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Review

Advancing Optimization Strategies in the Food Industry: From Traditional Approaches to Multi-Objective and Technology-Integrated Solutions

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Abstract: Optimization has become an indispensable tool in the food industry, addressing critical challenges related to efficiency, sustainability, and product quality. Traditional approaches, such as one-factor-at-a-time analysis, have been supplanted by more advanced methodologies like response surface methodology (RSM), which models interactions between variables, identifies optimal operating conditions, and significantly reduces experimental requirements. However, the increasing complexity of modern food production systems has necessitated the adoption of multi-objective optimization techniques capable of balancing competing goals, such as minimizing production costs while maximizing energy efficiency and product quality. Advanced methods, including evolutionary algorithms and comprehensive modeling frameworks, enable the simultaneous optimization of multiple variables, offering robust solutions to complex challenges. In addition, artificial neural networks (ANNs) have transformed optimization practices by effectively modeling non-linear relationships within complex datasets and enhancing prediction accuracy and system adaptability. The integration of ANNs with Industry 4.0 technologies—such as the Internet of Things (IoT), big data analytics, and digital twins—has enabled real-time monitoring and optimization, further aligning production processes with sustainability and innovation goals. This paper provides a comprehensive review of the evolution of optimization methodologies in the food industry, tracing the transition from traditional univariate approaches to advanced, multi-objective techniques integrated with emerging technologies, and examining current challenges and future perspectives.

Keywords: multi-objective; food; sustainable; response surface methodology; genetic algorithms; artificial neural networks

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1. Introduction

The food industry operates within an increasingly competitive and resource-constrained environment, where the demand for innovation and efficiency continues to grow. This sector faces multifaceted challenges, including the need to optimize critical resources such as time, financial investments, and energy consumption while ensuring high levels of process efficiency and sustainability. Addressing these challenges is vital for the industry to meet evolving consumer expectations, comply with regulatory requirements, and contribute to global sustainability goals. Within this context, optimization has emerged as a key tool, enabling the systematic improvement of production systems by identifying the most favorable operating conditions to achieve optimal outcomes [1].

Historically, optimization efforts in food processes relied on simplistic, single-variable experimental approaches. These methods focused on evaluating the effect of one parameter at a time on a given response while maintaining all other factors constant. While effective for certain scenarios, this approach introduced substantial limitations. It neglected the potential interactions between variables, which are often critical in understanding the complexity of food production systems. Furthermore, it required a large number of experiments to comprehensively explore the variable space, resulting in higher costs, extended timelines, and inefficiencies in process development [1,2].

In recent decades, the food industry has shifted its priorities to align with key objectives such as cost reduction, productivity enhancement, and achieving optimal product quality. These goals have driven innovation in product development and process optimization, fostering the adoption of advanced tools and techniques that address the inherent limitations of traditional approaches. These advancements are critical for ensuring the industry's ability to deliver consistent, high-quality products while optimizing resource utilization and minimizing environmental impact [3].

To overcome the constraints of traditional methodologies, modern optimization techniques have been integrated into food production processes. Among these, the response surface methodology (RSM) has gained significant prominence. RSM combines mathematical and statistical methods to model and analyze systems influenced by multiple variables. This approach not only identifies significant relationships between factors but also determines optimal operating conditions, reducing the number of experiments needed and increasing the accuracy and reliability of results. The efficiency of RSM has made it a widely adopted tool in the food industry, contributing to significant advancements in process design and product innovation [2].

However, as food production systems have grown more complex, single-objective optimization methods like RSM alone have become insufficient for addressing multifaceted industrial challenges. Modern food production often requires balancing multiple, sometimes conflicting objectives, such as maximizing product quality, minimizing production costs, and improving energy efficiency. To address these challenges, multi-objective optimization techniques have emerged as indispensable tools.

Multi-objective optimization tackles problems that involve multiple responses or variables simultaneously, offering solutions that optimize various objectives concurrently. This approach is particularly relevant to food science, where competing goals often require trade-offs. Among the most widely used methods in multi-objective optimization are linear, non-linear, and evolutionary algorithms. Each method offers unique strengths and limitations, allowing practitioners to select the most appropriate technique based on the specific requirements of a given application. Evolutionary algorithms, for instance, excel in solving non-linear and multi-modal problems, making them highly effective in the dynamic and variable-rich environments of food production systems [4].

In recent years, the rapid advancement of computational technologies has further transformed the landscape of optimization in the food industry. The integration of artificial neural networks (ANNs) represents one of the most significant innovations in this field. ANNs, inspired by the structure and functioning of the human brain, are highly effective at modeling complex systems, detecting non-linear patterns, and providing accurate predictions even in scenarios involving extensive datasets and numerous variables.

When combined with established optimization techniques such as RSM or evolutionary algorithms, ANNs create powerful hybrid systems capable of addressing modern optimization challenges. These hybrid approaches have demonstrated remarkable success in enhancing both product quality and process efficiency, solidifying ANNs as essential tools in the optimization of food processes [3,5]. Additionally, the integration of Industry 4.0 technologies, including the Internet of Things (IoT), big data analytics, and machine learning, is enabling real-time optimization and adaptive process control, setting the stage for the next generation of food production systems.

While previous reviews have examined specific optimization techniques within the food industry, they often focus on individual methodologies and lack an integrative perspective. This review aims to provide a comprehensive analysis of the evolution and application of optimization methodologies in the food industry, emphasizing their role in addressing current challenges. It evaluates the transition from traditional approaches to advanced multi-objective optimization techniques and their integration with cutting-edge technologies such as artificial neural networks and Industry 4.0 tools. By providing a detailed understanding of the diverse optimization methods available—ranging from statistical techniques like response surface methodology to more complex frameworks such as neural networks and multi-objective optimization—this article offers valuable insights into their advantages, limitations, and specific applications. It sheds light on how these methodologies are employed to address various industry challenges, such as improving process efficiency, enhancing product quality, reducing resource consumption, and promoting sustainable practices.

Furthermore, the article highlights practical examples and success stories, showcasing the tangible benefits of implementing optimization techniques in areas such as product development, process improvement, and extraction technologies. By emphasizing their potential to enhance resource efficiency, improve product quality, and achieve sustainability goals, this review contributes to the growing body of knowledge aimed at driving innovation and progress in the food industry.

2. Optimization Using Response Surface Methodology

Before the 1950s, the methods employed for process optimization analyzed only one independent variable at a time, disregarding the influence of other variables. This approach resulted in imprecise data and an elevated number of experiments [6]. The response surface methodology (RSM), developed by Box and his colleagues in the 1950s, introduced a significant advancement by requiring fewer experiments to evaluate multiple parameters and their interactions [7,8]. The term Response Surface Methodology originated from the graphical representation obtained after fitting the mathematical model. This tool was initially developed as a modeling technique widely applied in industries such as chemical and pharmaceutical sectors [9], as well as in the food industry and fields like biological and medical sciences [10].

The versatility of RSM lies in its ability to analyze multiple independent variables, including their interactions, allowing for the identification of additive, synergistic, or antagonistic effects on one or more responses. This makes it particularly useful for making predictions, optimizing processes, and enhancing their interpretation [11]. Additionally, its implementation requires a reduced number of experiments without compromising result accuracy [12].

RSM is composed of a set of mathematical and statistical techniques that can be used to define the relationships between the response variable and the independent variables. It determines the effect of independent variables, whether individually or in combination, on processes. In addition to analyzing these effects, this experimental methodology generates a mathematical model. The graphical perspective of this mathematical model gave rise to the term Response Surface Methodology [11].

To understand the application of RSM in optimization, it is essential to clarify certain concepts. The experimental domain refers to the experimental space defined by the upper and lower limits of the independent variables. The experimental design denotes the specific system of experiments based on the combinations of the levels of independent variables. Independent variables are input variables that can change independently of one another, while experimental runs refer to the series of trials that make up an experiment. Dependent variables, or response variables, are the output variables influenced by the independent variables. Lastly, the residual is the difference between the experimental result and the calculated result. A low residual value is necessary for the mathematical model to adequately fit the experimental data [1,10].

As mentioned, RSM is defined by a mathematical model that describes the optimal combinations of factors to optimize the response. This model outlines the relationship between independent variables and the interaction between their combinations on the dependent variables within an experimental domain [13].

The general equation that relates and discriminates the dependent variable (y) and the independent variables (x) with their respective coefficients (f), as well as the estimated error (ε), is expressed in Equation (1) [10,14]:

$$y = f(x_{1,}x_{2,}x_{3,}\ldots, x_k) + \varepsilon \tag{1}$$

For more accurate analysis, the values of each independent variable are encoded and standardized, typically ranging from −1 to +1, as described by Equation (2) [14].

The coded variable (X) is generated from the actual variable (x) based on its minimum and maximum values (or levels):

$$X = \frac{x - \left(\frac{x_{max}+x_{max}}{2}\right)}{\left(\frac{x_{min}+x_{min}}{2}\right)} \tag{2}$$

Defining variables is essential for validating models. If the variables are inappropriate for optimization, independent variables should be removed, and the experimental trials should be repeated. A crucial step in this process is to identify dependent and independent variables by determining significant effects that can enhance the model's accuracy [12,14].

The multiple regression methodology, utilizing the least squares method, is frequently used to examine the relationship between independent and dependent variables. A multiple regression equation (Equation (3)) can represent a second-order polynomial based on experimental data, as demonstrated in previous studies [6,15]:

$$Y = \beta_o + \sum_{i=1}^{k1} \beta_i X_i + \sum_{i=1}^{k-1} \sum_{i=2}^{k} \beta_{ij} X_i X_j + \sum_{i=1}^{k} \beta_{ii} X_I^2 + \varepsilon_i \tag{3}$$

where Y represents the response or dependent variable; X_i is the independent variables; β_o is the intercept; $\beta_{i,}$ β_{ij}, and β_{ii} are the regression coefficients for the linear, quadratic, and interaction terms, respectively; and k is the number of variables [12,14].

