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INTELLIGENT ENGINEERING OF A SPECIALIZED MEAT-BASED PRODUCT

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Abstract
This article discusses the development and application of a digital twin (DT) for intelligent engineering of a specialized meat-based product. The focus is on the use of advanced intelligent optimization methods to create a virtual model capable of adaptively real-time managing the formula and process parameters, in accordance with the product's final purpose. To solve a food engineering problem (optimization of product formula and production modes), three metaheuristic intelligent algorithms were applied and compared: genetic algorithm (GA), particle swarm optimization (PSO), and sparrow search algorithm (SSA). The results of the comparative analysis demonstrated that SSA algorithm provided the best accuracy and convergence in solving the assigned optimization problems, making it the preferred tool for integration into the digital twin system. SSA algorithm demonstrates the ability to escape local optima, thereby avoiding the problem of premature convergence typical for some metaheuristic methods, such as GA and PSO algorithms. Based on an optimized digital twin, this approach enables dynamic prediction of physicochemical parameters, their compliance with the established medical and biological requirements for the final product, promptly adjusting its formula to meet the intended purpose of providing complete nutrition and enhancing the rehabilitation of patients with traumatic brain injuries (TBI), and ensures flexibility when scaling the technology or transferring production to another facility. Digital twins, integrating data from smart sensors and biosensors based on big data analysis, are the foundation for creating a safe, traceable, and adaptive food system. The study demonstrates that intelligent engineering based on a digital twin is a key technology for creating personalized, safe, and effective specialized food products within the framework of modern manufacturing principles and One Health concept.

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Introduction

Artificial intelligence (AI) and machine learning (ML) technologies enable the exploration and design of new food systems in a digital environment without need for extensive experimentation. Modern food formulation requires the expertise of researchers across multiple fields to achieve desired results through iterative development and innovation in the context of an intelligent engineering. To improve the result or bring parameters closer to the target, this approach requires significant time and funding for each iteration of product development, i.e. repeated data processing [1].

Algorithms, AI, and ML methods enable researchers to unlock vast opportunities for the scientific improvement (optimization) of traditional food formulas, as well as the creation of new food systems with defined compositions and properties for personalized (specialized) nutrition. With the increasing adoption of AI methods in the food industry, advances in food design increasingly move beyond traditional techniques, and the development of functional food formulas opens up entirely new possibilities [2].

The study by Lončar et al. [3] involves the use of advanced machine learning techniques in the development of dried peach cookie formulas to understand the complex relationships between input parameters (e.g., dehydrated peach and processing methods — lyophilization and lyophilization with osmotic pretreatment) and output variables representing various cookie quality characteristics. The authors used a support vector machine (SVM) and an artificial neural network (ANN) to optimize the cookie formulas. For each of the 32 output datasets, including the chemical composition of cookie samples, mineral content, moisture content, as well as baking characteristics (moisture loss, cookie thickness and diameter, hardness), color coordinates (L*, a*, b*, and ΔE), sensory characteristics and antioxidant properties, separate models were created using SVM and ANN. The obtained data demonstrated superior performance of ANN in predicting quality parameters with coefficient of determination (R^2) + 1, while when using SVM, R^2 + 0.981. Along with this, the optimal amount of dried peach (15%) and the best technology for its dehydration (lyophilization with osmotic pre-treatment) were determined.

Pasta is primarily composed of wheat flour and water. However, flour may be partially replaced with fiber to provide the diet with additional functional ingredients. However, uneven fiber distribution may affect the technological characteristics of pasta. Typically, methods for determining pasta parameters are time-consuming and destructive. To improve the efficiency of fiber distribution analysis in pasta, Badaro et al. [4] used near-infrared hyperspectral imaging (NIR-HSI) in combination with machine learning methods (multivariate curvilinear regression, MCR-ALS). The method has high potential for application in non-destructive testing. The object of study was a fettuccine formula with the addition of 2 %, 3.5 %, 5 %, and 7 % of seven different fiber types to the dough mass. This method made it possible to evaluate both the fiber distribution depending on the formula and the spatial distribution of different fiber types. The results showed R^2 values ranging from 0.28 to 0.89, % LOF[1] < 6 %. The variance explained was greater than 99 %, and the similarity between the pure and reconstructed spectra was greater than 96 % and 98 % in the models using pure flour and control as initial estimates, respectively, demonstrating the applicability of NIR-HSI and MCR-ALS for identifying fibers in pasta. However, the significant variation in R^2 values (0.28 to 0.89) across models indicates instability in predictive ability depending on the analyzed component or initial conditions.

In a sociological study, Califano et al. [5] examined the consumer perception of food products (dishes and beverages) created using AI. The key finding of the study is that trust in AI-based formulas for innovative dishes is currently low.

Ali et al. [6] used the results of tomographic studies (more than 460 3D images) obtained from a synchrotron to study bread dough formulas during rising and baking. The aim of the research was to study the effect of different bread dough formulas, especially those including flour with different protein contents and salt additives, on the microstructure, texture, and porosity of bread during fermentation and baking in order to automate the process. The authors used automatic segmentation and analysis using U-Net deep learning algorithms. Automation of dough microstructure segmentation allows for an objective and efficient study of the formula effect on porosity. The trained U-Net model outperformed previously used segmentation methods. The developed automated data segmentation model may reduce the labor intensity of the process and open up opportunities for conducting experiments in 4D format. However, a critical limitation of this approach is the opacity of the neural network ("black box"): the high accuracy of the model's predictions is not accompanied by the ability to interpret the patterns embedded within it, which prevents the identification of cause-and-effect relationships between the formula and the formation of the product structure.

Using artificial neural networks (ANN) and simplex-lattice mixture design (MD), Patil et al. [7] predicted and optimized the quality characteristics of functional cookies enriched with finger millet and jaggery as a natural sweetener. The authors used advanced optimization approaches to identify complex relationships between input variables, such as whole wheat flour (WWF) and finger millet flour (FMF), and output metrics representing various cookie quality characteristics. The resulting range of R^2 values for ANN is extremely wide (0.20 to 0.99). R^2 value of 0.20 indicates a virtually ineffective model, explaining only 20 % of the data variance. There is no explanation for such significant variation in ANN performance across different output variables. This may be due to insufficient training data, an incorrect network architecture, or the highly stochastic nature of the measured parameters themselves.

Designing specialized and functional food products based on intelligent simulation methods is a modern interdisciplinary paradigm. This approach combines advanced computational technologies with fundamental knowledge in food science, enabling the targeted creation of food systems with specified functional, technological, and consumer properties.

Lisitsyn et al. [8] and Ivashkin et al. [9] proposed a methodological approach to solving the problem of personalized (individualized) nutrition based on the principles of structural parametric simulation. A key aspect lies in the systematic formalization of accumulated data and expert knowledge of the product using modern digital technologies.

Türkmenoglu et al. [10] addressed the problem of developing personalized nutrition plans using multicriteria optimization methods. The proposed methodology is based on the application of multicriteria optimization, i.e. an evolutionary algorithm (non-dominated sorting genetic algorithm III or NSGA-III), to a real dataset consisting of prepared dishes or foods. In the presented study, the main criteria for diet optimization are: 1) the economic component (cost of food); 2) personal consumer preferences; 3) the technological aspect of dish preparation. Moreover, the model integrates daily nutrient restrictions for each meal, specified in the form of acceptable ranges (minimum — maximum) of nutrient intake. Key results demonstrate the ability of the algorithm to generate balanced daily menus, adapting them to individual user parameters: preferences, age, gender and body mass index, while adhering to recommended intake standards. The approach has a high degree of adaptability and can be expanded for individuals with special medical indications by introducing additional restrictions and modifying the regulatory requirements for the diet or dish.

Razali et al. [11] optimized menu planning for Malaysian adolescents (13 to 18 years old) using a self-adaptive hybrid genetic algorithm (SHGA). The main optimization factors in the study were: 1) minimizing the cost of the diet per student; 2) maximizing the variety of daily meals; 3) taking into account the capabilities of the caterer;

[1] LOF (Local Outlier Factor) is an algorithm for detecting anomalies in data.

