Journal of Food Protection, Vol. 66, No. 10, 2003, Pages 1900–1910

Comparison of Monte Carlo and Fuzzy Math Simulation Methods for Quantitative Microbial Risk Assessment

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MS 02-284: Received 28 August 2002/Accepted 27 April 2003

ABSTRACT

The objective of food safety risk assessment is to quantify levels of risk for consumers as well as to design improved processing, distribution, and preparation systems that reduce exposure to acceptable limits. Monte Carlo simulation tools have been used to deal with the inherent variability in food systems, but these tools require substantial data for estimates of probability distributions. The objective of this study was to evaluate the use of fuzzy values to represent uncertainty. Fuzzy mathematics and Monte Carlo simulations were compared to analyze the propagation of uncertainty through a number of sequential calculations in two different applications: estimation of biological impacts and economic cost in a general framework and survival of *Campylobacter jejuni* in a sequence of five poultry processing operations. Estimates of the proportion of a population requiring hospitalization were comparable, but using fuzzy values and interval arithmetic resulted in more conservative estimates of mortality and cost, in terms of the intervals of possible values and mean values, compared to Monte Carlo calculations. In the second application, the two approaches predicted the same reduction in mean concentration (−4 log CFU/ml of rinse), but the limits of the final concentration distribution were wider for the fuzzy estimate (−3.3 to 5.6 log CFU/ml of rinse) compared to the probability estimate (−2.2 to 4.3 log CFU/ml of rinse). Interval arithmetic with fuzzy values considered all possible combinations in calculations and maximum membership grade for each possible result. Consequently, fuzzy results fully included distributions estimated by Monte Carlo simulations but extended to broader limits. When limited data defines probability distributions for all inputs, fuzzy mathematics is a more conservative approach for risk assessment than Monte Carlo simulations.

The objective of food safety risk assessment is to quantify risk levels for consumers in order to prevent unacceptable exposures, as well as to design improved processing, distribution, and preparation systems that reduce exposures to acceptable limits. Recent publications *(4, 6, 11, 13, 15, 16, 19, 20)* have focused on general approaches and tools for quantitative risk assessment. Monte Carlo simulation tools have been used extensively to develop general frameworks *(13, 15, 19)* and to analyze specific microbial risks: *Bacillus cereus* in milk *(16), Salmonella* Enteriditis in eggs *(20), Escherichia coli* O157:H7 in ground beef hamburgers *(4), E. coli* O157:H7 in fermented sausage *(11),* and *Campylobacter jejuni* in poultry *(6, 10).* It requires considerable effort to develop Monte Carlo simulations of complete food production systems because appropriate probability distributions must be defined to represent uncertainty and variability in risk factors, such as microbial loadings, processing effects, consumption levels, and health effects. In early stages of risk assessment, limited data often is available from which to estimate credible probability distributions for model parameters. If the probability distributions are suspect, confidence in a Monte Carlo sampling design is undermined, and the credibility and reliability of the simulation results are questionable. Furthermore, it is often necessary to rely on the judgements of experts to estimate uncertain and variable parameters. Probability distributions might not be the best representation of this type of uncertainty. There is a need to use alternative tools and methodologies to represent uncertainty and variability, particularly in early stages of risk assessment when limited data are available. Ideally, these techniques would be developed so that, as appropriate information and data are collected, statistical methods could be integrated without the need to completely rebuild a quantitative risk assessment model.

The simplest approach in early stages of risk assessment would be to define the limits of possible values for each variable (i.e., the best and worst cases). Hoornstra and Notermans *(11)* proposed scenario analysis for microbial risk assessment as a way to estimate the effect of processing interventions and to identify areas where improved control is needed. The worst-case approach calculates overall risk on the basis of a succession of extreme situations in a process. This approach does not consider the distribution of possible values, simply extreme limits.

Fuzzy values are defined on an interval of possible values, and a membership function is used to define weightings between 0 and 1 for all values within the interval. The membership function can be considered as a possibility distribution for values within the interval limits. Interval values with higher membership grades are "more likely" than those with lower membership grades. Interval arithmetic can be used for computations involving several fuzzy values and is explained in more detail in the next section. The

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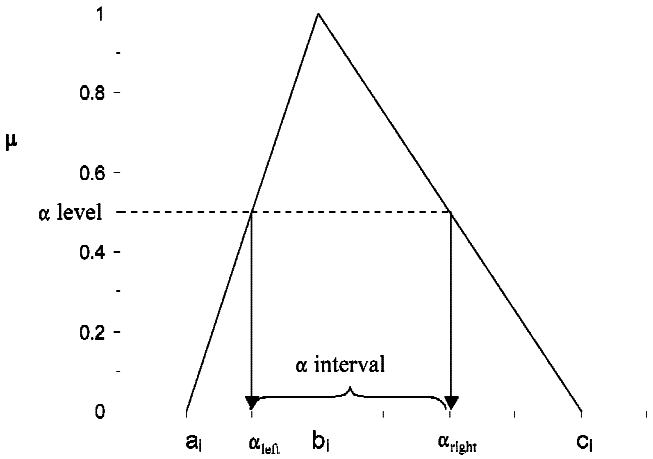

FIGURE 1. *General form of triangular fuzzy number and an alpha interval.*

result of a fuzzy computation includes all possible combinations of interval values, and the membership grade of any combination is the maximum membership grade of any of the individual terms. This is quite different from a Monte Carlo approach, where combinations of values in a computation are based on probability. Quelch and Cameron *(18)* proposed the use of fuzzy values to represent uncertainty in risk assessment and considered the propagation of uncertainty in a simple consequence model for gas release from a pressurized ammonia storage vessel. Fuzzy sets were used to represent uncertainty in physical parameters related to gas flow and dispersion in order to estimate concentration downwind and number of fatalities. The authors concluded that fuzzy sets were an acceptable means to represent uncertainty, particularly in early stages of assessment. However, in sequential calculations with fuzzy values, the uncertainty limits became very large because all combinations were included.