The model employed to optimize food processes within the RSM framework is not always a second-order model. It is essential to include regression coefficients that have a statistically significant effect on the response in the equation. Consequently, if quadratic terms are determined to be statistically insignificant, those coefficients are excluded, resulting in a linear equation [16].

When selecting the model, it must undergo statistical validation to ensure it accurately reflects the relationship between the variables. This validation is achieved through an analysis of variance (ANOVA), which assesses the model's predictive accuracy by examining the coefficient of determination (R^2). In addition, other methods, such as the lack-of-fit test, mean absolute deviation and residual analysis are utilized [17].

The visualization of the predicted model equation can be illustrated through contour and response surface plots. These three-dimensional representations, generated by response surface methodology (RSM), highlight the relationship between dependent and independent variables. Both contour and surface plots demonstrate how the response varies as independent variables change. Contour plots enhance our understanding of the shape of the response surface. When the target point—whether minimum, maximum, or any point within the operational range—resides at the center of the system (experimental area), the contour plots typically depict a circular or elliptical shape [1,16].

In the food industry, it is common to optimize multiple responses simultaneously, a task that is inherently more complex than optimizing processes focused on a single response. To tackle this challenge, a desirability function is employed, serving as a multi-criteria methodology. This approach assigns a desirability score to each individual response, operating under the premise that the overall "quality" of a product or process is deemed unacceptable if any one of the quality characteristics falls outside the "desired" range. The method identifies the operating conditions (X) that yield the "most desirable" response values. For each response Yi(x), a desirability function di(Yi) assigns values between 0 and 1 [1,14]:

$$D = ((d_1 * Y_1)(d_2 * Y_2) \ldots (d_n * Y_n))^{\frac{1}{n}} \quad (4)$$

where di(Yi) = 0 represents a completely undesirable value, and di(Yi) = 1 indicates an ideal or completely desirable value. Individual desirabilities are then combined using the geometric mean, resulting in overall desirability (D) (Equation (4)).

To confirm the validity of the generated equation, the difference between predicted and experimental responses should be less than 5% [1].

Another critical step in response surface methodology (RSM) analysis is the selection of experimental design. The primary goal of RSM is to guide experimentation to identify optimal conditions. The experimental design specifies the points at which the response should be evaluated [10].

The most used RSM designs are the central composite design (CCD) and the Box–Behnken design (BBD). When optimizing experimental variables using RSM, it is essential to validate the quadratic model, as this verification stage determines the critical conditions of the method. Thus, analysis of variance (ANOVA) remains one of the most effective techniques for evaluating these designs.

2.1. Central Composite Design (CCD)

This methodology consists of a two-level factorial design, a star design, and a central point. For two and three factors, this design requires nine and fifteen experiments, respectively, with factors analyzed at three and five levels. In two-factor CCDs, variables are generally studied at five levels: $-\sqrt{2}$, -1, 0, +1, and $+\sqrt{2}$. However, when $\alpha = 1$, factors are studied at three levels: -1, 0, and +1.

One advantage of this approach is the complete two-level factorial design, which can be preliminarily performed as a step to evaluate the factors. However, a drawback of this design is that it includes experiments where all factors are at extreme negative or positive levels. These extreme conditions can sometimes yield unsatisfactory results [1,12].

The number of experiments required by this design is defined by Equation (5):

$$N = 2^k + 2k + Co \tag{5}$$

where k represents the number of factors, and Co denotes the number of central points.

Table 1 provides an overview of various studies employing RSM, specifically using central composite designs applied in different fields of the food industry over recent years.

Table 1. Applications of optimization using response surface methodology with central composite designs.

Central Composite Design (CCD)								
Objective Function	**Raw Materials**	**Technique**	**Independent Variables**	**Levels**	**Optimal Conditions**	**R^2**	**Desirability**	**References**
Maximizing extract yield and total phenolic content	Moringa	Microwave-assisted extraction	Power Temperature Extraction time	500–700 W 30–50 °C 20–40 min	600 W 40 °C 30 min	0.9923	-	[18]
Minimize aw, maximize pH, density and flow index (n) and keep SS stable	Strawberry	Spray drying	Arabic gum Maltodextrin	5–15% 10–30%	11.7% 23.3%	-	0.7664	[19]
Minimize particle size, maximize loading capacity and encapsulation, and keep the zeta potential in the range	Vitamin C	Electrospraying	Chitosan Voltage Vitamin C-chitosan ratio	1–2% *w*/*v* 21–25 kV 0.25–0.75 *w*/*w*	2% 21 kV 0.746	-	0.94	[20]
Maximizing extract of betacyanin, betaxanthin and total phenolic content	Dried beetroot powder	Ultrasound-assisted extraction	Time Temperature Citric Acid Solution	15–3 (min) 20–40 (°C) 3–5 pH	10 min 30 °C 5 pH	-	0.928	[21]
Minimize acid ascorbic content and a* degradation, maximum b*, and rehydration capacity	Ginkgo biloba L. seeds	Intermediate-wave infrared dryer	Temperature Time Distance between infrared emitter and material	63.2–96.8 °C 99.5–200.4 min 1.9–22.1 cm	74.6 °C 172.93 min 22 cm		0.731	[22]
Minimize drying time, gumminess and maximizing ascorbic acid, L* value, chewiness	Sapota bar	Refractance window drying method	Water temperature Initial pulp thickness Pectin concentration	84.3–97.7 °C 3.32–6.68 mm 0.32–3.68%	91 °C 5 mm 2%		0.66	[23]
Minimize mineral and carbohydrate requirement, maximizing protein and lipid requirement	Egg Custard formulation	Feed Formulation	Curcuma longa Moringa olifera	0–1% 0–17.1%	1% 17.1%		0.738	[24]
Maximizing overall acceptability	High fiber biscuits formulation	Formulation	Sorghum Inulin Guar gum	25–45% 5–10% 1–2%	40.8% 6.5% 1%		0.827	[25]

2.2. Box–Behnken Design (BBD)

The Box–Behnken matrix for three factors is a spherical and rotational design that, when visualized in a cube, consists of the central point and the midpoints of the edges [12,26]. The Box–Behnken design (BBD) is an efficient response surface methodology tool that optimizes experimental variables with a minimal number of runs while maintaining high symmetry and rotatability [27]. The number of experiments required to construct the model is defined by Equation (6):

$$N = 2k * (k - 1) + Co \quad (6)$$

It organizes factorial points at the midpoints of the cube's edges, along with replicated runs at the central point, significantly reducing the required runs compared to designs such as the central composite design (CCD). Although it allows the inclusion of both numerical and categorical factors, the use of categorical factors increases the number of runs. Its specialized structure and high resolution make it suitable for quadratic models, maximizing experimental information at a lower operational cost. In the food and pharmaceutical industries, BBD has proven valuable for the development and optimization of products and processes, standing out for its flexibility, precision, and ability to evaluate experimental effects and global errors in complex designs [27,28].

Table 2 provides an overview of various studies employing RSM, specifically using Box–Behnken designs.

Table 2. Applications of optimization using response surface methodology with Box–Behnken designs.

Box–Behnken Design (BBD)								
Objective Function	**Raw Materials**	**Technique**	**Independent Variables**	**Levels**	**Optimal Conditions**	**R^2**	**Desirability**	**References**
Maximizing extract yield and total phenolic content	Garlic	Microwave-assisted extraction	Irradiation power Extraction time Solid-liquid ratio	520–1040 W 2–10 min 0.4–1 g/100 mL	826.67 W 7.62 min 0.55 g/mL	-	0.924	[29]
Minimize foam density, maximize foam expansion, and maintain stable other physico-chemical properties	Tomato	Foam-mat drying	Egg albumin Carboxymethyl cellulose Drying temperature	1–5% 1–1.5% 60–70 °C	4.59% 0.70% 60 °C	-	-	[30]
Minimize acid ascorbic content and a* degradation, maximum b*, and rehydration capacity	Ginkgo biloba L. seeds	Intermediate-wave infrared dryer	Temperature Time Distance between infrared emitter and material	70–90 °C 120–180 min 6–12 cm	79.29 °C 120 min 6 cm		0.711	[22]
Maximizing encapsulation efficiency	Acid Galic solution	Encapsulation by the ionotropic gelation technique	Sodium alginate concentration Calcium chloride concentration Gallic acid concentration	1–3% 2–6% 0.5–1.5%	3% 2.163% 1.5%	0.9945	0.991	[31]
Maximizing DPPH and ABTS radical scavenging activity	Pumpkin seed cake	Enzymatic hydrolysis process	Papain concentration Temperature Hydrolysis time	1–3% 20–40 °C 60–180 min	1% 40 °C 60 min		0.86	[32]
Maximizing production of reduced sugars	Wheat bran	Enzymatic saccharification	Time Substrate charge Enzymatic charge	4–12 h 1–3% 3–5%	8 h 2% 4%		0.998	[33]

3. Multi-Objective Optimization

Multi-objective optimization (MOO) has become an essential approach for addressing the multifaceted challenges of the food industry. This sector operates at the confluence of numerous, often conflicting goals, such as economic viability, nutritional quality, environmental sustainability, and alignment with global frameworks like the United Nations' 2030 Agenda for Sustainable Development. MOO offers a structured methodology for balancing these diverse objectives, providing a pathway to innovation, resilience, and sustainability in food production and distribution systems [34].