4) maintaining the structure of dishes in meals; 5) fulfilling standard recommendations for nutrient intake. The methodological novelty of the study lies in the development and hybridization of two new local search methods: insertion search (IS) and insertion search with delete-and-create (ISDC). ISDC, unlike IS, expands the search area, which ensures the generation of 100 % feasible solutions. An additional improvement is the implementation of a self-adaptive strategy for adjusting the parameters of the mutation operator, which significantly reduces the computation time (to several minutes) and prevents the problem of premature convergence. The developed SHGA approach demonstrates a significant performance improvement compared to the traditional genetic algorithm due to a balanced combination of exploitation (search intensification) and exploration (diversification) strategies. The algorithm effectively avoids local optima and ensures the generation of high-quality and feasible solutions in the conditions of a high variability in menus.

The paper [12] presents a range of AI technologies applied in manufacturing optimization. One subsection of the paper examines in detail two classes of AI optimization methods:

Class 1 — machine learning as a tool for analyzing big data from sensors (Industry 4.0/5.0). This tool identifies complex parameter-response relationships and supports real-time decisions to improve efficiency and accuracy.

The paper [13] defines available machine learning methods, focusing on potential benefits and examples of successful application in manufacturing environments. Kumar et al. [14] analyzed the current state of machine learning technology, with an emphasis on modern manufacturing methods, specifically additive manufacturing. The paper [15] examines a relevant problem of the production management: effective decision-making regarding rescheduling of a flexible manufacturing system. The authors note that in real-world stochastic environments, rescheduling decisions are often made based on simplified (greedy) heuristics, which does not guarantee an optimal balance between the frequency of equipment rescheduling and the accumulation of delays in the production schedule. As a solution, an integrated framework combining machine learning (ML) methods and optimization algorithms is proposed. The framework aims to justify the feasibility of rescheduling at a specific point in time. The review [16] presents the synergy between deep reinforcement learning (DRL) algorithms and the concept of digital twins. Digital twins are considered as a critical component compensating for the lack of an accurate analytical model of a complex production environment. Their use allows for the creation of a virtual testing ground for training and tuning DRL agents, potentially improving the performance, safety, and velocity of algorithm deployment.

Class 2 — evolutionary algorithms (genetic algorithm (GA), particle swarm optimization (PSO), differential evolution (DE)) are bioinspired metaheuristics effective for solving multicriteria (multi-objective) optimization problems in manufacturing. Their ability to work in changing conditions and integrate into the concept of Industry 5.0 is emphasized [17,18].

Genetic algorithm is a heuristic method for finding solutions based on the principles of natural selection and genetic operations [19]. Genetic algorithms are a class of evolutionary algorithms made popular by Holland in the 1970s [20]. They are used to find exact or approximate solutions to optimization problems, as demonstrated in the works by Goldenberg [21] and Sivanandam and Deepa [22]. The classical genetic algorithm includes the following stages: population initialization, fitness assessment, selection, recombination, mutation, formation of a new population, and testing of stopping criteria. This approach enables efficient search for optimal solutions in complex parameter spaces.

PSO algorithm models social interaction within a swarm, where each particle adjusts its trajectory based on individual and collective experience [23,24]. PSO was first introduced by Kennedy and Eberhart in 1995 [25]. This method is based on the concepts of social behavior found in groups of birds, fish, or insects. The algorithm's strategy is to use this group intelligence to find the best solution in a complex one-dimensional area, where each agent, called particle, changes its direction based on personal and social experience to navigate the search area. PSO uses particle swarm, where each particle points to a possible solution [26]. These particles "fly" through the search space and change their position depending on the best position found and the position best known to their neighbors. Using this collaborative mechanism, PSO can effectively perform both exploration and exploitation: exploration by allowing particles to move to different areas, preventing them from premature convergence, and exploitation by concentrating the search in promising areas to improve the search. This balance is necessary to cover complex search spaces and efficiently find solutions. In the context of the food product formula selection, each particle is a vector whose components correspond to the mass fractions of ingredients. After each iteration, the vector is normalized to ensure consistency with the percentage composition. Formula quality is assessed using a fitness function that accounts for deviations from the specified protein, carbohydrate, and fat content recommendations.

Sparrow search algorithm (SSA) is a bioinspired swarm intelligence method that models the behavior of a flock of sparrows during foraging and threat avoidance. The algorithm was presented in 2020 by Xue and Shen [27]. It divides the population into functional groups, each of which plays a specific role in the optimization process, ensuring a balance between exploring new search areas and exploiting identified promising solutions. The same fitness function as in PSO algorithm is used to evaluate solutions.

A systematic analysis of relevant scientific publications led to a categorization of the key intelligent methods used in this field:

1. Artificial intelligence and machine learning methods

- application of artificial neural networks to predict the degradation kinetics and stability of functional ingredients in heterogeneous food matrices;
- development of formula optimization algorithms aimed at simultaneously achieving target nutritional value and sensory characteristics (taste, texture);

These methods, based on the analysis of big data describing the properties of ingredients, their synergistic and antagonistic interactions, and their impact on physiology, serve as the basis for the creation of personalized food products adapted to individual genetic predispositions or metabolic profiles.

2. Bioinformatics and omics technologies

- integration of genomics, proteomics, metabolomics, and transcriptomics methods for screening and studying the bioactive components of food raw materials;
- molecular modeling (docking, molecular dynamics) to study the mechanisms of interactions at the molecular level, for example, the binding of biologically active peptides or polyphenols to cellular or taste receptors.

These approaches enable the targeted identification and selection of compounds with target properties, such as peptides with antihypertensive or antimicrobial activity.

3. Mathematical simulation and optimization methods

- use of bioinspired metaheuristic algorithms (genetic algorithms, swarm intelligence methods) to solve combinatorial optimization problems when searching for rational ratios of multicomponent mixtures;
- formalization and solution of systems of balance equations for nutrients (proteins, fats, carbohydrates, vitamins, minerals) taking into account their bioavailability.

These methods enable multicriteria optimization of product composition based on specified fitness functions, enabling the identification of compromise solutions between often conflicting requirements.

4. Computer-aided design (CAD) and digital twin technologies

- development of virtual simulations (*in silico*) of key production processes (mixing, heat treatment, drying) to analyze their impact on the final product properties;
- predictive modeling of shelf life, component migration, and the physicochemical stability of products under various storage conditions.

A comparative analysis revealed the key advantages of these methods: 1) significant reduction in time and resources during the research and development phase by minimizing real experiments; 2) the ability to create targeted products for specific population groups (patients with various diseases, children, older adults, athletes, etc.); 3) improved safety through proactive modeling of potential risks (microbiological, chemical, and technological ones).

However, there are also drawbacks (limitations) to the application of these methods: 1) the critical dependence of the accuracy and reliability of the models on the volume, representativeness, and quality of the input data; 2) the need for mandatory experimental validation of the *in silico* results under real-world conditions; 3) high capital costs for the implementation and support of the corresponding technological platforms, as well as the need for skilled personnel.

The introduction of intelligent methods marks the digital transformation of the food industry, shifting the development of functional products from an empirical to a knowledge-intensive and targeted approach.

The goal of our study is to develop and validate (verify) an optimization model based on genetic algorithms for solving the problem of multicriteria selection of optimal combinations and quantitative ratios of ingredients in a specialized meat-based product.

Objects and methods

The object of the study was a digital model of a specialized meat-based product (SMP) intended for the rehabilitation of individuals with traumatic brain injuries. The formula of the SMP included 14 functional ingredients selected based on their nutritional potential, biochemical and technological compatibility. Particular attention was paid to the content of target proteins and peptides in the meat raw materials, as these components play a key role in neural regeneration and metabolic restoration in this category of patients. Product quality criteria were developed based on the medical and biological requirements developed for the specific product and regulating the composition of specialized food products for neurorehabilitation. Restrictions included: 1) ranges of protein, fat, and carbohydrate content; 2) acceptable levels of macro- and micronutrients, as well as bioactive compounds.

The digital model of the formula was developed not only for technological feasibility but also considering the physiological and metabolic characteristics of the target consumer group.

