in June 2005 according to European Commission (2014, 2020).

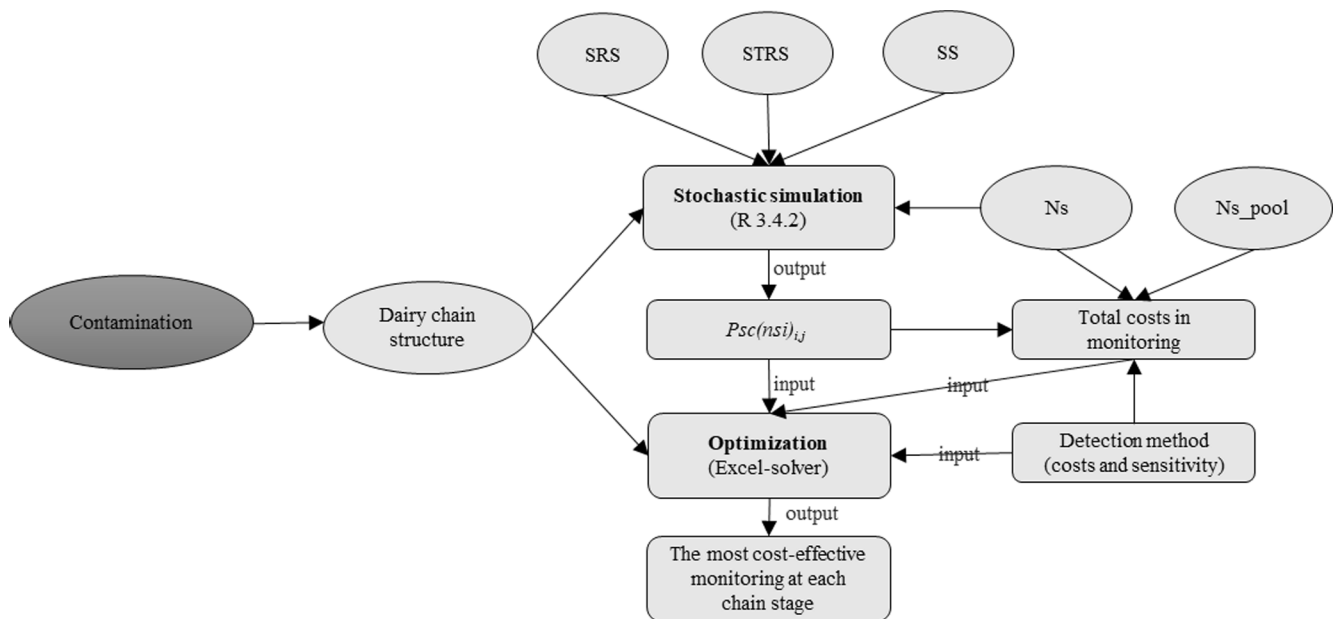


Fig. 1. Outline of the modeling approach to design a cost-effective monitoring scheme. SRS: Simple random sampling; STRS: Stratified random sampling; SS: Systematic sampling;  $Psc(nsi)_{ij}$ : Probability of collecting at least one contamination at chain stage  $i$  with strategy  $j$ ;  $Ns$ : Number of samples;  $Ns_{pool}$ : Pooling rate.

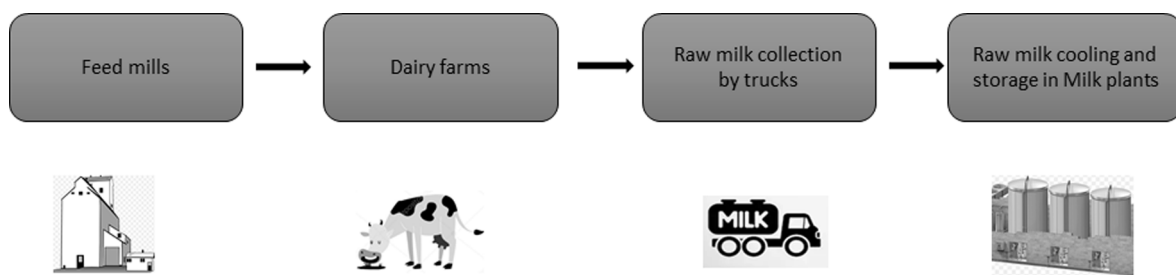


Fig. 2. Flow chart of the hypothetical Western dairy chain from feed to raw milk storage in dairy plants.

incidents, national monitoring results, and EC legal limits (European Food Safety Authority, 2012; Malisch, 2017). Then, using the simulation module, the contaminations in the consecutive stages of the chain were estimated based on the equations presented in Table 2. In our study, spatial autocorrelation was assumed in the contaminated feed mills and dairy farms, in which the low and middle level fractions of contaminated FM and DF were all localized in one region, and the high level fraction of contaminated FM and DF were randomly localized in two regions. Each dairy processing plant collected raw milk from different dairy farms by milk trucks. Milk from different dairy farms was mixed in the milk bulk at truck and in the silos in processing plants, and as a consequence, contaminated milk was mixed with non-contaminated milk in truck bulk milk and in silos. It was assumed that one contaminated milk truck had collected milk from only one contaminated farm (as well as from three other non-contaminated farms), and that one contaminated silo in a processing plant contained the milk from one contaminated truck only (worst-case situation from monitoring perspective). Then, the contaminated milk was randomly distributed among all regions in both DT and SP stages. All contamination distributions—among the ten regions and at the different dairy chain stages—were generated in the simulation module (further contamination simulation descriptions and one example are shown in Appendix B, Figure B1).

### 2.3. Monitoring scheme

The monitoring scheme was defined by the number of samples collected ( $ns_i$ ) in each production unit ( $TN_f$ ,  $TN_{df}$ ,  $TN_t$  and  $TN_s$ ), the

sampling strategy ( $STR_{ij}$ ), the pooling rate ( $ns_{pool_i}$ ), the analysis methods, and the acceptance number ( $C_i = 0$ ) at each control point  $i$ . Batches with one positive sample are assumed to be rejected and replaced by a new clean batch (at the chain stage at which they were sampled) during the monitoring period (two weeks).