In mathematical optimization, deterministic and metaheuristic methods represent two distinct approaches for finding optimal solutions (Figure 1). Deterministic methods follow a predefined sequence of operations, ensuring reproducibility and guaranteeing the optimal solution, if one exists. These methods, such as LP and branch and bound, offer algorithmic precision and proofs of convergence but can be computationally expensive for large or complex problems, e.g., highly non-convex or non-differentiable functions. These algorithms are best suited for problems with well-defined and continuous objective functions and constraints. In contrast, metaheuristic methods employ flexible, adaptive search strategies using probabilistic rules to explore the solution space and escape local optima. While they do not guarantee to find the exact optimal solution, they aim to achieve near-optimal solutions efficiently, making them scalable and suitable for large-scale or real-time problems. Metaheuristics are particularly useful for complex, discontinuous, or poorly defined problems. However, some metaheuristics algorithms can also be computationally expensive due to the need to evaluate several potential solutions. In summary, deterministic methods provide precision and reliability for exact optimization, whereas metaheuristic methods offer flexibility and efficiency for tackling complex and large-scale problems.

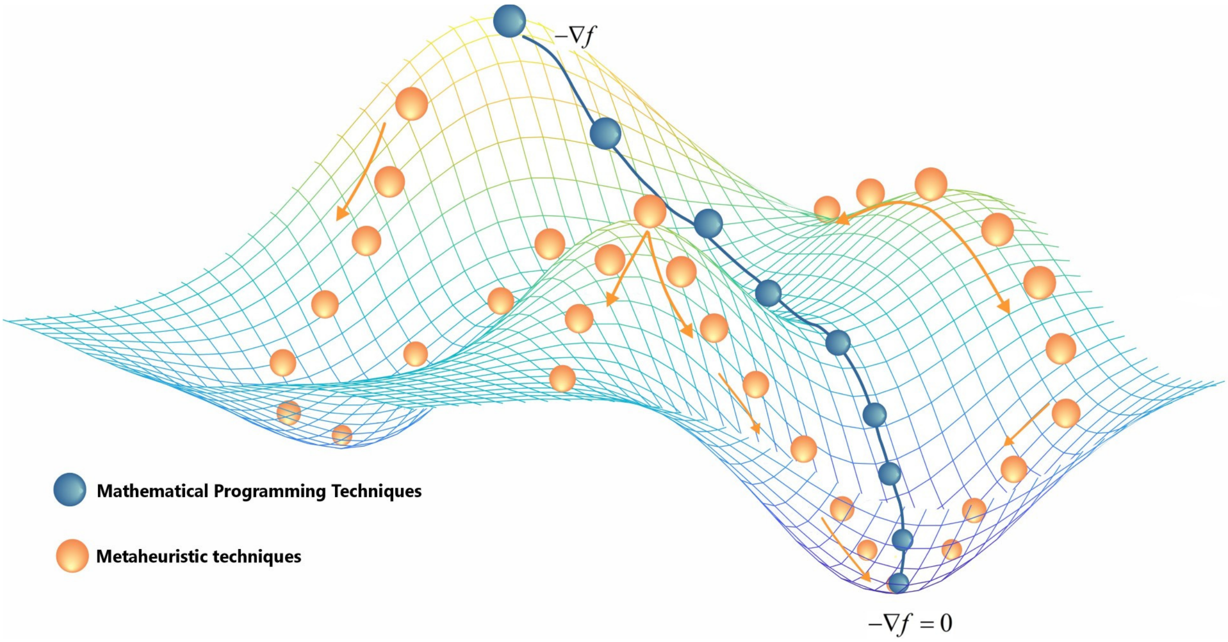

Figure 1. Graphical interpretation of search methodology for metaheuristic and deterministic optimization.

One of the core strengths of MOO is its ability to manage trade-offs between conflicting objectives. In the food industry, achieving cost-efficiency can sometimes come at the expense of nutritional value or environmental sustainability. Similarly, prioritizing environmental goals may increase production costs or limit operational flexibility. MOO frameworks address these challenges by enabling decision-makers to identify Pareto-optimal solutions, which represent the best possible trade-offs between competing objectives. This capability is crucial in a sector where diverse stakeholders, including manufacturers, consumers, and regulators, have varied and sometimes contradictory priorities.

Economic considerations remain a cornerstone of the food industry's operations. Rising global food demand and resource constraints necessitate cost-effective solutions that ensure profitability while maintaining affordability for consumers. MOO plays a vital role in optimizing production processes, supply chain logistics, and pricing strategies, enabling businesses to enhance their economic resilience [34]. For instance, by optimizing transportation routes and inventory management, MOO reduces operational costs while minimizing waste and energy consumption. Such strategies not only improve financial performance but also contribute to the industry's long-term sustainability.

In parallel with economic goals, the food industry must address increasing consumer demand for products that meet high nutritional standards. As public awareness of health and nutrition grows, manufacturers face the challenge of delivering food that balances taste, texture, and nutritional content while remaining cost-effective. MOO offers a powerful tool for designing recipes and formulations that meet these criteria. For example, it can optimize the combination of ingredients to reduce sugar or sodium content, enhance protein levels, or fortify products with essential vitamins and minerals. These advancements contribute to public health while ensuring that food products remain appealing and accessible to a wide range of consumers.

The environmental impact of the food industry has become a critical concern in the context of global sustainability. Agriculture, food production, and distribution are significant contributors to greenhouse gas emissions, deforestation, water usage, and waste generation. MOO addresses these challenges by optimizing resource use, reducing waste, and minimizing the carbon footprint of food systems. Whether through energy-efficient production processes, sustainable packaging design, or water-saving agricultural practices, MOO enables the industry to align its operations with environmental objectives. These efforts are instrumental in advancing a circular economy and mitigating the sector's contribution to climate change [35].

Beyond individual objectives, MOO aligns seamlessly with the Sustainable Development Goals (SDGs) outlined in the 2030 Agenda. Several SDGs directly relate to the food industry, including Zero Hunger (SDG 2), Responsible Consumption and Production (SDG 12), Climate Action (SDG 13), and Good Health and Well-being (SDG 3). MOO provides actionable strategies to achieve these goals. For instance, it facilitates efficient food production and equitable distribution, ensuring access to nutritious food (SDG 2). By optimizing resource use and minimizing waste, MOO supports sustainable production patterns (SDG 12). Moreover, by reducing energy consumption and emissions, it contributes to climate action (SDG 13), while simultaneously enhancing public health through the development of healthier food products (SDG 3) [36,37].

The practical applications of MOO in the food industry are diverse, reflecting its flexibility and broad relevance. In supply chain management, MOO optimizes logistics to balance costs, delivery times, and environmental impacts. In manufacturing, it enhances production processes to maximize yield and energy efficiency while maintaining product quality. MOO also supports product development by optimizing formulations for sensory attributes, nutritional value, and shelf life. Additionally, it plays a crucial role in designing sustainable packaging solutions and identifying optimal materials that balance cost, durability, and environmental impact. These applications underscore MOO's ability to address complex challenges across the food value chain [37,38].

The integration of MOO with advanced technologies, such as artificial intelligence (AI), machine learning, and digital twins, has further expanded its capabilities. These technologies enable MOO to handle large datasets, predict outcomes with high accuracy, and adapt to dynamic conditions. For example, digital twins—virtual replicas of physical systems—allow food manufacturers to simulate and optimize processes in real-time, reducing risks and costs associated with experimentation. Similarly, the integration of machine learning models enhances MOO's predictive power, making it particularly valuable for real-time process control, quality assurance, and supply chain optimization [34].

In the long term, the value of MOO lies in its ability to create adaptive systems that respond to evolving circumstances. As consumer preferences, regulatory requirements, and environmental conditions change, MOO provides the flexibility to re-optimize processes and products. This adaptability is critical for ensuring the competitiveness and sustainability of the food industry in an uncertain future. Multi-objective optimization is a cornerstone of modern food industry practices, addressing economic, nutritional, environmental, and societal goals in a comprehensive manner. By enabling the identification of balanced, sustainable solutions, MOO not only enhances the efficiency of food systems but also supports the achievement of global priorities, such as the SDGs outlined in the 2030 Agenda [37]. Its application across supply chains, production processes, and product development highlights its transformative potential. As the food industry navigates increasingly complex challenges, MOO will remain an indispensable tool for fostering innovation, ensuring resilience, and delivering value to all stakeholders [4].

Figure 2 illustrates the multiple applications and goals of multi-objective optimization in the food industry, focusing on key objectives such as operational cost reduction, environmental sustainability, food quality, and food safety. These goals are strategically integrated to maximize overall benefits across the food value chain.