A digital model of a food product typically represents a parametric description or algorithm focused on individual properties (e.g., composition, formula, sensory properties) and used to solve specific design problems. In contrast, a digital twin is a dynamic, continuously updated virtual copy of a physical product throughout its entire lifecycle. A digital twin integrates real-time data (from raw materials to consumer experience), uses feedback for self-learning, and is designed for comprehensive modeling, forecasting, and optimization.

Digital twin

Evolutionary optimization methods, specifically genetic and swarm algorithms, were used in the research on developing a digital twin of a food product.

Genetic algorithm is an evolutionary numerical optimization method based on the principles of natural selection, recombination, and mutation (Figure 1).

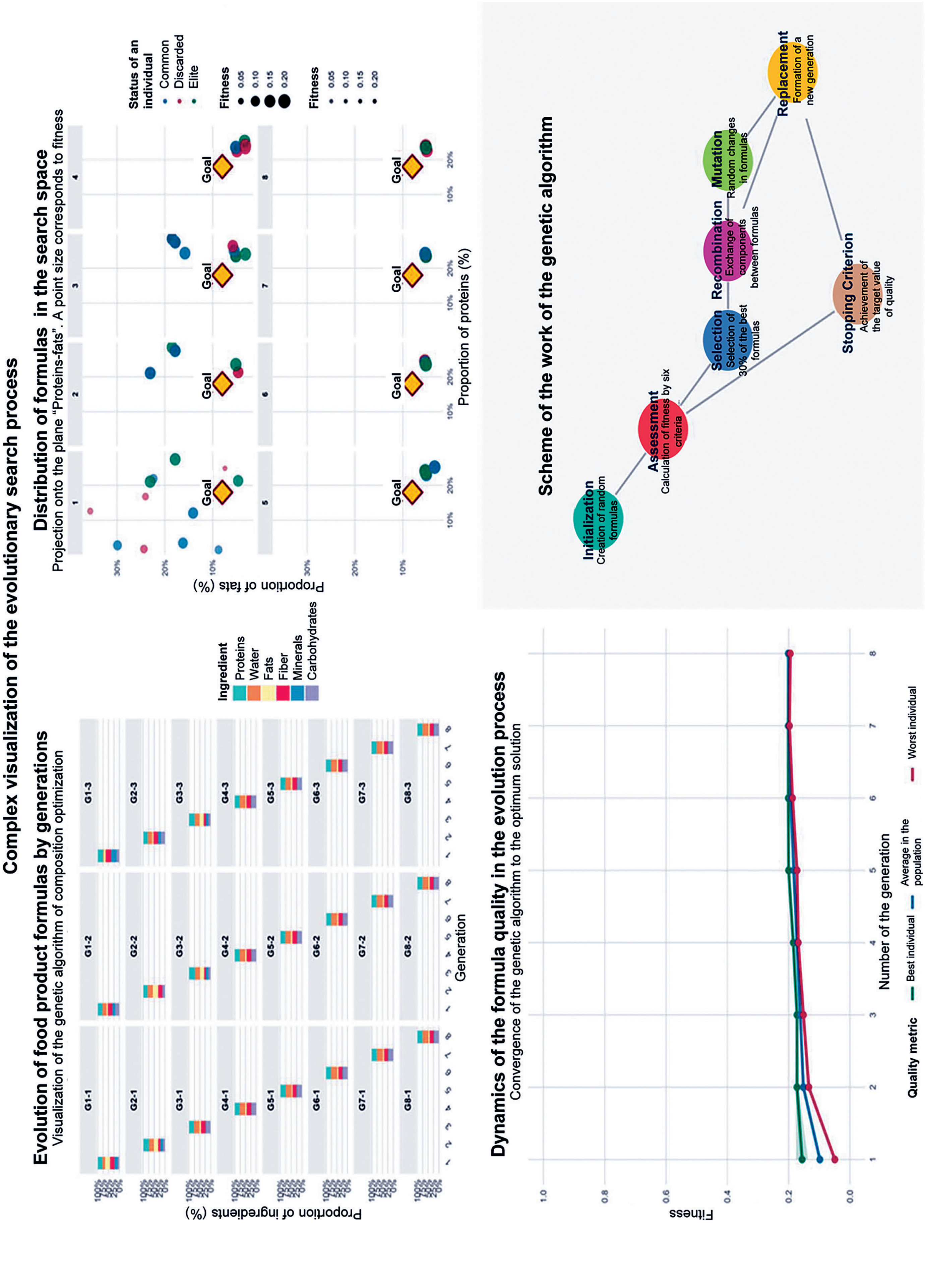


Figure 1. Genetic algorithm for food product formula optimization

In the context of food product formula optimization, the algorithm functions as an iterative process for finding the optimal composition and proportions of ingredients, minimizing or maximizing a given fitness function. The sequential implementation of the algorithm's stages forms a closed evolutionary cycle, ensuring targeted improvement of the developed formula.

The initial stage, "Initialization", involves forming an initial population, i.e. a set of formulas (individuals) whose parameters (mass fractions of the components) are randomly generated within technologically acceptable limits. This creates the initial diversity necessary to initiate the optimization process.

Stage 2, "Fitness Assessment", is the key stage for the formula synthesis problem. For each individual (formula variant), a fitness function is calculated, which quantitatively evaluates the quality of the solution. In food technology, such a function may integrate multiple criteria: compliance of the nutrient profile with specified regulatory requirements, sensory assessments, raw material cost, process parameters (e.g., viscosity, pH), and predicted digestibility. Thus, the fitness function formalizes the complex technical, economic, physiological, and hygienic requirements for the final product.

Stage 3, "Selection", selects parent formulas to create the next generation. The probability of selecting an individual is proportional to the value of its fitness function, implementing the principle of "survival of the fittest". The frequently used tournament selection method, in which a random subset of individuals competes, effectively combines selective pressure with stochasticity.

Stage 4, "Recombination (Crossing)", simulates biological crossing: selected pairs of parent formulas exchange parts of their parameters, generating new recombinant offspring formulas. This operator allows for combining successful combinations of ingredients from different solutions, exploring central areas of the search space.

Stage 5, "Mutation", introduces random changes to the offsprings with a specified low probability (for example, a minor adjustment to the proportion of one component). This operator maintains population diversity and provides the ability to escape local optima by exploring new, potentially promising areas of the formula space.

At stage 6, "Formation of a New Population", elitism occurs, i.e. keeping the few best formulas of the current generation unchanged and replacing the least fit individuals with new offsprings. This strategy guarantees a monotonic (non-degrading) improvement in the quality of solutions from generation to generation.

At stage 7, "Checking the Stopping Criterion", the optimization process terminates when one of the following conditions is reached: 1) exhaustion of the computational resource (maximum number of iterations); 2) stagnation, i.e. no significant improvement in the fitness function over a specified number of generations. If this condition is not met, the cycle repeats from stage 2, "Fitness Assessment", for a new generation of formulas.

Thus, the sequential implementation of genetic algorithm provides a systematic, directed, yet stochastic search in the multidimensional space of formula parameters. This enables the finding of compromise solutions that simultaneously satisfy multiple, often conflicting, requirements (sensory, nutritional, technological, and economic), making this method a powerful tool for computer-aided design and optimization of food products.

In addition to genetic algorithm, swarm intelligence algorithms were used in the study, i.e. particle swarm optimization (PSO) and sparrow search algorithm (SSA).

Unlike genetic algorithm, PSO algorithm includes the following stages.

At stage 1, "Population Initialization", an initial swarm of particles is created. Each particle corresponds to a possible solution to the problem. In the context of formula selection, this is a vector whose components represent the proportions of ingredients. The initial values are randomly assigned within acceptable limits, after which normalization is performed to ensure the correct percentage ratio.

At stage 2, "Initialization of Individual and Global Experience", each particle remembers its best position achieved over the entire duration of the algorithm's execution. Simultaneously, the best position among all particles in the population is determined, which is considered the current global optimum.

