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MULTI-CRITERIA OPTIMIZATION OF DIGITAL MARKETING FOR ENTERPRISES IN THE AGRO-INDUSTRIAL COMPLEX BASED ON NSGA-III ALGORITHM AND MACHINE LEARNING

The object of this study is the process of optimizing digital marketing for agro-industrial enterprises under conditions of multi-criteria and uncertainty. A formal statement of the problem of optimizing marketing strategies for agricultural production has been given by using the genetic algorithm NSGA-III. A hybrid method was devised to solve the task of multi-criteria optimization of marketing strategies for agro-industrial enterprises. The method is based on the NSGA-III algorithm in combination with the XGBoost software library and adapted to industry constraints for marketing strategies in the agricultural markets of Ukraine and Kazakhstan Republic. This allows for the generation and interpretation of Pareto-optimal strategies taking into account such criteria as efficiency, coverage, return on investment (ROI), costs, and engagement.

A cluster analysis of solutions has been performed; three characteristic scenarios were identified – balanced, cautious, and aggressive. Empirical validation by regression analysis demonstrated the high accuracy of the model, as well as its ability to extrapolate new solutions. In particular, the mean square error on the test sample was 0.0316 with the achieved coefficient of determination of 0.9041. The results confirm the effectiveness of the devised method to support decision-making under conditions of multi-criteria and limited resources.

The proposed method was used as the basis for the development of software implemented in practice at enterprises of the agro-industrial complex. However, the scope of method application also includes the activities by other business entities that devise marketing strategies to achieve the efficiency of their activities

Keywords: hybrid method, digital marketing, multi-criteria optimization, NSGA-III algorithm, cluster analysis

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1. Introduction

Conventional marketing methods, such as outdoor advertising, direct mail, radio broadcasts, and other established approaches, are gradually losing their effectiveness under the pressure of digital technologies [1, 2]. This fully applies to the agro-industrial complex (AIC). The widespread introduction of information and communication technologies in the global information space has become a powerful incentive for the transformation of marketing activities in various industries, including AIC. Successful business development today largely depends on the use of effective digital marketing strategies based on technological approaches to retaining and expanding the customer base [3]. Digital marketing is a modern tactic and strategy for interacting with consumers both in traditional markets and in the online space, which, in particular, can be implemented through machine learning technologies [4].

The digital transformation of the agricultural sector brings to the fore the task of increasing the effectiveness of marketing strategies aimed at promoting agricultural products under conditions of limited resources and a high level of uncertainty [5, 6]. The AIC specificity is determined by a combination of factors such as the spatial dispersion of agricultural producers, seasonality of demand, low level of digitalization in rural regions, and the dominance of B2B sales models over classic B2C. Additional difficulties in forming effective marketing solutions are created by climatic instability, institutional restrictions, and ethno-regional differentiation of consumer demand.

Under conditions of growing competition and limited budgets, agricultural enterprises are faced with the need for a rational distribution of advertising resources among different communication channels. In particular, agri-food enterprises can achieve economic efficiency if the main investments in digital marketing are directed to search engine optimization of communication channels [7]. Today, there is a wide range of conventional methods, technologies, and tools for planning marketing strategies that can be adapted to digital marketing with an emphasis on the agricultural sector [8]. However, existing methods for planning marketing activities are usually based on heuristics or single-criteria optimization, which often leads to inefficient use of resources and suboptimal coverage of target segments. Therefore, the use of modern multi-criteria optimization methods seems to be a promising direction, allowing one to simultaneously take into account several performance indicators, including reach, engagement, advertising costs, and return on investment (ROI).

Despite the progress made in the field of digital marketing, current methods for distributing advertising budgets in the agricultural sector, especially for developing countries, still suffer from limited adaptability and inability to take into account numerous performance criteria. Typically, marketing campaigns in the agricultural sector are designed on the basis of expert assessments or heuristic approaches based on past experience. And this does not make it possible to fully take into account the dynamic nature of demand, seasonality, institutional constraints, and regional specificity. In addition, conventional single-criteria optimization tools cannot simultaneously take into account such multidirectional metrics as reach, efficiency, cost, ROI, and depth of involvement.

Therefore, the relevance of the chosen research topic is determined by the need to devise a method capable of synthesizing management decisions regarding the promising activities of agricultural companies in the market under limited resources. This will make it possible to balance key metrics and simultaneously adapt digital marketing to the industry context of the agricultural sector. In addition, taking into account the trends in the development of information technologies, the method of optimizing marketing strategies of the agricultural and industrial complex should be based on modern evolutionary algorithms and machine learning methods. From a practical point of view, this will make it possible to implement multi-criteria optimization of digital marketing strategies using multi-directional metrics, which is difficult to perform using conventional expert methods.

2. Literature review and problem statement

As agricultural production intensifies worldwide, there is an active development of multi-criteria optimization and machine learning methods in the field of agromarketing. Moreover, many researchers pay attention to the use of evolutionary algorithms, such as NSGA-III, to solve resource allocation problems in the agricultural sector. Thus, in [9], an improved multi-criteria optimization method using NSGA-III for accurate fertilizer distribution was proposed, which makes it possible to increase accuracy and reduce equipment setup time. However, the authors of [9] note that for the effectiveness of the method, careful preliminary processing of input data is necessary, which requires development in subsequent studies. Namely, the output data should be pre-grouped according to factors influencing the final forecast result and checked for integrity (data integrity). This problem arose due to the use of an insufficient set of real data for effective generation by the evolutionary algorithm.

In addition, the integration of machine learning methods, in particular XGBoost, with evolutionary algorithms demonstrates high efficiency in forecasting and optimizing marketing strategies. In study [10], XGBoost was used to analyze consumer data, which made it possible to improve the accuracy of forecasting and the effectiveness of advertising strategies. However, the results of the cited study do not take into account the influence of various factors on the implementation of the strategy depending on the type of enterprise and its main product. Also, in [10], the issue of substantiation of parameters such as the number of regression trees, the speed of the machine learning algorithm, and the sampling frequency remained open. In the agricultural sector, approaches to optimizing sowing strategies using improved genetic algorithms and big data analysis are also considered. For example, in [11], a model for optimizing sowing strategies for agricultural crops using improved genetic algorithms and big data analysis is proposed, which contributes to increasing the efficiency of agricultural production. However, [11] does not examine how this would affect marketing strategy of the agricultural company as a whole.

Studies [12–15] show that such hybrid approaches make it possible to significantly expand the application of conventional optimization methods by including predictive analytics mechanisms that increase the generalizability of the model and reduce the need for repeated calculations when new data is received. In particular, in [12] it is proven that, compared to classical cost optimization, multi-objective Pareto optimization makes it possible to design a non-dominant set of alternative projects. In [13], the optimization of complex hybrid energy systems using a multi-objective algorithm and a Pareto-optimal approach for sets of renewable and non-renewable technologies is considered. In this case, the sensitivity of the forecast values of the net current costs of the energy system to certain parameters (interest rate, investment costs, electrical and thermal loads, and radiation) is determined. However, the authors of [12, 13] note that the method does not take into account the uncertainty associated with the system parameters and input variables. In particular, [12] noted that each objective function should be given clear restrictions on the variables, which still requires further research. And according to the results of study [13], it was determined that the sensitivity of the forecast values manifests itself in relation to factors in a certain order and this requires re-running the algorithm. Studies [14, 15] report devising a method of multi-objective optimization in the energy sector, but it is not determined whether these results could be applied to another area of economic activity, for example, to decision-making regarding the efficiency of agricultural production. This issue requires further study and testing.

