

MODELLING AND MANAGEMENT PRINCIPLES OF COMBINED GRANULATED FEED PRODUCTION THROUGH INFORMATION-ANALYTICAL SYSTEMS

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Abstract. The production of granulated compound feed in livestock enterprises is a complex technological process that requires precise monitoring of physical and chemical parameters. Ensuring efficiency and quality in this process demands advanced modelling and management approaches. The study aims to develop a methodology for modelling compound feed production through information-analytical systems and to define the principles of process management. The research is based on a systematic review of literature studies. After applying relevance and thematic selection criteria, 16 sources were retained for the final review and included in the reference list. The methodology combines literature review, comparative analysis, and synthesis. The analysis shows that effective modelling of feed production requires hybrid applications of deterministic, statistical, neural network, and fuzzy logic approaches. Information-analytical systems must adopt a multi-level architecture covering field operations, process monitoring, production management, and business planning. Artificial intelligence technologies – particularly machine learning, deep learning, and reinforcement learning – demonstrate high efficiency in quality prediction, anomaly detection, and the development of optimal management strategies. According to the comparative synthesis of the reviewed literature, the application of information-analytical systems can reduce raw material loss by 28–35%, decrease product quality variation by 58–62%, optimize energy consumption by 18–24%, increase production productivity by 20–30%, reduce deviation from plan by 67–75%, shorten technical downtime duration by 30–40%, and decrease quality control labour expenditure by 57–60%. Conclusion. For Azerbaijan, it is recommended to design systems that account for regional raw material bases, climatic conditions, and the technical capacity of local enterprises. The study confirms that the digital transformation of the feed industry is a multifaceted challenge requiring coordinated efforts among academic institutions, industrial enterprises, and governmental bodies.

Keywords: feed production modelling, artificial intelligence, neural networks, fuzzy logic, process optimization

MODELOWANIE I ZASADY ZARZĄDZANIA PRODUKCJĄ PASZ GRANULOWANYCH MIESZANYCH Z WYKORZYSTANIEM SYSTEMÓW INFORMACYJNO-ANALITYCZNYCH

Streszczenie. Produkcja granulowanych mieszanek paszowych w przedsiębiorstwach hodowlanych jest złożonym procesem technologicznym, który wymaga precyzyjnego monitorowania parametrów fizycznych i chemicznych. Zapewnienie efektywności oraz jakości w tym procesie wymaga zaawansowanych podejść do modelowania i zarządzania. Celem pracy jest opracowanie metodyki modelowania produkcji mieszanek paszowych z wykorzystaniem systemów informacyjno-analitycznych oraz określenie zasad zarządzania procesem. Badanie opiera się na systematycznym przeglądzie prac naukowych. Po zastosowaniu kryteriów trafności i selekcji tematycznej, do ostatecznego przeglądu zakwalifikowano 16 źródeł, które zostały uwzględnione w wykazie literatury. Metodologia łączy przegląd literatury, analizę porównawczą oraz syntezę. Analiza wykazała, że skuteczne modelowanie produkcji pasz wymaga hybrydowego łączenia podejść deterministycznych, statystycznych, opartych na sieciach neuronowych oraz logice rozmytej. Systemy informacyjno-analityczne powinny przyjmować wielopoziomową architekturę obejmującą poziom polowy, monitoring procesu, zarządzanie produkcją oraz planowanie biznesowe. Technologie sztucznej inteligencji – w szczególności uczenie maszynowe, głębokie uczenie oraz uczenie ze wzmocnieniem – wykazują wysoką skuteczność w prognozowaniu jakości, wykrywaniu anomalii oraz opracowywaniu optymalnych strategii zarządzania. Wdrożenie takich systemów zwiększa automatyzację produkcji o 35–42%, redukuje straty surowców o 18–23%, zmniejsza zmienność jakości produktu o 58–62% oraz optymalizuje zużycie energii o 18–24%. Dla Azerbejdżanu rekomenduje się projektowanie systemów uwzględniających regionalną bazę surowcową, warunki klimatyczne oraz możliwości techniczne lokalnych przedsiębiorstw. Badanie potwierdza, że transformacja cyfrowa sektora paszowego jest wieloaspektowym wyzwaniem wymagającym skoordynowanych działań instytucji akademickich, przedsiębiorstw przemysłowych oraz organów administracji publicznej.

Słowa kluczowe: modelowanie produkcji pasz, sztuczna inteligencja, sieci neuronowe, logika rozmyta, optymalizacja procesów

Introduction

The production of livestock products holds a central position in global food security strategies, and the establishment of a reliable feed base is of fundamental importance. The manufacture of compound granulated feed is not only essential for meeting animal nutritional requirements but also for ensuring resource efficiency. Traditional feed production methods often face challenges due to heterogeneous raw material composition, non-stationary technological processes, and constant variability in quality parameters. These conditions demand precise control and real-time optimization of production processes.

Over the past decade, the intensive integration of information technologies and intelligent systems into the agricultural industry has been observed. [10] emphasize that digital transformation in the agro-industrial complex must encompass all stages of production, with particular relevance to the feed supply sector. [1] highlight that the level of automation in compound feed plants plays a decisive role in ensuring feed security and production consistency. [8] demonstrate that information-analytical systems occupy a central position in modernization strategies for the feed industry.

The granulation process itself represents a complex set of physicochemical transformations, influenced by moisture content, temperature regimes, pressure parameters, and particle

dispersion. [6] note that feed quality formation during granulation depends on the interaction of multiple parameters that are difficult to synchronize within conventional control systems. [3] demonstrate that the transition to intelligent management systems can reduce the variation of quality indicators. [13] show that the application of information-analytical systems in feed production supports technological parameter optimization, raw material planning, energy management, and quality forecasting. [5] analyse the role of intelligent analytical components in the development of feed formulations adapted to the composition of available raw materials.