Stage 3, "Iteratively Update of Particle Velocity and Position". At each iteration of the algorithm, each particle adjusts its motion, taking into account three components: 1) inertial component, i.e. maintaining the previous direction of motion; 2) individual experience, i.e. the desire to return to its best historical position; 3) collective experience, i.e. the desire to approach the globally best position found by the entire swarm. Based on the updated velocity, the particle changes its position in the solution space.

Stage 4, "Formula Normalization". After changing the position, the vector is normalized so that the sum of all components remains equal to a specified value, for example, 100 %, ensuring the physical correctness of the formula.

At stage 5, "Solution Quality Assessment", a fitness function is calculated for each particle, reflecting the quality of the corresponding solution. In the context of the food product composition problem, the function takes into account compliance with target protein, carbohydrate, and fat content and may also include penalties for deviations from the standard.

Stage 6, "Updating Individual and Global Experience". If a particle's current position is better than its previous best position, the individual experience is updated. After evaluating all particles, the globally best solution for the entire population is adjusted if necessary.

Stage 7, "Checking the Stopping Condition". The algorithm continues iterating until the specified number of steps is reached or until the quality of the global solution stabilizes within an acceptable error. When the stopping criterion is met, the best solution found is returned.

PSO algorithm combines elements of global and local search, enabling efficient exploration of multidimensional solution spaces and finding balanced optima in problems with multiple constraints, such as food formula optimization.

Another alternative metaheuristic algorithm used in this study was the sparrow search algorithm. Its implementation is as follows.

At stage 1, "Population Initialization", an initial population of sparrows is created, each representing a possible solution to the problem. In this case, this is a vector specifying the proportions of ingredients in the formula. Initial values are assigned randomly within acceptable ranges, after which normalization is performed to ensure correct percentages.

At stage 2, "Sparrow Role Classification", the population is divided into three groups based on their role in the search process: 1) producers, the fittest sparrows, responsible for actively searching for new areas with high-quality solutions; they act as leaders, directing the movement of the flock; 2) scroungers, sparrows that follow the producers and utilize the resources they have discovered; their behavior is aimed at local exploration of areas around the current best solutions; 3) watchers, a randomly selected subset of the population whose task is to detect potential threats and prevent premature convergence to suboptimal solutions.

Stage 3, "Updating Producer Positions". The positions of the producers are updated based on the "alarm" level, which simulates the presence of a threat. At low alarm levels, producers intensively explore areas around their current best positions. At high alarm levels, they may make random movements to find new, safer areas.

At stage 4, "Updating Scrounger Positions", the scroungers adjust their positions based on two strategies: 1) some scroungers in unfavorable conditions leave their current positions in search of new areas; 2) the remaining scroungers approach the producers and explore the surrounding space, which allows them to refine their solutions.

At stage 5, "Updating Watcher Positions", the positions of the watchers are adjusted so that sparrows move away from potentially dangerous areas while simultaneously moving closer to the current best solutions. This mechanism helps maintain a balance between safety and search efficiency.

Stage 6, "Formula Normalization". After each position update, the vectors are normalized to ensure the sum of all components remains constant, which satisfies the physical requirements for the formula composition.

At stage 7, "Solution Quality Assessment", a fitness function is calculated for each sparrow. This function evaluates the quality of the solution based on specified criteria, such as compliance with protein, fat, and carbohydrate content standards. This function includes both the target component and penalty components for deviations from the requirements.

Stage 8, "Checking the Stopping Condition". The algorithm continues iterating until the specified number of generations is reached or until the fitness function values stabilize. Upon completion, the best solution found is returned.

SSA algorithm combines elements of social interaction, adaptive behavior, and threat avoidance mechanisms, ensuring a high convergence velocity, search accuracy, and resistance to premature stabilization in local optima. This makes it an effective tool for solving multicriteria optimization problems, such as complex food formula selection.

All computational experiments were implemented in R Studio software using the R programming language, which ensured reproducibility and flexibility in algorithm parameters [19,28–30].

Results and discussion

To design a food system with the target composition and characteristics, genetic algorithm was used, the pseudocode for which is shown in Figure 2.

The use of evolutionary algorithms to optimize the formula for a specialized meat-based product (SMP) involved three key steps: 1) coding the solutions; 2) defining the fitness function; 3) assigning the search operators.

Step 1, coding the solutions. Each solution (individual) was represented by a vector of the proportions of 14 ingredients in the formula, formed based on their composition in terms of key nutrients: proteins, fats, carbohydrates, and other functional components (Figure 3).

Algorithm Genetic algorithm pseudocode

```
    # Run the genetic algorithm
    GA <- ga(
     type = "real-valued",
     fitness = fitness,
     lower = min_proportions,   # Vector of minimum values
     upper = max_proportions,   # Vector of maximum values
     popSize = 100,             # Population size
     maxiter = 500,             # Number of iterations
     pcrossover = 0.8,          # Crossover probability
     pmutation = 0.1,           # Mutation probability
     elitism = 6,               # Number of best individuals to keep
     run = 50,                  # Stop after 50 generations
     seed = 123,                # For reproducibility
     monitor = gaMonitor,       # Enable monitoring
keepBest = TRUE                 # Keep the best solutions
```

Figure 2. Genetic algorithm pseudocode

```
# Ingredient Data
ingredients <- matrix(
 c(23.37, 3.60, 0.00, 64.33, # Ingredient_1
 85.00, 5.00, 3.00, 7.00, # Ingredient_2
 0.00, 99.85, 0.00, 0.00, # Ingredient_3
 0.00, 99.00, 0.00, 0.00, # Ingredient_4
 5.00, 0.00, 28.00, 0.00, # Ingredient_5
 0.00, 0.00, 93.00, 4.00, # Ingredient_6
 40.1, 0.20, 26.40, 0.00, # Ingredient_7

 29.50, 8.50, 0.00, 0.00, # Ingredient_13
 0.00, 0.00, 0.00, 100.00), # Ingredient_14
 nrow = 14, byrow = TRUE
```

Figure 3. A fragment of "Ingredient Data" R code listing

Step 2, defining the fitness function. The energy value of the product was used as the target criterion. The fitness function assessed caloric content and included penalty points for deviations from the specified medical and biological requirements for nutrient content.

Step 3, assigning the search operators. Standard operators were used for evolutionary search: 1) crossover (cxBlend) — combining the solutions; 2) mutation — introducing random changes using a normal distribution; 3) selection — selecting the best solutions using a tournament method.

Mathematical model for SMP included: 1) optimization criterion; 2) a system of constraints on formula components and elemental composition; 3) balance equations with coefficients accounting for thermal losses, obtained experimentally.

The optimization criterion is presented as the minimization of the sum of the squared deviations of the calculated values from the target values:

$$P(z) = \sum_{j=1}^{m}\left(x_j^0 - x_j^{calcul.}\right)^2 \to \min . \tag{1}$$

The model includes four calculation blocks reflecting the main characteristics of the food system:

1. Nutritional value block (protein, fat, and carbohydrate content, taking into account loss factors).

$$\boldsymbol{Protein} = (23.37 \cdot x_1 + 85 \cdot x_2 + 5 \cdot x_5 + 40.1 \cdot x_7 + 29.5 \cdot x_{13}) \cdot \mathbf{0.96} \tag{2}$$

$$\begin{aligned}\boldsymbol{Fat} = (3.6 \cdot x_1 + 5 \cdot x_2 + 99.85 \cdot x_4 + 99 \cdot x_5 + 0.2 \cdot x_7 + \\ + 100 \cdot x_{12} + 8.5 \cdot x_{13}) \cdot \mathbf{0.92}\end{aligned} \tag{3}$$

$$\boldsymbol{Carbohydrates} = (3 \cdot x_2 + 28 \cdot x_5 + 93 \cdot x_6 + 26.4 \cdot x_7) \cdot \mathbf{0.99} \tag{4}$$

Nutritional value block restrictions: (a) protein is 6–6.5 g; (b) fat is 4.5–5.5 g; (c) carbohydrates are 14.5–15.5 g.