In summary, it should be concluded that the scientific literature [9–15] lacks studies focused on the agricultural specificity of marketing, especially under the conditions of stochastic constraints and seasonality inherent in the agro-industrial complex. In particular, the results of studies [9–10] do not take into account the influence of various factors on the implementation of the strategy as a whole [9], including depending on the type of enterprise [10]. In addition, models that simultaneously take into account industry constraints, adaptive interpretation of decisions, and the possibility of predictive extrapolation of new scenarios without repeated use of the evolutionary kernel [11] are not sufficient. When implementing existing methods, the parameters of the genetic algorithm used for optimization [10] are not justified, and they also do not take into account uncertainty [12] and the problem of the need to re-run the algorithm [13]. And more holistic studies on the application of multi-objective optimization to forecasting enterprise development strategies [14, 15] require additional testing on the example of agricultural production in order to clarify the parameters regarding their adaptability to industry conditions. Thus, there is a need to conduct research aimed at filling the indicated research gaps by solving the problem of multi-criteria optimization of marketing strategies by enterprises of the agro-industrial complex under conditions of uncertainty.

3. The aim and objectives of the study

The purpose of our research is to devise and programmatically implement a hybrid method for optimizing marketing strategies in the agribusiness, which combines the modified NSGA-III algorithm and machine learning methods. This will make it possible, taking into account industry restrictions, to carry out adaptive interpretation of strategic decisions regarding the activities of agricultural enterprises. In practice, this will contribute to increasing the speed of processing big data to obtain predictive extrapolation of new scenarios without repeated use of the evolutionary kernel.

To achieve the goal, the following tasks were set:

– to state the problem of optimizing marketing strategies for the agribusiness using NSGA-III;

– to devise a methodology for conducting numerical experiments using the proposed method;

– to test the proposed hybrid method for optimizing marketing strategies.

4. The study materials and methods

The object of our study is the process of optimizing digital marketing for agro-industrial enterprises.

The principal hypothesis of the study assumes that digital marketing optimization should be based on the generation of Pareto-optimal strategies taking into account such criteria as efficiency, reach, ROI, costs, and engagement. The basic assumption of our study is to take into account industry constraints for the formation of marketing strategies in product markets. The method is based on the use of the NSGA-III machine learning algorithm in combination with the XGBoost software library. The study used a modified NSGA-III algorithm, according to [16]. At the first stage, the generation of support directions was implemented, for which the Das-Dennis method [17] was used to uniformly cover the unit simplex in the criteria space. Then evolutionary operators are used. First, the SBX crossover with probability $p_c = 0.9$ and distribution parameter $\eta_c = 15$ is applied, according to [17]. The computational complexity parameter of the modified NSGA-III was adopted according to study [16], which depended on the number of goals and population size. The algorithm efficiency prediction using the XGBoost software library was performed according to the methodology from [18]. Cluster data analysis and scenario approach were used to analyze strategic decisions [18]. This approach included building a decision tree (marketing strategies of an agro-industrial complex enterprise), with their subsequent analysis according to the boosting convergence theorem. To evenly cover the multidimensional search space with a minimum number of scenarios, the statistical method of spatial filling Latin Hypercube Sampling (LHS) was used [19]. Thus, our research methodology is based on the analysis of methods for solving optimization problems [16–19] and on the approaches of benchmarking of enterprises in the agricultural markets of Ukraine and the Republic of Kazakhstan. The method devised has been implemented in the form of the MOMS software, developed in the Python programming language (USA) in the PyCharm IDE environment. To quantitatively assess the quality of the formation of the Pareto front of strategies, the program provides for the calculation of the hypervolume indicator and the performance of regression analysis.

The method was tested on the basis of enterprises in the agricultural sector of Ukraine and the Republic of Kazakhstan. In this case, a 5-dimensional space of criteria (efficiency, coverage, costs, involvement, ROI) was given for the generation of Pareto-optimal strategies. A matrix of scatter and density diagrams was used for visualization. This representation option helps not only to see the relationships between different criteria but also distinguish different behavioral profiles of the enterprise's marketing strategies in the process of multifactor optimization. In order to assess the ability of the XGBoost model to approximate the dependence between the configuration of the marketing budget and the values of the criteria, a regression procedure was performed on the set of solutions obtained from NSGA-III.

5. Results of devising a hybrid method for optimizing marketing strategies

5. 1. Statement of the problem of optimizing marketing strategies for the agro-industrial complex using NSGA-III

The problem of optimizing marketing strategies for the agro-industrial complex using NSGA-III is considered in the case when the number of objective functions is taken equal to 5. If necessary, they can be increased to 15. In this case, the set of marketing channels can be specified in the following form:

$$K = \{1, ..., m\}, \quad (1)$$

where $m = 5$ and corresponds to digital (Digital), television (TV), radio (Radio), print (Print), and event (Events) channels, respectively.

For each channel $k \in K$, the following key parameters are given for evaluation:

1. Efficiency $e_k \in [0, 1]$, which characterizes the conversion of the digital channel.
2. Reach $c_k \in \mathbb{R}^+$, which measures the audience of the channel.
3. Cost $s_k \in \mathbb{R}^+$, which determines the specific costs.

The optimization vector $x = (x_1, \ldots x_m)^T \in \mathbb{R}^m$ represents budget allocation among channels, where $x_k \in [l_k, u_k]$ is the share of the budget allocated to channel k, with lower l_k and upper u_k bounds.

The following objective functions are considered for the case $m = 5$:

1. Maximization of overall efficiency

$$f_1(x) = \sum_{k=1}^{m} e_k \cdot x_k \to \max. \tag{2}$$

2. Maximizing overall reach

$$f_2(x) = \sum_{k=1}^{m} c_k \cdot x_k \to \max. \tag{3}$$

3. Minimization of total costs

$$f_3(x) = \sum_{k=1}^{m} s_k \cdot x_k \to \min. \tag{4}$$

4. Relative cost efficiency. In fact, it is a kind of ROI metric

$$f_4(x) = -\frac{E(x,s)}{C(x)+\varepsilon} \to \max, \tag{5}$$

where $E(x,s) = \sum x_i \cdot e_{s,i}$, $C(x) = \sum x_i \cdot e_{s,i}$, $\varepsilon > 0$ – small constant to avoid division by zero.

5. Depth of interaction with the audience that should be maximized

$$f_5(x,s) = -\sum_{i=1}^{n} x_i \cdot v_{s,i}, \tag{6}$$

where $v_{s,i}$ is the engagement estimate for channel i in segment s.

