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Review Paper

Application of mathematical modelling in the meat chain

Ilija Đekić[1]*

[1] *University of Belgrade, Faculty of Agriculture, Nemanjina 6, 11080 Belgrade, Serbia*

A R T I C L E I N F O

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A B S T R A C T

The objective of this study was to give an overview on the application of mathematical modelling in the meat sector. The literature review employed VOSViewer as a bibliometric tool and showed three directions of research. The first is associated with models related to meat consumption, mainly in terms of consumer patterns, exposure assessment and potential health risks. The second is linked with modeling various intrinsic and extrinsic meat quality cues. The third explores modeling environmental impacts in the meat chain.

The main conclusion of this study is that mathematical modeling is an emerging scientific dimension but with limited application by the main meat chain actors. There is a need to develop user-friendly guidelines for application of this type of modeling in the meat sector.

1. Introduction

Mathematical modelling is a tool that enables understanding system/process characteristics and predicts its outcomes (*Sandeep & Irudayaraj*, 2001). The main approach when setting a mathematical model is to articulate an idea behind the model, to analyze potential theories associated with the phenomenon and to define the mathematical language (*Bender*, 1978). However, modelling in food science is a challenge due to three reasons: (i) (mis)understanding of the phenomena in focus, (ii) mathematical problems when setting the experiment and (iii) uncertainties related to food data (*Trystram*, 2012).

Mathematical modeling throughout the food chain aims to model and/or simulate different phenomena from the micro-scale to the entire food chain, with the potential to upscale certain phenomena across the chain (*Djekic et al.*, 2019). In order to successfully develop a model, it is crucial to understand the phenomenon through both theory by exploring existing knowledge and practice by performing different measurements (*Trystram*, 2012). However beside building a model by formulating the problem and outlining it mathematically, it is important to test the model and verify its robustness (*Bender*, 1978). This can be obtained by checking various what-if scenarios. Depending on the model, it may focus on optimizing a product/process or enhancing predictive simulation and improving control (*Djekic et al.*, 2019). In general models can be categorized as product-based, process-based or product-process based (*Fito et al.*, 2007).

A cross-European survey on the application of mathematical models through the food chain outlined that the main predictors for the use of models are the country where companies operate (developed opposed to less developed) and the size of the food company (large opposed to small and medium-sized companies), while the food sector is less important (*Djekic et al.*, 2019). These results reveal the lack

***Corresponding author:** Ilija Djekić, *idjekic@agrif.bg.ac.rs*

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of resources and knowledge as an issue of importance, since different competencies are needed for developing and using various models. These competences comprise food science, applied mathematics, advanced statistics, food engineering etc. (*Trystram*, 2012). Unfortunately, despite the scientific development of different models, their application is still scarce. This is even pronounced when validation of the models needs to be applied in the food companies (*Djekic & Smigic*, 2024). Some authors suggest the development of user-friendly guidelines (*Allais et al*., 2007), especially for small food companies.

When it comes to the meat sector, there are different modelling approaches from product-based models, considering meat as an orthotropic material with independent mechanical/thermal characteristics across three perpendicular directions (*Djekic et al*., 2022), consumer based models by applying Monte Carlo simulation associated with the exposure assessment of a certain population to meat product additives (*Petrović et al*., 2022), to different lifecycle assessment models throughout the meat chain (*Djekic & Tomasevic*, 2016).

Since meat science is a promising research field with many interesting phenomena where mathematical tools may be applied, the main objective of this paper was to give an overview of different mathematical models associated with the meat sector and to identify scientific breakthroughs in future studies.

2. Materials and methods

To conduct a literature review associating mathematical modelling and meat science, a text mining concept was applied using VOSViewer tool. This bibliometric analysis enabled the understanding of the current research flows. The detailed search string was as follows: ("mathema*" OR "model" OR "predictive" OR "simulation") AND ("meat" OR "meat science" OR "meat chain")). This bibliometric string was applied in the scientific database Web of Science. The cut-off criterion was the inclusion of keywords more than seven times.