2. Biological value block (content of essential amino acids: valine, leucine, isoleucine, methionine + cystine, threonine, lysine, phenylalanine + tyrosine, tryptophan).

$$\begin{aligned}\boldsymbol{Valine} = (4.11 \cdot x_1 + 6.5 \cdot x_2 + 8.92 \cdot x_5 + \\ + 6.48 \cdot x_7 + 4.02 \cdot x_{13}) \cdot \mathbf{0.82}\end{aligned} \tag{5}$$

$$\begin{aligned}\boldsymbol{Leucine} = (9.88 \cdot x_1 + 5.7 \cdot x_2 + 8.84 \cdot x_5 + \\ + 11.97 \cdot x_7 + 7.58 \cdot x_{13}) \cdot \mathbf{0.83}\end{aligned} \tag{6}$$

$$\begin{aligned}\boldsymbol{Isoleucine} = (4.96 \cdot x_1 + 9.6 \cdot x_2 + 4.18 \cdot x_5 + \\ + 5.24 \cdot x_7 + 2.41 \cdot x_{13}) \cdot \mathbf{0.52}\end{aligned} \tag{7}$$

$$\begin{aligned}\boldsymbol{Methionine} + \boldsymbol{Cysteine} = (4.07 \cdot x_1 + 4.3 \cdot x_2 + \\ + 2.2 \cdot x_5 + 9.48 \cdot x_7 + 2.71 \cdot x_{13}) \cdot \mathbf{0.24}\end{aligned} \tag{8}$$

$$\begin{aligned}\boldsymbol{Threonine} = (5.95 \cdot x_1 + 4.1 \cdot x_2 + 5.42 \cdot x_5 + \\ + 6.23 \cdot x_7 + 3.91 \cdot x_{13}) \cdot \mathbf{0.92}\end{aligned} \tag{9}$$

$$\begin{aligned}\boldsymbol{Lysine} = (11.81 \cdot x_1 + 4.9 \cdot x_2 + 3.92 \cdot x_5 + \\ + 10.72 \cdot x_7 + 6.9 \cdot x_{13}) \cdot \mathbf{0.46}\end{aligned} \tag{10}$$

$$\begin{aligned}\boldsymbol{Phenylalanine} + \boldsymbol{Tyrosine} = (11.21 \cdot x_1 + 10.2 \cdot x_2 + \\ + 5.42 \cdot x_5 + 22.94 \cdot x_7 + 7.22 \cdot x_{13}) \cdot \mathbf{0.56}\end{aligned} \tag{11}$$

$$\boldsymbol{Tryptophan} = (2 \cdot x_2 + 0.96 \cdot x_5 + 2 \cdot x_7) \cdot \mathbf{0.88} \tag{12}$$

Biological value block restrictions for essential amino acids: (a) isoleucine is 4.20–4.64 g/100 g protein; (b) leucine is 7.63–8.43 g/100 g protein; (c) lysine is 7.44–8.22 g/100 g protein; (d) methionine + cystine are 3.30–3.64 g/100 g protein; (d) phenylalanine + tyrosine are 7.78–8.60 g/100 g protein; (e) threonine is 3.95–4.35 g/100 g protein; (g) tryptophan is 1.12–1.24 g/100 g protein; (g) valine is 5.31–5.87 g/100 g protein.

3. Vitamin block (B_1, B_2, B_3, B_5, B_6, E, C, D_3).

$$\boldsymbol{B1} = (0.16 \cdot x_1 + 375 \cdot x_{10} + 1.31 \cdot x_{13}) \cdot \mathbf{0.55} \tag{13}$$

$$\boldsymbol{B2} = (283 \cdot x_{10} + 1.88 \cdot x_{13}) \cdot \mathbf{0.30} \tag{14}$$

$$\boldsymbol{B3} = (6.98 \cdot x_1 + 2571 \cdot x_{10} + 14.25 \cdot x_{13}) \cdot \mathbf{0.55} \tag{15}$$

$$\boldsymbol{B5} = (0.28 \cdot x_1 + 1985 \cdot x_{10}) \cdot \mathbf{0.37} \tag{16}$$

$$\boldsymbol{B6} = (286 \cdot x_{10}) \cdot \mathbf{0.74} \tag{17}$$

$$\begin{aligned}\boldsymbol{E} = (0.1 \cdot x_1 + 3.62 \cdot x_3 + 23.32 \cdot x_4 + 1900 \cdot x_{10} + \\ + 8.18 \cdot x_{12} + 1.44 \cdot x_{14}) \cdot \mathbf{0.66}\end{aligned} \tag{18}$$

$$\boldsymbol{C} = (50000 \cdot x_{10} + 21.9 \cdot x_{13}) \cdot \mathbf{0.56} \tag{19}$$

$$\boldsymbol{D3} = (0.95 \cdot x_1 + 2660 \cdot x_{10}) \cdot \mathbf{0.74} \tag{20}$$

Vitamin block restrictions: (a) thiamine (vitamin B1) is 0.15–0.2 mg; (b) riboflavin (vitamin B2) is 0.17–0.21 mg; (c) niacin (PP, vitamin B3) is 1.83–2.7 mg; (g) vitamin C is 10–15 mg; (d) vitamin B6 is 0.17–0.3 mg; (e) pantothenic acid (vitamin B5) is 0.6–0.7 mg.

4. Mineral substances block (Ca, K, Na, Mg, Fe, Zn, Cu, I).

$$\boldsymbol{Ca} = (8.681 \cdot x_1 + 4706 \cdot x_9 + 4.5 \cdot x_{14}) \cdot \mathbf{0.91} \tag{21}$$

$$\boldsymbol{K} = (368.188 \cdot x_1 + 11176 \cdot x_9) \cdot \mathbf{0.72} \tag{22}$$

$$\begin{aligned}\boldsymbol{Na} = (108.002 \cdot x_1 + 12 \cdot x_7 + 43 \cdot x_8 + \\ + 7059 \cdot x_9 + 0.9 \cdot x_{14}) \cdot \mathbf{0.86}\end{aligned} \tag{23}$$

$$\boldsymbol{Mg} = (28.537 \cdot x_1 + 1353 \cdot x_9 + 1 \cdot x_{14}) \cdot \mathbf{0.96} \tag{24}$$

$$\boldsymbol{Fe} = (3.673 \cdot x_1 + 94 \cdot x_9 + 0.0012 \cdot x_{14}) \cdot \mathbf{0.93} \tag{25}$$

$$\boldsymbol{Zn} = (4.979 \cdot x_1 + 1200 \cdot x_{10}) \cdot \mathbf{0.85} \tag{26}$$

$$\boldsymbol{Cu} = (0.126 \cdot x_1 + 150 \cdot x_{10} + 0.0006 \cdot x_{14}) \cdot \mathbf{0.99} \tag{27}$$

$$\boldsymbol{I} = (15.96 \cdot x_{10}) \cdot \mathbf{1.00} \tag{28}$$

Mineral substances block restrictions: (a) sodium (Na) is 120–134 mg; (b) potassium (K) is 190–234 mg; (c) calcium (Ca) is 80–112 mg; (d) magnesium (Mg) is 23–30 mg; (d) iron (Fe) is 1.6–2.4 mg; (e) zinc (Zn) is 1.2–1.8 mg; (g) copper (Cu) is 0.15–0.27 mg; (h) iodine (I) is 13.3–20 µg.

Each equation includes weighting factors obtained and verified during real experiments under real food production conditions. These factors quantitatively characterize the losses of specific nutrients at various stages of the technological process (e.g., during heat treatment).

For each block, restrictions were imposed based on medical and biological requirements for the composition of products for patients with traumatic brain injuries.

Execution of the program code resulted in 479 iterations (generations) of the evolutionary algorithm. Generation 479 proved to be the best, achieving the target ranges of key nutrient content based on the specified optimization criteria. Maximizing the energy value of the product was used as the fitness function. The resulting optimization yielded a caloric value of approximately 129 kcal per 100 g of the product. The calculated nutritional value of the optimized composition per 100 g: 1) protein is 6.22 g; 2) fat is 4.91 g; 3) carbohydrates are 15.00 g.

These values comply with the established restrictions and confirm the effectiveness of the applied algorithm in solving the problem.