Ferson *(7, 8)* has developed an integrated approach to deal with different aspects of uncertainty in risk assessment. Interval analysis based on possibility theory was used to describe ignorance, and probability theory was used to describe variability. Simple algebraic operations were defined for values associated with probability or possibility distributions *(8).* All cumulative distributions for a calculated

TABLE 1. *Alpha cuts for two fuzzy fractions (*k2 *and* k4*) and summation (*k2 + k4*)*

	α interval					
	k2 ⟨0.40, 0.50, 0.60⟩		*k4* ⟨0.10, 0.20, 0.40⟩		*k2 + k4*	
α level	Left	Right	Left	Right	Left	Right
0	0.40	0.60	0.10	0.40	0.50	1.0
0.2	0.42	0.58	0.12	0.36	0.54	0.94
0.4	0.44	0.56	0.14	0.32	0.58	0.88
0.6	0.46	0.54	0.16	0.28	0.62	0.82
0.8	0.48	0.52	0.18	0.24	0.66	0.76
1	0.50	0.50	0.20	0.20	0.70	0.70

TABLE 2. *Estimation of fuzzy product (*k2 × k3*) by two approximation methods*

	α interval			
	Standard		Giachetti and Young *(9)*	
α level	Left	Right	Left	Right
0	0.040	0.24	0.040	0.24
0.2	0.052	0.21	0.049	0.21
0.4	0.064	0.18	0.060	0.18
0.6	0.076	0.16	0.072	0.15
0.8	0.088	0.13	0.085	0.12
1	0.10	0.10	0.10	0.10

value were plotted to show regions or envelopes of uncertainty for the result.

The objective of this study was to evaluate the use of fuzzy values to represent uncertainty and variability in risk assessment when there is insufficient data available to justify the use of probability distributions. We think that this approach would be useful in early stages of risk assessment and would allow an evolution to probability-based approaches as information is developed, without the need to completely rebuild the risk assessment model. The work is presented in two parts. The first section considers computational issues and the propagation of uncertainty in sequential calculations with fuzzy values. To make the analysis relevant to microbial risk assessment, a subsection of McNab's *(15)* general framework for quantitative risk assessment was considered. Estimates of biological impact, including various endpoints among infected people, were chosen as a basis for comparing uncertainty propagation in Monte Carlo and fuzzy calculations. The purpose of these comparisons is to highlight similarities and differences in the two approaches.

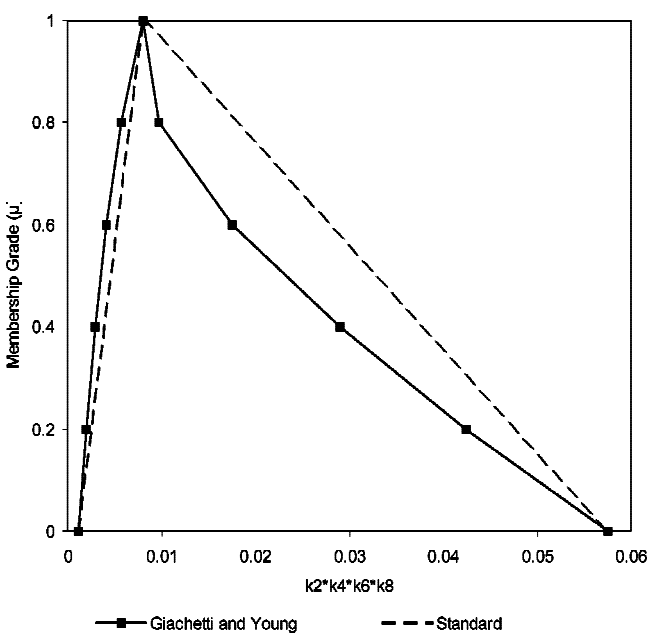

FIGURE 2. *Comparison of the standard approximation and Giachetti and Young (9) approximation for product of four fuzzy values.*

TABLE 3. *Triangular distributions and calculations for estimates of biological impact, including various endpoints among infected people (McNab (15))*

	Minimum	Mode	Maximum	Expected value	Calculation
K: Biological impact: various end points among infected people					
k2 Proportion of infected people who have clinical disease	0.40	0.50	0.60	0.5000	RiskTriang(0.40, 0.50, 0.60)
k4 Proportion of infected clinically diseased people who require hospitalization	0.10	0.20	0.40	0.2333	RiskTriang(0.10, 0.20, 0.40)
Estimates of the fraction of infected people who require hospitalization				0.1167	$k2 \times k4$
k6 Proportion of hospitalized people who require aggressive treatment and end in permanent disability	0.10	0.20	0.40	0.2333	RiskTriang(0.10, 0.20, 0.40)
Estimates of the fraction of infected people who end up with a permanent disability				0.0272	$k2 \times k4 \times k6$
k8 Proportion of *k6* that die	0.30	0.40	0.60	0.4333	RiskTriang(0.30, 0.40, 0.60)
k8 Estimates of the fraction of infected people who die				0.0118	$k2 \times k4 \times k6 \times k8$
L: Direct economic impact: costs among infected people					
l7 Direct costs for hospitalized patients who die ($)	1.0×10^6	2.0×10^6	3.0×10^6	2.0×10^6	RiskTriang(1.0×10^6, 2.0×10^6, 3.0×10^6)
Estimate of the proportion of the cost for each infected person who dies				2.36×10^4	$k2 \times k4 \times k6 \times k8 \times l7$

The second section presents a process risk model for *C. jejuni* on chicken. Fazil et al. *(6)* have developed a "farm-to-fork" process risk model for *C. jejuni* on chicken. On the basis of their review of the literature, five processing steps were considered to be the most important: scalding, defeathering, evisceration, washing, and chilling. In the case of campylobacter organisms, significant growth during processing is unlikely; however, there is a potential for contamination of carcasses during processing, and specific measures are taken to reduce the concentration of *C. jejuni* (e.g., addition of free chlorine to process water). A process model was developed to assess the effects of processing steps on *C. jejuni* concentration. Model results based on fuzzy values for parameters and interval arithmetic were compared to results based on probability distributions and Monte Carlo simulations.