The parameters $v_{s,i}$ can be determined based on expert judgment or, for example, based on data on conversion, clicks, participation in events, etc. For example, click data can be collected using Google Analytics.

The following constraints are set for the objective functions:

1. Total budget constraints

$$g_1(x) = \sum_{k=1}^{m} x_k - B \le 0, \tag{7}$$

where $B = 1.5$.

2. Minimum fractions for channels

$$g_{2k}(x) = l_k - k \le 0, \ \forall k \in K. \tag{8}$$

3. Maximum fractions for channels

$$g_{3k}(x) = x_k - u_k \le 0, \ \forall k \in K. \tag{9}$$

4. Combined restrictions

$$g_4(x) = \Theta - (x_1 - x_5) \le 0, \tag{10}$$

where $\Theta = 0.3$.

Thus, the formalized system of restrictions in the proposed hybrid model reflects the fundamental economic and technological features of the agribusiness. For example, the budget restriction takes into account the specificity of financial planning in the agribusiness, where the nominal budget is allowed to be exceeded by up to 150% through seasonal credit lines, which corresponds to the practice of financing agricultural enterprises. The thresholds for distributing funds by channel are due to the need to maintain a minimum presence in all market segments – from digital platforms to conventional printed catalogs. The restriction on the minimum share of digital marketing channels reflects the strategic priority of the digitalization of the agribusiness, enshrined in state programs for the development of agriculture. The combined restriction on the sum of the shares of digital and event channels provides a balance between new and conventional methods for promoting agricultural produce, taking into account the need to combine online sales with participation in conventional agricultural exhibitions and fairs. The upper limit for event marketing was introduced to control costs associated with the high cost of organizing events and their limited scalability under the conditions of low rural population density in the Republic of Kazakhstan. For print channels, a minimum threshold was set (to ensure presence in the B2B segment through specialized publications).

For 5 objective functions and N-splits, the generation of reference directions was performed

$$W = \left\{ w \in \mathbb{R}_+^5 \,\middle|\, \sum_{i=1}^{5} w_i = 1, w_i = \frac{k}{N}, k \in N_o \right\}, \tag{11}$$

where w are the reference directions in the space of objective functions (2) to (6).

These vectors define a uniform distribution of points on the unit simplex to ensure a representative coverage of the Pareto front. Each direction $w \in \mathbb{R}_+^5$ is a normalized vector of weight coefficients. Geometrically, they determine the directions of searching for optimal solutions in the space of criteria (2) to (6) considered in the study.

Next, evolutionary operators are used. First, an SBX crossover with probability $p_c = 0.9$ and distribution parameter $\eta_c = 15$ is applied

$$x_i^{(new)} = \frac{1}{2}\left[(1+\beta)\cdot x_i^{(1)} + (1+\beta)\cdot x_i^{(2)}\right], \tag{12}$$

where

$$\beta \sim U[0,1]^{\eta}{}_c{+1},$$

and for polynomial mutation

$$x'_k = x_i + \delta_i, \ \delta_i \sim N(0, \sigma_i^2), \ \sigma_i = \frac{(u_i - l_i)}{\eta_m}. \tag{13}$$

In the next step, cluster analysis of solutions is implemented. For the analysis of the Pareto front, the method of k-means with the Euclidean metric is used

$$\min_{\{\mu_j\}_{j=1}^{s}} \sum_{i=1}^{N} \min_j \left\| f\left(x_i\right) - \mu_j \right\|^2, \; j = 1 \ldots k, \tag{14}$$

where $f(x) = (f_1(x), f_2(x), f_3(x), f_4(x), f_5(x))$ is the vector of criteria, $k = 5$ is the number of clusters.

The multi-criteria optimization problem now implies finding

$$\min_{x \in F} F\left(x, s\right) = \begin{pmatrix} -\sum x_i \cdot e_{s,i} - \sum x_i \cdot c_{s,i}, \\ \sum x_i \cdot p_i, -\dfrac{\sum x_i \cdot e_{s,i}}{\sum x_i \cdot p_i + \varepsilon}, -\sum x_i \cdot v_{s,i} \end{pmatrix}^T, \tag{15}$$

where p is the cost of one conditional impact through channel i.

Then the solution $x^* \in X$ for this problem will be Pareto-optimal if $\nexists x \in X$

$$f_i\left(x\right) \geq f_i\left(x^*\right) \forall i \in \{1,2,3,4,5\} \text{ and } \exists j : f_j\left(x\right) > f_j\left(x^*\right), \tag{16}$$

where $X = \{x \in \mathbb{R}^m \mid g_j\left(x\right) \leq 0, \; j = 1 \ldots p\}$ is the admissible set.

The computational complexity of the modified NSGA-III is $O(MN^2)$, where M is the number of targets, N is the population size.

The prediction of channel efficiency using XGBoost in the study was determined based on a retrospective data sample for a specific region or agro-industrial complex enterprise

$$D = \left\{\left(x^{(i)}, y^{(i)}\right)\right\}_{i=1}^{N}, \tag{17}$$

where $x^{(i)} \in \mathbb{R}^m$ – budget allocation vector, $y^{(i)} \in \mathbb{R}^m$ – observed efficiency.

The XGBoost model builds an ensemble of K decision trees. For XGBoost, $\hat{y}\left(x\right) \to E\left[y \middle| x\right] >$ if $N \to \infty, K \to \infty$ (according to the boosting convergence theorem) is fulfilled.

After training, model (2) to (17) is used to quickly predict the efficiency of new budget strategies without re-running the evolutionary algorithm. Our model (2) to (17) was implemented in the Python programming language (USA) in the PyCharm IDE.

5. 2. Methodology for conducting numerical experiments using the method devised

The methodology for conducting numerical experiments is represented in the pseudocode format of the developed MOMS program (Method for Optimizing Marketing Strategies Program in agro-industrial complex).

```
1: procedure HYBRID_NSGA3_ML_OPTIMIZATION
2:   Input:
3:      channels ← {Digital, TV, Radio, Print, Events}
4:      params ← {e_k, c_k, s_k, eng_k, roi_k} ∀k ∈ channels
5 criteria
5:      bounds ← [l_k, u_k] ∀k ∈ channels
Partial constraints
6:      constraints ← {g_1,...,g_6}                Budget rules
7:      ref_dirs ← Das-Dennis(5, 12)               For 5D space
8:
9:   # Phase 1: Multi-criteria optimization (NSGA-III)
10:  algorithm ← NSGA-III(
11:      pop_size=100,
12:      ref_dirs=ref_dirs,
13:      sampling=LHS(),
14:      crossover=SBX(prob=0.9, η=15),
15:      mutation=PM(η=20),
16:      constraints_handling="adaptive"
17:  )
18:  results ← minimize(problem, algorithm,
termination('n_gen', 100))
19:  P ← non_dominated_sorting(results.F)
5D Pareto front
20:
21:  # Phase 2: Cluster analysis
22:  features ← StandardScaler().fit_transform(P[:, 0:5])
Normalization
23:  clusters ← KMeans(n_clusters=3).fit(features)
24:  silhouette ← calculate_silhouette(features, clusters)
Quality metrics
25:
26:  # Phase 3: Predictive model
27:  model ← XGBRegressor(
28:      objective='reg:squarederror',
29:      n_estimators=200,
30:      max_depth=5
31:  ).fit(P, composite_score)       Training on composite
indicator
32:
33:  # Phase 4: Interpretation of results
34:  explainer ← KernelSHAP(model)
35:  shap_values ← explainer.shap_values(P)
36:  channel_importance ← mean(|shap_values|, axis=0)
37:
38:  Output:
39:     P, clusters, silhouette,
40:     model_metrics ← {MSE, R²},
41:     channel_importance
42: end procedure
```

