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Original Scientific Paper

The concept of intelligent control system for mincing meat with specified dispersion

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A R T I C L E I N F O

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A B S T R A C T

The use of a digital twin (DT) in modelling the technological process of single-stage grinding of frozen meat in real time is described. The DT concept provides for the use of its "digital shadow". Due to the significant heterogeneity of meat, the parameters of chemical composition and dispersion are determined in ranges of values with fuzzy boundaries. Fuzzy control based on the theory of fuzzy sets was applied. The developed DT ensures the stabilization of a given degree of dispersion of the grinding meat and calculates the predicted particle size. The hardware design of the process involves its use in the operation of a continuous production line for meat products. The control system operates without operator involvement, which reduces the risks of producing low-quality products and minimizes possible economic losses.

1. Introduction

The food industry faces many challenges, including inefficient production systems. To cope with this, digital twins (DT) are used, which create a digital representation of physical objects by integrating real-time and real-world data into digital space (*Saranya & Subhashini*, 2023, *Tao et al*., 2018). The application of the DT concept with the development and digitalization of Industry 4.0 has increased significantly, as evidenced by the exponential growth of publications on this topic in recent years (*Cimino et al*., 2019, *Emmert-Streib,* 2023a). DT has been widely used in agriculture (*Verdouw & Kruize,* 2017); applications focus on plant growth control (*Skobelev et al*., 2020, *Turgay et al*., 2022, *Verdouw et al*., 2021), systems for growing plants in greenhouses and fields (*Ghandar et al*., 2021, *Jans-Singh et al*., 2020), and monitoring animal conditions (*Alves et al*., 2019). A number of authors note the successful use of DT at the stages of raw material processing or packaging, as well as in the food supply chain (*Defraeye et al*., 2019, Kampker *et al*., 2019, Shoji *et al*., 2022). *Vignali et al*. (2017) developed a DT pasteurizer taking into account the dynamic parameters and properties of a non-Newtonian fluid. *Gericke et al*. (2019), considered the creation of a DT to optimize a water bottling plant on a production line. *Koulouris et al.* (2021) presented a DT for modelling the production and planning process of a brewery, taken as an example.

The DT of the process of grinding meat (GM) on continuous production lines should contain a predictive computational model identified using data obtained as a result of measuring and calculating

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model parameters during the operation of technological equipment (*Ivashov et al*., 2018). This approach will allow for continuous forecasting and measures to be taken to prevent problems before they become a serious factor affecting the quality of the final product. The mechanism of fuzzy solutions using the results of the DT provides great opportunities for implementing optimization processes in a flexible production environment (*Amrita & Ashok,* 2024). The DT of the process provides continuous learning in the production system and self-regulation (*Emmert-Streib,* 2023b). Fuzzy mathematical models, developed on the basis of fuzzy set theory (*Azeem*, 2012), have proven useful in the management of biotechnological and food processes (*Birle et al*., 2013, *Mavani et al*., 2025).

Thus, the DT in food production provides data availability and advanced analytics in real time, helping to make more informed, balanced and rational decisions. The use of DT leads to a more effective risk assessment and mitigation strategies based on an "IF...THEN" analysis as a result of modelling. The purpose of this study was to develop a concept for the use of DT to control the technological process of single-stage grinding of frozen meat.

2. Materials and methods

Frozen meat blocks (beef, 70 × 75 × 300-400 mm, core temperature -8°C to -12°C) were chopped with a laboratory single-stage grinder with capacity of 400 kg/h (Fig. 1). Mathematical calculations and plotting were carried out in the MATLAB (Fuzzy Logic Toolbox) (MathWorks, USA, https://www.mathworks.com/) computing environment (*Eshkabilov*, 2022, *Xue & Pan*, 2024). Fuzzy interval analysis (FIA)—a hybrid method combining fuzzy logic and interval mathematics—was used.