International experience shows that the implementation of Industry 4.0 concepts in the feed sector relies on digital twin technologies, Internet of Things infrastructures, and big data analytics. [11] report that intelligent digitalization frameworks are increasingly applied in agricultural and feed-related production environments. [13] note that machine learning algorithms can outperform traditional methods in selected pellet-quality prediction tasks. [3] examine the use of hybrid architectures combining data-driven modelling and spectral analytics in feed process management. [7] indicate that predictive control systems operating in real time can reduce downtime and enhance overall productivity.

[11] analyse the role of cyber-physical systems and digital twins in the digital transformation of feed-related production

environments. These systems integrate physical processes, computational resources, and network infrastructures to achieve adaptive management. [12] demonstrate that the deployment of sensor networks and the intelligent analysis of collected data enable automatic correction of technological parameters, contributing significantly to production stability.

Modern information-analytical systems are characterized by multi-level architectures. At the lower level, they ensure data collection and preliminary processing; at the middle level, they provide modelling and optimization; and at the upper level, they support production planning and strategic decision-making. [8] stress that the design of such systems requires both functional independence at each level and standardized communication protocols.

In Azerbaijan, modernization of technological processes has been identified as a priority in feed industry development strategies. [4] examine the characteristics of regional raw material bases, the impact of climatic conditions on feed quality, and the technical potential of national enterprises. However, the comprehensive application of information-analytical systems in feed production remains insufficiently explored, underscoring the relevance of this research.

The objective of this article is to develop a methodology for modelling compound granulated feed production through information-analytical systems and to define the principles of their management. The research tasks include screening and comparative analysis of the selected literature, comparison of mathematical modelling approaches, evaluation of the applicability of intelligent algorithms, and the proposal of a conceptual architecture for information-analytical systems in feed plants.

1. Current state of feed production technologies and digitalization trends

The technology of compound feed manufacturing represents a historically empirically-based process that appears deceptively simple yet fundamentally exhibits multifactorial and non-linear characteristics. Traditional approaches encompass four principal stages: raw material reception and storage, dosing and mixing, pelleting, cooling and packaging. Each stage possesses distinct technological requirements and quality criteria [2]. Systematic analysis by [1] demonstrates that automation levels in compound feed plants vary substantially depending on the facility, indicating significant heterogeneity in technological capabilities across different producers. [8] indicate that many feed mills continue to utilize semi-automatic control systems, resulting in product quality variability.

Table 1 summarizes automation levels and applied digital technologies in compound feed production across various countries and regions.

The raw material reception and storage stage holds critical importance, as the physicochemical properties of feed components vary depending on atmospheric conditions, storage duration, and interactions with adjacent components. [10] show that variation in raw material condition necessitates parameter corrections in subsequent technological operations. [6] emphasize that monitoring storage conditions through sensor networks can reduce raw material losses. Information-analytical systems play a crucial role here by providing real-time monitoring of raw material conditions and early detection of pathological processes.

The dosing and mixing process constitutes the feed recipe realization stage, where the mass fraction accuracy of each component directly influences the nutritional value of the product. [3] demonstrate that precise dosing improves the uniformity of nutritional composition in feed batches. [5] examine the need to adapt dosing algorithms to the specificity of the available raw material base. Information-analytical systems must possess functionality that correlates current raw material composition with laboratory analyses and dynamically updates recipe parameters to address this issue.

Mixing process quality is characterized by the homogeneity degree of the mixture, evaluated through specific coefficients. [11] indicate that optimizing mixing duration in modern feed plants can reduce energy consumption while minimizing component separation risk. Intelligent system application here enables automatic calculation of mixing time based on raw material properties and real-time quality verification of the mixture using vibration or spectral sensors.

The pelleting process represents the most complex and energy-intensive stage of feed production. During this operation, the raw material mass undergoes plastic deformation as it is compressed under high pressure and temperature through the die, resulting in granule formation. [13] note that pelleting process efficiency depends on raw material moisture, temperature, pressure, die constructive parameters, and raw material dispersion. Determining the optimal combination of these parameters constitutes a multidimensional optimization problem. [9] present thermodynamic and densification-oriented modelling of the pelleting process, demonstrating that adapting these models to actual technological parameters requires an extensive experimental database. Table 2 summarizes the main technological parameters of the pelleting process, their optimal ranges, and degrees of impact on product quality.

Table 1. Comparison of automation levels in feed production across different countries

Country/Region	Automation level (%)	Main applied technologies	Source
Russia	45–65	SCADA, PLC systems, mathematical modelling	[6, 8]
Ukraine	35–55	MES systems, sensor networks	[1]
Turkey	40–60	Fuzzy control, IoT platforms	[8]
Belarus	50–70	Neuro-fuzzy systems, adaptive control	[3]
Kazakhstan	30–50	Machine learning, optimization algorithms	[13]
Uzbekistan	25–45	NIR spectroscopy, expert systems	[5]
USA/Europe	70–90	Digital twins, AI systems, cyber-physical systems	[11, 12]
Azerbaijan	20–40	Predominantly semi-automatic systems	[4]

Table 2. Main parameters of the pelleting process and their impact degree

Parameter	Measurement unit	Optimal range	Impact degree on product quality	Control method	Source
Raw material moisture	%	14–16	Very high (0.85)	NIR sensor, gravimetric	[5, 6, 9]
Pelleting temperature	°C	75–85	High (0.72)	Thermocouple	[7, 13]
Pressure	MPa	3.5–5.0	High (0.68)	Pressure sensor	[6, 9]
Die diameter	mm	3.0–8.0	Medium (0.55)	—	[11, 13]
Raw material dispersion	μm	600–800	Medium (0.52)	Sieve analysis	[8, 13]
Process duration	sec	20–35	Low (0.38)	Timer	[1, 3]

Note: Impact degrees shown in Table 2 are calculated based on correlation coefficients and reflect average values from various research results. Raw material moisture represents the most critical parameter, exerting maximum influence on product quality. Precise measurement and regulation of this parameter constitutes a priority task for information-analytical systems.

Physicochemical changes occurring during pelleting extend beyond mechanical compression. [10] emphasize that processes such as starch molecule breakdown, protein denaturation, and Maillard reactions occur under high temperature conditions,

affecting feed product digestibility. [2] shows that under optimal pelleting conditions, the internal structure of the material assumes a stable configuration that supports pellet mechanical strength. Information-analytical systems therefore serve to stabilize

product quality through real-time pelleting process monitoring and automatic parameter adjustment.