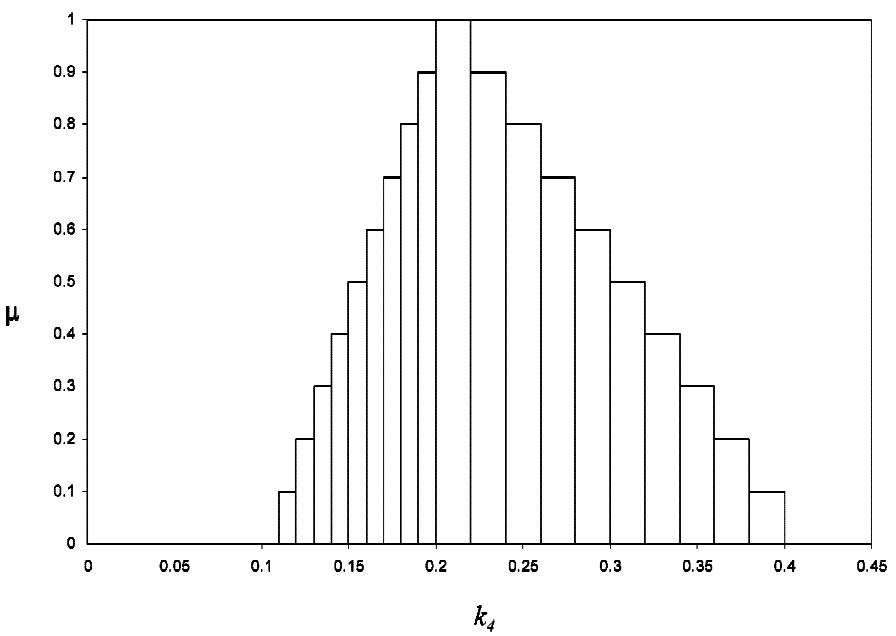

FIGURE 3. *Discrete representation for membership function of a fuzzy value (*k4*).*

TABLE 4. *Log change in* C. jejuni *levels on chickens as a result of soft scald (<55°C)*

No. of samples	Reference	Sample point	Mean log CFU/unit	Mean log change
8	Izat et al. 1988 *(12)*	Prescald	3.74	−3.11
		Postscald	<1.26	
8	Izat et al. 1988 *(12)*	Prescald	3.56	−2.30
		Postscald	1.26	
8	Izat et al. 1988 *(12)*	Prescald	3.03	−1.84
		Postscald	1.19	
8	Oosterom et al. *(17)*	Postbleed	3.99	−2.62
		Postscald	1.37	
8	Oosterom et al. *(17)*	Postbleed	3.30	−1.62
		Postscald	1.68	
8	Oosterom et al. *(17)*	Postbleed	2.18	0.22
		Postscald	2.4	
5	Berrang and Dickens *(2)*	Prescald	2.90	−1.90
		Postscald	1.0	
5	Berrang and Dickens *(2)*	Prescald	5.00	−3.00
		Postscald	2.0	
5	Berrang and Dickens *(2)*	Prescald	5.00	−3.30
		Postscald	1.7	
5	Berrang and Dickens *(2)*	Prescald	3.10	−0.70
		Postscald	2.4	
5	Berrang and Dickens *(2)*	Prescald	5.80	−3.40
		Postscald	2.4	
5	Berrang and Dickens *(2)*	Prescald	4.60	−3.10
		Postscald	1.5	

MATERIALS AND METHODS

Fuzzy values and interval arithmetic. In general, a fuzzy value X with a triangular membership function is defined by a triple.

$$X \rightarrow \langle \text{minimum, apex, maximum} \rangle$$

The minimum and maximum limits of the interval have membership grades (μ) of 0, and the apex value has a membership grade of 1. Although there are some similarities in form between a triangular fuzzy number (TFN) and a triangular probability distribution, there are differences in the interpretations of membership grade and probability. Also, the value at the apex of a triangular probability distribution depends on the size of the interval and is usually less than 1.

A TFN can be represented as a series of intervals at different grades of membership called α-cuts. Figure 1 illustrates an interval defined by an α-cut for a TFN. In a general notation, α-cuts for two TFNs, A and B, are defined as follows.

$$A \rightarrow \langle a_1, b_1, c_1 \rangle$$

$$\rightarrow [(b_1 - a_1)\alpha + a_1, -(c_1 - b_1)\alpha + c_1)] \quad \forall\alpha \in [0, 1]$$

$$B \rightarrow \langle a_2, b_2, c_2 \rangle$$

$$\rightarrow [(b_2 - a_2)\alpha + a_2, -(c_2 - b_2)\alpha + c_2)] \quad \forall\alpha \in [0, 1]$$

It is convenient to perform arithmetic operations with fuzzy numbers using alpha intervals. The sum of two fuzzy numbers is calculated by summing all combinations of interval values and assuming the maximum membership grade for each combination.

$$C = A \oplus B$$

$$= \{[(b_1 + b_2) - (a_1 + a_2)]\alpha + (a_1 + a_2),$$

$$[(b_1 + b_2) - (c_1 + c_2)]\alpha + (c_1 + c_2)\}$$

Because the addition of two TFNs is also a TFN, the operation can be simplified to summations at the vertices of the membership functions.

$$C = \langle a_1 + a_2, b_1 + b_2, c_1 + c_2 \rangle$$

The multiplication of two TFNs is more complex because the product is not a TFN

$$C = A \otimes B$$

$$= \{[(b_1 - a_1)\alpha + a_1] \times [(b_2 - a_2)\alpha + a_2],$$

$$[-(c_1 - b_1)\alpha + c_1] \times [-(c_2 - b_2)\alpha + c_2]\}$$

which expands as follows.