First, samples were collected through one out of three sampling strategies (see next section and one example in Appendix Figure B2) under the following assumptions: no replacement upon collection, and maximum one sample per production unit (one feed mill, one dairy farm, one milk truck and one silo) at each control point. Collected incremental samples were transported to the laboratory where a certain number of collected samples were pooled into one aggregated (analytical) sample applying a certain pooling rate. From the aggregate sample, the laboratory analytical sample (aliquot) was obtained and analyzed (in our case, one analytical sample was attained from one aggregate sample), initially by the DR CALUX® screening method. In case of a positive screening result, i.e., the concentration of dioxins in the analyzed sample exceeded a pre-set decision limit (set by Eq. (14)), the sample was also analyzed by GC/HRMS for confirmation. The analytical methods were assumed to be 100% specific (all bad quality samples would be rejected) and sensitivity ( $Se$ ) was set as 98% (in total).

### 2.4. Simulation module for sampling strategies

The module simulated the probability of collecting at least one contaminated sample ( $Psc_i$ ) at control point  $i$  using three different sampling strategies (see the following section). The module was run for

**Table 1**

Model parameters and input values for the estimation of contamination of dioxins throughout the dairy supply chain.

Description	Variable	Value	Unit	Explanation
Total number of feed mills producing for dairy cattle	$TN_f$	100	mills	Assumed dairy chain input variable <sup>1</sup>
Number of regions where feed mills are distributed		10	regions	Assumed dairy chain input variable <sup>1</sup>
Fraction of contaminated feed mills	$Fcf$	1–5–10	%	Assumed contamination input variable
Concentration of dioxins in contaminated compound feed	$C_{fm}$	0.75–2.5–5–7.5	pg of TEQ/g feed	Assumed contamination input variable <sup>2</sup>
Background level of dioxins in compound feed	$C_{bf}$	0.2	pg of TEQ/g feed	The concentration of dioxins in non-contaminated products <sup>2</sup>
Carry over	$CO$	40	%	Transfer rate of dioxins from animal feed to bovine milk <sup>3&amp;4</sup>
Background level of dioxins in the milk	$C_{bm}$	0.5	pg of TEQ/g of fat	The concentration of dioxins in non-contaminated products <sup>5</sup>
Daily production of milk per cow	$Prod\_milk$	30	kg	Average daily production <sup>3</sup>
Daily intake of compound feed per cow	$In_{cf}$	8	kg	Common situation <sup>3</sup>
Total number of dairy farms	$TN_{df}$	20,000	farms	Assumed dairy chain input variable <sup>5</sup>
Fraction of fat in milk	$Ffat$	4	%	Normal nutrient fraction in raw milk <sup>3</sup>
Milk truck capacity	$Q_{truck}$	20,000	liter	Common situation <sup>5</sup>
Milk collected per each farm per delivery	$Q_{milk}$	5,000	liter	Assumed value when 4 farms are collected by the same truck and it is always full <sup>5</sup>
Total number of processing plants	$TN_p$	100	plants	Assumed input variable
Size of the storage silos	$S_s$	40,000	liter	One of the normally used size of silo
Number of silos in each plant to storage and cooling milk	$N_{sp}$	25	silos	Average value: $Q_{truck} * Q_{milk} / (TN_p * S_s)$
Possible positive deviation of the background level	$PosD$	50	%	Assumed input value <sup>5</sup>

<sup>1</sup> Assumption based on database (FEFAC, 2016; Zuivel, 2016).

<sup>2</sup> (Adamse et al., 2015).

<sup>3</sup> (Malisch, 2017).

<sup>4</sup> (Adekunte et al., 2010).

<sup>5</sup> (Lascano-Alcoser et al., 2013).

the different contamination scenarios (different fractions and concentrations) and different sampling processes, varying in terms of sampling strategy, number of collected samples, and control points along the dairy chain. For each combination of contamination scenario (in both the feed contamination and farm contamination case) and sampling process, 1000 iterations were done. The whole simulation procedure was developed using the program R, version 3.4.2 (R Core Team, 2017). The corresponding R codes are listed in Appendix B.

#### 2.4.1. Simple random sampling (SRS)

With SRS, each sample drawn from the population is independent of

**Table 2**

Variables and formulas used to estimate the contamination at each control point.

Description	Variable	Formula
Number of contaminated feed mills	$N_{cf}$	$TN_f * Fcf^1$
Concentration of dioxins in contaminated milk from dairy farms	$C_{df}$	$CO * C_{fm} * In_{cf} / (Prod\_milk * Ffat)^2$
Number of contaminated dairy farms	$N_{cdf}$	$Fcf * TN_{df}^3$
Number of dairy farms one truck collects from	$N_{dft}$	$Q_{truck} / Q_{milk}^3$
Total number of milk trucks	$TN_{ct}$	$TN_{df} / (Q_{truck} / Q_{milk})^3$
Number of contaminated trucks	$N_{ct}$	$N_{ct} = N_{cdf}^4$
Fraction of contaminated trucks	$FcfT$	$FcfT = N_{ct} / TN_{ct}$
Number of contaminated silos	$N_{cs}$	$N_{cs} = N_{cdf} = N_{ct}^4$
Concentration of dioxins in the truck milk	$C_{tm}$	$(C_{df} + (N_{dft} - 1) * C_{bm}) / N_{dft}^4$
Number of dairy trucks delivered to one silo	$N_{ts}$	$N_{ts} = S_s / Q_{milk}^3 \&^4$
Total number of silos	$TN_s$	$TN_s = TN_p * N_{sp}^5$
Fraction of contaminated silos	$FcfS$	$FcfS = N_{cs} / TN_s$
Concentration of dioxins in the silo milk	$C_s$	$(C_{tm} + (N_{ts} - 1) * C_{bm}) / N_{ts}^4$

<sup>1</sup>  $TN_f$ : Total number of feed mills producing for dairy cattle;  $Fcf$ : Fraction of contaminated feed mills.