3. Results

The search revealed 15,584 results. To narrow the results, the following criteria applied: (i) only research and review papers, (ii) papers from 2015 to date; (iii) papers only in English language. The outcome was 9,718 results. This search showed that these publications were written by 37,181 authors, with 8,004 affiliations from 150 countries. The top five countries/regions for the selected period were China with 2,340 publications (24.1% of total publications), USA with 1,526 (15.7%), Brazil with 563 (5.8%), Spain with 536 (5.5%) and Italy with 511 (5.3%). Out of 9,718 publications, 82 were highly cited papers with one paper reaching over 3,700 citations. These 82 papers were further processed.

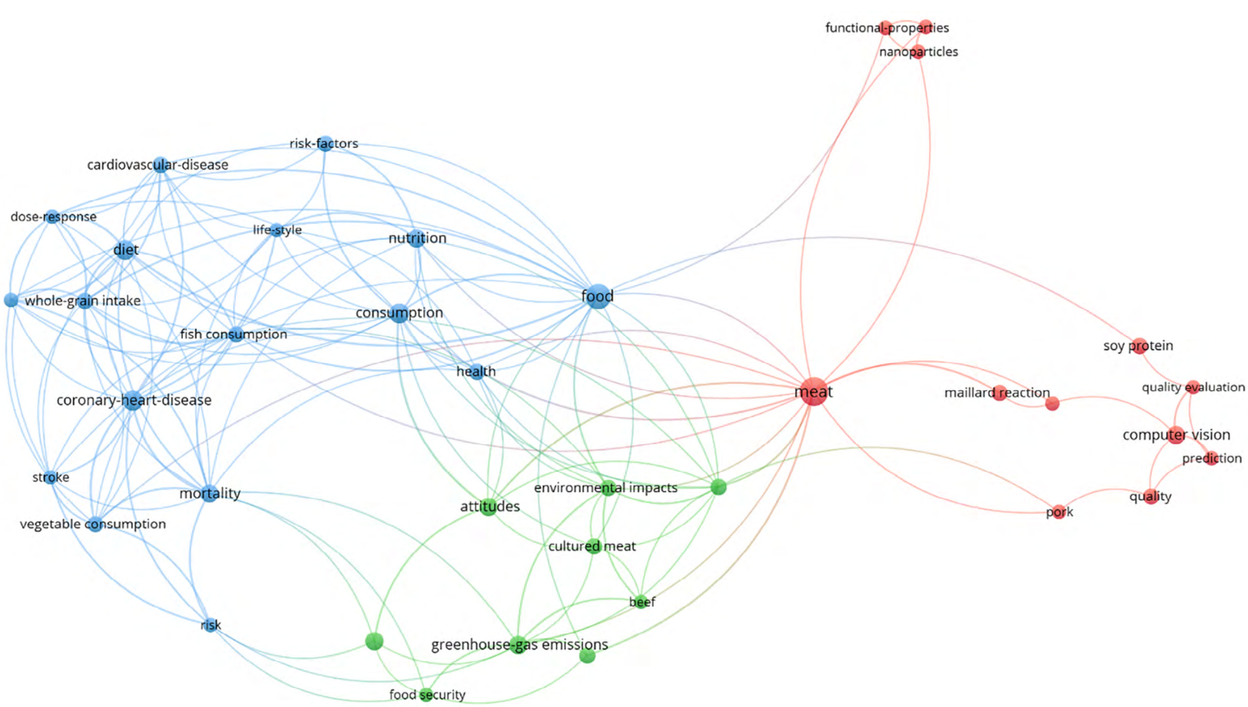

Figure 1. Network visualization of inter-linkage between meat and mathematical modelling

Figure 1 depicts the network visualization of titles, abstracts and keywords of the highly cited manuscripts that were published in the last 10 years, based on the selected strings of keywords as three clusters (outlined in different colors).

The blue cluster (consumption) is associated with models relating to meat consumption and potential health risks, such as cardiovascular or coronary heart issues. The red cluster (quality) is mainly related to different models with the aim of explaining different physico-chemical and intrinsic quality cues of meat and meat products. The green (environmental) cluster is related to modelling environmental impacts and the carbon footprint of meat throughout the meat chain.

