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SCIENTIFIC CHALLENGES IN MODELING MASTICATION OF MEAT USING ENGINEERING TOOLS

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Abstract
This paper gives an overview of scientific challenges that may occur while performing modelling meat (as a product) and simulating mastication by using engineering tools. To evaluate these challenges, Failure Mode and Effect Analysis method has been employed to assess six engineering tools often used in analyzing different perspectives of food oral processing. As a result, a risk priority number comprising of severity of the failure, occurrence probability of a failure and difficulty to detect the failure has been calculated. Results show that finite element method and emotion detection are two tools with highest levels of risks. The first method is a known engineering solution used for analyzing different types of materials, but when it comes to meat as a very complex and anisotropic material, risk of inadequate calculations is high. Emotion detection is not so much dependent on meat as a product consumed but on imperfections of software and risk of recognizing false emotions is high. Findings indicate that more research is needed for a more sophisticated use of these engineering tools. Further studies should include other engineering models that simulate meat breakdown during mastication, the role of saliva and jaw movement with the aim to carry out full modelling of mastication of an average meat consumer.

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Introduction

Modelling of food is very complex due to three constraints: knowledge about a food product, reliability of experimental data and uncertainties associated with food properties [1]. Predictive models and simulations enable development of new scientific approaches and optimizations of food products and food processes [2]. Also, modelling of food behavior can provide information related to food characteristics [3]. This is even more pronounced for multiscale modelling of food tissues with different mechanical properties [4]. Therefore, the main purpose for food engineering is to understand a certain engineering phenomenon combining existing theoretical understanding and available measurements [5].

Meat is considered as a postmortem skeletal muscle tissue of different animals used for human consumption [6]. After slaughter, it undergoes numerous changes, both physiological and biochemical [7]. As a material, it is considered as a matrix comprised of three main elements: muscle fibers, intramuscular connective tissue, and intramuscular fat [8]. However, its standardization is difficult as all these elements depend on a variety of factors such as the species/breed of the animal, age of the animal when slaughtered, type of feeding and other different animal husbandry aspects and finally position of the specific sample in the carcass [9].

Consumption of meat and meat products on a global scale demonstrates two tendencies: (i) an overall rise in consumption mainly caused by the growth of the global population, and (ii) an increase in consumption of meat expressed per capita [10]. Several authors have determined reasons for such a trend, just to mention two most important: dietary habits and nutritional needs for food with animal origin (meat) proteins [11], and sensory enjoyment when consuming meat and meat products [12]. Besides these two trends associated with nutrition and hedonisms, mastication also plays its role in overall perception of meat associated with textural perception) [13,14]. To better understand this quality attribute, it is of utmost importance to understand meat as a material and its mechanical characteristics.

Depending on mechanical properties under load, material science recognizes three types of materials, commonly associated with food: (i) isotropic materials directionally independent; (ii) orthotropic materials (interchangeable across the three main orthogonal axes), and (iii) anisotropic with different mechanical properties in all directions [15]. Meat is a very complex system dependent on the interaction between processes and forces of the meat matrix [16]. As such, meat is an anisotropic material, but for different studies/simulations authors consider it as an

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orthotropic material [17]. Figure 1 depicts some key words associated with modelling meat.

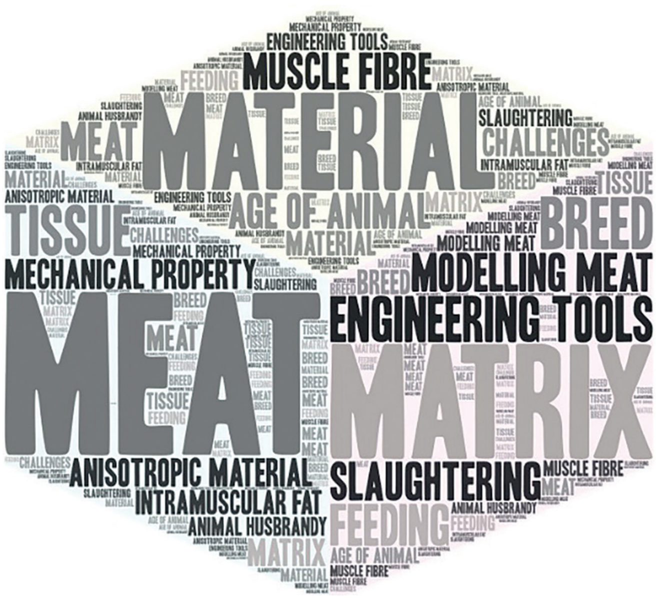


Figure 1. Word cloud figure associated with meat modelling

Mastication starts from the first bite and ends with swallowing. Food undergoes several phases, from the first bite when incisors initiate the food breakage and first deformation, followed by fractures, bite acceptance in the oral cavity, initial comminution, transportation and distribution of particles inside oral cavity, further comminution, formation of a swallowable bolus and finally swallowing [18]. The latest research confirms that the mastication behavior is more a rhythmic action that creates a pattern and it is dependent on mechanical properties of food rather than its predominant taste [19].