<sup>2</sup> (Adekunte et al., 2010; Malisch, 2017);  $CO$ : Carry over;  $C_{fm}$ : Concentration of dioxins in compound feed;  $In_{cf}$ : Daily intake of compound feed per cow;  $Prod\_milk$ : Daily production of milk per cow;  $Ffat$ : Fraction of fat in milk.

<sup>3</sup>  $TN_{df}$ : Total number of dairy farms;  $Q_{truck}$ : Milk truck capacity;  $Q_{milk}$ : Milk collected per farm per delivery.

<sup>4</sup> Based on the assumption above, the worst contamination scenario was simulated in milk trucks and processing plants;  $S_s$ : Size of the storage silos;  $C_{bm}$ : Background level of dioxins in compound feed.

<sup>5</sup>  $TN_p$ : Total number of plants;  $N_{sp}$ : Number of silos per plant.

previous draws. Every draw has the same probability to hit the contaminated fraction. The probability that a certain unit of the population is included in the sample is  $P_{SRS}$ , and the inclusion probability in the Eq. (1) is the same for each unit.

$$P_{SRS} = ns_i / ns_{max_i} \quad (1)$$

Where,

$ns_i$  is the number of collected samples at control point  $i$ ;

$ns_{max_i}$  is the maximum number of collected samples at control point  $i$ , which equals the total number of production units at control point  $i$ .

#### 2.4.2. Stratified random sampling (STRS)

With STRS, the population is first divided into  $L$  subpopulations of  $N_1$ ;  $N_2$ ; ...;  $N_L$  units, and together they comprise the whole population  $N$ , so that  $N_1 + N_2 + \dots + N_L = N$ . The subpopulations are called strata and a sample is drawn from each stratum, the drawings being made independently in different strata. In our study, the total number of production units at each stage of the supply chain was divided by the number of regions where feed mills or processing plants are distributed, and thus  $L$  equaled 10. The number of samples collected in this strategy is defined in Eq. (2), as:

$$ns_i = L * ns_{str_i} \quad (2)$$

Where,

$L$  is the number of subpopulations;

$ns_{str_i}$  is the number of collected samples from each stratum at control point  $i$ .

#### 2.4.3. Systematic sampling (SS)

With SS, samples are collected at fixed intervals ( $ns_{int_i}$ ), e.g. every ten feed mills. SS is based on the number of total units in the population and the interval size. In case the population size is not a multiple of sample size, circular systematic sampling is used (Uthayakumaran,



1998). To select  $ns_i$  samples at each point, the first sample starts randomly from the whole population, followed by collection of the remaining samples at fixed intervals. Thus, the selection of the first sample (in this case generated randomly) determines the location of all samples. The number of collected samples in this strategy is defined in Eq. (3).

$$ns\_int_i = \text{Int}\left(\frac{ns\_max_i}{ns_i}\right) \quad (3)$$

Where,

$\text{Int}(x) = \text{largest integer} \leq x$ , truncated integer (Uthayakumaran, 1998);

$ns\_int_i$  is the number of units defined as the fixed interval at control point  $i$ ;

$ns\_max_i$  is the maximum number of collected samples that is equal to the total number of product units at control point  $i$ .

Samples can be collected at each control point individually, and all production units (e.g. feed mills, dairy farms, dairy trucks, and silos) at control point  $i$  were regarded as studied populations. The number of production units ( $TN_f$ ,  $TN_{df}$ ,  $TN_t$ , and  $TN_s$ ) in control point  $i$  was estimated based on the relevant parts of the hypothetical dairy supply chain (Table 1 and Table 2). The probability  $Psc(ns_i)_{ij}$  of collecting at least one contaminated sample for a certain contamination scenario at control point  $i$  using sampling strategy  $j$  for each sampling process during the monitoring period was calculated by Eq. (4).

$$Psc(ns_i)_{ij} = TIC_{ij}/TIS_{ij} \quad (4)$$

Where,

$TIC_{ij}$  is the number of iterations that collected at least one contaminated sample for each sampling process with sampling strategy  $j$  at control point  $i$ ;

$TIS_{ij}$  is the total number of iterations of each sampling process with sampling strategy  $j$  at control point  $i$  (i.e. 1000 iterations in our case).

## 2.5. Optimization module

In our study, a monitoring of dioxins scheme could be implemented at four control points, i.e. FM, DF, DT, and SP. The results of the simulation module ( $Psc(ns_i)_{ij}$ , see Appendix Table A1) are used as inputs for the optimization module; they are combined in the optimization process for the number of collected samples and the pooling rate, given the sensitivity of the analytical method and the calculated costs for sampling and analysis. In the optimization module, the probability of the monitoring of dioxins method to identify at least one contaminated sample at a certain control point is maximized. The optimization module was developed based on mixed integer programming in Microsoft Excel 2016 in combination with the Solver command from Frontline Systems Inc (Inc, 2015).

The objective function:

$$\text{Max} : P_m(ns_i, STR_{ij})_i = \sum_j (STR_{ij} * (Psc(ns_i)_{ij} * Se(ns\_pool_i))_{ij} \quad (5)$$

Constraints:

$$TMC(ns_i, ns\_pool_i)_i = SC_i + TC_i \leq \text{Budget} \quad (6)$$

$$ns\_pool_i \leq ns_i \leq ns\_max_i \quad (7)$$

$$1 \leq ns\_pool_i \leq ns\_poolmax_i \quad (8)$$

$$\sum_j STR_{ij} = 1 \quad (9)$$

Where,

$ns_i$  and  $ns\_pool_i$  are integer and nonnegative;  $i = 1, 2, 3, 4$ , represent control points,

$STR_{ij}$  are binary variables;  $j = 1, 2, 3$ , represent sampling strategies. If sampling strategy  $k$  was chosen at control point  $i$ , the corresponding  $STR_{i,k}$  was equal to 1 and  $STR_{ij}$  was 0 for  $j \neq k$ .