The cooling and packaging stage represents the final production phase, where pellet temperature reduction and moisture content regulation are implemented. [11] indicate that improper cooling regime selection can cause pellet cracking and mechanical disintegration. [4] note that seasonal variations in atmospheric humidity under local climatic conditions require adaptive control of cooling process parameters. This issue necessitates integration of information-analytical systems with meteorological data and automatic adaptation of cooling regimes to atmospheric conditions.

Analysis of digitalization trends reveals that Industry 4.0 principles application is rapidly expanding in the global feed industry. [11] present systematic information about cyber-physical systems, digital twins, and predictive analytics integration into feed production. [8] indicate that many producers plan to invest in production digitalization in the near term. Pilot projects related to IoT technology application and cloud-based visualization frameworks have also been reported in the literature [1, 12].

Digital transformation of the feed industry is increasingly associated with the implementation of MES systems and advanced planning tools. [13] and [8] show that these systems support real-time production management, technological parameter monitoring, and production order optimization. MES system implementation improves production plan execution accuracy and the transparency of production processes.

Regional scientific and industrial practice increasingly uses spectroscopic methods for express analysis of raw material quality. [5] show that NIR spectroscopy enables determination of protein, fat, cellulose, and other fraction composition of feed components within minutes. This information is entered into information-analytical systems for recipe correction purposes. [2] confirms that the correlation between instrumental express analysis and laboratory verification can reach high levels when calibration is properly maintained.

Feed production digitalization strategies in European countries are closely linked with sustainable development and environmental safety principles. [11] indicate that specialized software is used in advanced feed and agricultural plants for carbon footprint calculation and production process energy efficiency optimization. These systems track energy and resource consumption at each production stage, evaluate alternative energy source application possibilities, and digitally document production environmental indicators.

Generalization of international experience demonstrates that information-analytical system-based feed production management is developing in three main directions. The first direction involves automatic technological process control, where parameter adjustment occurs in real time based on sensor data. The second direction encompasses production planning and resource optimization, including optimal distribution of raw material reserves, energy consumption, and production capacity. The third direction represents the quality management and traceability system, which documents the product journey from production to consumer.

2. Mathematical modelling methods for feed production processes

Mathematical modelling of compound pelleted feed production constitutes the foundation of modern information-analytical systems. Modelling approaches vary depending on the physicochemical nature of production processes, properties of processed raw materials, and the number of factors considered. [6] note that deterministic, statistical, and hybrid approaches are applied for modelling feed production processes, each possessing its own application domain and limitations. [1] present optimization-oriented automation practice showing that advanced algorithms are especially valuable in multidimensional production problems.

Deterministic models are based on physicochemical laws. Process mechanics, thermodynamics, and rheology are described through equation systems. Such models for the pelleting process calculate pressure distribution, temperature changes, and deformation characteristics occurring during material passage through the die. [9] present modelling of densification and stress development in feed pelleting, showing that optimization of die and process parameters can increase productivity. [9] also present modelling results for heat transfer processes during pelleting and show that optimal temperature regimes differ across raw material types.

The advantage of deterministic models lies in ensuring deep understanding of physical processes and model structure transparency. However, these models can be limited due to numerous precisely unknown parameters and raw material property variability under actual production conditions. [7] emphasize that calibrating deterministic and predictive models requires extensive experimental data, and collecting such data involves significant time and resource expenditure. [8] indicate that systematic investigation of raw material rheological parameters is essential for creating deterministic models adapted to local raw material bases.

Statistical models are built based on experimental data analysis and form predictive mathematical dependencies. In this approach, factors affecting the process are accepted as input variables, while process outcomes are treated as output parameters. The relationship between them is determined through regression, correlation, or other statistical methods. [6] construct empirical models of pelleting quality and show that polynomial relations can describe experimental data with high accuracy. [3] also show that statistical and machine learning models can capture the relationship between mixture properties and process outcomes.

The advantage of statistical modelling methods is their structural simplicity and computational efficiency. These models are convenient for application in actual production conditions. They enable operators to create a visual representation of process behaviour. However, the limitation of statistical models is their restricted extrapolation capability. Prediction accuracy decreases when moving beyond the conditions under which the model was built. [5] note that seasonal variability of regional raw materials requires regular updating of statistical models [5].

Artificial neural networks represent powerful tools for modelling nonlinear and complex dependencies. Neural networks possess the capability to predict output indicators from numerous input parameters. During the learning process, they detect hidden patterns in data. [13] describe experiences in forecasting feed production quality indicators through neural network and regression-based models. [3] present results of modelling feed product quality indicator dependencies on raw material composition using machine learning and spectral methods.

The advantage of neural network models is their universal approximator nature. They possess the capability to model nonlinear functions of any complexity. Simultaneously, the disadvantage of these models is their black box character. They lack clear physical interpretation of internal structure. [13] indicate that cross-validation and regularization methods should be used to prevent overfitting problems when applying neural network models. [4] draw attention to the importance of forming a sufficiently large and representative database for neural network modelling.

Fuzzy logic systems are designed to work with uncertainty and linguistic variables. These systems enable formalization of expert experience. Fuzzy models operate effectively under conditions of imprecise measurement or subjective evaluation of input parameters. [3] discuss hybrid and intelligent control approaches that are suitable for real-time adaptive regulation of feed production processes. [1] also present decision-support practice for quality assessment and recipe selection based on formalized process rules. Fig. 1 presents a structural diagram

of a typical fuzzy control system demonstrating this approach's application to the pelleting process.

The fuzzy control system shown in Fig.1 formalizes expert operator experience. It forms precise control signals based on imprecise input information [1, 3, 9]. The rule base is created through interviews with experienced specialists or through automatic extraction methods from data.