The main objective of this study was to evaluate challenges when modelling mastication of meat using available engineering tools through the Failure Mode and Effect Analysis and as a result weigh potential risks associated with selected tools. As the mastication process has many activities that can be modelled, only the following steps have been investigated: modeling first bite by using results from the following engineering tools — the Warner-Bratzer (BW) test, compression test and Finite Element Method (FEM); modelling bolus characteristics necessary for swallowing using the computer vision system (CVS) for particle size distribution and analyzing the mastication process itself, through video capturing and emotions detection.

Objects and methods

Ranking of risks associated with using engineering tool in modeling meat was performed by professionals with expertise in meat science and food quality, also holding engineering and technological skills. To calculate these risks, the Failure Mode and Effects Analysis (FMEA) has been used as an analytic tool [20]. This technique is very useful as it identifies possible failure modes as well as their causes but in parallel investigates effects of the failures [21]. When using FMEA, it is necessary to use previous knowledge related to similar items or problems [22]. Therefore, it is common to develop an inventory of possible failure modes and evaluate associated risks [23]. For the purpose of this study, a list of potential nonconformities has been populated. The FMEA risk also known as the "risk priority number — RPN" was calculated as follows [21]:

$$RPN = S \times O \times D \tag{1}$$

where:

(S) is the severity of the failure;
(O) stands for occurrence probability of a failure;
(D) stands for difficulty to detect the failure.

Table 1. Severity, Occurrence and Detection rating scale

Severity		
Rank	**Consequence**	**Description**
1	None	No failure(s)
2	Minor	Failure(s) associated with results for one characteristic, not critical-to-quality
3	Low	Failure(s) associated with results within one critical-to-quality meat characteristic
4	Major	Failure(s) associated with results within more than one critical-to-quality meat characteristics
5	Severe	Failure(s) associated with results affecting entire quality of meat
Occurrence		
Rank	**Probability**	**Description**
1	Very unlikely	Minimal probability of occurrence of failure(s) because of *force majeure*
2	Unlikely	Occurrence of failure(s) only because of misuse of software / instrument
3	Possible	Occurrence of failure(s) only because of errors in previous calculations/estimations
4	High probability	Occurrence of failure(s) because of human errors / mistakes
5	Certain	Occurrence of failure(s) because of lack of knowledge
Detection		
Rank	**Criteria**	**Description**
1	Very high	Failure(s) associated with results is easily detected
2	High	Failure(s) associated with results is detected during initial calculations/estimations
3	Low	Failure(s) associated with results is detected during simulation / validation
4	Remote	Failure(s) associated with results is detected during verification
5	Never	No possibility of identifying failure(s) associated with results of modelling

Table 1 outlines weighting factors of the three factors, adopted and modified from [22,24,25]. Experts who participated in the session confirmed that all important nonconformities that might occur while modelling meat were identified. Consensus for each weighting factor was reached with no opposed and/or conflicting opinions linked with final RPN score.

Results and discussion

FMEA Analysis

Results of the FMEA analysis are depicted in Table 2 for the following six selected engineering tools: the Warner-Bratzer (BW) test, compression test, Finite Element Method (FEM), computer vision system (CVS), video capturing and emotion detection.

Warner-Bratzer test

The WB test has been used for many years in order to assess meat tenderness. It measures maximum force calculated as a function of knife movement and compression shear off showing the hardness of meat [26]. As pointed in Table 2, two main issues may occur associated with this test — choice of device parameters and preparation of meat.

When it comes to the choice of test parameters, it has been confirmed that the angle of the cutting edges of the blade may affect results (an increase in shear force), as well as different blade thicknesses and the width between the blade that may influence rupture force values [27]. The RPN value of this issue is 18 mainly as this test is standardized, with the standardized 'Warner-Bratzler' blade used for different texture analysis instruments.

Preparation of a meat sample for testing is of utmost importance. The first criterion is the diameter of the sample as it must be uniformly round. This is easier to obtain from large animals' muscles with a proposed diameter of 1.27 or 2.54 cm [26]. A culinary method used for preparation is the second criterion [28] followed by chilling to 2–5 °C for obtaining consistency of the material [26]. The final criterion is the direction of fibers as this test has to be performed normally on the axis of the muscle fibers [28]. For this test, the RPN value is 36, mainly dependent on human errors associated with preparation of meat samples.