4. Discussion

Modelling related to meat consumption has two main directions: (a) exposure assessment modelling and (b) health risk modelling. An exposure assessment is a qualitative and/or quantitative estimation of the probability that a certain population is exposed to a biological, chemical, or physical agent through food consumption (*Udovicki & Djekic*, 2024). To calculate the exposure of a certain a target compound, such as additives in meat products, it is essential to obtain data on meat consumption habits, to know the main demographic characteristics of the population (age, sex, weight and body mass index) and to perform chemical analysis of the presence of additive concentrations in meat products (*Petrović et al.*, 2022). The modelling approach to any exposure assessment is either deterministic or probabilistic (*Udovicki & Djekic*, 2024). A further step in exposure assessment is to perform a health risk assessment by combining exposure diet levels and food contamination levels to predict death and mortality *(Udovicki et al.*, 2019).

Quality-related modelling is focused on meat products, meat technology processes or both and is the most diverse area of research throughout the multiverse of intrinsic and extrinsic meat quality cues (*Rajic et al.*, 2022). An interesting quality-based modelling approach was proposed where consumer sensory scores were used as a basis for eating quality prediction scores further associated with individual quality grades for different cuts as outlined in the Meat Standards Australia (*Pannier et al.*, 2025). Other examples are the application of mathematical models predicting pig carcass composition by using total lean meat percentage and carcass weight (*Tomovic et al.*, 2019), or the application of the structural equation model on investigating relationships between carcass and meat quality traits in cattle (*Bresolin et al.*, 2022)**.**

Novel food technologies are also being modelled, such as the application of a sarcoplasmic model to investigate the effects of high-pressure processing on beef color (*Denzer et al.*, 2023). The same technology modelled whether high-pressure processing increased the *in vitro* protein digestibility (*Lee et al.*, 2023). Color was subject to analyses by applying computer vision systems (*Tomasevic et al.*, 2019, 2021). Mass transfer is a subject of different studies, such as the case of wet salting of caiman meat with the application of mathematical models enabling the prediction of mass transfer kinetics until equilibrium conditions (*Sanches et al.*, 2023).

When it comes to food safety, machine learning was used as a tool for microbial predictive modelling to anticipate the growth of *Escherichia coli* in raw ground beef depending on storage temperatures (*Al et al.*, 2024). Other examples are the use of interaction models in predicting growth of *Staphylococcus aureus* in beef (*Cheng et al.*, 2023) or predictive modeling of the growth of *Clostridium perfringens* during the cooling process of cooked pork (*Juneja et al.*, 2021).

Food oral processing and digestion are also subject to modelling. Food breakdown during mastication, eating pattern and bite size are important quality cues associated with meat (*Đekić*, 2023). Modelling food oral processing has three milestones: (i) *ex ante*, associated with testing meat properties prior to mastication, (ii) ongoing, analyzing oral processing parameters, and (iii) *ex post,* studying swallowing and digestibility (*Djekic et al.*, 2022). *In vitro* gastrointestinal models can further study if freezing-then-aging treatment of beef has any effect on the protein digestibility and release of potentially bioactive compounds (*Lee et al.*, 2024).

Environmental modelling is mainly performed using life-cycle assessment approach as outlined in ISO 14040 (*ISO*, 2006). Depending on the boundaries, the life cycle in the meat chain can span from “the cradle to the gate” covering livestock farm, slaughterhouse, meat processing plant, retail and households (*Djekic & Tomasevic*, 2016), or part of the life-cycle such as “cradle-to-gate” covering meat production and processing, “gate-to-gate” analyzing only the meat processing phase, “gate-to-grave” analyzing environmental impacts associated with the consumers and food waste or different other combinations such as "cradle-to-market" or "cradle-to-use" (*Djekic et al*., 2018). Apart from in modelling, the environmental impacts, such as global warming potential, acidification potential, eutrophication potential or ozone layer depletion, are the most often used environmental potentials in the meat chain (*Djekic & Tomasevic*, 2019).

5. Conclusion

The main conclusion of this overview is that mathematical modelling in meat science is a scientific perspective with various innovations and novelties being developed, but its application by meat producers and other actors in the meat chain is at a very low level. Future research should focus on developing user-friendly models applicable in the meat chain continuum.

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Authors info

Ilija Đekić, https://orcid.org/0000-0002-8132-8299