Figure 4 shows a 3D visualization of the dependence of the fitness function on the content of proteins and fats, reflecting the trajectory of solution improvement during the evolution of the population.

The 3D model visualizes the evolutionary trajectory of the system, showing formula changes across generations, and also allows tracking the values of key nutritional parameters (protein, fat, and caloric content) at each point in space. The latter parameter is used as the fitness function of the algorithm. The model also supports the visualization of other food nutrients.

For example, protein may be characterized by its profile of essential and nonessential amino acids. Figures 5 and 6 show point clouds demonstrating all possible combinations of amino acid content obtained during the genetic algorithm's transition from the initial random formula to the optimized one. Examples include branched-chain amino acids (BCAAs), as well as aromatic amino acids and their precursors.

The red line indicates the trajectory of formula improvement toward the optimum.

To compare the effectiveness of the classical genetic algorithm, two evolutionary algorithms were also used: particle swarm optimization (PSO) and sparrow search algorithm (SSA). Table 1 presents the semantic analogy between PSO/SSA terminology and the elements of food system simulation.

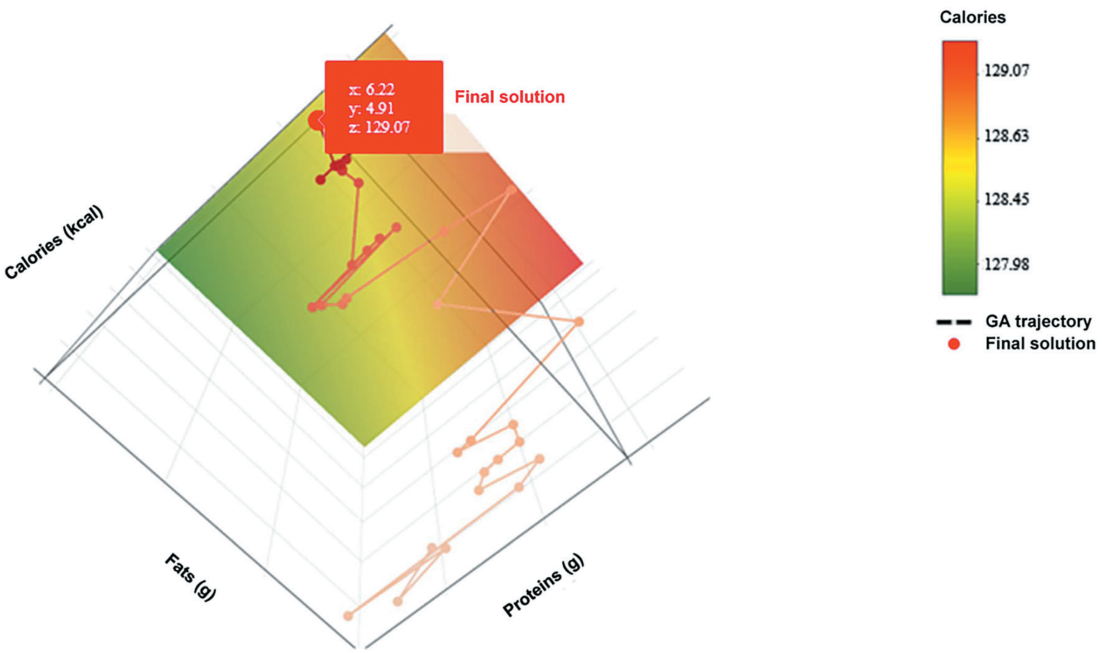
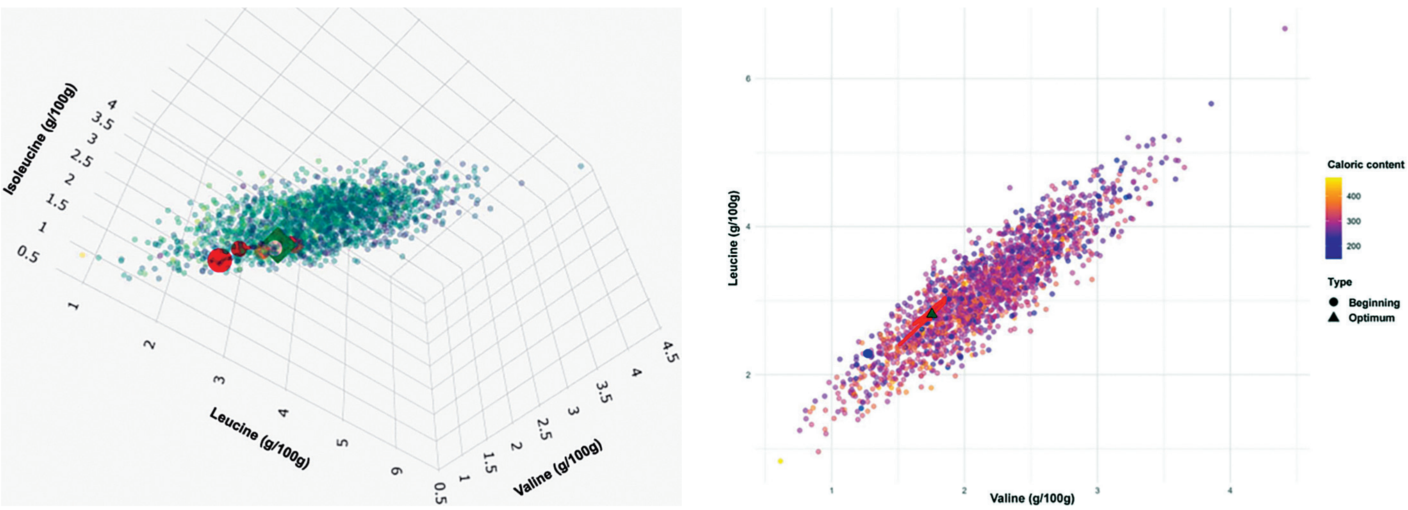
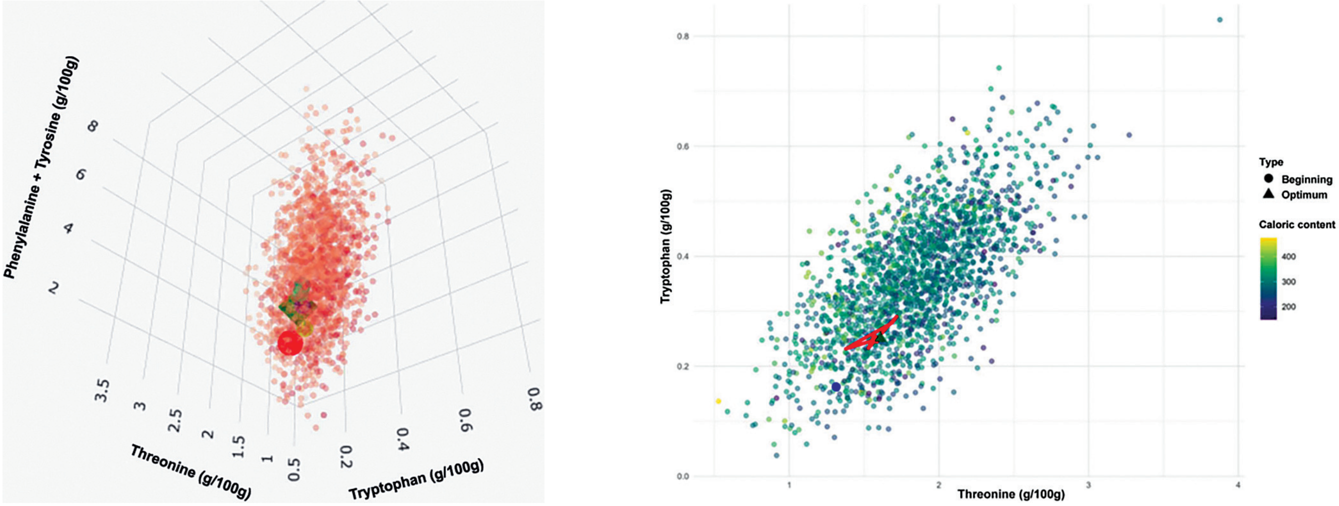