The objective function specified in Eq. (5) maximizes  $P_m(ns_i, STR_{ij})_i$ , i.e. the probability of identifying at least one contaminated sample at control point  $i$  for each monitoring scheme. The probability ( $Psc_{ij}$ ) of the sampling process to collect at least one contaminated sample at control point  $i$  with strategy  $j$  was computed by the simulation module. The  $Se$  (test sensitivity) is the probability of the analytical method to identify contaminated samples when the concentration of the contaminant in the collected samples is higher than or equal to the limit. In our study, based on literature, the  $Se$  of the analytical methods to correctly identify the contaminated samples equals 98% (if the  $ns\_pool_i$  exceeded the maximum limit and then  $Se$  was assumed to be 0) (Lascano-Alcoseer et al., 2014; Lascano-Alcoseer et al., 2013).

$TMC(ns_i, ns\_pool_i)_i$  in Eq. (6) represents the total costs of the sampling and analytical activities in the monitoring scheme at one control point and is comprised of sampling ( $SC_i$ ) and testing costs ( $TC_i$ ). The value of  $TMC(ns_i, ns\_pool_i)_i$  was the main constraint in this model, as it was set equal to or lower than pre-defined budgets, based on estimates of historical monitoring costs (Table 5).  $ns_i$  represents the number of collected samples at control point  $i$ ;  $ns\_max_i$  is the maximum number of  $ns_i$ , which was set as the total number of production units at each stage;  $ns\_pool_i$  represents the number of collected samples pooled into one aggregated sample at control point  $i$ ;  $ns\_poolmax_i$  represents the maximum number of  $ns\_pool_i$ , set by Eq. (15).

$$SC_i = (lc\_s + mc + tsc) * ns_i \quad (10)$$

The sampling costs function ( $SC_i$ ) consists of labor ( $lc\_s$ ), material ( $mc$ ), and transport costs ( $tsc$ ) required for the collection of one sample (See Table 3) in Eq. (10).

$$TC_i = ((TC\_scree + lc\_test) * ns_i / ns\_pool_i) + ((TC\_conf + lc\_test) * Ppt_i * ns_i / ns\_pool_i) \quad (11)$$

In Eq. (11), testing costs ( $TC_i$ ) are composed of both the screening and confirmatory method costs (See Table 3). All laboratory samples ( $ns_i / ns\_pool_i$ ) are first analyzed using the screening method. Costs of one screening test included labor ( $lc\_test$ ) and screening test costs ( $TC\_scree$ ), thus costs for one screening test are equal to

**Table 3**

Model variables and input values to estimate the costs of the sampling plan.

Parameters	Abbreviation	Value	Unit	Explanation
Labor cost	$Lc\_s$	12.25	€/sample	Take milk samples at milk truck; time/sample: 15 min; salary: €49/h. <sup>1</sup>
Materials cost	$Mc$	0.4	€/sample	Cost of materials in sampling activities. The materials are used for labelling, collecting and storing samples in these processes. <sup>2</sup>
Transport cost	$Tsc$	1	€/sample	Cost of transporting samples to laboratory based on post NL (€10 / 2 kg). Ten samples are assumed to weigh 2 kg. <sup>3</sup>
Screening test cost	$TC\_scree$	100	€/sample	Cost of screening method based on literature. <sup>3</sup>
Confirmatory test cost	$TC\_conf$	350	€/sample	Cost of confirmatory method based on expert's experience. <sup>3</sup>
Labor cost in detection	$Lc\_test$	21	€/sample	Time: 20 min/sample, €63/h. <sup>1</sup>

<sup>1</sup> Tariffs, Dutch Gov., LNV, 2011, medium tariff.

<sup>2</sup> (Reber, Reist, & Schwermer, 2012).

<sup>3</sup> (Lascano-Alcoseer et al., 2013).

$(TC_{scree} + lc_{test}) * (ns_i / ns_{pool_i})$  In a second step, suspect samples were analyzed by the confirmation test, which also comprises both labor and test costs ( $TC_{conf}$ ). The  $Ppt_i$  is the probability that at least one positive pooled sample was screened at control point  $i$  and this value was equal to  $Psc(ns_i)_{ij}$ . To simplify the confirmatory testing procedure, it was assumed that only one positive pooled sample is tested by the confirmation method. Thus, costs of the confirmation test were equal to  $(TC_{conf} + lc_{test}) * Ppt_i * 1$ .

$$Ccp_i = (Cct_i + (Cnct_i * (ns_{pool_i} - 1))) / ns_{pool_i} \quad (12)$$

In Eq. (12),  $Ccp_i$  represents the average concentration of the chemical in the contaminated test samples at point  $i$ .  $Cct_i$  is the concentration in all contaminated samples at point  $i$  (i.e.  $C_{fm}$ ,  $C_{df}$ ,  $C_{tm}$  and  $C_{s}$ ).  $Cnct_i$  is the average concentration in non-contaminated samples at point  $i$ , which equals the background level of the contaminant in feeds or milk ( $C_{bf}$  or  $C_{bm}$ ).  $(ns_{pool_i} - 1)$  is the number of non-contaminated samples mixed into one pooled sample at point  $i$ . It was assumed that only one contaminated sample was mixed into a pooled sample that tested positive, accounting for the worst-case situation in which the highest number of samples were collected to get the required effectiveness.

$$Ccp_i \geq C_{DL_i} \quad (13)$$

The contaminated samples could only be identified by the testing procedure when the concentration in the tested sample reached or exceeded the decision limit ( $C_{DL_i}$ ).