Within the framework of our research, the pseudocode reflects the phased implementation of the above algorithm. Lines 1–8 implement the initialization of the developed software (MOMS) for the hybrid method of optimization of marketing strategies in the agricultural and industrial complex described in our paper, which combines the modified NSGA-III algorithm and machine learning methods. Here, a 5-dimensional space of criteria (efficiency, reach, costs, involvement, ROI) is specified. Then, a modified Das-Dennis scheme is used to generate reference directions in 5D space.

Lines 9–19 implement the optimization procedure. In these lines, adaptive NSGA-III with processing of constraints through the penalty function (line 16) and LHS sampling (statistical method of spatial filling) provides uniform coverage of the initial population. In the context of the problem of optimizing marketing strategies in the agricultural and industrial complex, where the solution space is five-dimensional (Digital, TV, Radio, Print, Events), LHS sampling initializes the initial population, guaranteeing the projection uniformity of the distribution of points on each of the coordinate axes.

The initial population generated by the LHS method has two key properties for the problem. In particular, this is the absence of clustering of points in separate regions of the solution space, which is important for the correct start of the evolutionary algorithm, and guaranteed consideration of all boundary conditions, including combinational constraints. Next, SBX crossover and PM mutation with adaptive parameters are performed.

Lines 21–24 describe clustering. Standardization of criteria before clustering is line 22. The silhouette score metric assesses the quality of clustering.

Lines 26–36 are machine learning components. SHAP analysis reveals the contribution of channels to the objective function.

For $m = 5$ criteria, the number of reference directions is calculated in the 6th line of the pseudocode. Adaptive processing of constraints is given in line 16. Feature normalization is implemented in line 22.

The remaining lines are needed to visualize our research results.

5. 3. Testing the devised hybrid method for optimizing marketing strategies

Based on data on the agricultural markets of Ukraine and the Republic of Kazakhstan, modeling was performed using the devised hybrid method (Tables 1, 2, Fig. 1–5).

The analysis of Pareto-optimal solutions (Table 1, Fig. 1–3) reveals a pronounced dichotomy in the efficiency of different channels. This conclusion is also confirmed by the cluster structure of the solution space. Three-dimensional visualization of the Pareto front for the triad "cost-reach-efficiency" shows the presence of three qualitatively different groups of strategies. For Fig. 1, the most promising strategies (cluster 1, in Fig. 1, blue dots) are characterized by the dominance of the television channel (39.8–69.5% of the budget) with a significant share of digital technologies (20.4–21.1%) and event marketing (26.4–30.0%).

At the same time, the quality assessment of the formed Pareto front indicates that the devised hybrid method for optimizing marketing strategies of agricultural and industrial enterprises effectively solved the multi-criteria problem since the hypervolume indicator was $HV = 2.4602$. The mean square error on the test sample is $MSE = 0.0316$, and the value of the coefficient of determination R^2 reaches 0.9041. This confirms the good consistency of the predictive data of the model with the original ones.

As a result of clustering (Fig. 1–3), three stable scenario types can be distinguished. The first cluster, corresponding to moderately balanced strategies with the dominance of radio and digital channels, demonstrated an average efficiency of 1.098 and an average coverage value of 0.976 at a relative cost of about 1.347. At the same time, the average level of audience involvement in this class was 0.837. The expected ROI is at the level of 0.817. Such strategies are a compromise between coverage and cost-effectiveness, focused on mass communication channels.

Table 1

Optimal digital marketing strategies

Digital (%)	TV (%)	Radio (%)	Print (%)	Events (%)	Efficiency	Coverage	Cost	Composite	Cluster
20.41	39.82	11.74	39.77	29.99	1.101	0.950	1.169	0.820	1
21.14	69.52	10.17	17.50	29.85	1.182	1.024	1.264	0.820	1
22.48	59.70	13.96	19.51	26.37	1.134	0.986	1.219	0.815	1
22.21	28.26	10.29	38.39	28.11	0.994	0.857	1.057	0.812	2
41.51	57.24	11.87	14.85	24.40	1.233	1.077	1.342	0.812	1

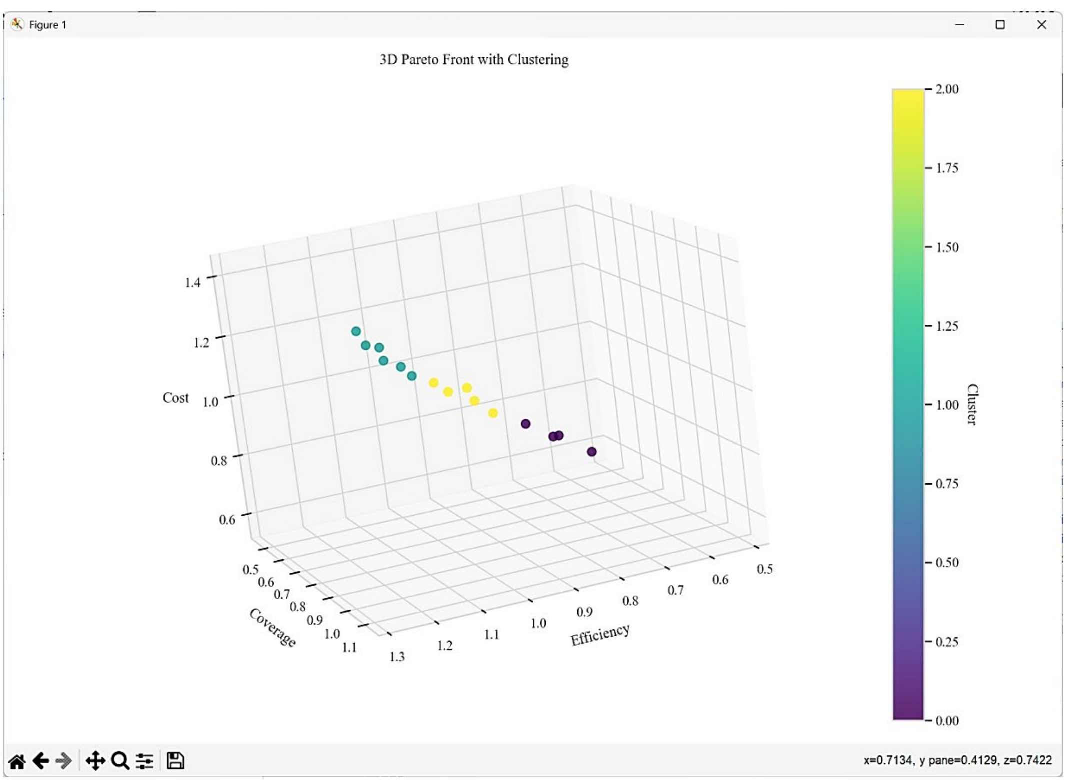

Fig. 1. Three-dimensional visualization of the Pareto front for the criteria of overall effectiveness, reach, and total costs of the marketing strategy (output from the MOMS program)