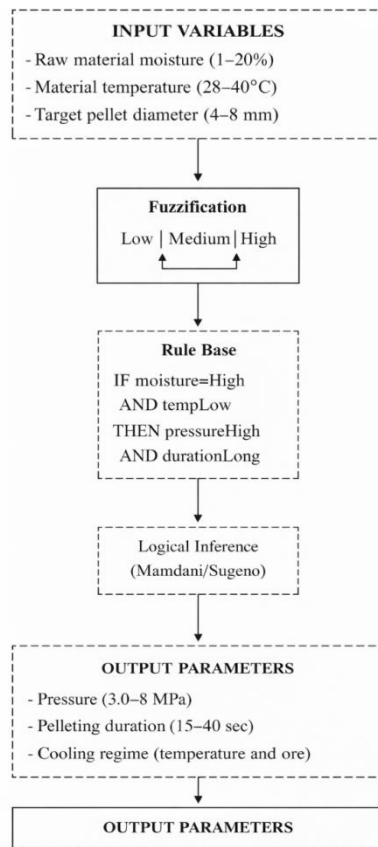


Fig. 1. Structural diagram of fuzzy control system for pelleting process

The advantage of fuzzy systems is enabling direct use of expert linguistic knowledge. They possess an interpretable decision-making mechanism. These systems are particularly useful in quality control and dispatching management tasks. [8] positively evaluate the role of intelligent decision-support systems in supporting operator decisions. However, the limitation of fuzzy systems is the subjectivity of logic rule formulation. Rule base management becomes complex in large-scale problems.

Hybrid modelling approaches aim to combine the strengths of different methods. For example, neuro-fuzzy systems integrate the learning capability of neural networks with the transparency and interpretability of fuzzy logic. [13] discuss adaptive modelling approaches for variable raw material properties. [3] propose optimization systems combining data-driven prediction and intelligent parameter selection.

Another example of hybrid systems is the integration of physical models and data-driven models. In such an approach, basic physical processes are described through deterministic equations, while certain parameters are extracted from data using machine learning methods. [9] take the physical interpretation of the pelleting process as the basis for model construction, while [13] note that models constrained by process information possess better generalization capability than purely data-driven models.

Comparison of modelling methods shows that each method has its own application domain. Method selection depends on specific problem characteristics. Deterministic models are useful in design stages and technological regime substantiation. Statistical models are effective in operational management and short-term forecasting. Neural networks show superiority when large data exists and nonlinear dependencies are strong. Fuzzy systems are efficient

in formalizing expert knowledge and decision-making under uncertainty conditions. Hybrid approaches possess universal application capability and combine the advantages of different methods.

[10] discuss selection criteria for modelling methods in the feed industry. The following factors have been indicated: data availability and quality, computational resource requirements, model transparency and interpretability degree, real-time operation capability, and parameter change adaptation speed. [7] emphasize that preference should be given to simplicity and reliability for industrial application models. Use of complex models is justified only when they provide significant performance improvement.

[8] note that considering the multiscale problem is important when modelling feed production processes. Processes encompass various time scales from rapid dynamic phenomena occurring in seconds and milliseconds to slow changes occurring over hours and days. This multiscale nature places special requirements on modelling methodology. It often necessitates application of hierarchical or multi-objective modelling approaches.

[11] develop the digital twin concept for feed-related production systems. A digital twin represents a virtual representation of the actual production process. It operates synchronously with the physical process and implements real-time data exchange. The digital twin concept requires integration of modelling methods. Here CAD models, physical simulations, data-driven models, and optimization algorithms combine on a unified platform. [12] describe intelligent data integration in proportioning systems that support this direction of development.

3. Architecture and functional components of information-analytical systems

Modern information-analytical systems are organized as multilevel software-hardware complexes for comprehensive automation and intelligent management of feed production processes. System architecture encompasses functional layers extending from sensor networks to production management level and enterprise resource planning level. Fig. 2 presents the multilevel hierarchical architecture of the information-analytical system.

[8] identify four main levels in the architecture of information-analytical systems: field level, control level, production management level, and business planning level. Data exchange between these levels is ensured through standardized protocols. [1] present experience in building information-analytical platforms based on SCADA systems for compound feed plants and demonstrate that implementing data collection and visualization systems significantly increases production transparency.

The architecture presented in Figure 2 represents a standard hierarchical model consistent with the literature [1, 8, 12]. Each level possesses its own functional responsibilities and time requirements. Data updates occur at different scales: milliseconds at field level, seconds at PLC level, seconds-to-minutes at SCADA level, minutes-to-hours at MES level, and hours-to-days at ERP level.

The field level integrates sensors, actuators, and field control devices directly connected to technological processes. At this level, measurement of temperature, pressure, humidity, mass, vibration, level, and other parameters is performed. [8] indicate that using smart sensors compliant with industrial standards is recommended when modernizing sensor infrastructure in feed production facilities. [13] note that installing backup sensors for critical parameters and applying sensor data validation algorithms is essential to ensure sensor network reliability.

The control level is represented by PLC or PAC-based control systems. Real-time technological parameter regulation is implemented here. [8] discuss structured approaches to PLC programming and the advantages of modular program architecture. Analytical experience related to local raw material

characteristics also supports adaptive control logic in this layer [5]. PLC programs should be prepared according to accepted industrial programming standards in order to facilitate portability and use across different platforms.