Compression test

Compression tests are used to assist true stress and strain calculations as proposed by Vallespir et al. [29] and Nieto et al. [30]. In parallel, it enables rupture stress (σR, MPa) and strain (εR) to be extracted from the first peak of the stress-strain curve. Like the WB test, this test also has two main issues that may occur related to the instrument and meat sample.

Opposed to the WB test that may be considered as standardized in terms of the blade characteristics and other instrument parameters, for the compression test a larger number of variables occur such as the test speed, compression percentage, load cell and probe selection. Also, since different mechanical properties associated with texture as a quality characteristic are obtained and/or calculated, the RPN values is 36.

When it comes to meat sample preparation, first, it has to be performed by thin-bladed sharp knives to minimize the damage of the fibers [31]. Second, besides preparation of samples, direction of fibers is in direct correlation with the results [26]. When it comes to 3D modelling, this issue is even more pronounced when it comes to under-

Table 2. Failure Mode and Effect Analysis of modelling meat using engineering tools

No	Tool	Non-conformity	Potential Failure Effect	Severity (S)	Occurrence (O)	Detection (D)	Risk
1	Warner-Bratzler	Inadequate instrument parameters	Variations in maximum force value	3	2	3	18
	Warner-Bratzler	Wrong direction of fibers	Inadequate reading of maximum force values	3	4	3	36
2	Compression test	Inadequate instrument parameters	Variations in values of tested parameters	4	3	3	36
	Compression test	Wrong direction of fibers	Inadequate reading of tested parameters	4	4	3	48
3	Finite element method	Inadequate assumptions	Wrong values and inadequate modelling	5	4	4	80
4	Computer vision system	Inadequate color detection	Wrong reading of color parameters	3	2	4	24
		Inadequate particle preparation	Incorrect calculation of particle size distribution	2	4	4	32
5	Video capturing	Video clips of low quality	Difficulty in oral processing characterization	4	4	3	48
	Video capturing	Inadequate categorization chews / consumption time	Detection of wrong oral processing characteristics	4	2	4	32
6	Emotion detection	Video clips of low quality	Difficulty in detecting emotions	5	4	4	80
	Emotion detection	Inadequate categorization of emotions	Detection of incorrect emotions	5	2	3	30

standing the direction of compression/expansion related to the fibers [17].

Finite element method

One of the most popular engineering tools is FEM and as such it has found its application in food science and food engineering. This tool enables performing different types of analyses and modelling focused on solving complex mechanical problems [32]. In meat science, its common use is mass/heat transfer [33–35], but with limited application in other dimensions of meat science such as simulating the first bite [17]. When modelling meat is performed using FEM, it is typical to define the shape of the piece (usually as cubic pieces leading to 3D simulation) to enable the use of different software. This is the first assumption when modelling meat. In parallel, other assumptions are usually a type of material (orthotropic for 3D simulation), direction of fibers and direction of forces within the material [17].

To simulate the first bite, the following assumptions are needed: the shape and size of the sample, direction of the first bite related to the direction of fibers, and position of the incisors when initiating the first bite [17]. Also, the following rules apply: (i) WB test values divided by two correspond to the first bite force; (ii) compression test values allow assumption of expansion of meat when subject to specific loading direction and values for this test enable calculation of the Poisson's ratio. These inputs are minimal requirements for mesh construction in FEM using four-node tetrahedral elements [36]. The RPN value for this tool is very high as it is directly dependent on all assumptions and pre-calculations serving as inputs in FEM simulations. Any mistake in pre-calculations and assumptions directly causes wrong values and inadequate modelling.

Computer vision system

CVS is considered as a novel tool used for instrumental evaluation of the meat color [37]. It has advantages compared to traditional colorimeters as latest studies confirm significant differences between L*, a*, b* color values of different types of meat and meat products measured with CVS opposed to colorimeters traditionally used [16,38]. This equipment also has the potential of being used for particle size distribution analysis, as these high-quality photos enable further computational processing of the number of particles and 2D calculation of the surface area of each particle [28,39].