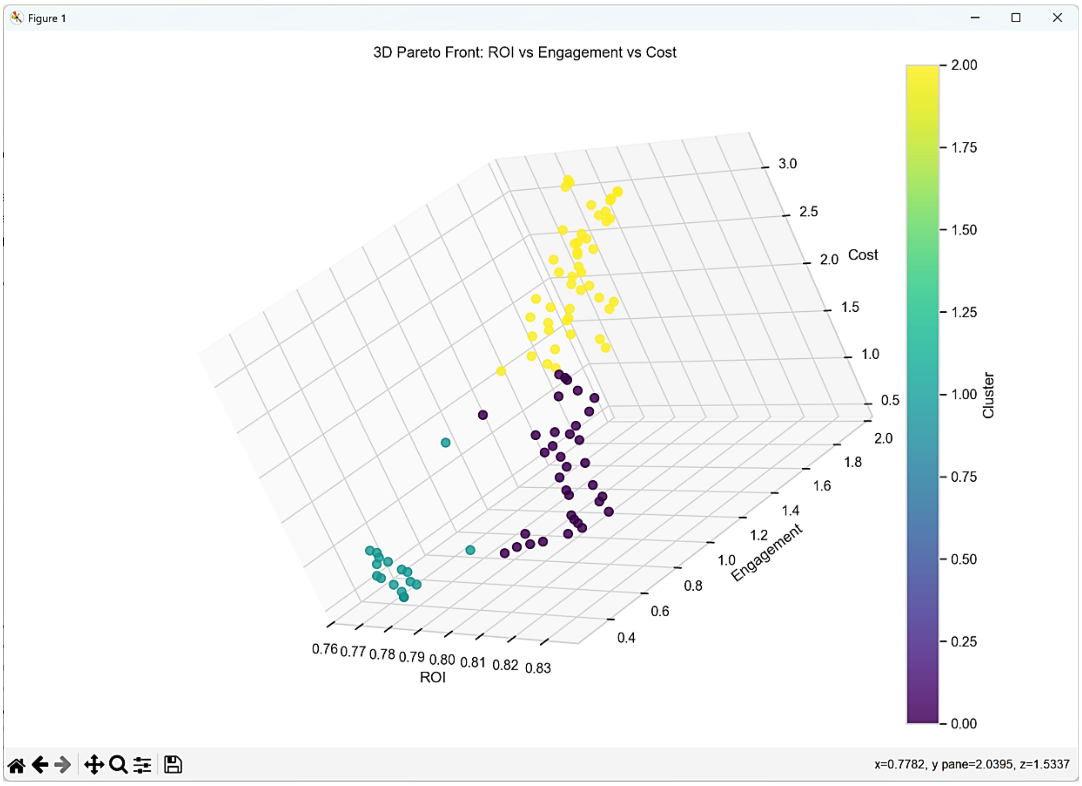

Fig. 2. Three-dimensional visualization of the Pareto front taking into account the criteria of costs, engagement, ROI for marketing strategy (output from the MOMS program)

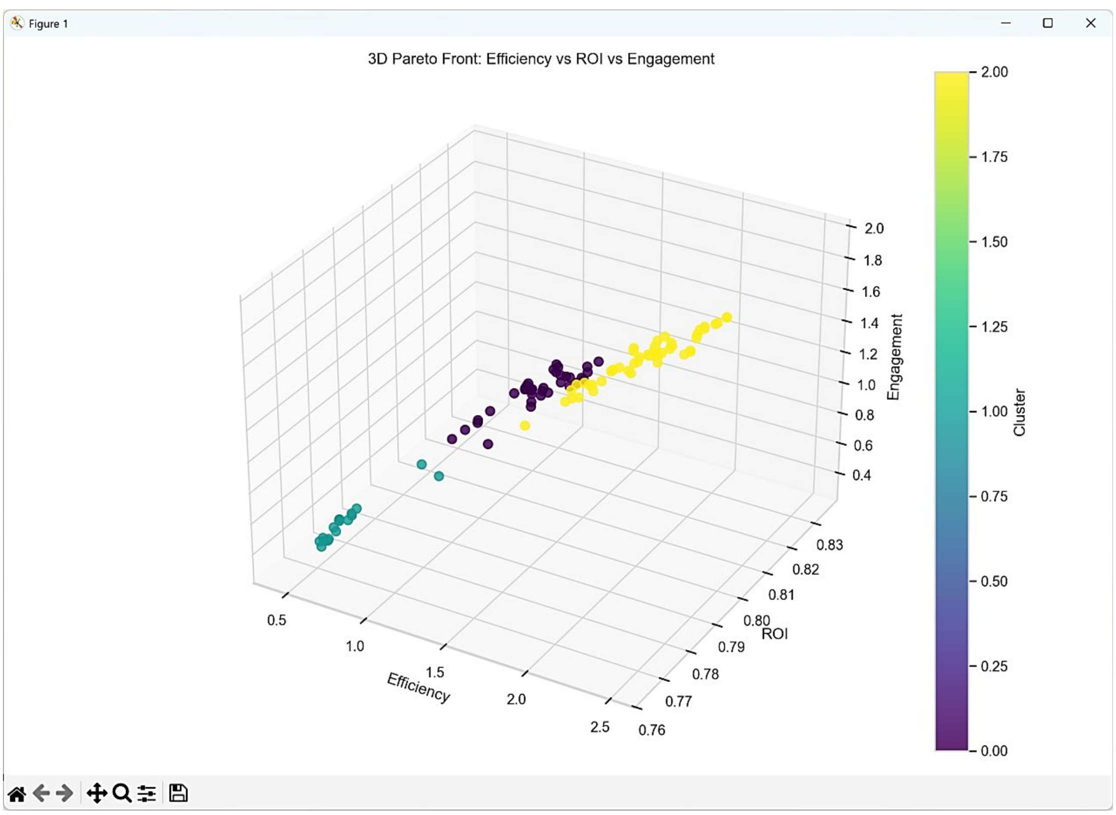

Fig. 3. Three-dimensional visualization of the Pareto front taking into account the criteria of effectiveness, engagement, ROI for marketing strategy (output from the MOMS program)

The most resource-intensive and aggressive strategies in terms of reach constitute the third cluster. This cluster has the maximum values for all key criteria. The average efficiency is 2.032, reach – 1.791, engagement – 1.563. Despite the fact that the average cost of implementing strategies in this class is significantly higher (2.541), the ROI indicator remains at a stable level and is 0.800. This level of ROI indicates the justification of investments with the availability of appropriate financial resources and the need to maximize the reach of the advertising audience.