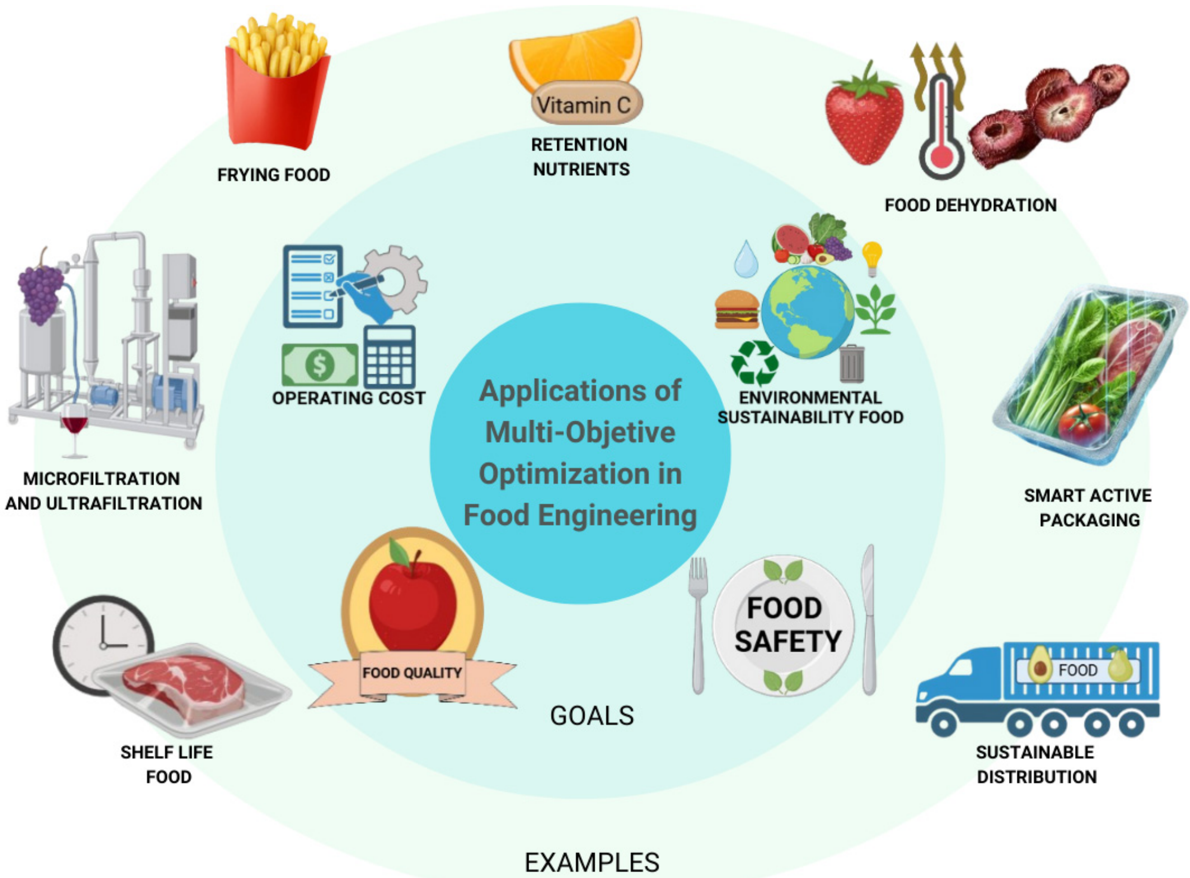

Figure 2. Applications of multi-objective optimization in food engineering.

The figure also highlights various practical applications, including extending shelf life, applying microfiltration and ultrafiltration processes for quality improvement, nutrient retention in frying, efficient food dehydration, active packaging development, and sustainable distribution.

4. Overview of Optimization Methods in Food Science: Linear, Non-Linear, and Evolutionary Approaches

Optimization is critical in food science for achieving balanced solutions that address multiple objectives, such as maximizing product quality, reducing costs, and ensuring environmental sustainability. Three main optimization methods—linear, non-linear, and evolutionary—play pivotal roles in solving different types of problems. Each method has unique characteristics, strengths, and limitations that determine when it should be used or avoided in food science applications [4,39], as shown in Table 3.

Table 3. Comparison of methods [40,41].

Aspect	Linear Methods	Non-Linear Methods	Evolutionary Methods
Complexity	Low	Moderate to High	High
Accuracy	Exact solutions	High accuracy	Approximate solutions
Problem types	Linear	Non-linear	Non-convex, discontinuous
Computation	Fast and efficient	Computationally intensive	Resource-intensive
Use Cases	Supply chains, diets	Fermentation, energy use	Recipe optimization, supply chains

4.1. Linear Methods

Linear optimization methods address problems where the relationships among variables are represented as linear equations or inequalities. In this approach, both the objective function and constraints are linear, making the problem relatively simple to model and solve using techniques such as linear programming (LP). Linear methods are highly effective for situations where the relationships between inputs and outputs are proportional and straightforward [4].

Linear methods are particularly advantageous in scenarios that require fast and reliable solutions with minimal computational resources. For instance, they are commonly used in resource allocation problems, where constraints and objectives can be clearly defined in linear terms. However, their applicability diminishes in cases involving non-linear dependencies, discontinuities, or multiple local optima. Such limitations make linear methods unsuitable for modeling complex phenomena such as chemical reactions or biological processes, which often exhibit non-linear behavior [40].

4.2. Non-Linear Methods

Non-linear optimization methods extend the capabilities of linear approaches by addressing problems with non-linear relationships among variables. These relationships, which may involve curved or exponential interactions, are prevalent in food science due to the intricate physical, chemical, and biological processes involved in production systems. Non-linear methods are indispensable for modeling and optimizing such complex systems, as they provide a rigorous mathematical framework for capturing non-linearities [41].

Applications of non-linear methods are diverse and include optimizing heat transfer processes, enzymatic reactions, and fluid dynamics. These methods are particularly valuable when high accuracy is required in modeling system behavior. However, their computational intensity can be a drawback, especially for problems with a large number of variables or constraints. Additionally, non-linear methods are less suitable for scenarios requiring rapid, approximate solutions, as their complexity often demands significant computational resources [39,42].

4.3. Evolutionary Algorithms

In contrast to traditional optimization methods, evolutionary algorithms are heuristic and probabilistic, drawing inspiration from the principles of natural selection. These methods, which include genetic algorithms (GAs), particle swarm optimization (PSO), and differential evolution (DE), are designed to tackle highly complex, multi-objective, or poorly understood problems. Unlike deterministic methods, evolutionary algorithms do not guarantee exact solutions but are capable of identifying near-optimal solutions in challenging problem spaces [43].

Evolutionary algorithms excel in addressing optimization problems characterized by non-convex, discontinuous, or high-dimensional relationships. Their iterative nature allows them to explore a wide range of potential solutions, making them ideal for applications where traditional methods fail. For example, they are particularly effective in multi-objective optimization scenarios, where conflicting objectives such as quality, cost, and sustainability must be balanced. However, the resource-intensive nature of evolutionary methods can be a limitation, as they often require substantial computational power and time. Moreover, their reliance on probabilistic processes means that the quality of the solution depends on the algorithm's design and parameters.

By categorizing optimization methods and problems in food science, a clearer understanding of their applications and limitations emerges. Traditional methods, such as linear and non-linear optimization, offer precise and reliable solutions for well-defined problems, while evolutionary algorithms provide the flexibility needed to tackle complex, multi-objective challenges. Understanding when and how to apply these methods is essential for advancing optimization efforts in food science, enabling the industry to achieve its goals of quality, efficiency, and sustainability [35]. Figure 3 presents a classification of optimization methods, including mathematical programming (both continuous and discrete), metaheuristic optimization, and learning-based approaches. Each category is outlined with key characteristics, highlighting the strengths and specific applications of each method in the context of food science.

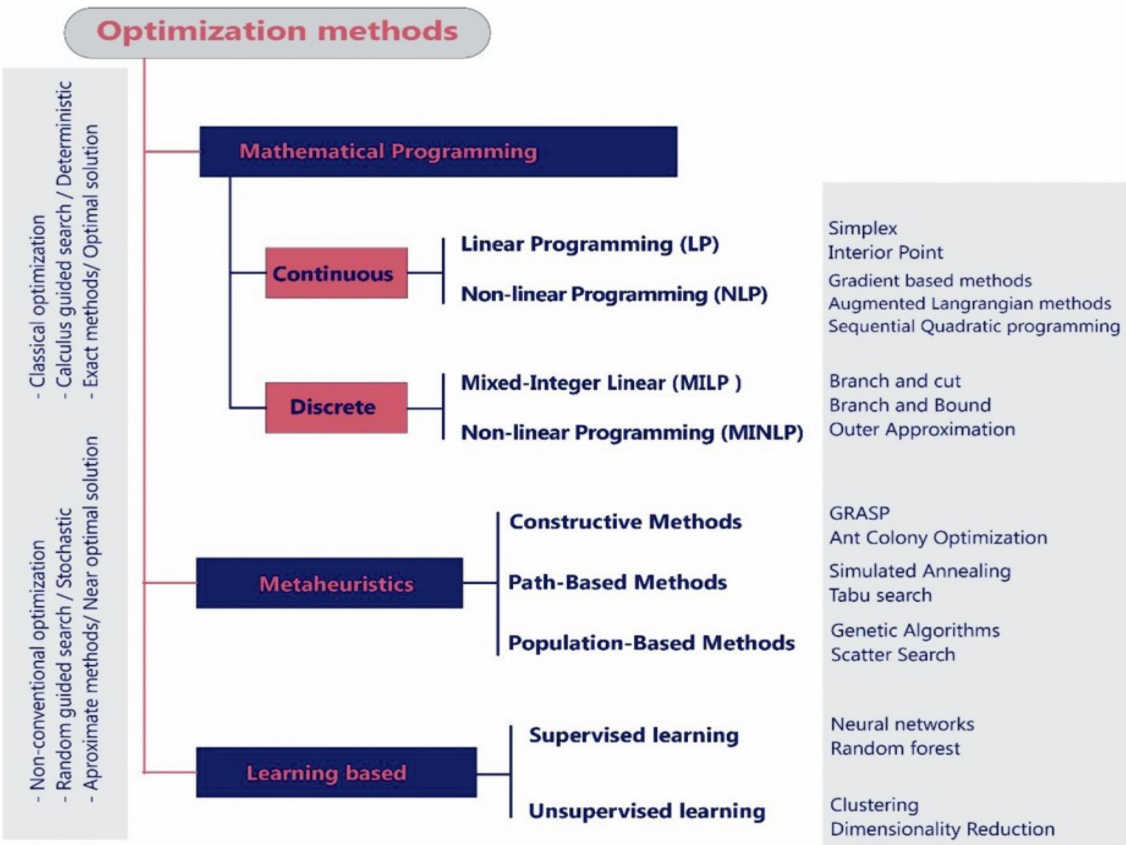

Figure 3. Optimization methods.

4.4. Integrating Methods for Optimal Solutions

In food science, hybrid approaches that combine these methods are becoming increasingly popular. For instance, linear methods can be used to simplify initial problem formulations, non-linear methods can refine the model, and evolutionary methods can tackle the most complex aspects. Linear, non-linear, and evolutionary methods each offer unique advantages and limitations, making them suitable for different types of optimization problems in food science. Understanding the differences and similarities among these methods allows practitioners to choose the most appropriate approach for their specific needs, balancing efficiency, accuracy, and computational resources [35].

5. Linear Methods

Linear methods in multi-objective optimization (MOO) have emerged as powerful tools for addressing a wide range of challenges in the food industry. These methods, which rely on linear relationships among variables, offer simplicity, computational efficiency, and clear interpretability. Their applicability to problems such as resource allocation, supply chain optimization, and production scheduling makes them invaluable for achieving economic, nutritional, and environmental objectives.