$$C_{DL_i} = Cnct_i + (Cnct_i * PosD) \quad (14)$$

$Cnct_i$  is the average dioxins concentration in the non-contaminated tested samples at point  $i$ , which is equal to the background level of the contaminant in compound feeds or milk.  $PosD$  is the assumed possible positive deviation of the background level (Table 1), and this value was based on existing literature for dioxins (Lascano-Alcoser et al., 2013). Thus, based on Eq. (12), (13), and (14), the number of samples mixed into one pooled sample can be limited (15). Note that compound feed by itself could be considered as one pooled sample (since it consists of the combination of many different ingredients), in which contaminations of dioxins can be effectively detected.

$$ns_{pool_i} \leq (Cct_i - C_{DL_i}) / (C_{DL_i} - Cnct_i) + 1 \quad (15)$$

## 2.6. Application of the monitoring of dioxins in Dutch dairy farms

As a second case study, the farm contamination case, the developed

modelling approach was applied to assumed scenarios for contamination at the dairy farm (fraction of farms contaminated and concentration of dioxins) and using historical monitoring data for dioxins in raw milk in DF in the Netherlands from 2008 to 2016 to estimate the monitoring effectiveness. Three contamination scenarios were considered (Farm1%C2, Farm5%C2 and Farm10%C2), in which the contamination fraction of contaminated DF varied (1%, 5%, and 10%), and the concentration was 2 pg of TEQ /g in contaminated milk fat. All contaminated farms were assumed to be spatially auto-correlated. The total number of DF and number of samples collected at the dairy farms were obtained from different data sources (Wageningen Economic Research, 2018; WFSR, 2016). DF were assumed to be evenly distributed across four large regions (Baars et al., 2004). Table 6 presents the data used, including the year of sampling, the number of collected samples, the monitoring costs, as well as the estimated effectiveness of the monitoring scheme (based on the simulation and optimization, using equations above). The effectiveness in Table 6 presents the model results using SS, SRS, and STRS sampling strategies for each contamination scenario.

## 3. Results and discussion

### 3.1. Contaminated scenarios at each stage

In the feed contamination case, we simulated twelve contamination scenarios through the hypothetical dairy supply chain based on pre-defined initial contaminations at the FM (Table 4) and in the second case study, i.e. the farm contamination case, we simulated three contamination scenarios for Dutch dairy farms (Table 6). The contamination in milk are diluted at later stages of the chain from DF, although the contaminated fraction increased from DF to SP (Table 4). The contaminated farms were localized in certain regions, but most regions were contaminated at later stages in the chain (see Appendix Figure B1).

After dioxins appear in the individual dairy cows' milk, the farm milk and bulk milk are recommended to be monitored before milk processing, according to EFSA (EFSA, 2012). So we also set DF, DT and SP as control points in the feed contamination case. In this case study, we assumed that contaminated dairy farms could be classified based on their network to feed mills. Nevertheless, it is difficult to classify the truck bulks and plant silos by their related dairy farms since exact information on this aspect is missing and the networks between these milk chain actors are too complicated to be simulated. Because one milk truck would collect raw milk from different farms, dioxins from different contaminated farms would randomly spread and be diluted in the mixed raw milk

**Table 4**

Contamination scenarios of the feed contamination case in different control points with contamination fraction and concentration of dioxins in contaminated products.

Initial contamination at FM	Fraction contaminated units at each control point				Concentration of dioxins in contaminated samples(pg of TEQ/g in feed) (pg of TEQ/g of milk fat)			
	FM <sup>1</sup>	DF <sup>1</sup>	DT <sup>2</sup>	SP <sup>3</sup>	FM	DF	DT	SP
F1%C0.75 <sup>4</sup>	1%	1%	4%	— <sup>5</sup>	0.75	2.00	0.88	0.69 <sup>5</sup>
F1%C2.5	1%	1%	4%	8%	2.50	6.67	2.04	1.27
F1%C5	1%	1%	4%	8%	5.00	13.33	3.71	2.10
F1%C7.5 <sup>6</sup>	1%	1%	4%	8%	7.50	20.00	5.38	2.94
F5%C0.75	5%	5%	20%	—	0.75	2.00	0.88	0.69
F5%C2.5	5%	5%	20%	40%	2.50	6.67	2.04	1.27
F5%C5	5%	5%	20%	40%	5.00	13.33	3.71	2.10
F5%C7.5	5%	5%	20%	40%	7.50	20.00	5.38	2.94
F10%C0.75	10%	10%	40%	—	0.75	2.00	0.88	0.69
F10%C2.5	10%	10%	40%	80%	2.50	6.67	2.04	1.27
F10%C5	10%	10%	40%	80%	5.00	13.33	3.71	2.10
F10%C7.5	10%	10%	40%	80%	7.50	20.00	5.38	2.94

<sup>1</sup> FM: feed mills; DF: dairy farms. Contamination was randomly localized in one region or two regions at these control points.

<sup>2</sup> DT: dairy trucks; the worst-case scenario was assumed, i.e. the maximum number of dairy farms were contaminated.

<sup>3</sup> SP: silos in plants; the worst-case scenario was assumed, i.e. the maximum number of storage silos were contaminated.

<sup>4</sup> Fx%Cy: the contamination fraction is x% of total feed mills with y pg of TEQ/g of dioxins in compound feed; 0.75 pg of TEQ/g of fat is the maximum level of dioxins in compound feed.

<sup>5</sup> '—' means that there is no contaminated products in this control point, and 0.69 pg of TEQ/g of milk fat is lower than the decision limit.

<sup>6</sup> This value was assumed based on the milk incident in the Netherlands in 2004 (Hoogenboom et al., 2015).

**Table 5**

Optimal monitoring schemes for the feed contamination case with sampling strategies, sampling size, pooling rate, and effectiveness for three pre-defined budgets at different control points.