$$C = [(b_1 - a_1)(b_2 - a_2)\alpha^2 + (b_2 - a_2)a_1\alpha$$

$$+ (b_1 - a_1)a_2\alpha + a_1a_2,$$

$$(c_1 - a_1)(c_2 - b_2)\alpha^2 - (c_1 - b_1)c_2\alpha$$

$$- (c_2 - b_2)c_1\alpha + c_1c_2]$$

The vertices of the membership function for C (i.e., α-cuts of 0 and 1) are defined, but there are no analytical solutions for values of α between 0 and 1. A standard approximation has been developed that assumes linear membership functions between the vertices *(5),*

$$C = A \otimes B$$

$$= [(b_1b_2 - a_1a_2)\alpha + a_1a_2, (b_1b_2 - c_1c_2)\alpha + c_1c_2]$$

which can be further simplified to a TFN.

$$C = \langle a_1a_2, b_1b_2, c_1c_2 \rangle$$

The use of the standard approximation for repeated multiplication operations leads to large errors in membership grades, not at the vertices of the membership function but over the intervals between the vertices. Giachetti and Young *(9)* developed a new approximation method that corrects for the errors of the standard approximation method but is still reasonable in terms of computations. It is based on empirical coefficients (τ_{left} and τ_{right}) to estimate membership grades between the vertices. Giachetti and Young *(9)* showed that their empirical approximation is accurate for calculations including up to six fuzzy terms.

To illustrate interval arithmetic with typical values for microbial risk assessment, TFNs *k2, k4, k6,* and *k8* are defined as $k2 = \langle 0.40, 0.50, 0.60 \rangle$, $k4 = k6 = \langle 0.10, 0.20, 0.40 \rangle$, and $k8 = \langle 0.30, 0.40, 0.60 \rangle$.

These values could represent proportions of a population or subpopulation that are at risk of infection or of becoming seriously ill. Table 1 defines left- and right-side limits of alpha intervals at increments of 0.2 between 0 and 1 for *k2, k4,* and *k2 + k4.* As noted earlier, the sum of two TFNs is also a TFN, so calculations at alpha levels of 0 and 1 are sufficient. Table 2 compares the product of *k2* and *k4* using the two approximation methods and shows the difference between linear interpolation (standard approximation) and the empirical approximation of Giachetti and Young *(9).* For the product of two terms, the two approximation methods are in close agreement. Figure 2 shows results using both approximation methods for the product of four fuzzy fractions. The overall limits of a fuzzy product are identical for both approximation methods, but membership grades over the interval

TABLE 5. *Log change in* C. jejuni *levels on chickens as a result of defeathering*

No. of samples	Reference	Sample point	Mean log CFU/unit	Mean log change
8	Oosterom et al. *(17)*	After scald (>55°C)	0.61	0.46
		After defeather	1.07	
8	Oosterom et al. *(17)*	After scald (>55°C)	1.25	0.74
		After defeather	1.99	
8	Oosterom et al. *(17)*	After scald (>55°C)	1.26	1.59
		After defeather	2.85	
8	Oosterom et al. *(17)*	After scald (>55°C)	1.37	1.09
		After defeather	2.46	
8	Oosterom et al. *(17)*	After scald (>55°C)	1.68	0.41
		After defeather	2.09	
8	Oosterom et al. *(17)*	After scald (>55°C)	2.40	−0.22
		After defeather	2.18	
8	Izat et al. *(12)*	Postscald (<55°C)	<1.26	1.74
		Postpick	2.37	
8	Izat et al. *(12)*	Postscald (<55°C)	1.26	2.42
		Postpick	3.68	
8	Izat et al. *(12)*	Postscald (<55°C)	1.19	1.63
		Postpick	2.82	
5	Berrang and Dickens *(2)*	Postscald (<55°C)	1.00	0.50
		Postpick	<3	
5	Berrang and Dickens *(2)*	Postscald (<55°C)	2.00	1.20
		Postpick	3.20	
5	Berrang and Dickens *(2)*	Postscald (<55°C)	1.70	2.80
		Postpick	4.50	
5	Berrang and Dickens *(2)*	Postscald (<55°C)	2.40	0.70
		Postpick	3.10	
5	Berrang and Dickens *(2)*	Postscald (<55°C)	2.40	1.70
		Postpick	4.10	
5	Berrang and Dickens *(2)*	Postscald (<55°C)	1.50	2.20
		Postpick	3.70	

are quite different. The Giachetti and Young *(9)* approximation results in substantial corrections to membership grades over the interval on the right-hand side of the apex in this calculation because three of the underlying values (*k4, k6,* and *k8*) are asymmetric. In contrast to fuzzy addition, the product of three or more fuzzy numbers requires calculations at intermediate alpha levels between 0 and 1.

Comparing uncertainty propagation in Monte Carlo and fuzzy calculations. The first objective was to compare Monte Carlo simulations and fuzzy calculations in a context that was directly relevant to microbial risk assessment in order to understand similarities and differences in the two approaches. The distributions defined by McNab *(15)* for high biological impact and economic cost calculations were used to define membership functions for fuzzy values as well as probability distributions for Monte Carlo simulations. The characteristics of the distributions and significance of each calculation are defined in Table 3. The four fractions (*k2, k4, k6,* and *k8*) used in the discussion of interval arithmetic take on practical significance as proportions of an infected population with different health outcomes.

To conduct Monte Carlo simulations, Palisade's @RISK software was used as an add-in to Microsoft Excel. Each simulation was run with 10,000 iterations using Latin-Hypercube sampling. A probability density graph was constructed from the simulation data by creating 100 equally sized intervals and calculating the fraction of sample values within each interval to estimate the probability density. Probability density values were converted to relative values between 0 and a maximum value of 1 by dividing each probability density value by the maximum probability density value. This allowed comparisons between probability density functions and membership functions for fuzzy values.