5.1. Economic Efficiency and Resource Allocation

Linear programming (LP), a cornerstone of linear methods, is widely employed to optimize resource allocation in the food industry. From minimizing production costs to maximizing output efficiency, LP models enable manufacturers to make data-driven decisions. For instance, a study on bakery production demonstrated that LP could reduce costs by up to 15% by optimizing ingredient proportions and production schedules. Similarly, in dairy processing, linear optimization has been used to allocate raw milk effectively across multiple products, ensuring minimal waste and maximum profitability [44].

Another key application of linear methods is in optimizing the use of agricultural resources. In regions with constrained land, water, and labor, LP models guide farmers in selecting crop combinations that maximize yields while adhering to resource limitations. For example, the application of LP in crop planning increased farm income by 20% while reducing water usage by 10%, demonstrating the dual economic and environmental benefits of linear methods [45].

5.2. Supply Chain Optimization

The food industry's supply chain is characterized by its complexity and sensitivity to disruptions, such as those caused by climate change or geopolitical instability. Linear methods provide robust solutions for optimizing transportation, inventory management, and distribution networks, ensuring cost-effectiveness and reliability.

For example, LP models have been successfully applied to optimize transportation routes for food products, reducing fuel consumption and delivery times. A case study in Europe revealed that optimizing delivery routes for perishable goods using linear methods reduced transportation costs by 12% and carbon emissions by 8% [46]. Such improvements not only enhance economic performance but also contribute to the environmental goals outlined in SDG 13 (Climate Action).

In inventory management, linear methods play a crucial role in minimizing holding costs and preventing overstocking or stockouts. For instance, a linear optimization model applied to a frozen food manufacturer helped balance inventory levels, reducing storage costs by 18% while ensuring consistent product availability. This efficiency directly supports the goals of SDG 12 (Responsible Consumption and Production) by minimizing waste and optimizing resource use [47].

5.3. Nutritional Optimization and Public Health

Linear methods also contribute significantly to improving nutritional outcomes in the food industry. By optimizing food formulations, LP models enable manufacturers to develop products that meet specific nutritional criteria at a minimal cost. For instance, linear optimization has been used to design fortified food products tailored to address micronutrient deficiencies in vulnerable populations [48].

A notable example is the application of LP in school meal programs. A linear optimization model was developed to plan nutritionally balanced menus for schoolchildren, ensuring compliance with dietary guidelines while minimizing costs. The model achieved a 25% reduction in food expenses without compromising nutritional quality, demonstrating its potential to improve public health outcomes [49].

Similarly, LP has been applied to optimize the formulation of livestock feed, balancing protein, energy, and micronutrient levels while minimizing costs. This optimization not only enhances the nutritional quality of animal products but also supports sustainable agricultural practices by reducing the environmental impact of feed production [50].

5.4. Environmental Sustainability and Circular Economy

Linear methods align closely with sustainability objectives by facilitating resource efficiency and waste minimization. For instance, linear optimization has been used to design sustainable packaging solutions that balance material costs, durability, and recyclability. A study on food packaging optimization showed that LP could reduce material usage by 20%, cutting costs and reducing plastic waste in landfills [51].

In waste management, LP models have been applied to optimize the logistics of food waste collection and recycling. In the United States, a linear optimization framework was used to design a food waste recycling network, minimizing transportation costs and maximizing energy recovery from organic waste. This approach supports the goals of SDG 12 and SDG 13 by promoting a circular economy and reducing greenhouse gas emissions [52].

5.5. Production Planning and Process Optimization

Linear methods are also instrumental in optimizing production planning and scheduling in the food industry. By modeling production processes as linear systems, these methods ensure efficient resource allocation, minimize downtime, and enhance overall productivity.

For instance, in beverage production, LP models have been used to optimize bottling schedules, balancing production capacity and demand variability. A case study in a soft drink manufacturing facility demonstrated that linear optimization reduced production costs by 10% and improved on-time delivery rates by 15% [53].

In food processing, LP models facilitate energy optimization by identifying the most efficient allocation of heat and power across different stages. For example, an LP-based energy management system in a food processing plant reduced energy consumption by 12%, contributing to cost savings and environmental sustainability [54].

5.6. Quantitative Impacts and Alignment with the 2030 Agenda

The quantitative impacts of linear methods in the food industry are significant, with measurable benefits in cost reduction, waste minimization, and efficiency improvements. For example, studies have shown that the adoption of LP in production and supply chain management can reduce operational costs by 10–20% and greenhouse gas emissions by 5–15% [38]. These achievements directly contribute to the SDGs, particularly those related to sustainable consumption and production (SDG 12), climate action (SDG 13), and zero hunger (SDG 2).

Moreover, the scalability and adaptability of linear methods make them suitable for addressing global challenges in the food industry. Whether optimizing resource use in small-scale farms or improving logistics in multinational food corporations, LP models provide actionable insights that drive progress toward the 2030 Agenda's goals.

5.7. Challenges and Future Directions

While linear methods offer substantial benefits, their applicability is limited to problems with linear relationships among variables. Many challenges in the food industry, such as non-linear supply chain dynamics or complex biochemical processes in food production, require hybrid approaches that combine linear methods with non-linear or heuristic techniques. Future research should focus on integrating linear methods with advanced technologies like artificial intelligence (AI) and machine learning to enhance their predictive and adaptive capabilities. For example, AI-powered LP models could analyze large datasets in real-time, enabling dynamic optimization of supply chains and production processes [55]. Additionally, the development of robust algorithms for handling uncertainty and variability in linear models will further expand their relevance in the food industry. Finally, linear methods in multi-objective optimization represent a cornerstone of modern food industry practices, providing efficient solutions to complex problems in resource allocation, supply chain management, and production planning. Their ability to balance economic, nutritional, and environmental objectives aligns seamlessly with the principles of sustainability and the SDGs outlined in the 2030 Agenda. By reducing costs, improving nutritional outcomes, and minimizing environmental impacts, linear methods drive innovation and resilience in the food industry. As global challenges intensify, the continued evolution and integration of linear optimization techniques will be essential for ensuring a sustainable and equitable food system for future generations [56].

6. Non-Linear Methods

Non-linear methods are indispensable in tackling the complex optimization problems characteristic of the food industry. Unlike linear methods, which assume proportional relationships among variables, non-linear methods capture the intricacies of real-world systems where interactions and responses are often non-linear. These methods, including non-linear programming (NLP), quadratic programming, and dynamic optimization, provide a robust framework for addressing challenges in energy consumption, ingredient formulation, and production planning. Their capacity to model non-linear relationships aligns with the industry's goals to meet economic, nutritional, and environmental criteria while contributing to the Sustainable Development Goals (SDGs) of the 2030 Agenda [36].

6.1. Modeling Complex Physical, Chemical, and Biological Processes

The food industry frequently deals with processes governed by complex physical, chemical, and biological interactions. Non-linear methods excel in modeling such systems, enabling the optimization of intricate processes that linear methods cannot adequately address. For instance, fermentation, a common process in food and beverage production, involves non-linear dynamics influenced by factors such as temperature, pH, and nutrient availability. Using NLP, producers can optimize fermentation conditions to maximize product yield and quality while minimizing energy consumption [57].

Quantitative studies highlight the efficacy of non-linear methods in this domain. For example, an optimization model for yogurt production demonstrated a 20% increase in probiotic bacteria viability by fine-tuning fermentation parameters using non-linear methods [58]. This approach not only improved product quality but also enhanced consumer health benefits, aligning with SDG 3 (Good Health and Well-being).

6.2. Energy Optimization and Environmental Sustainability

Energy-intensive processes such as drying, freezing, and pasteurization are critical in food manufacturing. These processes often exhibit non-linear relationships between energy input and output efficiency. Non-linear methods enable manufacturers to identify optimal energy usage patterns, thereby reducing costs and minimizing environmental impacts.

A notable application is in optimizing drying processes for agricultural products. Non-linear optimization models have been used to minimize energy consumption in grain drying systems, achieving up to 15% energy savings compared to conventional approaches.

6.3. Ingredient Mixing and Food Formulation

Ingredient formulation in the food industry often involves non-linear interactions among components, where changes in one ingredient affect the properties of the entire product. Non-linear methods enable precise optimization of these interactions, ensuring that products meet nutritional, sensory, and economic criteria.

For example, in the development of plant-based meat alternatives, non-linear optimization models have been used to balance protein content, texture, and flavor. A case study in this domain reported a 10% improvement in product texture and a 5% reduction in production costs by optimizing ingredient proportions using NLP. Similarly, in bread-making, non-linear models have been applied to optimize dough rheology, resulting in improved loaf volume and reduced waste [59].

In nutritional optimization, non-linear methods allow manufacturers to design fortified foods tailored to specific dietary requirements. For instance, a non-linear programming model for infant formula optimization achieved a 15% reduction in production costs while ensuring compliance with stringent nutritional standards, contributing to SDG 2 (Zero Hunger) and SDG 3 [60].

6.4. Supply Chain and Inventory Management

Supply chains in the food industry are characterized by non-linear dynamics, including variable demand patterns, perishable inventory, and transportation constraints. Non-linear methods are instrumental in optimizing these complex systems, ensuring efficiency and sustainability.

A study on perishable food distribution utilized non-linear programming to optimize delivery schedules, reducing waste by 8% and transportation costs by 10%. Another application involved dynamic inventory management for a frozen food company, where non-linear models helped balance holding costs and spoilage rates, achieving a 12% cost reduction while minimizing product loss [38].

6.5. Production Planning and Scheduling

Production planning in the food industry often involves non-linear relationships between production variables, such as equipment capacity, processing time, and product quality. Non-linear methods provide a sophisticated approach to optimizing these variables, ensuring efficient and cost-effective operations.