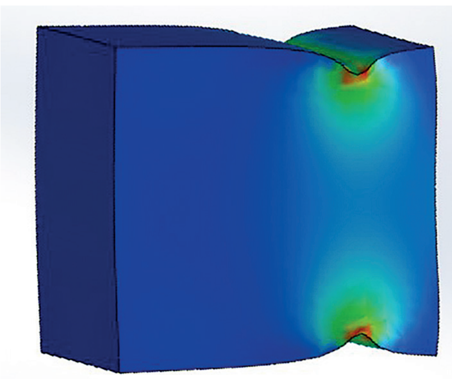
The use of this tool for color evaluation has a low RPN as this method has been developed and validated [16] and potential failures may be associated with misuse of software for color processing and/or CVS itself. However, for particle size distribution analysis, computational processing of the number of particles and their surface is more dependent on humans (in terms of spreading out the boluses with care in order not to damage the size of the particles, [28]) and consequently RPN has been calculated as 32.

Video capturing

In order to perform oral processing studies for the purpose of calculating the number of chews and consumption time, and calculating different attributes such as chewing cycle duration (s/chew), chewing rate (chews/s), eating rate (g/s) and average bite size (g) [19,40,41], it is common to video capture the mastication process involving human subjects. It is important to position the camera so that the complete upper part of the subject's body is visible and recorded [42]. When video clips are replayed, two potential solutions occur. The first one is the use of a software video analysis that has the feature to analyze graphs of time (x-axis) vs. vertical jaw displacement (y-axis) where chews are visible as peaks [40]. The second solution is the use of humans to count chews while replaying clips and cross checking for accuracy [43]. The latest research on food oral processing confirms that mastication characteristics and behavior from a consumer point of view affects consumer satisfaction in parallel with sensorial properties [19].

Video clips of low quality may cause wrong calculation of key parameters (time/number of chews) and consequently all other oral processing attributes. Therefore, the calculated RPN value is 48. However, if validated software is used, the similar issue may arise, but the RPN is 32 as all potential mistakes and errors are minimized.

a)



b)

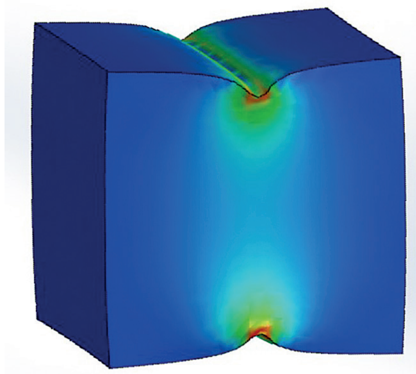


Figure 2. Stress distribution during impact of the upper and lower jaw shown for two positions:
a) at the edge of the sample; b) at the exact middle of the sample. Colors indicate gradient areas of the stress in the direction of pressure

Emotion detection

It is common to use collected video clips (from oral processing/mastication studies) for analyzing emotions [43]. The first criterion for performing this type of studies is good illumination of the face of the panelists to ensure reliable results [44]. The second one is the categorization of different emotions based on internally developed models using some databases such as DeepFace — face recognition and facial attribute analysis framework [45]. Some publications have detected five types of emotions during mastication — 'neutral', 'angry', 'sad', 'happy', and 'surprise', [43] while others have up to seven — 'angry', 'disgusted', 'happy', 'neutral', 'sad', 'scared', 'surprised' [46]. Finally, before starting these types of studies, it is necessary to avoid all types of biases such as unintended detection of wild facial expression [47] and taking off glasses (if any) as some may mask emotions [46]. Therefore, clear protocol for this type of studies is to have panelists being instructed to look directly into the camera from the first bite to swallowing [43].

Two issues may occur when detecting emotions using video capturing. The first one is in case of low quality of video clips. This issue seriously affects emotion detection and causes incorrect results and as such, the RPN value is 80. The second issue is in case of inadequate categorization of emotions mainly caused by using inadequate software and/or incorrect programing of software. Hence, the calculated RPN value for this failure is 30.

Conclusion

The FMEA-based approach for evaluating risks in using engineering tools needed for modelling meat can provide guidance to meat scientists and food engineers to concentrate efforts on the hot spots that are most influential. Our results recognize the finite element method and emotion detection as two tools with the highest level of risks and tools that are still evolving their industrial and scientific application in meat modelling. Results for the first tool are mainly linked with the complexity of meat as a material and difficulties in modelling, in spite of developed software. On the other side, emotion detection is a promising tool but dependent on the human factor and settings for video capturing of emotions associated with meat consumption and hedonism.

Limitation of this paper is the fact that only six engineering tools have been analyzed associated with the first bite, swallowing of bolus and mastication. Further studies should deploy these (and other) tools for modelling food breakdown from the first bite to swallowing, saliva incorporation, understanding jaw movement and finally modelling the chewing trajectory of an average meat consumer. As the final goal, modelling should utilize all meat changes and bolus breakdown and clearly enable validated simulations in relation with the mechanical and physical properties of all types of meat.

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The author bears responsibility for the work and presented data.

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