Fuzzy membership functions were partitioned into discrete intervals based on 0.1 increments of α-cuts (Fig. 3) for ease of computation. The Giachetti and Young *(9)* approximation was used to estimate fuzzy products for three or more terms. The mean of a fuzzy value was calculated as the center of gravity or first moment of the discrete membership distribution

$$\text{mean} = \frac{\sum_{i=1}^{19} x_{\text{mid},i}\,\mu_i \Delta x_i}{\sum_{i=1}^{19} \mu_i \Delta x_i}$$

where μ_i is the membership grade over an interval Δx_i and $x_{\text{mid}\,i}$ is the midpoint of the interval value.

Effects of processing steps on *C. jejuni* in fresh poultry. The second objective was to simulate the effects of five processing steps (scalding, defeathering, evisceration, washing, and chilling) on concentrations of *C. jejuni* on poultry carcasses using fuzzy and statistical approaches. A prescald concentration of campylobacter on carcasses (log CFU/ml rinse) was defined as a triangular distribution (log γ_0). The effects of three steps (soft scald, washing, and chilling with chlorine) were defined in terms of absolute changes (log values) achieved by each operation. It was assumed

TABLE 6. *Log change in* C. jejuni *levels on chickens as a result of evisceration*

No. of samples	Reference	Sample point	Mean log CFU/unit	Mean log change
8	Oosterom et al. *(17)*	After defeather	1.07	1.51
		After evisceration	2.58	
8	Oosterom et al. *(17)*	After defeather	1.99	0.45
		After evisceration	2.44	
8	Oosterom et al. *(17)*	After defeather	2.85	−0.25
		After evisceration	2.60	
8	Oosterom et al. *(17)*	After defeather	2.46	−0.22
		After evisceration	2.24	
8	Oosterom et al. *(17)*	After defeather	2.09	0.53
		After evisceration	2.62	
8	Oosterom et al. *(17)*	After defeather	2.18	0.32
		After evisceration	2.50	
8	Izat et al. *(12)*	Postpick	2.37	0.75
		Post–viscera removal	3.12	
8	Izat et al. *(12)*	Postpick	3.68	−0.19
		Post–viscera removal	3.49	
8	Izat et al. *(12)*	Postpick	2.82	0.67
		Post–viscera removal	3.49	
5	Berrang and Dickens *(2)*	Postpick	<3.00	0.50
		Postevisceration	1.60	
5	Berrang and Dickens *(2)*	Postpick	3.20	0.00
		Postevisceration	3.20	
5	Berrang and Dickens *(2)*	Postpick	4.50	−0.80
		Postevisceration	3.70	
5	Berrang and Dickens *(2)*	Postpick	3.10	−0.57
		Postevisceration	2.53	
5	Berrang and Dickens *(2)*	Postpick	4.10	−0.10
		Postevisceration	4.00	
5	Berrang and Dickens *(2)*	Postpick	3.70	0.00
		Postevisceration	3.70	
11	Abu-Ruwaida et al. *(1)*	After defeather	5.75	−0.05
		After long sucking	5.70	

TABLE 7. *Log change in* C. jejuni *levels on chickens as a result of washing*

No. of samples	Reference	Sample point	Mean log CFU/unit	Mean log change
5	Berrang and Dickens *(2)*	Postevisceration	1.60	−1.10
		Prechill	<1.00	
5	Berrang and Dickens *(2)*	Postevisceration	3.20	−1.10
		Prechill	2.10	
5	Berrang and Dickens *(2)*	Postevisceration	3.70	−0.40
		Prechill	3.30	
5	Berrang and Dickens *(2)*	Postevisceration	2.53	−0.53
		Prechill	2.00	
5	Berrang and Dickens *(2)*	Postevisceration	4.00	−2.40
		Prechill	1.60	
5	Berrang and Dickens *(2)*	Postevisceration	3.70	−1.00
		Prechill	2.70	
8	Izat et al. *(12)*	Prewash	2.83	−1.12
		Postwash	1.71	
8	Izat et al. *(12)*	Prewash	2.94	−0.55
		Postwash	2.39	
8	Izat et al. *(12)*	Prewash	3.50	−0.46
		Postwash	3.04	
11	Abu-Ruwaida et al. *(1)*	Postevisceration	5.70	−0.60
		Postwash	5.10	

TABLE 8. *Log change in* C. jejuni *levels on chickens as a result of chilling, chlorine added to chill tank*

No. of samples	Reference	Sample point	Mean log CFU/unit	Mean log change
5	Berrang and Dickens *(2)*	Prechill	2.10	−0.90
		Postchill	1.20	
5	Berrang and Dickens *(2)*	Prechill	3.30	−2.20
		Postchill	1.10	
5	Berrang and Dickens *(2)*	Prechill	2.00	−1.10
		Postchill	0.90	
5	Berrang and Dickens *(2)*	Prechill	1.60	1.60
		Postchill	3.20	
5	Berrang and Dickens *(2)*	Prechill	2.70	−1.60
		Postchill	1.10	
90	Cason et al. *(3)*	Prechill	5.35	−1.50
		Postchill	3.86	
20	Line *(14)*	Prewash	2.76	−1.89 (−1.39)[a]
		Postchill	0.86	
20	Line *(14)*	Prewash	3.50	−2.28 (−1.78)[a]
		Postchill	1.22	
20	Line *(14)*	Prewash	2.27	−1.54 (−1.04)[a]
		Postchill	0.73	
20	Line *(14)*	Prewash	2.54	−1.64 (−1.14)[a]
		Postchill	0.90	
20	Line *(14)*	Prewash	3.01	−2.09 (−1.59)[a]
		Postchill	0.92	
20	Line *(14)*	Prewash	3.32	−2.31 (−1.81)[a]
		Postchill	1.01	
20	Line *(14)*	Prewash	2.61	−1.80 (−1.30)[a]
		Postchill	0.81	
20	Line *(14)*	Prewash	2.95	−1.78 (−1.28)[a]
		Postchill	1.17	
20	Line *(14)*	Prewash	1.96	−1.17 (−0.67)[a]
		Postchill	0.79	

[a] Line data include the effects of washing, corrected by 0.5 log for washing.

that defeathering and evisceration were conducive to cross-contamination with microorganisms from one carcass transferring to other carcasses. For each operation, it was assumed that carcass concentration could change by a fraction (f_i) of the level of contamination from the previous stage. Calculation of the scald effect was

$$\log \gamma_0 + \log \Delta_{scald} = \log \gamma_1$$

where $\log \Delta_{scald}$ is the estimate of concentration change due to scalding (log values) and γ_1 is the concentration distribution after scalding.