For example, in beverage manufacturing, NLP models have been used to optimize production schedules, balancing demand fluctuations and resource constraints. A case study in a brewery reported a 15% reduction in production costs and a 10% increase in on-time delivery rates through non-linear optimization. Similarly, in meat processing, non-linear methods have been applied to optimize cutting and packaging operations, achieving a 20% reduction in waste and a 12% increase in yield [38].

6.6. Quantitative Impacts and Alignment with the 2030 Agenda

The quantitative benefits of non-linear methods in the food industry are significant. Studies have shown that the application of non-linear optimization can result in cost savings of 10–20%, energy reductions of 10–15%, and waste reductions of 5–10% [36]. These outcomes align with the SDGs, particularly those related to sustainable consumption and production (SDG 12), climate action (SDG 13), and zero hunger (SDG 2).

Moreover, non-linear methods enable a more nuanced understanding of trade-offs among competing objectives, allowing decision-makers to prioritize sustainability without compromising economic viability. For instance, a multi-objective non-linear optimization model for a dairy processing plant demonstrated that energy consumption could be reduced by 12% while maintaining profitability, illustrating the balance between environmental and economic goals [40].

6.7. Challenges and Future Directions

Despite their advantages, non-linear methods are computationally intensive and require advanced expertise to implement. This complexity limits their adoption in small- and medium-sized enterprises in the food industry. Addressing these challenges requires the development of user-friendly tools and the integration of non-linear methods with emerging technologies such as artificial intelligence (AI) and machine learning.

AI-powered optimization models can enhance the predictive capabilities of non-linear methods, enabling real-time decision-making in dynamic environments. For example, machine learning algorithms can be used to update non-linear models based on changing market conditions, ensuring continuous optimization of supply chains and production processes [61].

Additionally, research should focus on developing hybrid optimization approaches that combine non-linear methods with other techniques, such as metaheuristics or evolutionary algorithms. These hybrid methods can address the limitations of non-linear optimization while expanding its applicability to more complex problems.

By enabling cost savings, waste reduction, and efficiency improvements, non-linear methods contribute significantly to the SDGs outlined in the 2030 Agenda. As global challenges intensify, the continued advancement and adoption of non-linear optimization techniques will be essential for building a sustainable and equitable food system. Investing in research, tools, and training to overcome the barriers to adoption will ensure that non-linear methods remain at the forefront of innovation in the food industry.

7. Evolutionary Methods

Evolutionary methods, inspired by the principles of natural selection and biological evolution, are indispensable in addressing the complex and multidimensional optimization challenges prevalent in the food industry. Algorithms such as genetic algorithms (GAs), particle swarm optimization (PSO), differential evolution (DE), and evolutionary strategies (ESs) have proven effective in solving intricate multi-objective optimization problems, enabling advancements in recipe formulation, flavor optimization, process efficiency, and supply chain management. These methods are uniquely suited to tackling non-convex, discontinuous, and high-dimensional problems, where traditional optimization techniques often fall short. By leveraging evolutionary methods, the food industry can make significant strides toward achieving nutritional, sustainable, and economic goals in alignment with the 2030 Agenda for Sustainable Development [62].

7.1. Optimizing Recipe Formulation and Nutritional Profiles

Recipe formulation in the food industry often involves balancing nutritional content, sensory attributes, and production costs. Evolutionary algorithms, particularly GA and PSO, excel at exploring complex solution spaces to identify optimal formulations. For instance, in developing fortified foods, evolutionary methods have been used to maximize nutrient content while maintaining acceptable taste and texture.

A study applying GA to optimize breakfast cereal formulations demonstrated a 25% improvement in fiber content and a 10% reduction in sugar, all while maintaining consumer preference ratings. Similarly, PSO has been employed in designing plant-based meat alternatives to achieve a 15% enhancement in protein content and a 20% improvement in texture quality [63]. These applications contribute directly to Sustainable Development Goal 2 (Zero Hunger) by promoting healthier and more accessible food options.

7.2. Enhancing Flavor and Sensory Quality

Consumer preferences for flavor and texture drive much of the innovation in the food industry. Evolutionary methods are particularly adept at optimizing these attributes, which are often governed by non-linear and interactive variables. DE and ESs have been applied to optimize flavor profiles in beverages and snacks, balancing sweetness, acidity, and aromatic compounds [64].

In one notable application, GA was used to optimize the flavor profile of a fruit juice blend, increasing consumer satisfaction ratings by 18%. Similarly, DE was applied to balance bitterness and sweetness in chocolate formulations, leading to a 12% increase in market share for the optimized product [65]. These improvements align with the industry's economic goals while enhancing consumer satisfaction, indirectly supporting SDG 12 (Responsible Consumption and Production).

7.3. Process Optimization and Energy Efficiency

The food industry is characterized by energy-intensive processes such as drying, freezing, and pasteurization. Evolutionary algorithms provide a robust framework for optimizing these processes, reducing energy consumption, and enhancing overall efficiency.

For example, PSO has been used to optimize drying conditions for fruits and vegetables, achieving a 15% reduction in energy usage while preserving nutritional quality. Similarly, GA has been applied to optimize freezing protocols, reducing energy consumption by 12% and minimizing texture degradation. These advancements directly support SDG 13 (Climate Action) by reducing the carbon footprint of food production [65].

Quantitative data underscore the impact of evolutionary methods in process optimization. A study on thermal processing optimization using GA reported a 10% improvement in energy efficiency, translating to annual savings of over $1 million for a mid-sized food manufacturing plant. These savings not only improve economic viability but also enhance the industry's sustainability credentials [65].

7.4. Supply Chain and Logistics Optimization

Efficient supply chain management is critical for minimizing costs, reducing waste, and ensuring timely delivery of perishable goods. Evolutionary methods, particularly GA and PSO, have been widely used to optimize supply chain networks in the food industry, addressing challenges such as vehicle routing, inventory management, and demand forecasting.

In one application, GA was used to optimize delivery routes for a dairy company, reducing transportation costs by 15% and delivery times by 20%. Similarly, PSO was applied to optimize inventory management in a frozen food supply chain, achieving a 12% reduction in spoilage rates and a 10% increase in order fulfillment accuracy [66].

7.5. Addressing Sustainability Challenges

Sustainability is a core priority for the food industry, encompassing environmental, social, and economic dimensions. Evolutionary methods enable the industry to address sustainability challenges by optimizing resource use, minimizing waste, and reducing environmental impacts.

For instance, DE has been applied to optimize water usage in food processing plants, achieving a 10% reduction in water consumption without compromising product quality. Similarly, GA has been used to optimize the use of alternative, eco-friendly packaging materials, reducing plastic waste by 20% [67] and aligning with SDG 14 (Life Below Water) and SDG 15 (Life on Land).

Furthermore, evolutionary methods have been employed to optimize renewable energy integration in food production facilities. A case study on a bakery that integrated solar power into its operations reported a 25% reduction in energy costs and a 15% decrease in greenhouse gas emissions [67], supporting SDG 7 (Affordable and Clean Energy) and SDG 13.

7.6. Multi-Objective Optimization for Trade-Off Analysis

One of the defining advantages of evolutionary methods lies in their capacity to manage multi-objective optimization challenges effectively. These methods excel in scenarios where conflicting objectives must be addressed simultaneously, offering solutions that balance competing goals. In food systems, such optimization problems often involve trade-offs between minimizing costs, maximizing product quality, and enhancing environmental sustainability. For instance, in supply chain optimization, balancing economic efficiency with environmental impact is a recurring challenge. A notable application of genetic algorithms (GAs) in this context demonstrated their effectiveness: a multi-objective optimization model applied to a food distribution network achieved a 10% reduction in costs while simultaneously lowering carbon emissions by 15% [68,69].

Similarly, particle swarm optimization (PSO) has been applied to optimize food packaging design, addressing objectives such as cost-effectiveness, environmental impact, and consumer preferences. By leveraging the ability of PSO to explore complex, multi-dimensional solution spaces, researchers achieved a 12% reduction in packaging costs alongside a 10% improvement in consumer satisfaction ratings. These examples underscore the versatility of evolutionary methods in solving multi-objective problems, particularly in scenarios requiring a nuanced understanding of trade-offs between competing goals [68].

Recent advancements have further enhanced the scope of these methods. The research highlighted in "A learning-driven multi-objective cooperative artificial bee colony algorithm for distributed flexible job shop scheduling problems with preventive maintenance and transportation operations" (2024) showcases the integration of evolutionary techniques with learning-driven strategies. These hybrid approaches improve the efficiency of convergence and the quality of solutions, particularly in dynamic and distributed systems [70]. Similarly, the integration of Q-learning into evolutionary frameworks, as demonstrated in "Multi-objective integrated harvest and distribution scheduling for fresh agricultural products with farm-to-door requirements" (2025) highlights the potential of adaptive learning to tackle real-time optimization challenges. These studies represent significant progress in addressing the inherent complexities of multi-objective problems, particularly in industries with dynamic operational environments [71].

7.7. Applications in Smart and Digitalized Food Systems

The ongoing digital transformation of the food industry has significantly broadened the applications of evolutionary methods. As smart technologies and the Internet of Things (IoT) become integral to food production and supply chains, evolutionary methods are being adapted to handle real-time decision-making requirements. For example, PSO has been integrated with IoT sensors to monitor and optimize storage conditions for perishable goods. By enabling real-time adjustments to environmental variables, such as temperature and humidity, this approach has reduced spoilage rates by 12% [72].

In another example, GAs combined with predictive analytics have been employed to enhance production scheduling. This integration allows food manufacturers to dynamically forecast demand and adjust production plans accordingly, resulting in a 10% improvement in operational efficiency [73]. These applications highlight the growing importance of evolutionary methods in managing the complexity and variability of modern food systems, particularly as these systems become increasingly reliant on real-time data.