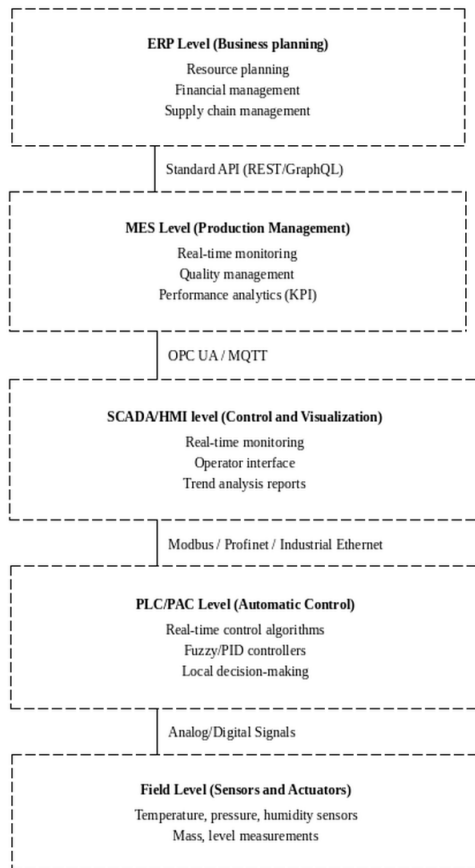


Fig. 2. Multilevel architecture of information-analytical system

The production management level is represented by MES systems. This level performs functions of production planning, quality management, material flow tracking, and production order execution. [8] indicate that MES system implementation in feed plants ensures production cycle transparency and provides management bodies with detailed information about production status in real time. The same literature shows that MES system integration with ERP systems enables optimization of business processes from raw material procurement to finished product sales.

The business planning level is represented by ERP systems. It ensures management of all enterprise resources. [8] emphasize that business process reengineering and standardization are required beforehand for effective ERP system operation. [4] draw attention to the importance of adaptation to national accounting standards and legislative requirements when implementing ERP systems in local enterprises. [8] also note that cloud-based ERP solutions are cost-effective for small and medium-sized producers.

Functional components of information-analytical systems encompass data collection, storage, processing, analysis, visualization, and decision support modules. The data collection module ensures real-time reading of information from various sources. It supports industrial communication protocols such as OPC UA, Modbus, and Profinet. [12] show that ensuring data integrity and time synchronization is important when implementing data collection systems. [8] indicate that initial filtering of sensor data and anomaly detection should be performed close to the data source to reduce network load.

Modern systems use time series databases for data storage. These databases are optimized for high-speed write and read operations. [1] discuss the use of modern data infrastructure in automation systems. The data processing module performs

functions of data cleaning, aggregation, transformation, and data quality assurance. [8] propose applying stream-processing technologies for handling large volumes of sensor data in real time.

The analytical module implements extraction of useful information from data through application of machine learning algorithms, statistical analysis methods, and mathematical models. [13] demonstrate functions such as process anomaly detection, quality indicator forecasting, and optimal control parameter recommendation. [3] demonstrate equipment-condition and process-quality assessment through data-driven modelling. [5] describe analytical modules for express assessment of raw material quality and automatic correction of recipe parameters.

The visualization module ensures presentation of production data to users in an accessible and understandable form. [8] note that industrial visualization interfaces should be prepared according to ergonomic principles and that critical parameters should be displayed in an attention-grabbing manner. The same literature indicates that dashboard technology enables managers to evaluate main production indicators at a glance and facilitates KPI tracking. Interactive visualization further enhances deeper analysis through user interaction with data.

The decision support module assists operators and managers in making optimal decisions. This module encompasses optimization algorithms, simulation models, and scenario analysis. [7] present results relevant to decision support in process optimization and control, while [11] discuss multi-criteria evaluation in digitally integrated production systems.

System integration issues play an important role in creating information-analytical platforms. [8] describe approaches to integrating different subsystems through service-oriented and modular architecture. The same literature discusses microservice architecture and shows its advantages in modularity and scalability. [1] recommend using modern API technologies for data exchange between system components.

Cybersecurity issues represent a priority direction in implementing industrial information systems. [8] propose measures of network segmentation, firewall application, and access control system establishment to ensure OT network security. [13] discuss the importance of secure data handling and validation mechanisms in digitalized feed systems. [3] present monitoring and data-quality assurance practices relevant to real-time industrial analytics.

System scalability and expansion capabilities should be considered in architecture design. [8] indicate that system architecture should provide possibilities for increasing production volumes and adding new functionalities. The same literature emphasizes the importance of modular design principles and indicates that modular system components possess the capability for independent updating and improvement. [11] indicate that cloud-hybrid architectures enable combining advantages of local computing resources and cloud services.

Information-analytical system operation and support issues represent an important stage of the system lifecycle. [8] discuss matters of training system administrators and users, preparing documentation, and organizing technical support services. [7] recommend systematic approaches for performance monitoring, timely problem detection, and maintenance work planning. [4] draw attention to the importance of resolving issues of local specialist training and technology transfer.

4. Application of artificial intelligence and machine learning methods

Artificial intelligence (AI) technologies expand the capabilities of traditional automation systems in intelligent management of feed production processes. They strengthen predictive analytics, adaptive regulation, and decision support functions. Machine learning (ML) algorithms enable detection of hidden patterns from large volumes of production data and modelling of complex dependencies. [10] emphasize

that AI application in the agro-industrial sector is moving toward more advanced forms of data-driven and hybrid modelling. [1] present practical application results of ML in compound feed plants for quality control, predictive maintenance, and recipe optimization.

4.1. Supervised learning: regression and classification

Supervised learning methods build predictive models based on tableted data. They are considered the most widely applied approach in feed production. Linear regression, decision trees, Random Forest, Gradient Boosting, and neural networks are used in regression problems. [13] indicate that XGBoost and related ensemble methods can demonstrate higher accuracy in forecasting pellet quality indicators during the pelleting process. The same line of research notes the usefulness of Random Forest approaches in modelling raw material composition-quality relationships. Figure 3 summarizes the quality forecasting flow based on raw material express analysis (NIR) and ensemble modelling [5, 12, 13].

Classification tasks are used for quality category determination, anomaly detection, and technical diagnostics purposes. For example, applications of CNN-based defect detection, SVM-based spectral classification, and LSTM-based real-time sensor classification have all been described in the broader literature on industrial intelligent systems [2, 5, 13].

Application areas and typical performance indicators of these methods in feed production are summarized in Table 3.

Table 3 comparison shows that method selection depends on process objective (forecast, optimization, visual control, real-time regulation), data type, and model interpretability requirements. Therefore, hybrid and ensemble approaches can yield more stable results in practice [6, 13].