Defeathering and evisceration effects were

$$\gamma_1 + \Delta_{defeath} + \Delta_{evisc} = \gamma_2$$

where $\Delta_{defeath} = f_{defeath}\gamma_1$, $\Delta_{evisc} = f_{evisc}(\gamma_1 + \Delta_{defeath})$, and γ_2 is the concentration distribution after evisceration ($f_{defeath}$ and f_{evisc} are fractions between 0 and 1).

Washing and chilling effects were

$$\log \gamma_2 + \log \Delta_{wash} + \log \Delta_{chill} = \log \gamma_3$$

where $\log \Delta_{wash}$ is an estimate of concentration change from washing (log values), $\log \Delta_{chill}$ is an estimate of concentration change from chilling (log values), and γ_3 is the concentration distribution after chilling.

A triangular distribution was defined for $\log \gamma_0$ on the basis of data in Berrang and Dickens *(2)* for a recent processing plant study. The literature survey by Fazil et al. *(6)* was used to estimate triangular distributions for the Δ and f values. The reference studies for each processing step are summarized in Tables 4 through 8. Triangular distributions were used as probability distributions or fuzzy numbers as appropriate for the two simulation methods. Minimum, maximum, and expected or mean values for each distribution are shown in Table 9.

Monte Carlo simulations were performed using Palisade's @RISK software as an add-in to Microsoft Excel as described in

TABLE 9. *Distributions used to define prescald concentration and effect of poultry processing steps*

	Triangular distributions for Monte Carlo and fuzzy simulations		
	Minimum	Maximum	Expected value
Prescald (log CFU/ml of rinse fluid)	4.2	5.2	4.7
Process step (all values represent log change)			
Soft scald	−3.5	0.0	−2.2
Washing	−1.5	0.0	−0.7
Chill (with Cl)	−2.5	0.0	−1.3
Fraction			
$f_{defeath}$	0	0.8	0.53
f_{evisc}	0	0.5	0.25

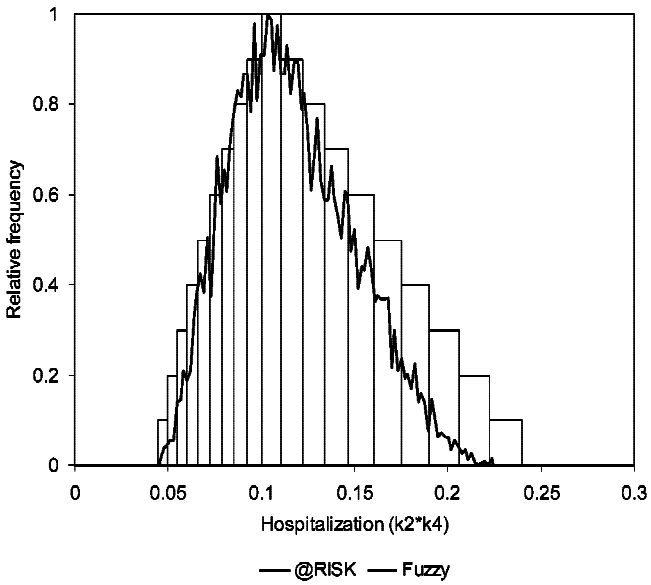

FIGURE 4. *Predicted fraction of infected people who require hospitalization (each fraction is a triangular distribution defined as minimum, mode, and maximum, where* k2 *is the fraction of infected people with clinical disease and* k4 *is the fraction of* k2 *requiring hospitalization).*

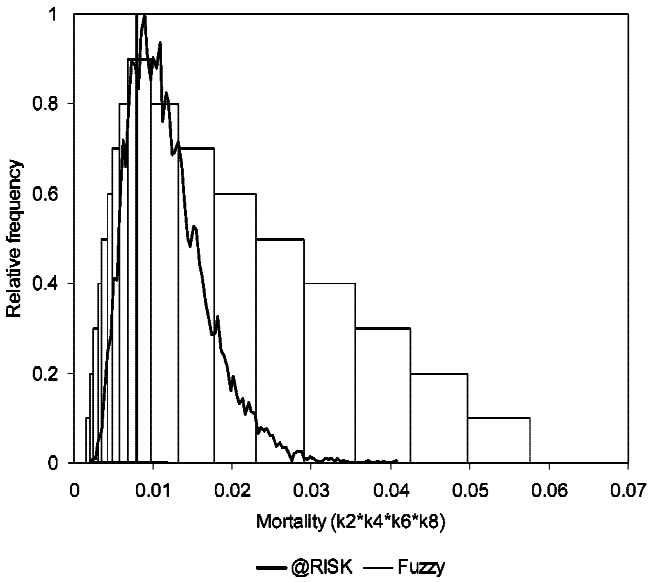

FIGURE 5. *Predicted fraction of infected people who die, where* k6 *is the fraction of infected people requiring hospitalization who do not fully recover and* k8 *is the fraction of* k6 *who die.*

the previous section. Fuzzy computations were calculated with spreadsheet software, and membership functions were discretized at 0.1 increments for each fuzzy value.

RESULTS AND DISCUSSION

Fuzzy values and computations. A subsection of the McNab *(15)* framework for quantitative risk assessment (Biological impact: various endpoints among infected people) was chosen as a basis for comparing Monte Carlo and fuzzy calculations. As shown in Figure 4, the two approaches produced similar estimates of the fraction of infected people requiring hospitalization (i.e., product of two fractions *k2* and *k4*). However, when the number of terms in a product calculation increased to four (Fig. 5) or five (Fig. 6), there were substantial differences between results for Monte Carlo and fuzzy simulations. After a number of successive operations, probability density functions tended to concentrate around a central value. Fuzzy calculations resulted in a maximum membership grade at approximately the same central value, but the membership functions were skewed and extended to much higher limits. As a result, differences in mean values for the two approaches grew larger as the number of terms in the product increased (Table 10). As shown in Figure 6, the estimate of costs based on fuzzy calculations fully included the Monte Carlo estimate but was extremely conservative (i.e., much higher average cost).