Figure 4. 3D chart of the fitness function versus fat and protein content in the food system: generational improvement trajectory and final solution



Valine-Leucine-Isoleucine **Valine-Leucine 2D cross-section**

Figure 5. Virtual space of amino acids



Tryptophan-Threonine-Phenylalanine + Tyrosine

Tryptophan-Threonine 2D cross-section

Figure 6. Virtual space of amino acids

Table 1. Correspondence between PSO/SSA terminology and food system simulation concepts

PSO term	SSA term	Interpretation in the food system model
Particle	Sparrow	Formula variant (set of ingredients, process parameters)
Position	Position	Point in parameter space (specific values of nutrient content, mass fractions, processing modes) or Vector of component percentages
Velocity	— (movement without a direct velocity analog)	Formula change step from the current state to a new one or Direction and magnitude of the composition change
Individual best experience (pbest)	— (functionally corresponds to the producer's memory of the best state)	Best fitness function value achieved by a given formula variant in previous iterations
Global best experience (gbest)	Best producer	Optimal formula found so far among all variants
—	Producer	Active search for a new solution, i.e. a scenario in which the formula is purposefully modified (e.g., increasing protein)
—	Scrounger	Adoption of a successful solution, i.e. copying or slightly modifying the best formula
—	Scout	Random search/anti-stagnation, i.e. abrupt formula change to escape the local optimum
Fitness	Fitness	Target product quality indicator: maximizing nutritional value, minimizing losses, cost, and deviation from the standard
Premature convergence	Local optimum trap	Stopping the search on a suboptimal formula without further improvement
Search space	Search area	Set of acceptable combinations of ingredients and processing modes (restrictions regarding safety, sensory properties, regulations)

PSO algorithm yielded an optimal solution, visualized in Figure 6. The highlighted area (red square) shows the nutrient values for the optimal formula: protein (x) + 6.30 g, fat (y) + 5.10 g, and carbohydrates (z) + 14.81 g per 100 g of product. The calculated energy value is 130 kcal per 100 g.

These values meet the medical and biological requirements for specialized nutritional products intended for the rehabilitation of patients with traumatic brain injury (TBI). Compared to the solution obtained using a classical genetic algorithm (GA), the optimum achieved by PSO method is characterized by higher target nutrient values: protein content increased by 0.78 g and fat increased by 0.19 g (per 100 g). The resulting increase in nutritional value is statistically significant ($p < 0.05$) and has an apparent dietary value in the context of nutritional support for TBI.

The gray dots in Figure 7 represent the set of intermediate formulas (2,341 iterations in total) explored during the directed search for the optimum. The search trajectory,

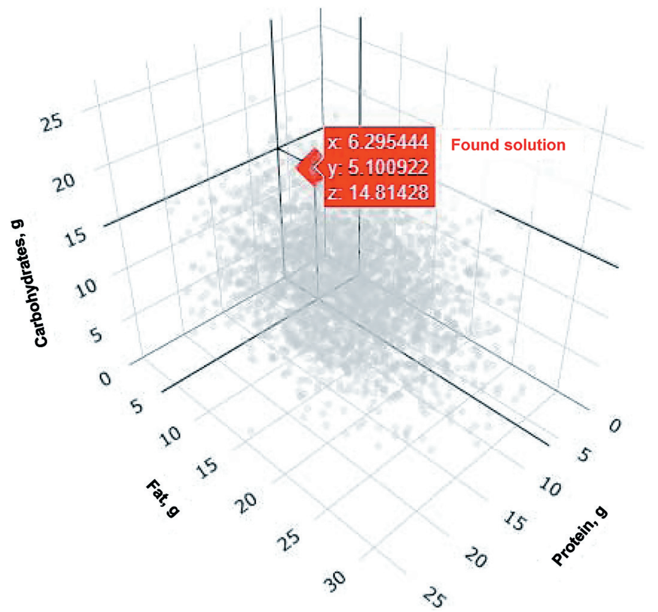


Figure 7. Visualization of the search space for the optimal solution

represented by the set of gray dots, demonstrates the stable convergence of PSO algorithm to the global optimum areas, while the spread of fitness function values at the final iterations does not exceed 2.1%. The absence of pronounced local optimum clusters indicates the effectiveness of the chosen inertial weighting and cognitive-social balancing strategies.

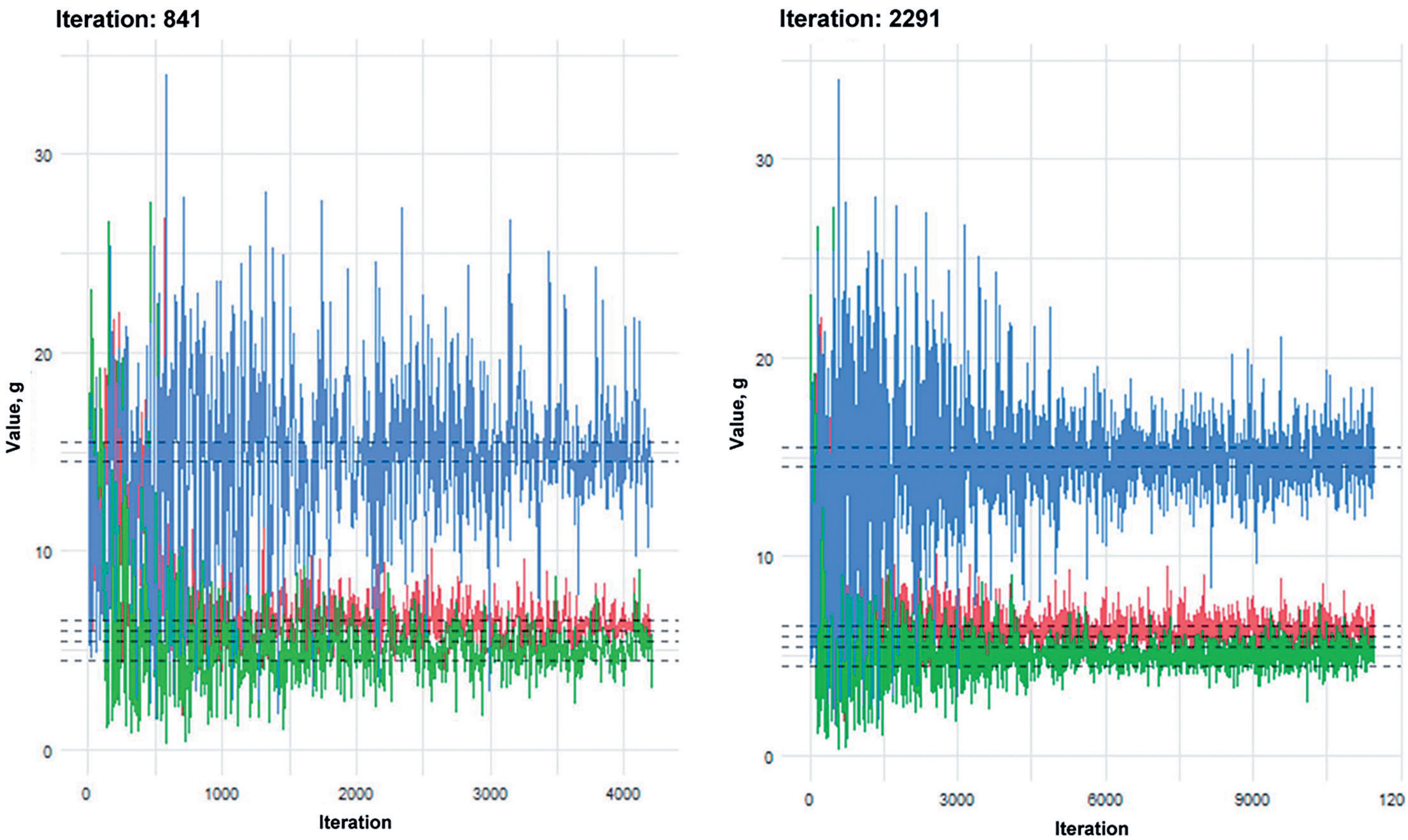
Using SSA algorithm, we obtained an alternative optimal SMP formula with the following composition (per 100 g of product): protein ≈ 6.50 g, fat ≈ 5.40 g, carbohydrates ≈ 14.50 g. The energy value of this variant was ≈ 133 kcal/100 g. Comparative analysis showed that the solution found by SSA algorithm exceeds the results obtained using GA and PSO in protein content by 0.28 g and 0.20 g, respectively. In terms of fat content, the advantage is 0.49 g relative to GA and 0.30 g relative to PSO. Moreover, the carbohydrate content was lower by 0.50 g and 0.31 g, respectively, which does not conflict with the dietary requirements for products of this class and is compensated by the increased proportion of the protein and lipid component.