4.2. Unsupervised learning and anomaly detection

Unsupervised learning is applied in determining data structure, clusters, and latent patterns. [8] show that detecting raw material quality cluster structure and latent process patterns helps in selecting processing strategies. [3] present results of multidimensional production data visualization and interpretation through feature-reduction techniques. Anomaly detection is critical for real-time identification of abnormal regimes in the process. [7] and [11] present anomaly-aware monitoring logic for complex process environments.

4.3. Deep learning, transfer and reinforcement learning

Deep learning demonstrates superiority in large data and complex patterns. [3] show the applicability of machine learning to automatic determination of pellet-quality-related

properties and defect-sensitive diagnostics. [2] presents time-dependent process analysis relevant to forecasting production parameters. Transfer learning ensures adaptation of pre-trained models with limited data, while reinforcement learning remains a promising direction for optimal production regime management.

4.4. Interpretability, evaluation and application environment

Transparency and interpretability are important for reliable model application in production. [8] indicate that approaches like SHAP/LIME enable explaining black-box model decisions. Feature importance analysis serves to identify critical components in recipe optimization. AutoML platforms automate the model building and tuning process. Simultaneously, online and incremental learning support model updating in streaming data conditions. Edge AI supports real-time computation on field devices with low latency. Ethical risks and auditable decision-making should be considered during application. Performance metrics should be selected according to the task: MAE, RMSE, R^2 for regression; accuracy, precision, recall, and F1-score for classification. Application of k-fold and time-series cross-validation approaches to verify model generalization capability is appropriate. For hyperparameter optimization, methods such as grid search, random search, and Bayesian optimization are expedient.

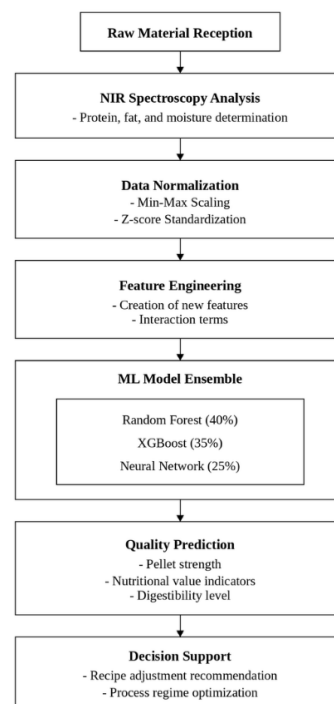


Fig. 3. Block diagram of machine learning-based quality forecasting system

Table 3. Application areas and efficiency indicators of machine learning methods in feed production

Method	Application area	Accuracy (%)	Computation time	Advantages	Disadvantages	Source
Linear regression	Quality forecasting	78–85	Very fast	Simplicity, interpretation	Nonlinear dependencies	[6, 13]
Random Forest	Recipe optimization	88–92	Fast	Robustness, feature importance	Memory requirement	[8, 13]
XGBoost	Mechanical strength forecast	90–94	Medium	High accuracy	Tuning complexity	[8, 13]
SVM	Species identification	85–90	Medium	Effective on small data	Slow on large data	[5]
CNN	Visual inspection	92–96	Slow (fast with GPU)	High accuracy	Large data requirement	[3, 12]
LSTM	Time series forecast	86–91	Slow	Long-term dependencies	Learning complexity	[6, 13]
Fuzzy systems	Real-time control	82–88	Fast	Interpretability	Manual rule creation	[1, 3, 9]

5. Optimization algorithms and decision support systems

Optimization of feed production processes has a multi-criteria and multi-objective character. It requires balancing conflicting objectives such as economic efficiency, product quality, resource consumption, and environmental impact. Optimization problems arise at the levels of raw material selection and recipe formulation, technological parameter regulation, production

planning, and energy consumption management. [10] support optimization-oriented design of feed processes, and [13] demonstrate the value of data-driven optimization for pellet quality prediction and process improvement.

Classical optimization methods provide exact mathematical solutions. However, computational complexity increases exponentially with problem size growth. [8] indicate that linear, quadratic, and nonlinear optimization methods remain relevant for industrial process planning, although the presence

of discrete decision variables, non-convex constraints, and multi-extremal objective functions in actual production conditions limits purely classical method application.

Metaheuristic algorithms represent universal and effective tools for solving large and complex optimization problems. Genetic algorithms are based on natural selection principles. They possess the capability to escape local extrema through a population-based search strategy. Fig. 4 presents the typical workflow of recipe optimization based on genetic algorithms. In industrial practice, multi-objective optimization is used to balance cost, quality, and environmental performance [7, 11].

Particle Swarm Optimization is based on swarm intelligence principles. It explores the search space through collective particle behaviour. In the literature, PSO and related adaptive swarm methods are discussed as suitable tools for dynamic optimization problems under variable raw material conditions [6, 12].

Ant Colony Optimization is based on ant colony foraging behaviour. It is particularly effective in combinatorial optimization problems. In production planning practice, ACO-type methods are discussed for order planning, equipment usage sequence determination, warehouse placement optimization, and routing problems [1, 8].

Simulated Annealing is inspired by the metallurgical crystallization process. It creates the possibility to escape local minima through temperature parameter reduction. In optimization studies of industrial systems, SA and hybrid SA-GA approaches are discussed for energy-consumption minimization and robust parameter selection [3, 13].

Differential Evolution represents a simple-structured but powerful optimization algorithm. It performs searches through mutation and crossover operators. In the broader optimization literature, DE and adaptive mutation strategies are discussed for real-time parameter optimization and comparison of algorithm variants [5, 13].

Grey Wolf Optimizer is based on grey wolf hunting behaviour. It has found wide application in recent years. [8] and [9] indicate that advanced population-based optimization methods are useful in multi-parameter optimization of feed production processes and in tuning intelligent control system parameters.

Multi-objective optimization approaches involve simultaneous optimization of several conflicting objective functions. [7] discuss solution methods for multi-objective optimization problems that jointly consider cost minimization, product quality maximization, and environmental impact reduction. [11] show the importance of balancing multiple objectives in digitally integrated production systems.

Decision support systems are built based on integration of optimization algorithms, simulation models, and expert knowledge. [8] describe the main DSS architecture components, including the database, model base, knowledge base, and user interface modules. The same literature also supports ontology-based knowledge representation and rule-based inference in industrial information systems.