Fig. 4 shows estimates of the distribution density for each metric (efficiency, reach, cost, engagement, and ROI) in different clusters.

Analysis of the distributions of metrics (Fig. 4) revealed that within each cluster the statistical structure is significantly different. For example, the yellow cluster (Cluster 2) demonstrates pronounced unimodal distributions (distributions with one peak). In such distributions, the values are shifted to higher indicators for all metrics. This result indicates that marketing strategies in this cluster are focused on maximizing marketing efficiency by significantly increasing the budget and media presence of product advertising. The turquoise cluster (Cluster 0) shows more concise values in the lower part of the range. This was interpreted as strategies aimed at minimizing costs with limited reach and efficiency.

The middle purple cluster (Cluster 1) is something in the middle, where the distributions of values are more uniform. That is, for Cluster 1 we can talk about a balanced approach to the distribution of marketing resources.

Of particular interest to marketers is the distribution of points by ROI. Despite the fact that the values are in a narrow range from 0.75 to 0.85, there is a noticeable difference between the clusters within this interval. The strategies of the purple (Cluster 1) and yellow clusters (Cluster 2) have high ROI values. This result indicates their high profitability at different levels of investment in marketing and advertising of agricultural products. Turquoise solutions, on the contrary, are concentrated in the lower part of the range, which indicates a low return on investment. And this is despite the lower costs. In general, the visualizations in Fig. 4 demonstrate that the set of solutions not only differs in numerical indicators but also has a variety of behavioral models.

Fig. 5 shows the analysis of solutions using parallel coordinates that make up the Pareto set, classified according to the clustering results.

Each line on the plot (Fig. 5) corresponds to one alternative strategy, which is displayed through the projection of the values of the objective functions. This representation allows for a visual interpretation of the trade-offs between different goals and also made it possible to identify stable patterns within the clusters. The lines are grouped by color, which corresponds to the cluster membership. The turquoise color in Fig. 5 denotes cluster 0, purple – Cluster 1, yellow – Cluster 2. Already at the first visual level, it can be noted that each group demonstrates a characteristic trajectory along the coordinate axes, which reflects its inherent strategic vector.

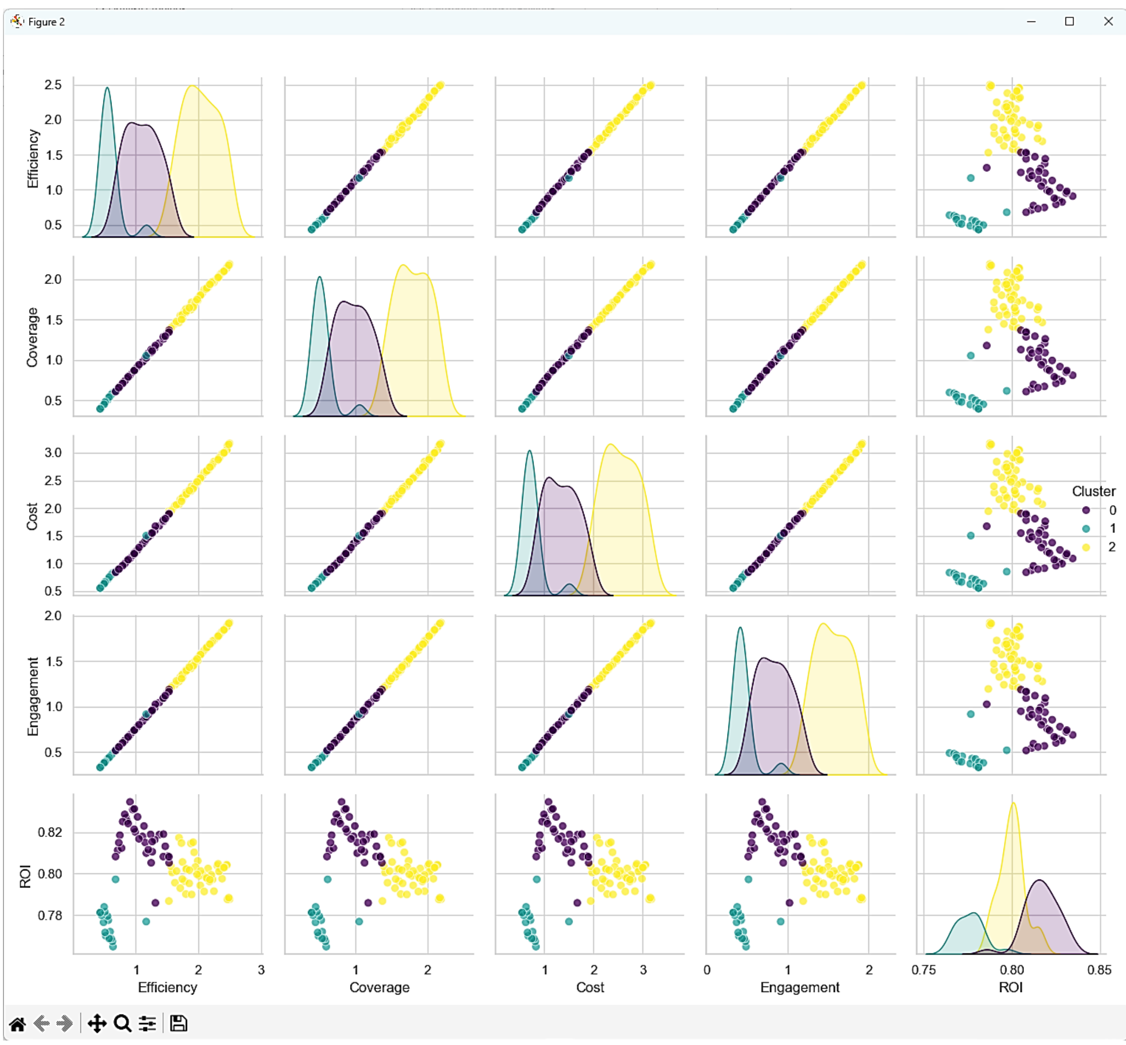

Fig. 4. Output from the developed MOMS program of the results of clustering solutions included in the Pareto set, taking into account five key metrics