There is a fundamental difference in statistical and fuzzy approaches. For each iteration, the Monte Carlo simulation chooses values for every parameter described by a distribution that is based on a probability sampling design. The probability of combinations of extreme values for all inputs (i.e., all high or all low values) decreases as the number of inputs in a calculation increases. So the proportion of iteration results near the overall mean value increases as the number of inputs for a calculation increases. Fuzzy calculations, including the Giachetti and Young *(9)* approximation for multiplication, assume that all combinations of input values are possible and that the membership grade for any combination is the maximum of all membership grades for inputs. Consequently, the distributions for fuzzy results define higher membership grades at the extremes relative to probability densities. This has a significant effect on calculations of mean values for distributions.

In Monte Carlo simulation, the propagation of uncertainty through sequential calculations is limited by the probabilities of combinations of values, and these depend on the sampling design and probability distributions for model parameters. The sampling design (i.e., number of iterations,

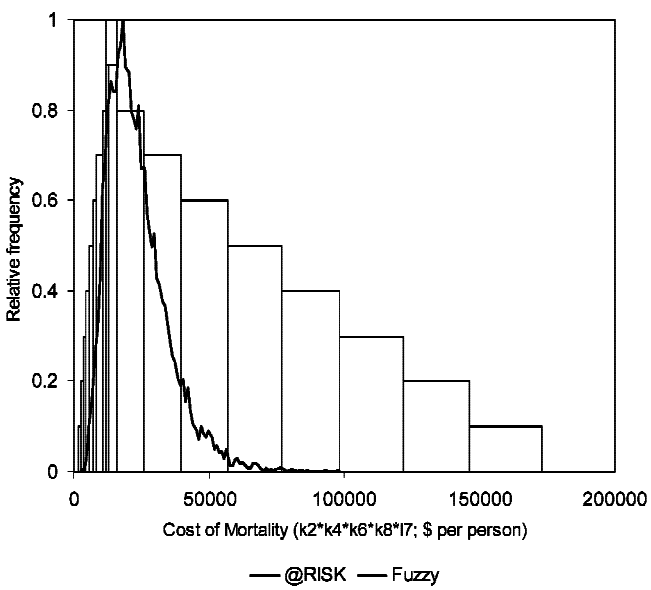

FIGURE 6. *Predicted costs of treatment and lost production, where* I7 *is the cost for hospitalized patients who die.*

TABLE 10. *Comparison of mean values for biological impacts and cost*

Biological impact		Mean value	
		Monte Carlo	Fuzzy
Predicted fraction of infected people requiring hospitalization	$k2 \times k4$	0.12	0.12
Predicted fraction of infected people who die	$k2 \times k4 \times k6 \times k8$	0.012	0.019
Predicted costs ($)	$k2 \times k4 \times k6 \times k8 \times l7$	24×10^3	52×10^3

random versus Latin-Hypercube) is not usually limiting given the sophisticated features of several commercial software tools. However in early stages of risk assessments, there is limited data to develop good estimates of probability distributions (i.e., good estimates of parameter variability). Fuzzy calculations assume that all combinations are possible at the maximum values defined by membership functions, and extreme combinations are not constrained by sampling procedures. As a result, intervals defining possible values can be large after a sequence of fuzzy calculations relative to probability-based sampling. This conservative approach might be more appropriate when estimates of variability are based on limited evidence and confidence in probability estimates is low. If this is the case, any sampling design is questionable, even if a large number of iterations is performed for a Monte Carlo simulation.

Effects of processing steps on *C. jejuni* in fresh poultry. Changes in log concentrations over a sequence of five processing steps were estimated by Monte Carlo and fuzzy simulations. The distribution for starting concentration of campylobacter (γ_0) was based on the 95% confidence interval reported by Berrang and Dickens *(2)* for a recent processing plant study. The intent was to set a realistic but conservative estimate as a starting point for the fuzzy and Monte Carlo simulations. Hence, the literature values for samples found positive were used, and the potential for some carcasses to be below detection limits was not included in this analysis. The intent was to compare fuzzy and Monte Carlo methods for a simple but realistic model of process changes. The mathematical form for the process model was the same for both simulation approaches. The effects of scalding, washing, and chilling were treated as absolute rather than proportional changes in concentration. Cross-contamination during defeathering and evisceration was treated as a process that increased the concentration on some birds and had no effect on others.

Results for the two simulation approaches were compared at each processing step (Fig. 7). Mean concentrations (log values) were close, and both simulations followed a pattern that was reasonably consistent with literature reports. The scald step achieved a 2-log reduction in the mean concentration, and the lower concentration values decreased substantially for both fuzzy and probability distributions. Subsequent defeathering and evisceration steps resulted in small increases in mean values with minimal changes in the limits of the concentration distributions. For both simulations, the mean concentration changes (log values) after defeathering were low relative to some of the literature reports. This indicated a weakness in the process model rather than the computation method. Changes predicted for the evisceration operation were consistent with literature reports. Relative to the prescald concentration distribution, washing and chilling with chlorine decreased the mean concentrations, but the intervals of possible concentration values increased in both the fuzzy and Monte Carlo simulations. The fuzzy and probability estimates of concentration distribution after chilling were also compared in Figure 7.

Fuzzy and Monte Carlo simulation methods have been presented here to show a practical application in food safety risk assessment. The literature values used to describe processing effects are realistic, but it is not possible to validate results of either simulation. Validation would only be meaningful at the level of a particular processing plant with appropriate model parameters for that plant. The objective of the comparison presented here was to evaluate fuzzy and Monte Carlo simulation results when the same descriptions of process variations are used. Although fuzzy results covered wider intervals, mean values differed only by a maximum of 0.2 log CFU/ml of rinse over the five processing steps.