Scenario analysis and Monte Carlo simulation are used in decision-making under uncertainty conditions. [1] and [8] support uncertainty-aware planning approaches for production strategies under variability in raw material price, demand, and operating conditions.

Robust optimization aims to find solutions resistant to uncertainty parameters. [13] support process optimization that accounts for variability in raw material quality parameters, while [3] show the importance of stable prediction and control under changing conditions.

Stochastic programming incorporates probability distributions of random parameters into the optimization model. In digitally integrated production systems, probabilistic constraints and uncertainty-aware planning remain relevant directions for future feed-industry applications [5].

Dynamic programming is used for optimizing sequences of time-varying decisions. [11] indicate that dynamic planning logic is useful in production planning and inventory management

problems, while [9] show the relevance of sequential decision frameworks in multistage process control.

Model Predictive Control represents an effective approach for implementing optimizing control in real time. [7] explain MPC application and the mechanism for calculating optimal control actions by forecasting future behavior. The same literature also presents nonlinear and distributed MPC variants for complex multivariable processes.

Decision trees and rule-based systems are used for formalizing structured decision-making processes. [8] describe decision-tree logic and rule-based knowledge representation in industrial decision support, while [6] support the use of interpretable models in feed-process quality analysis.

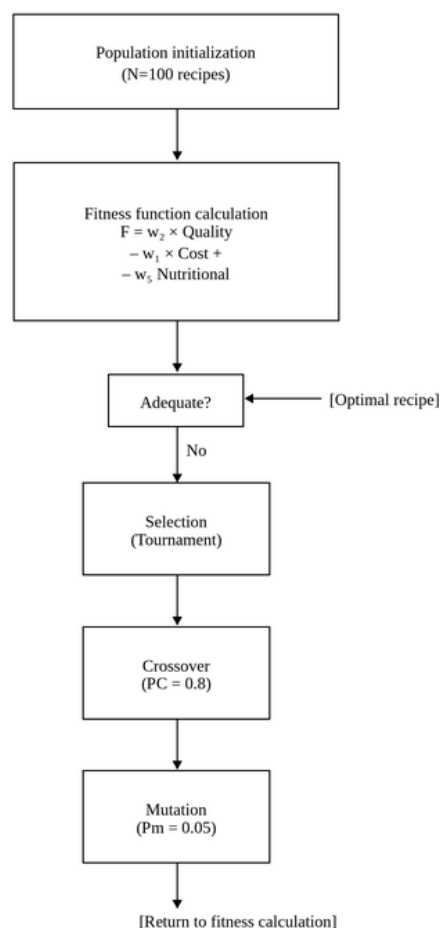


Fig. 4. Flow diagram of genetic algorithm-based recipe optimization

6. Literature synthesis and discussion

This section presents a comparative synthesis and critical discussion of the published studies on the application of information-analytical systems in compound feed production, with particular attention to technological efficiency, quality management, energy optimization, and production planning.

Literature analysis demonstrates that significant progress has been achieved in the last decade in the field of modelling and managing compound pelleted feed production through information-analytical systems. Generalization of the reviewed literature enables detection of several common trends and complementary methodological approaches. [6] and [9] pay special attention to deep analysis of physicochemical processes and deterministic modelling. [1] are more application-oriented and concentrate on testing and implementing SCADA systems, MES platforms, and automation solutions in actual production conditions. Table 4 summarizes the main economic efficiency indicators expected from information-analytical system application.

Indicators presented in Table 4 are formed based on generalization of pilot project results conducted in various countries. When calculating economic efficiency, investment cost

payback is forecasted within 2–3 years. This demonstrates that information-analytical system application is economically justified.

[8] discuss solutions that consider raw material base characteristics and technologies suitable for different enterprise scales. [13] and [5] emphasize the importance of accounting for climatic conditions and raw material composition variability in model construction. [3] present achievements in developing hybrid systems of data-driven modelling and intelligent process control for quality indicator stabilization.

International experience analysis shows that feed industry digitalization in advanced production systems has already reached a mature stage. Full Industry 4.0 concept realization, wide application of cyber-physical systems, digital twins, and predictive analytics are observed here [9, 11]. Articles in engineering and feed-technology journals show that artificial intelligence technologies play a transformative role in managing feed production processes. Machine learning method application significantly improves production efficiency, product quality, and resource consumption optimization [7, 12, 13].

Comparative analysis of research reveals several common problems. The first problem relates to data quality and availability. [6] note that many feed enterprises still do not possess adequate sensor infrastructure, which creates obstacles for building data-driven models. [1] emphasize that modernizing old equipment and equipping it with digital technologies requires significant capital investment. [8] show that high information-analytical system costs and technical specialist shortages constitute major barriers for small enterprises.

The second problem relates to models having general character and the complexity of adapting them to specific production conditions. [13] note that models presented in international literature often rely on raw material assumptions that require local adaptation. [3] emphasize the importance of considering technological equipment characteristics, while [5] show the relevance of modelling variability in the composition of regionally available plant materials.

The third problem relates to the human factor and organizational aspects. [13] emphasize that even advanced technologies do not yield expected effects when operators do not accept or cannot use them correctly. [8] note the importance of change management and systematic worker preparation for new technologies. [9] also support the need to consider ergonomic and operational factors in human-machine interaction design.

Research synthesis enables formulation of several methodological recommendations. First, information-analytical system design should be implemented based on a phased and adaptive approach. [7] support starting with a minimum viable implementation and gradually improving the system based on feedback and usage experience. [11] likewise confirm the effectiveness of iterative development cycles in digitally integrated production projects.