Hybrid optimization approaches are also gaining traction in smart food systems. Studies such as "Multiobjective scheduling of energy-efficient stochastic hybrid open shop with brain storm optimization and simulation evaluation" demonstrate the effectiveness of combining evolutionary algorithms with advanced simulation techniques [74]. These hybrid methods are particularly well-suited for addressing stochastic and uncertain conditions, ensuring that optimized solutions remain effective across a wide range of scenarios. This capability is essential in smart food systems, where operational decisions must often account for variability in supply chains, consumer demand, and environmental conditions.

7.8. Quantitative Impact and Future Directions

The quantitative impact of evolutionary methods in the food industry is profound. Studies have consistently shown that these methods can achieve significant cost savings, waste reductions, and energy efficiency improvements. For example, their application has led to cost reductions of 10–20%, waste reductions of 15–25%, and energy savings of 10–15% [66]. These improvements are not only economically significant but also critical for advancing the food industry's sustainability objectives [61].

Looking to the future, the potential of evolutionary methods can be expanded through the development of hybrid optimization frameworks. By integrating these methods with neural networks, fuzzy logic, and reinforcement learning, researchers can address the limitations of individual algorithms and enhance their applicability to increasingly complex problems. For instance, combining Q-learning with cooperative evolutionary algorithms, as highlighted in recent research, allows for more effective decision-making in dynamic and distributed environments [75].

Another promising direction is the integration of evolutionary methods with emerging technologies such as big data analytics and digital twin systems. These technologies enable more precise modeling and simulation of real-world systems, enhancing the ability of evolutionary methods to identify optimal solutions. For example, digital twins can provide real-time feedback on system performance, allowing evolutionary algorithms to adapt and refine their solutions dynamically [76].

Evolutionary methods represent a cornerstone of modern optimization strategies, offering unparalleled capabilities for addressing the multifaceted challenges of the food industry. Their ability to handle complex, non-linear, and high-dimensional optimization problems makes them uniquely suited to advancing nutritional, economic, and sustainability goals. By enabling cost savings, waste reduction, and efficiency improvements, these methods contribute significantly to the Sustainable Development Goals (SDGs) outlined in the 2030 Agenda [75].

As the food industry continues to evolve, the adoption of advanced multi-objective optimization techniques will be instrumental in building a sustainable and resilient food system. By integrating evolutionary methods with cutting-edge technologies such as IoT, machine learning, and digital twins, researchers and practitioners can unlock new levels of precision and efficiency in food system optimization. These advancements will not only enhance the industry's economic and environmental performance but also ensure its ability to meet the growing demands of a global population. The future of evolutionary optimization in the food industry is bright, promising transformative solutions that align with the goals of sustainability and resilience.

8. Multi-Objective Optimization Integrated with Neural Networks ANN

The integration of multi-objective optimization (MOO) with artificial neural networks (ANNs) represents a transformative approach to addressing the complex and interconnected challenges of the food industry. MOO, which seeks to balance multiple, often conflicting objectives, becomes significantly more powerful when combined with ANNs due to their capacity for learning non-linear relationships, processing vast datasets, and improving predictive accuracy [5]

8.1. Optimizing Nutritional Profiles with MOO-ANN

Food products are increasingly required to meet diverse nutritional requirements, accommodate dietary restrictions, and satisfy consumer preferences. MOO integrated with ANNs allows for the precise formulation of food products by analyzing vast datasets of ingredients, nutritional properties, and sensory attributes. For instance, MOO-ANN can optimize recipes to enhance protein content while reducing sugar and fat, ensuring products align with health-conscious trends without sacrificing taste [77].

Quantitatively, studies using MOO-ANN to optimize functional foods have reported up to a 30% improvement in nutrient density while maintaining consumer acceptability ratings above 85%. For example, an application in optimizing baby food formulations resulted in a 20% reduction in added sugar and a 15% increase in essential micronutrients, directly contributing to Sustainable Development Goal (SDG) 2: Zero Hunger by addressing malnutrition [78].

8.2. Enhancing Sustainability in Food Production

Sustainability is a core challenge for the food industry, encompassing resource efficiency, waste reduction, and environmental impact. MOO-ANN systems are uniquely suited to optimizing these factors simultaneously, leveraging predictive capabilities to balance resource inputs and environmental outputs.

In one notable case, MOO-ANN was used to optimize water and energy consumption in dairy processing, achieving a 25% reduction in water use and a 15% decrease in energy costs without compromising product quality. Similar applications in bakery operations demonstrated a 20% reduction in flour waste by optimizing mixing and baking parameters [78]. These advancements align with SDG 12: Responsible Consumption and Production by promoting resource efficiency and waste reduction.

8.3. Optimizing Food Supply Chains with MOO-ANN

Supply chains in the food industry are highly complex, involving perishable goods, fluctuating demand, and diverse logistical challenges. MOO-ANN models enable real-time optimization of these systems by predicting demand patterns, optimizing transportation routes, and balancing inventory levels.

For instance, integrating MOO-ANN in a frozen food supply chain reduced spoilage rates by 18%, improved delivery time accuracy by 12%, and cut transportation costs by

15%. These quantitative gains contribute directly to SDG 9: Industry, Innovation, and Infrastructure by fostering efficient and resilient supply chain networks [36].

8.4. Energy Efficiency and Carbon Emission Reduction

The food industry is a significant energy consumer, and minimizing its carbon footprint is essential for meeting SDG 13: Climate Action. MOO-ANN models are increasingly employed to optimize energy use across production processes.

For example, an MOO-ANN application in a beverage manufacturing plant optimized heating and cooling processes, leading to a 10% reduction in energy consumption and a corresponding 8% decrease in greenhouse gas emissions. In another case, a bakery utilizing MOO-ANN for oven temperature and baking time optimization reported annual savings of $250,000, underscoring the economic and environmental benefits of such approaches [79].

8.5. Dynamic Decision-Making for Process Optimization

One of the standout features of MOO-ANN is its ability to enable dynamic decision-making in real time. By continuously learning from process data, ANN models integrated with MOO frameworks can adapt to changing conditions, such as variations in raw material quality or shifts in consumer demand.

For instance, an application in yogurt production utilized MOO-ANN to adjust fermentation times and temperatures dynamically, resulting in a 10% increase in production yield and a 5% reduction in production costs [5]. Such advancements not only enhance operational efficiency but also improve economic viability, supporting SDG 8: Decent Work and Economic Growth.

8.6. Integration with IoT and Big Data for Smart Food Systems

The rise of the Internet of Things (IoT) and big data analytics in the food industry has amplified the potential of MOO-ANN systems. IoT devices generate vast amounts of real-time data from production lines, storage facilities, and distribution networks, which MOO-ANN models can process to identify optimal solutions [80].

For example, integrating IoT sensors with MOO-ANN in a fruit storage facility optimized temperature and humidity settings, reducing spoilage rates by 15% and extending shelf life by 20%. Similar applications in meat processing plants have achieved a 10% reduction in energy costs by dynamically adjusting refrigeration settings based on predictive ANN model solutions [80].

8.7. Product Innovation and Customization

Consumer demands for personalized and innovative food products have surged in recent years. MOO-ANN enables manufacturers to develop tailored solutions that meet specific nutritional, sensory, and sustainability requirements.

For instance, a snack food company used MOO-ANN to design a new product line catering to gluten-free and vegan diets, achieving a 25% increase in market share within the first year of launch. By balancing ingredient costs, nutritional content, and consumer preferences, MOO-ANN facilitated the rapid development of high-quality products, supporting SDG 12: Responsible Consumption and Production [81].

8.8. Quantitative Evidence of Impact

The quantitative impact of MOO-ANN systems in the food industry is substantial. Studies report [82]:

A 10–20% reduction in production costs through process optimization.

A 15–25% decrease in waste by improving resource allocation.

A 10–15% improvement in energy efficiency across diverse manufacturing operations.

A 20–30% enhancement in the nutritional content of reformulated products.

These results highlight the transformative potential of MOO-ANN in achieving economic and sustainability goals while advancing public health and nutrition [83].

8.9. Aligning with the 2030 Agenda

MOO-ANN systems directly contribute to multiple SDGs within the 2030 Agenda:

- SDG 2: Zero Hunger: By optimizing food formulations and reducing waste, MOO-ANN supports global efforts to combat hunger and malnutrition.
- SDG 7: Affordable and Clean Energy: Energy optimization in production processes reduces the industry's reliance on fossil fuels.
- SDG 12: Responsible Consumption and Production: MOO-ANN promotes sustainable resource use and waste minimization.
- SDG 13: Climate Action: By reducing carbon emissions, MOO-ANN helps mitigate the food industry's environmental impact.

8.10. Future Directions for MOO-ANN in the Food Industry

The future of MOO-ANN lies in its integration with emerging technologies, such as:

- Digital twin models: Virtual replicas of production systems can be combined with MOO-ANN for enhanced simulation and optimization.
- Hybrid optimization approaches: Combining ANN with other machine learning techniques, such as reinforcement learning, to tackle even more complex problems.
- Blockchain integration: Ensuring traceability and transparency in supply chains while optimizing performance.

By embracing these innovations, the food industry can unlock new levels of efficiency, sustainability, and consumer satisfaction.

Multi-objective optimization integrated with artificial neural networks represents a paradigm shift in the food industry, enabling holistic and data-driven solutions to its most pressing challenges. From optimizing nutritional profiles and reducing waste to enhancing energy efficiency and supply chain performance, MOO-ANN systems provide actionable insights that align with economic, sustainability, and nutritional criteria [83].

9. Hybridization of MOO-ANN with Metaheuristics and Reinforcement Learning

Recent advancements in optimization highlight the potential of hybridizing MOO-ANN with metaheuristic algorithms and reinforcement learning (RL) techniques. These hybrid approaches have proven effective in addressing complex, dynamic, and multi-dimensional problems in various domains, including manufacturing scheduling and resource allocation [84].