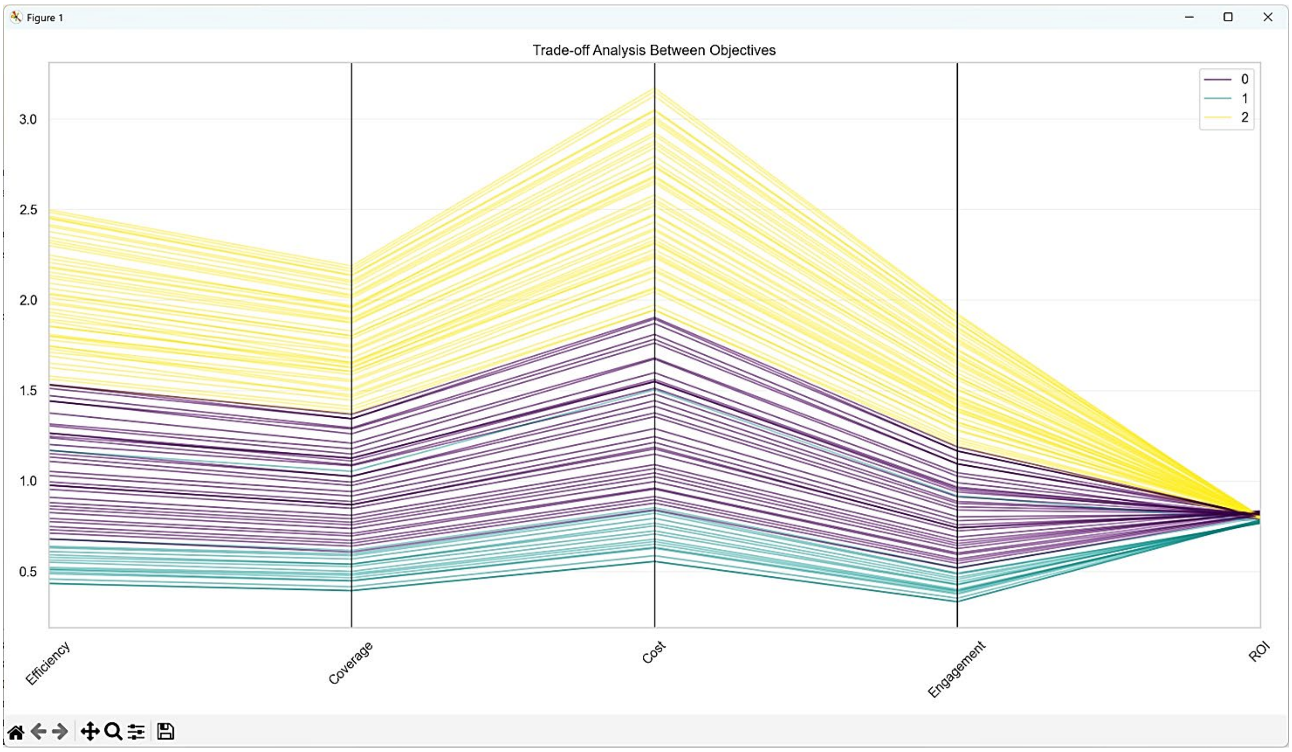

Fig. 5. Parallel coordinate analysis of solutions included in the Pareto set
(output from the MOMS program)

Cluster 2 (yellow), as before, is dominant in the space of high costs and high values of efficiency, reach and involvement. Such strategies tend to maximize non-monetary indicators, despite the pronounced burden on the marketing strategy budget. Unlike monetary indicators (such as profit, cost, or ROI), non-monetary indicators focus on non-valued aspects of doing business in the agribusiness. For example, such as quality, customer interaction, sustainability, or long-term effects. For the agribusiness, as shown in [1, 2], non-monetary indicators may include, for example:

– consumer satisfaction – that is, an indicator of how satisfied customers are with the quality of products or services of the agricultural sector. For example, farmers or agricultural enterprises operating in the agricultural market (both in Ukraine and the Republic of Kazakhstan) can take into account feedback on the quality of their products (vegetables, fruits, meat, etc.). This potentially contributes to improving product quality and strengthening loyalty;

– brand reputation and awareness – that is, how well the brand is known and how it is perceived in the agricultural market. For agricultural enterprises in the Republic of Kazakhstan, this means how buyers perceive their products and the company as a whole. For example, if we are talking about bio- or organic products, which require trust from consumers;

– environmental sustainability – that is, how much the marketing strategy complies with the principles of sustainable agriculture in the Republic of Kazakhstan. Such an indicator may include the use of environmentally friendly production methods, minimizing environmental impact, the use of organic fertilizers, etc.

Of course, there are other non-monetary indicators. However, they are sufficiently detailed in the specialized literature, and their inclusion in the list of objective functions was not provided for by the original objectives of this study.

It is worth noting that, despite the diversity of profiles, almost all lines from this cluster strive for the same ROI value (Fig. 5). This fact indicates an obvious limitation in the system's response to investment growth. In fact, a situation arises when additional investments are not accompanied by an adequate increase in profitability.

The purple cluster (cluster 1) occupied an intermediate position. Its lines form a dense bundle in the middle ranges of values along all axes. Such solutions can be interpreted as compromise, balanced in coverage, effectiveness, and cost. At the same time, they maintain a comparable level of return on investment in marketing strategies. This indicates a high efficiency of resource allocation in this segment of strategies.

The turquoise cluster (cluster 0), on the contrary, is characterized by uniformly reduced values for all parameters. The length of the lines of cluster 0 is minimal, which indicates an insignificant scale of use of marketing tools. At the same time, despite the restrained costs, the achievable ROI is not much lower than in the rest of the clusters. This gives grounds to consider this segment as representative of cost optimization strategies, that is, those when, with minimal investment, it is possible to maintain acceptable performance – even by abandoning wide coverage and deep audience involvement.

Summarizing the modeling results (Fig. 5), it is worth emphasizing that this visualization makes it possible to identify not only quantitative differences between clusters but also qualitatively different principles of forming marketing strategies for the agro-industrial complex.

For a systematic representation of internal differences in marketing strategies obtained as a result of multi-criteria optimization using the hybrid approach NSGA-III + XGBoost, it is necessary to distinguish a typology of strategies according to their belonging to stable clusters. Table 2 reflects the key differences between strategies and serves as a means of interpreting solutions included in the Pareto set.

Table 2

Comparison of characteristics of marketing strategies by clusters

Metric	Cluster 1 – balanced	Cluster 2 – cautious	Cluster 3 – aggressive
Audience reach	0.976	0.533	1.791
Effectiveness (Effect)	1.098	0.580	2.032
Engagement (Depth of interaction)	0.837	0.447	1.563
Total advertising spend	1.347	0.747	2.541
ROI	0.817	0.776	0.800
Preferred channels	Radio + Digital	Mostly offline	TV + digital
Strategy focus	Balance of reach and efficiency	Cost minimization	Maximizing the result
Targeting	Businesses with a moderate budget	Businesses in a time of constraints	Export-oriented agricultural enterprises

The division into three clusters reflects the fundamental scenarios of the behavior of agribusiness enterprises in Ukraine and the Republic of Kazakhstan depending on their resource constraints, market priorities, and goals. Comparison by metrics of coverage, efficiency, ROI, and costs allows managers to justify the choice of an appropriate strategy in the presence of specific production and financial conditions. In general, our results demonstrated the potential of the devised approach as a basis for building intelligent systems to support marketing management in the agribusiness. At the next stage of the study, it seems advisable to expand the number of objective functions, including non-monetary indicators (for example, sustainability, environmental friendliness, social coverage), as well as implement a multi-task method involving several agribusiness enterprises from Ukraine and the Republic of Kazakhstan, which differ in scale and region. In addition, in further research, it is planned to integrate dynamic aspects of changes in parameters over time into the model built.