3. Results

The virtual part of the DT—a virtual model—consists of two parts: digital master (DM) and digital shadow (DS). The DM contains comprehensive information about the object necessary for its manufacture and operation. The DS that a physical object "casts into virtual space" is a set of data obtained from sensors embedded in the object, and a mathematical model that can calculate a forecast of the results of the functioning of a real object in specific operating conditions. The developed concept of a DT provides for the use of the DS of this process. The physical object in our case was the real process of single-stage grinding of frozen meat. The actuator of the chopper grinding mechanism was equipped with devices (sensors) to measure the speed of rotation of the cutting shaft, as well as the electromagnetic torque (stator current) developed by the drive motor. The mathematical model of the DS was presented in *Kapovskiy et al*. (2023).

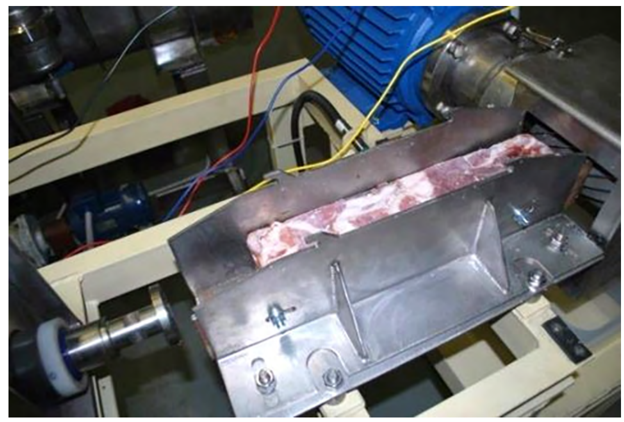

Figure 1. Laboratory single-stage frozen meat block grinder

The moment of resistance (M_c) to GM, brought to the cutting shaft of the meat chopper, is a random process due to the heterogeneity of the processed meat. Our research has shown that this process has the characteristics of a stationary ergodic random process. To solve the problem of stabilizing the established degree of grinding, we proposed hybrid control (clear and fuzzy) of the grinding process, using the mathematical model specified in *Kapovskiy et al*. (2023). This control takes into account the change in the plasticity of the meat as its temperature increases (*Kapovskiy et al*., 2020). The control computer that completes the processing line, using the DS, conducts a computational experiment of grinding virtual blocks of frozen meat using the statistical test method (Monte Carlo method), expanding the statistical base for calculating the predicted particle size of the GM (*Ivashov et al*., 2018). The computational experiment is carried out based on measurement data and calculation of a real random process $M_c(t)$. The calculated prediction of meat particle size ultimately makes it possible to more accurately determine the generalized quality criterion of the formulation mixture, taking into account the degree of its dispersion and mixing, with computer control of further processing.

Processed meat is characterized by significant heterogeneity, and as a result, the range boundaries of values of the fuzzy variables need to be determined—parameters of the chemical composition, as well as the dispersion of GM. Therefore, it is advisable to apply fuzzy control of the mixing process based on the theory of fuzzy sets (*Pujaru et al*., 2024). As a result of simulation modelling of single-stage grinding using the Monte Carlo method, a probabilistic range of particle size values with selected confidence limits was obtained. With fuzzy modelling of the process, a large width of the final fuzzy interval (range) was obtained, which leads to an increase in the uncertainty of the simulation results. At the same time, fuzzy modelling takes into account all factors, including the boundary values of the initial clear and fuzzy intervals, when describing the uncertain parameters of the model. Obtaining such guaranteed estimates using the traditional Monte Carlo approach is impossible due to the probabilistic nature of this type of modelling.

Thus, it was proposed to combine both the abovementioned approaches to formalize the uncertain parameters of the single-stage grinding. These approaches were suggested to formalize the uncertainties of the technological process consistently: 1) Conduct a simulation of the Monte Carlo single-stage grinding using the DT of the process, solving the problem of determining the boundaries of the range of finding the particle size of GM with a given accuracy and reliability. This problem is solved in the area of probability distribution (frequency domain); 2) Formalize the solution obtained in the first stage using the field of fuzzy interval analysis.