Although direct comparisons between fuzzy and Monte Carlo approaches were made in this study, we recognize that these simulation tools would not be used simultaneously in practice. If sufficient information is available to define credible probability distributions, Monte Carlo methods are powerful tools for quantitative risk assessment. However, in early stages of risk assessment, there is usually limited data, and probability distributions for model parameters are not always appropriate. Fuzzy values can describe variability in model parameters on the basis of a limited number of values from the literature, quality control data, or expert opinion. Fuzzy calculations include all combinations at maximum values of possibility or membership grade. They are computationally simple relative to the sampling design and iterative calculations that are part of Monte Carlo methods, and they produce identical numerical results for every simulation. As long as the model does not become too complex (i.e., a long chain of calculations), fuzzy estimates contain information that is useful for quantitative risk assessment (e.g., intervals of possible values, mean value). However, fuzzy simulation does not constrain the possibility of extreme values as does a probability-based technique.

The ultimate goal is to develop Monte Carlo simulations for quantitative risk assessment of food production systems, but we recognize the need for a progression of modeling tools as the risk assessment process evolves. Early-stage analysis might begin with fuzzy values and interval arithmetic followed by an intermediate stage that integrates

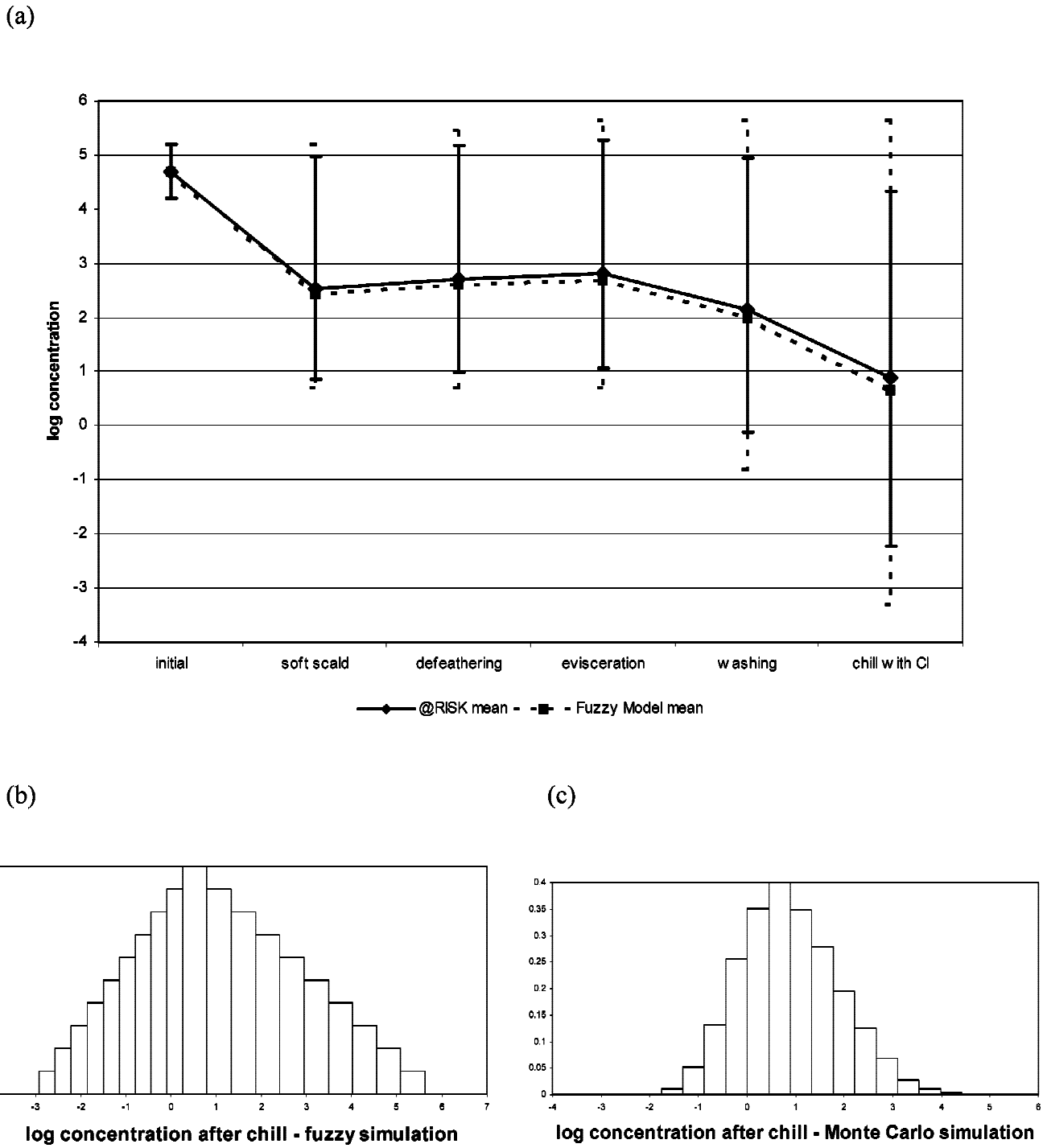

FIGURE 7. *Comparison of changes in carcass concentration of* C. jejuni *(log values) through five processing steps, where the limits indicate minimum and maximum values for each simulation method (a). Comparison of concentration distributions, postchill, estimated by fuzzy (b) and Monte Carlo (c) simulations.*

fuzzy and Monte Carlo analysis. We are working to develop a general computational framework for risk assessment that allows fuzzy values and probability distributions, as well as interval arithmetic and Monte Carlo simulation.

ACKNOWLEDGMENTS

This work was supported by the Ontario Ministry of Agriculture and Food (OMAF). Discussions with Anna Lammerding and Aamir Fazil (Heath Canada) were very helpful in the analysis and presentation of this work.

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