6. Discussion of results based on testing the devised hybrid method for optimizing marketing strategies

The devised hybrid method for optimizing marketing strategies is based on the proposed mathematical model (2) to (17), to which the NSGA-III algorithm is applied in combination with XGBoost. The software implementation of the devised method is carried out in the Python programming language (USA) in the PyCharm IDE environment. This allows for quick forecasting of the effectiveness of new budget strategies by agricultural enterprises. Unlike [11–15], in which the basis of strategic planning is multiple runs of the model, the proposed approach implements the hybrid method without re-running the evolutionary algorithm. Also, the advantage of the devised hybrid method is that it makes it possible to optimize a mathematical function according to five criteria simultaneously, which is difficult to perform using conventional expert methods, since a person is physically unable to synchronize the analysis of a large number of parameters. In particular, unlike [11], in which it was not determined how the proposed solutions would affect the marketing strategy of the agricultural company as a whole, our study provides for the clustering of strategies into three stable groups according to 5 criteria. The uncertainty associated with the system parameters and input variables, unlike [12, 13], is taken into account in this method by introducing a system of constraints to the objective functions (7) to (10). In addition, this system reflects the fundamental economic and technological features of the agricultural industry, which was also not taken into account in [14, 15].

A trial simulation was performed using the devised hybrid method based on data from the agricultural markets of Ukraine and the Republic of Kazakhstan (Tables 1, 2, Fig. 1–5). The obtained Pareto-optimal solutions were analyzed (Table 1, Fig. 1–3), which showed the existing pronounced dichotomy in the efficiency of various channels. A three-dimensional visualization of the Pareto front was performed using the criteria "cost-coverage-efficiency" (Fig. 1–3), according to which three stable scenario types (balanced, cautious, and aggressive) were identified. The results of clustering solutions included in the Pareto set, taking into account the five key metrics considered in the paper – efficiency, coverage, cost, involvement, and ROI, were visualized in the form of a matrix of scatter and density diagrams (Fig. 4). At the same time, the distribution forms, the relationships between metrics, and the cluster structure together (Fig. 4) confirmed that the model (2) to (17) is capable of generating a multitude of meaningful alternatives. Moreover, these alternatives (scenarios) can be used for strategic decision-making in order to optimize marketing strategies in the agribusiness. First of all, in situations where there is multi-criteria. The analysis of decisions performed using parallel coordinates, which make up the Pareto set, (Fig. 5) made it possible to determine the strategic trajectory of alternative decisions through the projection of the values of the objective function. This ultimately made it possible to graphically interpret trade-offs between different goals, as well as identify stable patterns within clusters. Such visualization determines the principles of forming marketing strategies for the agribusiness, and the use of parallel coordinates in this study turned out to be a fairly effective means of identifying compromise decisions. It should be noted separately that this special representation of modeling results for the decision-maker has visual advantages, as it is intuitive.

Our results (Fig. 1–3) were evaluated for the consistency of the predictive data with the initial ones. In particular, the hypervolume index was $HV = 2.4602$, the mean square error for the test sample was $MSE = 0.0316$, and the value of the coefficient of determination R^2 reached 0.9041. This demonstrated that the devised hybrid method for optimizing marketing strategies of agro-industrial enterprises effectively solved the multi-criteria problem. This is confirmed by the existing high consistency of the modeling results. In general, the modeling confirmed the feasibility of using a hybrid architecture that combines NSGA-III, cluster analysis, and predictive regression to design, analyze, and substantiate optimal marketing strategies. In particular, the devised hybrid method could become an effective tool for decision-making under conditions of multi-criteria and limited certainty, characteristic of agro-industrial enterprises.

The results obtained in the course of our study can become the basis for the construction of intelligent marketing planning support systems, or in general, marketing decision support systems (DSSs). Such DSSs will have in their computational core the ability to automatically generate recommendations and adapt to external conditions based on the learning model.

The limitation is that in this study, five criteria were used to solve the main problem, although the NSGA-III algorithm provides for the use of up to 15 criteria simultaneously. Therefore, in the future research, we plan the inclusion of dynamic change parameters in the mathematical model, as well as an expansion of the number of objective functions.

7. Conclusions

1. The problem of optimizing marketing strategies for agribusiness using NSGA-III has been stated. The method is based on the NSGA-III and XGBoost algorithms and adapted to the multi-criteria specificity of the agricultural industry. To solve the problem of optimizing marketing strategies for agribusiness enterprises, five objective functions have been set – maximizing overall efficiency, maximizing overall coverage, minimizing total costs, relative cost efficiency, and the depth of interaction with the audience that should be maximized. In order to take into account the specificity of digital marketing in the agricultural industry, a system of constraints has been proposed that takes into account seasonality, budget overruns, channel share structure, and digitalization priority. Based on the results of the optimization algorithm, a representative set of Pareto-optimal solutions is formed, which can be interpreted using cluster analysis. Clustering of strategies into three stable groups according to 5 criteria is provided – balanced, cautious, and aggressive. Each of the resulting clusters corresponds to certain financial conditions of enterprises.

2. A numerical experiment has been performed on the basis of the developed MOMS software in the Python programming language (USA) in the PyCharm IDE environment. At the same time, the program was initialized to implement a hybrid method for optimizing marketing strategies in the agribusiness, which combines the modified NSGA-III algorithm and machine learning methods. In the program, clusters of marketing strategies of an agribusiness enterprise are built according to the decision tree principle, with their subsequent analysis according to the boosting convergence theorem. At the same time, the uniformity of coverage of the multidimensional search space is ensured by using the statistical method of spatial filling Latin Hypercube Sampling (LHS). The developed software makes it possible to visualize our solutions in the form of a matrix of scatter and density diagrams, as well as parallel coordinates. The program also provides for the calculation of the hypervolume indicator and the performance of regression analysis for the quantitative assessment of the quality of the formation of the Pareto front of marketing strategies of agribusiness enterprises. Thus, the MOMS software is a full-fledged tool for making decisions regarding the activities of companies in the agricultural market.

3. The experimental modeling using the devised hybrid method was performed using data on the agricultural markets in Ukraine and the Republic of Kazakhstan. As a result of analyzing our Pareto-optimal solutions, it was confirmed that the proposed method can generate meaningful alternatives under conditions of multicriteria and uncertainty. The empirical results obtained during numerical experiments demonstrated the good quality of the model. Thus, the hypervolume of the Pareto front is 2.4602, the predictive accuracy of the XGBoost model reaches $MSE = 0.0316$, and the value of the coefficient of determination $R^2 = 0.9041$. Such results have confirmed the suitability of the model for both approximation and extrapolation of solutions. The initial graphical interpretation of trade-offs between different goals, as well as the identified stable patterns within clusters, make it possible to determine the principles of forming marketing strategies for the agro-industrial complex and make informed management decisions based on them. Since the identified strategic profiles demonstrate differences in terms of effectiveness, reach, ROI, and costs, this allows for the future use of this model in automated intelligent systems.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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