Contamination scenario	Limit budgets (€)	Optimal sampling strategy				Number of samples (ns) with pooling rate (ns_pool)				Effectiveness (%)			
		FM <sup>1</sup>	DF <sup>1</sup>	DT <sup>2</sup>	SP <sup>2</sup>	FM	DF	DT	SP	FM	DF	DT	SP
F1%C0.75 <sup>3</sup>	3,500 <sup>4</sup>	SS <sup>5</sup>	SS	SRS <sup>5</sup>	— <sup>6</sup>	25–1	84–6	24–1	—	25	83	61	—
F1%C2.5	3,500	SS	SS	SRS	SS	25–1	143–24	90–6	57–3	25	98	95	98
F1%C5	3,500	SS	SS	SS	SS	25–1	143–51	100–12	89–6	25	98	96	98
F1%C7.5	3,500	SS	SS	SS	SS	25–1	143–78	109–19	89–9	25	98	98	98
F5%C0.75	3,500	SS	SS	SRS	SS	24–1	78–6	23–1	—	81	98	97	—
F5%C2.5	3,500	SS	SS	SS	SS	24–1	96–24	52–6	32–3	81	98	98	98
F5%C5	3,500	SS	SS	SS	SS	24–1	96–51	52–12	32–6	81	98	98	98
F5%C7.5	3,500	SS	SS	SS	SRS	24–1	96–78	52–19	32–9	81	98	98	98
F10%C0.75	3,500	SS	SS	SS	SS	20–1	78–6	20–1	—	97	98	98	—
F10%C2.5	3,500	SS	SS	SS	SS	20–1	78–24	20–6	10–3	97	98	98	98
F10%C5	3,500	SS	SS	SS	SS	20–1	78–51	20–12	10–6	97	98	98	98
F10%C7.5	3,500	SS	SS	SS	SS	20–1	78–78	20–19	10–9	97	98	98	98
F1%C0.75	2,500 <sup>4</sup>	SS	SS	SS	—	18–1	59–6	17–1	—	20	58	49	—
F1%C7.5	2,500	SS	SS	SS	SS	18–1	123–78	102–19	77–9	20	98	98	98
F5%C0.75	2,500	SS	SS	SS	SS	16–1	60–6	16–1	—	68	96	95	—
F5%C7.5	2,500	SS	SS	SS	SS	16–1	97–78	49–19	27–12	68	98	98	98
F10%C0.75	2,500	SS	SS	SS	SS	20–1	51–6	20–1	—	97	98	98	—
F10%C7.5	2,500	SS	SS	SS	SS	20–1	51–51	20–19	10–9	97	98	98	98
F1%C0.75	1,000	SRS	SS	SRS	—	7–1	22–6	6–1	—	7	24	21	—
F1%C7.5	1,000	SRS	SS	SS	SRS	7–1	59–59	35–19	24–9	7	58	75	84
F5%C0.75	1,000	SS	SS	SRS	SS	6–1	23–6	5–1	—	32	78	66	—
F5%C7.5	1,000	SS	SS	SS	SS	6–1	60–60	28–21	12–9	32	96	98	98
F10%C0.75	1,000	SS	SS	SS	SS	6–1	24–6	5–1	—	55	97	90	—
F10%C7.5	1,000	SS	SS	SS	SS	6–1	39–39	29–21	5–5	55	98	98	98

<sup>1</sup> FM: feed mills; DF: dairy farms; contaminated production units was randomly localized in one region or two regions at these control points.

<sup>2</sup> DT: dairy trucks; SP: silos in the plants; contaminated products were evenly distributed among target area at these control points.

<sup>3</sup> Fx%Cy: the contamination fraction is x% of total feed mills with y pg of TEQ/g feed; 0.75 pg of TEQ/g feed is the legal maximum limit of dioxins in feed.

<sup>4</sup> These budgets were assumed based on estimation of costs in Dutch dioxins monitoring in dairy farms in 2015 and 2016 (see Table 6).

<sup>5</sup> SS: systematic sampling; SRS: simple random sampling.

<sup>6</sup> Concentration of dioxins was below the decision limit, thus, no monitoring was conducted.

among truck bulks and storage silos. In our study, the worst-case scenarios were chosen so as to randomly contaminate as many units as possible in dairy trucks or storage silos. In reality, if data on contaminant distribution among regions would be available, the monitoring schemes could be optimized to fit these networks more accurately at DT and SP stages.

### 3.2. Fixed budget optimal monitoring at all control points

Optimal dioxin monitoring schemes at each control point were estimated for the feed contamination case, given three predefined budgets (Table 5). Monitoring schemes involving SS were most effective in almost all contamination scenarios of this case study and chain stages. In a few scenarios, however, monitoring schemes involving SRS proved optimal at DT and SP. For most feed contamination scenarios, the effectiveness of monitoring at FM was lower than at DF, given the same budgets. Compound feed by itself can be considered as an aggregated sample, so we set the pooling rate for the FM monitoring scheme at one. This restricted the number of samples collected under the limited budget, and thus the effectiveness of monitoring at FM was lower than at DF for all contamination scenarios. So when the milk was contaminated via contaminated feed from the feed mill, the contaminated products at DF could be identified with low number of samples, whereas more samples should be collected and analyzed to identify the contamination at FM.