Figure 8 shows the dynamics of changes in the content of key macronutrients (protein, fat, and carbohydrates) during the iterative search for the optimal formula using SSA algorithm. Visualization of the trajectories allows to trace the algorithm's convergence and its ability to maintain a balance between exploration and exploitation of the solution space.

SSA algorithm demonstrated the highest efficiency in synthesizing an optimal SMP formula under conditions of uncertainty in the input raw material characteristics recorded in real time by the sensor system. Its high adaptability and resilience to variability in initial parameters make SSA a promising tool for intelligent decision support in the development of personalized food products.

A comparative analysis of GA, PSO, and SSA performance in the SMP formula optimization problem revealed significant differences in their search behavior, due to the conceptual features of each approach. The classical genetic algorithm, which simulates the mechanisms of hereditary variation and natural selection, demonstrated the ability to effectively explore the discrete space of formula combinations. Crossover and mutation operators generated new composition variants, including unconventional ones, as evidenced by the wide spread of intermediate solutions in early iterations (Figure 4). However, a relatively low convergence velocity was observed: reaching the optimum required over 800 generations, and the final solution was inferior in protein and fat content to the results obtained using swarm intelligence methods (PSO, SSA). This observation is consistent with a well-known limitation of GA, i.e. the need to fine-tune crossover and mutation probabilities to prevent premature stagnation or excessively slow drift [31,32].

In contrast, PSO algorithm ensured faster localization of promising search areas. Thanks to the cognitive-social learning mechanism and the inertial component, particle motion in the space of technological parameters was directed, which allowed an energy value of 130 kcal per 100 g to be achieved by the 340th iteration. However, as suggested by literature data [33,34,35], a decrease in swarm diversity and a tendency to concentrate around suboptimal areas were observed at



a) b)

Figure 8. Iterative process for changing nutrient content in a formula: red line, protein; green line, fat; blue line, carbohydrates, where a) 841 iterations, b) 2291 iterations

the final stage, limiting further improvement of the formula. The protein (6.30 g) and fat (5.10 g) contents in the solution obtained by PSO were lower than those obtained using SSA, confirming the vulnerability of classical PSO to premature convergence in multi-extreme landscapes.

The best results across all criteria were achieved using SSA algorithm. The hierarchical swarm structure it reproduced, including producers, scroungers, and watchers, ensured a qualitatively different balance between global exploration and local intensification. Producers actively explored new areas of the space, while scroungers concentrated around the most promising solutions, accelerating convergence. The watching detection mechanism played a critical role: upon detecting stagnation, some agents initiated random movement, allowing the population to leave the local optimum area and continue improving the formula. As a result, a composition variant was developed with increased protein (6.50 g) and fat (5.40 g) content while maintaining energy density within the specified range (≈ 133 kcal per 100 g). The obtained values meet stringent medical and biological requirements for products for the rehabilitation of patients with traumatic brain injury and outperform the results of GA and PSO in terms of the integral indicator of nutritional adequacy.

Thus, the comparative analysis confirms that SSA implements a more complex and adaptive model of collective intelligence, ensuring targeted management of diversification and search intensification. Given the variability of raw material characteristics recorded by the sensory system, this property takes on particular significance, allowing SSA to be considered a preferred intellectual support tool for the design of personalized food systems.

In addition, other key ratios were calculated. For example, the SFA: MUFA: PUFA ratio was found to be 1:3.39:1.81, and the linoleic (C18:2n-6) to linolenic (C18:3n-3) fatty acid ratio was 4.24:1. Maintaining these proportions is crucial for the physiological adequacy of the diet for patients with TBI, as the efficiency of their metabolism and, in particular, the normalization of lipid metabolism depend on the balance of fatty acids.

In addition to achieving the standard levels of macro- and micronutrients established in MR 2.3.1.0253-21[2], the study also determined the optimal proportions of mineral substances. The ratio of calcium, phosphorus, and magnesium was 1:0.9:0.29, respectively. This balance is a significant factor determining the efficiency of absorption of these elements in the body and the maintenance of acid-base balance.

Under natural conditions, there are no foods containing the full spectrum of nutrients necessary to meet human physiological needs. Therefore, combining various foods in the diet allows for optimal satisfaction of the body's need for physiologically active components [36].

[2] Methodological recommendations MR 2.3.1.0253-21 "Standards of physiological needs for energy and nutrients in various population groups of the Russian Federation" (approved by the Federal Service for Surveillance on Consumer Rights Protection and Human Wellbeing on July 22, 2021). Replaced MR 2.3.1.2432-08.

As Aguilera [37] notes, most modern food products are developed without a systematic engineering approach, which involves moving from a conceptual idea to a finished product based on scientifically valid methods and rigorous technological procedures. Over the past decade, the term "intelligent food design" has become established in scientific literature, implying the design of products that meet both functional nutritional requirements and consumer preferences [38,39].

Creating food systems with specified nutritional and functional health properties requires the application of modern scientific knowledge and technological solutions. In this study, metaheuristic algorithms were used to create one stage of the lifecycle of SMP digital twin.

Verification of the developed model by comparing the results of virtual simulation with data from a real experiment revealed a difference of 0.5–3.3% for individual nutrient groups. The obtained convergence indicates that all input parameters, restrictions, and weighting factors were correctly considered in the model. The proven model allows for real-time prediction of changes in the chemical composition of a food system when any ingredient is varied, and in the event of an unsatisfactory result, it promptly suggests alternative formula modifications.

The digital twin is a quantum leap in the evolution of food engineering (food combinatorics), overcoming the key limitations of traditional simulation approaches [40]. Unlike classical simulation, which operates with static, predefined models and scenarios, the results of which are analyzed and implemented post-factum, the digital twin functions as a dynamic, "living" entity. Its fundamental difference lies in the ability to continuously update based on data flow from the physical object, as well as the ability to implement conclusions directly into the operational circuit. This is achieved through feedback via actuators or personnel, enabling prompt corrective measures and immediate action in real-world production conditions. Thus, the digital twin transforms simulation from an analysis and preliminary design tool into an active component of the control system, ensuring real-time process optimization and improving product quality.

Along with this, the digital twin significantly expands the conceptual and applied boundaries of computer simulation. While traditional methods such as virtual prototyping and "What... If..." scenario analysis primarily focus on the process and product design stages, the digital twin extends simulation and data processing capabilities to the entire product lifecycle. This technology provides a comprehensive, holistic understanding of not only the product's design but also its behavior throughout its entire lifecycle. Consequently, the digital twin may be considered as a way to bridge the gap between the design-oriented digital space and the operation-oriented physical world, creating a continuous digital circuit that supports decision-making at both the strategic (design, planning) and tactical (operational management, optimization) levels.

Conclusion

Using the digital twin, a highly detailed virtual dynamic model of the SMP, enables real-time prediction of the final product's characteristics. This enables rapid adjustments to formulas and process parameters to meet the medical and biological requirements for a food system designed for the rehabilitation of patients with TBI. The digital twin enables rapid formula transformation for transferring production between facilities and adapting it to new equipment. The model simulates the product's physicochemical properties at all stages of production, creating the basis for predictive analysis and optimization of process modes. Thus, the use and implementation of the digital twin improve the flexibility, manageability, and efficiency of specialized food production, ensuring compliance with strict medical standards and accelerating adaptation to changing production conditions.

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