Next, the task of multi-criteria optimization of the process of composing and mixing a multicomponent mixture in a fuzzy area should be solved. It is advisable to use as criteria: a) meat chemical composition (protein, fat, moisture); b) dispersion; c) pH; d) viscosity; e) meat temperature, etc.

In the field of probability, only numerical characteristics of distributions are used (mathematical expectation, variance, median, mode, etc.). This can lead to a loss of initial information, or to a distortion of the qualitative picture of the phenomena under study. That is why, at the second stage, it is proposed to proceed to a fuzzy interval analysis. In this case, the differential distribution function $f(x)$ of the particle size of GM in the frequency domain is transformed into a membership function $\mu(x)$ of a fuzzy set by piecewise linear approximation. This will make it possible to operate with the advanced mathematical apparatus of fuzzy set theory. For the specified transformation $(f(x) \to \mu(x))$, it is advisable to use the description of membership functions of fuzzy sets using $\alpha -$ levels. This will preserve the bulk of the information provided by the differential probability distribution function $f(x)$. The $\alpha -$ level set of a fuzzy set *A* in *X* is called the set $A_{\alpha,}$ consisting of $x \in X$, whose degrees of membership in the fuzzy set *A* are not less than α (*Eshkabilov*, 2022, *Xue & Pan*, 2024):

$$A_{\alpha} = \{x(x \in X), \mu_A(x) \geq \alpha\} \quad (1)$$

The decomposition of a fuzzy set into a set of $\alpha -$levels can be written as $\cup_{\alpha} \alpha A_{\alpha}$.

Let us consider the differential function of the probability distribution of the particle size of GM obtained in a laboratory single-stage grinding (Fig. 2). The graph of the function $f(x)$ is obtained as an alignment of the histogram of the measured particle sizes determined as a result of microstructural analysis of GM. The specified histogram was given in *Kapovskiy et al*. (2023). It was hypothesized that the experimental statistical distribution of particle sizes obeys a normal law:

$$f(x) = [1/(\sigma^*(x) \cdot \sqrt{2\pi})] \cdot exp[-(x - m_x^*)^2/(2 \cdot 251.54)] \quad (2)$$

In our particular case, m_x^* = 42.28 (μm) – estimation of the statistical average meat particle size across all measurement ranges; $\sigma^*(x)$ = 15.86 (μm) – estimation of the mean square deviation for all measurement ranges. The plausibility of the hypothesis was confirmed by testing according to Pearson's criterion χ^2. Let us carry out the transformation $f(x) \to \mu(x)$. We transform the differential probability distribution function (2) into a trapezoidal fuzzy interval membership function $\mu(x)$ with four reference points that correspond to the vertices of the trapezoid. For practical (engineering) calculations, it is sufficient to have information about only two intervals corresponding to $\alpha -$ levels (1): 1) the lower base of the trapezoid $(\mu(x) = 0)$; 2) the upper base of the trapezoid, corresponding to the most possible values of the membership function $(\mu(x) \cong 1)$. For the lower base of the trapezoid, corresponding to the level $\alpha = 0$, we select an interval whose length will be $2|2{,}5\sigma^*(x)|$. Calculate the probability of the size of the meat particles falling into the specified interval:

$$P(|x - m_x^*| < 2.5 \cdot \sigma^*(x) = 2 \cdot F(2.5) \quad (3)$$

where *F* is the Laplace function. Since *F*(2.5)=0.4938, the value of the desired probability will be 0.9876. The coordinates of the two upper reference points can be determined by calculating the mean square deviation σ_i corresponding to the selected α_i − level:

$$\sigma_i = \sigma^*(x) \cdot \sqrt{-2ln(\alpha_i)} \quad (4)$$

For $\alpha_i = 0.9$:

$$\sigma_{0.9} = 15.86 \cdot \sqrt{-2ln(0.9)} = 7.28\ (\mu m).$$

Using the symmetry of the graph of the function $f(x)$ relative to m_x^* in our case, we construct the graph $\mu(x)$ in the form of a trapezoid with the bases defined above: the lower, corresponding to $\alpha = 0$, and the upper, corresponding to $\alpha = 0.9$, intervals of meat particle size values (Fig. 3). Note that for other types of distribution *x*, when transforming $f(x) \to \mu(x)$, the specific type of graph $f(x)$ should be taken into account. The approach proposed in this paper is consistent with other works (*Birle et al*., 2013, *Tao et al*., 2018), where it was noted that modelling and simulation are an integral part of the DT, and the lack of convergence between the physical and virtual space of the product data in the product lifecycle is isolated and useless for production.

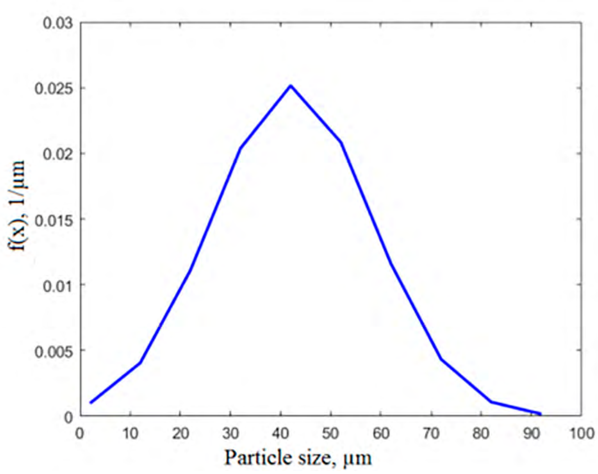

Figure 2. Differential probability distribution function (f(x)) of the particle size of GM as a random variable

Uhlemann et al. (2017) also emphasize the importance of using real-time data in DT work. Thus, as a result of the operation of the DT, the control computer has a forecast of the values of the boundaries of the particle size range of the GM, which is translated into a fuzzy region and further considered as an interval of values with fuzzy boundaries. Using the same method, the control computer processes a range of predicted chemical composition values (protein, fat, water). These parameters are considered as private quality criteria, which the control computer uses in multi-criteria process optimization and to calculate a generalized quality criterion in the form of a convolution of private criteria. Based on the calculation results, the control computer adjusts the process of grinding and composing the minced meat.

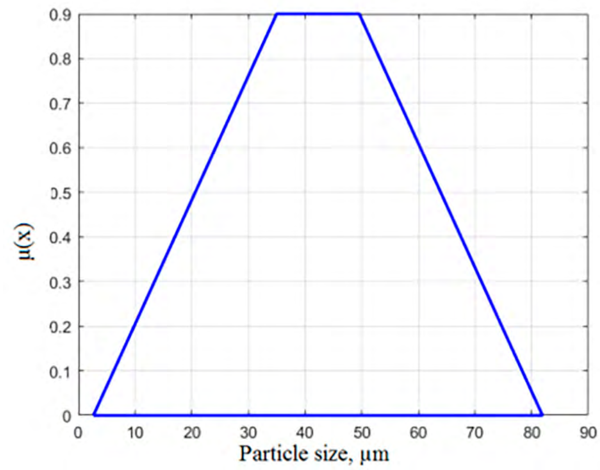

Figure 3. Trapezoidal membership function (μ(x)) of a fuzzy set of particle sizes of GM

4. Conclusion

The result of the work is a scientifically based concept of intelligent (fuzzy) control of the process of producing minced meat with a given nutritional value in the conditions of continuous technological lines. Application of the proposed process control supports on-line automated control of the preparation of minced meat of a given dispersion and chemical composition. The control system operates in real-time production without operator involvement, which reduces the risks of producing low-quality finished products and minimizes economic losses.

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