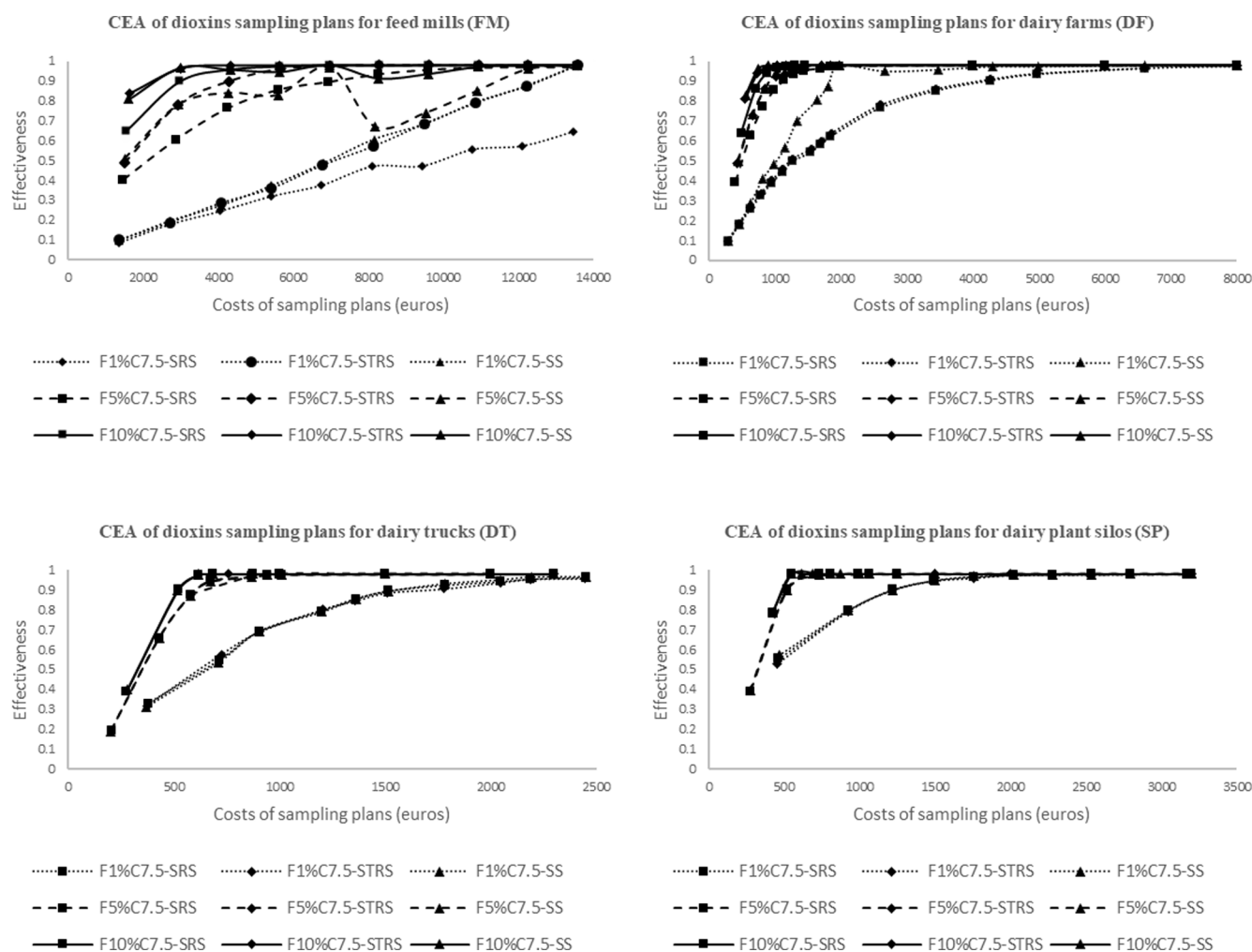
For monitoring at one control point with the same budget, the probability of identifying the contaminated sample increased with a higher contamination fraction and a higher concentration of dioxins. With the same contamination fraction and monitoring budgets, the pooling rate increased with higher concentrations of dioxins. In addition, the number of collected samples was positively related to the contamination fraction when other conditions were kept constant. For the same feed contamination scenario, optimal monitoring results varied

with the pre-defined budgets.

### 3.3. Cost-effectiveness of monitoring at all control points

Fig. 3 presents the cost-effectiveness of monitoring schemes with each sampling strategy at the four control points for all simulated feed contamination scenarios. The left vertical axis of this Figure corresponds to the calculated effectiveness of the optimal monitoring scheme. The results in Fig. 3 show that, generally, the monitoring effectiveness increases with an increasing monitoring budget. With the same pre-defined budget, the effectiveness of the monitoring schemes at the same control point decreased with decreasing dioxins concentration. Considering all feed contamination scenarios, the monitoring schemes with SS and STRS were generally more effective than those with SRS at both FM and DF. Previous studies showed that SS is more effective than SRS in terms of its ability to detect a localized or heterogeneous contamination (Bouzembrak & van der Fels-Klerx, 2017). In addition, the sampling strategy has been shown to have little influence on detecting a contamination that is evenly distributed within a population (Bouzembrak & van der Fels-Klerx, 2017; Jongenburger et al., 2011). Our results are consistent with both these earlier observations.

Although SS and STRS performed better than SRS at early control points in the dairy supply chain, these two strategies also have their limitations. With STRS, the target population was classified into ten strata (according to the number of regions), and by definition, the number of samples collected should be divisible by the number of strata in the STRS. As a result, the effectiveness of monitoring schemes with STRS were limited by a restricted number of samples, and we could not determine optimal monitoring schemes with STRS in Table 5. According to the circle sampling procedure in SS, the fixed interval in the sampling procedure is the truncated integer and, consequently, a low fixed interval could restrict the probability of sampling hitting the contamination fraction (Uthayakumaran, 1998). SS seems to be less effective in the



**Fig. 3.** Cost effectiveness analysis (CEA) of the monitoring schemes for four control points (FM: feed mills; DF: dairy farms; DT: dairy trucks; SP: processing plants) for three different contamination scenarios Fx%C7.5 of the feed contamination case. Fx%C7.5: representing 1%, 5%, and 10% of feed mills contaminated with concentration of 7.5 pg of TEQ/g of compound feeds.

cyclical data movement where the length of the period of the cycle tends to be equal or close to the interval value (Elsayir, 2014), which is a limitation of using circle sampling in our case.