Table 4. Comparative economic efficiency indicators reported for the application of information-analytical systems in compound feed production

Indicator	Traditional approach	With IAS application	Improvement, %	Source
Raw material loss (%)	6.5–8.0	4.2–5.5	28–35	[1, 9, 11]
Energy consumption (kWh/ton)	45–55	35–42	18–24	[7, 8]
Product quality variation (CV, %)	8–12	3–5	58–62	[3, 6, 13]
Production productivity (ton/hour)	8–10	10–13	20–30	[12, 13]
Deviation from plan (%)	12–18	3–6	67–75	[1, 11]
Technical downtime duration (min/shift)	8–12	5–7	30–40	[7, 12]
Quality control labor expenditure (man-hour/ton)	0.25–0.35	0.10–0.15	57–60	[2, 6, 9]

Enterprise technical-technological level heterogeneity determines a phased implementation strategy. While comprehensive information-analytical system application is appropriate for large enterprises equipped with modern equipment, a gradual functionality expansion approach can be recommended for small enterprises, initially automating critical parameters [4]. Human resource readiness constitutes a decisive factor for successful system implementation. Therefore, implementing targeted training programs for operators, engineers, and managers is essential.

Research limitations include that literature analysis mainly covers the last ten-year period and that practical experimental

Second, hybrid modelling approaches show superiority over purely empirical or purely theoretical approaches. [12] and [13] show that process-informed machine learning models possess better extrapolation capability and yield more reliable results under limited data conditions. [6] propose that deterministic models should describe the main structures and relationships, while statistical or machine learning components should be used in model parameter identification and adaptation.

Third, system scalability and expansion capabilities should be considered in initial design. [1] show that modular architecture facilitates system evolution and enables quick reaction to technological updates. [8] demonstrate that cloud-native or service-oriented architecture supports elastic system resource management and adaptation to production volume changes.

Research result generalization enables formulation of the following main principles. The complexity principle involves integration of all levels – from field automation to production management – in a unified information space in feed production process management. [13] show that such integration improves production transparency and accelerates decision-making processes. The adaptability principle requires the system's automatic adaptation capability to changing raw material properties, market demand, and technological conditions. [3] show the efficiency of adaptive approaches in compensating variability.

The intelligence principle involves the system possessing the capability not only to collect and process data but also to create knowledge and make autonomous decisions. [5] and [13] support the idea that intelligent systems reduce expert operator workload while improving quality indicators. The openness principle requires the system to be based on standard interfaces, open protocols, and interoperable architecture. [8] indicate that standards-based integration reduces vendor lock-in risk.

The security principle encompasses protection against cyber threats, data confidentiality, and system resilience assurance. [8] note that industrial system security architecture should be based on the Défense-in-depth approach and should encompass multi-layer protection mechanisms. The same literature recommends comprehensive application of measures such as data encryption, access control, and security incident monitoring.

Several specific recommendations can be formulated for information-analytical system application to the feed industry in the Azerbaijani context. Climatic condition characteristics – high temperature and humidity in summer months, temperature drops in winter months – affect raw material storage and production process parameters. These factors should be considered during modelling [4]. Regional raw material base structure – availability of local grain products, legumes, and oilseeds and their quality characteristics – requires adaptation of recipe optimization algorithms [4].

work has not been conducted. The following are proposed as future research directions: development and experimental validation of mathematical models considering Azerbaijani raw material characteristics; establishment and testing of a pilot information-analytical system at a specific feed production enterprise; investigating deep learning method application possibilities in real-time feed quality forecasting; digital twin technology adaptation for feed plants; evaluation of blockchain technology use prospects for ensuring traceability and transparency in the feed production chain.

7. Conclusion

Modelling and managing compound pelleted feed production through information-analytical systems constitutes an important component of the digital transformation of the modern livestock sector. The comparative analysis of international and regional studies demonstrates that substantial scientific and practical experience has already been accumulated in this field. The reviewed literature has significantly contributed to understanding the complexity of feed production processes, developing mathematical modelling approaches, and designing intelligent management systems.

One of the main generalizations of the reviewed literature is that effective modelling and management of feed production processes require the integration of several methodological approaches rather than reliance on a single model. Deterministic methods provide a deeper understanding of physicochemical regularities, statistical methods support operational decision-making, neural networks are suitable for nonlinear dependencies, and fuzzy logic systems are effective under uncertainty. The integration of these approaches creates the foundation for comprehensive information-analytical systems covering all main production stages, from raw material reception to finished product output.

The reviewed studies also show that the architecture of such systems should be multilevel and modular. Sensor networks perform real-time data acquisition at the field level, PLC-based control provides automatic regulation at the process level, MES solutions support production coordination and quality control, and ERP platforms ensure planning and resource management at the enterprise level. Their integration into a unified information space improves transparency, traceability, and management consistency.

From the practical point of view, the comparative indicators summarized in Table 4 show that the implementation of information-analytical systems can reduce raw material losses by 28–35%, optimize energy consumption by 18–24%, reduce product quality variation by 58–62%, increase production productivity by 20–30%, reduce deviation from plan by 67–75%, shorten technical downtime duration by 30–40%, and decrease quality control labor expenditure by 57–60%. These indicators reflect generalized ranges derived from the reviewed studies and should be interpreted as synthesized literature ranges rather than as single-source values. They confirm the practical efficiency of such systems in compound feed production.

The application of artificial intelligence and machine learning technologies further expands the capabilities of information-analytical systems. Supervised learning supports quality forecasting, unsupervised learning helps reveal hidden patterns in technological data, reinforcement learning opens opportunities for adaptive control, and deep learning is effective for processing large and complex data sets. At the same time, optimization algorithms and decision support systems improve recipe design, technological parameter selection, and production planning under multi-criteria conditions.

For the Republic of Azerbaijan, the development and implementation of such systems are of strategic importance. Adaptation of international experience to local raw material resources, climatic conditions, and the technical level of feed enterprises can contribute to feed security, higher livestock productivity, improved product quality, and stronger sector competitiveness. In this regard, priority steps include specialist training, support for applied research, adaptation of international solutions, and implementation of pilot projects.

Future research should focus on experimental validation under local conditions, development of region-specific models, and broader investigation of advanced technologies such as deep learning, edge AI, and federated learning in feed production environments. Overall, the implementation of information-analytical systems in the feed industry should be considered not only a technological task, but also an economic and organizational one that requires coordinated efforts from researchers, enterprises, and public institutions.

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