Metaheuristics integration: Combining MOO-ANN with metaheuristics such as genetic algorithms (GAs), particle swarm optimization (PSO), and ant colony optimization (ACO) can enhance global search capabilities, improve convergence speed, and address the challenges of high-dimensional optimization. For instance, GA-augmented MOO-ANN systems could optimize formulations by simultaneously balancing nutritional content, cost, and sensory attributes [71,84].

Reinforcement learning (RL) augmentation: Incorporating RL enables sequential decision-making under uncertainty, allowing real-time adaptability to changing conditions such as fluctuating raw material quality or consumer demand. An RL-enhanced MOO-ANN framework could dynamically optimize supply chain operations, ensuring resilience and efficiency [84].

Future Research Directions

To maximize the potential of MOO-ANN in the food industry, future research should explore:

Advanced hybrid models: Developing hybrid frameworks combining MOO-ANN with metaheuristics and RL for improved adaptability and scalability.

Digital twins: Utilizing digital twins to simulate and optimize production systems in real-time.

Blockchain integration: Ensuring transparency and traceability in food supply chains while optimizing performance.

Ensemble techniques: Leveraging ensemble metaheuristics to enhance solution robustness and adaptability in dynamic environments [71].

The hybridization of MOO-ANN with metaheuristics and reinforcement learning represents a significant advancement in the optimization of food industry processes. These systems address critical challenges, from improving nutritional profiles and reducing waste to enhancing energy efficiency and supply chain performance. By aligning with economic, sustainability, and nutritional objectives, MOO-ANN hybrid systems provide actionable, data-driven solutions to advance global food systems while contributing to the 2030 Agenda for Sustainable Development.

10. Future and Perspectives

The future of optimization in the food industry is poised to undergo transformative advancements driven by technological innovations, increasing system complexity, and the growing demand for sustainable and efficient production processes. These trends reflect a paradigm shift in how food systems are designed, managed, and optimized, paving the way for more robust, intelligent, and environmentally conscious solutions.

10.1. Integration of Artificial Intelligence and Machine Learning

The integration of artificial intelligence (AI) and machine learning (ML) is anticipated to revolutionize optimization approaches in the food industry. These technologies, equipped with unparalleled capabilities for handling large datasets and uncovering complex, non-linear relationships, offer a pathway toward more intelligent and adaptive optimization strategies. Deep learning models, including convolutional and recurrent neural networks, are expected to advance predictive modeling and decision-making, enabling real-time process adjustments based on dynamic production parameters. Moreover, AI-driven tools can incorporate vast arrays of data, such as environmental conditions, supply chain dynamics, and consumer preferences, providing comprehensive solutions to multi-objective optimization challenges [85].

10.2. Hybrid Optimization Techniques

As production systems grow increasingly intricate, the adoption of hybrid optimization techniques will become more prevalent. These approaches, which combine the strengths of various optimization methodologies, such as response surface methodology (RSM), metaheuristic algorithms, and evolutionary strategies, are designed to overcome the limitations of individual techniques. For example, the fusion of particle swarm optimization (PSO) with neural network-based modeling has demonstrated the potential to enhance process performance by simultaneously addressing multiple objectives, such as reducing energy consumption, improving product quality, and minimizing waste [86]. The flexibility and adaptability of these hybrid methods are expected to make them indispensable in tackling the multifaceted challenges of modern food production.

10.3. Sustainability-Driven Optimization

With sustainability emerging as a core priority across industries, optimization frameworks in the food sector will increasingly integrate sustainable development principles. Future strategies will emphasize resource efficiency, waste reduction, and lower carbon footprints, aligning with the objectives of the United Nations' Sustainable Development Goals (SDGs) and the 2030 Agenda. Optimization approaches will incorporate life cycle assessment (LCA), energy efficiency metrics, and circular economy principles, enabling decision-makers to balance environmental, social, and economic considerations effectively [87]. The development of sustainability-focused optimization algorithms, capable of quantifying trade-offs and providing actionable insights, will be crucial for addressing the global challenges of climate change and resource scarcity.

10.4. Advances in IoT and Industry 4.0

The advent of the Internet of Things (IoT) and Industry 4.0 technologies represents another transformative trend for the food industry. IoT-enabled systems, equipped with real-time data acquisition and advanced analytics, will facilitate dynamic process monitoring, predictive maintenance, and continuous optimization. Digital twins, virtual replicas of physical systems, are poised to play a pivotal role in simulating and optimizing food production processes, allowing for rapid scenario testing and performance evaluation without disrupting actual operations. The integration of IoT with multi-objective optimization frameworks will enable highly automated and intelligent systems, reducing inefficiencies and enhancing scalability [88].

10.5. Quantum Computing for Optimization

The potential application of quantum computing in the food industry is an exciting frontier. Although still in its developmental stages, quantum computing offers unprecedented computational capabilities for solving complex optimization problems that are currently beyond the reach of classical computing. These systems can process large-scale, multi-variable optimization challenges in record time, providing solutions to problems with numerous conflicting objectives, such as maximizing production yield while minimizing energy usage and environmental impact [89]. Research and development in this area are expected to unlock new possibilities for optimizing complex food production systems.

10.6. Personalized Nutrition and Optimization

Advances in optimization techniques are likely to contribute significantly to the growing field of personalized nutrition, where food products are tailored to meet individual dietary requirements and health goals. Multi-objective optimization models will play a crucial role in balancing nutritional content, sensory attributes, and production efficiency. By integrating genomic data, consumer preferences, and production constraints, optimization frameworks can drive the development of customized food products, meeting the rising demand for health-centric and functional foods [90].

10.7. Enhanced Collaboration and Innovation

Future progress in food process optimization will depend heavily on collaborative efforts between academia, industry stakeholders, and technology developers. Building interdisciplinary research networks and fostering partnerships will be essential to accelerate the translation of cutting-edge optimization methodologies into industrial applications. Furthermore, the development of user-friendly optimization tools and platforms will be critical to bridge the gap between advanced research and practical implementation, ensuring that small- and medium-sized enterprises (SMEs) can also benefit from these advancements [91].

10.8. Ethical and Regulatory Considerations

As optimization techniques evolve, addressing ethical and regulatory concerns will become increasingly important. The development of fair, transparent, and accountable algorithms will ensure that optimization processes do not inadvertently compromise product safety, consumer trust, or regulatory compliance [92]. Research into creating robust frameworks for evaluating the ethical implications of optimization strategies will be critical to ensuring their acceptance and widespread adoption.

The future of optimization in the food industry promises a wealth of opportunities driven by technological innovation, sustainability imperatives, and the pursuit of excellence in production systems. By embracing advanced techniques such as AI, hybrid methodologies, and quantum computing while integrating sustainability-focused frameworks, the food industry can address its most pressing challenges and unlock new avenues for growth and innovation. These advancements will not only enhance production efficiency but also contribute to global sustainability goals, positioning the industry as a leader in the transition to a more resilient and sustainable future.

11. Conclusions

The evolution of optimization methodologies within the food industry represents a pivotal advancement in addressing the increasing complexities of modern production systems. The transition from traditional, single-parameter optimization approaches to sophisticated multi-objective and technology-integrated techniques has been driven by the need to balance critical industry goals, such as cost reduction, resource efficiency, productivity enhancement, and product quality improvement. While traditional methods like one-factor-at-a-time analysis have historically provided insights into process behaviors, their limitations—such as neglecting variable interactions and requiring extensive experimentation—have prompted the adoption of more advanced tools. Among these, response surface methodology (RSM) has emerged as a widely adopted approach, offering significant advantages in reducing experimental demands, improving precision, and identifying critical operating conditions.

However, as production systems become increasingly intricate, the scope of optimization must expand beyond single-objective frameworks. Multi-objective optimization methodologies, including linear, non-linear, and evolutionary techniques, have proven instrumental in addressing scenarios involving multiple, often competing objectives. These methods enable the simultaneous consideration of diverse process variables, facilitating the development of balanced and efficient solutions tailored to specific operational needs. Furthermore, the integration of emerging technologies, such as artificial neural networks (ANNs), has revolutionized optimization practices. ANNs excel in modeling complex, non-linear systems, uncovering patterns within high-dimensional datasets, and delivering predictive accuracy that traditional methods cannot achieve. When combined with optimization techniques like RSM or evolutionary algorithms, these tools not only enhance solution robustness but also enable real-time decision-making and adaptive process control.

The incorporation of Industry 4.0 technologies further elevates the potential of optimization strategies. Advanced data analytics, Internet of Things (IoT) devices, and digital twins are transforming food production systems by enabling continuous monitoring, predictive maintenance, and autonomous process adjustments. These capabilities empower manufacturers to achieve greater operational resilience, minimize resource wastage, and meet stringent quality standards while adhering to sustainability objectives. Moreover, the integration of artificial intelligence (AI) with multi-objective optimization frameworks offers unprecedented opportunities for innovation, from intelligent supply chain management to the development of sustainable and personalized food products.

In conclusion, this paper highlights the critical role of advanced optimization methodologies and technological integration in addressing the evolving challenges of the food industry. By leveraging multi-objective optimization techniques, coupled with cutting-edge tools such as ANNs and Industry 4.0 solutions, the industry is well-positioned to achieve transformative improvements in efficiency, quality, and sustainability. Future research should focus on the development of hybrid optimization frameworks that integrate machine learning, AI, and digital technologies, as well as their practical applications in real-world scenarios. Additionally, further exploration of scalable and cost-effective implementation strategies will be essential to ensure that these advanced methodologies can be widely adopted across diverse food production settings. This concerted effort will play a vital role in meeting global sustainability goals and fostering innovation in the food industry for years to come.

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Abbreviations

MOO	multi-objective optimization
SDG	sustainable development goals
AI	artificial Intelligence
LP	linear programming
GA	genetic algorithim
RSM	response surface methodology
ANNs	artificial neural networks
PSO	particle swarm optimization
DE	differential evolution
ESs	evolutionary strategies
IoT	Internet of Things
ML	machine Learning
LCA	life cycle assessment

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