### 3.4. Model application

In the second case study, the farm contamination case, the model approach was applied to contamination scenarios for (only) dairy farms and historical monitoring data was used. Table 6 presents results of cost-effectiveness calculations for this real-life case of the monitoring dioxins

**Table 6**

Costs and monitoring effectiveness for three sampling strategies at dairy farms among four regions, considering three different contamination scenarios of the farm contamination case and using real monitoring data.

Data collected				Effectiveness (%)								
				Farm1%C2 <sup>4</sup>			Farm5%C2 <sup>4</sup>			Farm10%C2 <sup>4</sup>		
Year	$N_{df}$ <sup>1</sup>	$N_s$ <sup>2</sup>	$TMC(\epsilon)$ <sup>3</sup>	SRS	STRS	SS	SRS	STRS	SS	SRS	STRS	SS
2008	18,400	41	5,552	33	34	40	86	87	98	97	98	98
2009	20,300	47	6,367	37	37	47	89	92	98	97	98	98
2010	19,800	40	5,406	32	34	39	85	87	98	97	98	98
2011	19,200	39	5,279	31	32	35	85	87	98	96	98	97
2012	18,600	27	3,651	23	25	24	74	78	98	92	96	98
2013	18,700	23	3,131	20	22	22	68	72	98	89	93	98
2014	18,600	18	2,436	16	15	19	59	59	88	83	87	98
2015	18,300	19	2,578	17	19	20	61	67	93	85	91	98
2016	17,900	25	3,391	22	21	25	71	73	98	91	93	98

<sup>1</sup>  $N_{df}$ : total number of Dutch dairy farms in each year (Wageningen Economic Research, 2018).

<sup>2</sup>  $N_s$ : number of collected samples; pooling rate was assumed to be 1 in this case.

<sup>3</sup>  $TMC$ : total costs of the monitoring; these values are calculated by formula (11) in the model.

<sup>4</sup> FarmX%C2: 1%, 5% and 10% of total dairy farms were assumed to be contaminated with 2 pg of TEQ/g of fat dioxins (80% of legal limit).



at dairy farms in the Netherlands, given the three different contamination scenarios considered. Generally, for the lowest contamination level (Farm1%C2), the monitoring schemes were similarly effective at identifying a contaminated sample at dairy farms using each of the three different sampling strategies. For scenarios with a higher contamination level (Farm5%C2 and Farm10%C2), monitoring schemes involving SS were more effective in identifying a contaminated sample at dairy farms than those using the other two sampling strategies. This is consistent with results of first case study related to feed contamination.

In the farm contamination case, elevated concentration of dioxins in the milk could have been caused by different contamination sources (e.g. local environment pollution and contaminated feed ingredients). Regardless of the origin of the contamination, the contaminated farms with elevated concentrations of dioxins in milk were always adjacent or localized in certain regions, and the contamination source could be traced back to one common source of point contamination (Di meo et al., 2011; Desiato et al., 2014; Hoogenboom et al., 2015). This would lead to similar simulation results regarding the distribution of contaminated dairy farms for both case studies. Using these simulated results as inputs to the optimization module, optimal results for both the feed and farm case studies showed that monitoring schemes with SS at dairy farms were most effective.

### 3.5. Limitations

In order to model a hypothetical western European dairy chain, we assumed that production units at each dairy chain stage were evenly distributed among ten regions. However, in reality, the distribution of production units will differ geographically. With the current method, it is possible to change parameters of the dairy supply chain structure. The sampling strategies in the model were designed according to the number of regions in the target area, and can be altered to model the real-life situation. For example, the results in Table 5 were computed based on ten regions, and the results for the real Dutch dairy farms (Table 6) were computed based on four large regions (north, south, east and west) in the Netherlands. In both cases, monitoring schemes with SS at dairy farms were most cost-effective.

We mainly focused on improving the probability of identifying the contaminated sample at each control point instead of minimizing the uncertainty about unbiased contamination estimates derived from the data. The monitoring budgets in our study only covered costs in sampling and analysis procedures; thus, the costs for tracing the contamination sources and loss costs due to wrong decisions were not included in the model. The tracing costs should be discussed together with the traceability procedure (Lascano-Alcoser et al., 2013), but we did not optimize this procedure in the model. We made a strong assumption that the probability of testing results rejecting a good quality product due to false positives equaled 0 and the false negative rate was 2%, which would influence the final effectiveness of the monitoring schemes to identify the contaminated sample. However, the loss costs (e.g. the costs of releasing contaminated samples) due to false negative testing results were not taken into account, because the focus of the study was on how to allocate budgets in sample collection and testing fees in terms of identifying a positive sample. The results of this study cannot directly be applied as optimal control measures by the Food Safety Authority or food industry to control food safety hazards, but they can provide a basis for choosing appropriate sampling strategies when designing cost-effective monitoring schemes. For specific supply chains or cases at hand, more dedicated data should be added to the model.

### 4. Conclusions

We developed a modeling approach to compute cost-effective monitoring schemes for a chemical food safety hazard along the food production chain by optimizing sampling strategies, as well as sampling numbers and pooling rates, and applied it to two case studies for

contamination. The model allowed us to optimize monitoring schemes given the different spatial distribution of the contamination through the chain.

Although the model in our study was developed along with a case study of dioxins in the dairy supply chain, it is very flexible regarding the food supply chains from different countries and the chemical food safety hazard considered. For instance, with the model, we can design a cost-effective monitoring scheme for aflatoxin B1/M1 in the dairy chain, by adapting the model constraints, variables, the related dataset and the maximum permitted level in milk. We also recommended that in the future other risk like epidemiology impacts or economic loss due to hazard contamination could be studied together with this modelling approach.

### CRedit authorship contribution statement

**Z. Wang:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing. **H.J. van der Fels-Klerx:** Conceptualization, Funding acquisition, Methodology, Supervision, Validation, Writing - review & editing. **A.G.J.M. Oude Lansink:** Conceptualization, Methodology, Supervision, Validation, Writing - review & editing.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.foodres.2021.110110>.

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