

Alina HLUSHKO, Oleksandr LAKTIONOV, Alina YANKO, Oleksandr ISAIIEV

National University «Yuri Kondratyuk Poltava Polytechnic», Poltava, Ukraine

MODELS FOR INDUSTRY DIFFERENTIATION IN DECISION-MAKING SYSTEMS WITH AN APPLICATION TO THE UKRAINIAN ECONOMY

*This article is devoted to the study of the problem of using adaptive models of differentiation of sectors of the real sector of the economy as a key component of modern decision support systems (DSS). The **subject** of the study is models of differentiation of real sectors of the Ukrainian economy for integration into decision support systems to optimize public administration. This research **aims** to develop and validate adaptive models of industry differentiation into clusters (groups) to improve the effectiveness of decision-making systems applied to the real sector of Ukraine's economy. The **research object** is the process of sectoral differentiation, which allows determining the structural features and patterns of economic sector functioning. DSS architecture is proposed that integrates multifactor analysis and machine learning algorithms for automated selection of strategic scenarios. For clustering, we used production volume indicators and the number of strategically important enterprises in Ukraine for the pre-war period (2015–2021), which serve as a benchmark model for comparative analysis. A comparative assessment of the effectiveness of the classical K-means, DBSCAN, and Ensemble model algorithms was conducted with quantitative verification of the results using the Silhouette Score and Davies-Bouldin Score metrics. Empirical analysis showed that the DBSCAN and Ensemble models provide the highest quality of clustering (Silhouette Score 0.8387; Davies-Bouldin Score 0.0777), forming a reliable grouping of economic sectors. DSS module was developed based on the results obtained to form indicative tactical support measures, in particular, infrastructure strengthening of high-potential clusters and structural reorganization of vulnerable ones. **Conclusions.** The developed models form a universal methodological framework that is suitable for use in different countries, particularly in countries with a “peaceful” economy. DSS specialists can use the research results to identify key sectors of the economy, develop adaptive policies, and increase the stability and competitiveness of economic systems in a dynamic environment.*

Keywords: clustering; economic management; public policy; ensemble model; digital solutions; adaptive strategy; decision support system.

1. Introduction

The current stage of Ukraine's economic development is characterized by profound structural transformations amidst globalization challenges, heightened geopolitical instability, and increasing risks to national security, particularly economic security. This necessitates the improvement of state economic management mechanisms based on the principles of socio-economic development predictability and adaptability to external and internal challenges [1]. Military-political instability, energy and food security risks, and global technological shifts underscore the need for developing new approaches to decision-making systems. Optimizing decision-making systems requires the development of adaptive models that not only account for the specific functioning of various economic sectors, their resource base, technological development level, and macroeconomic dynamics but also ensure economic security and resilience to crises. The utilization of modern mathematical methods and models, along with artificial intelligence

technologies, in decision-making systems [2] will enable not only objective assessments of real sector development trends and efficiency forecasting but also the identification of potential threats, including those in cyberspace, and the development of neutralization mechanisms. In this context, the issue of differentiating the real sector's industries becomes particularly significant, serving as a prerequisite for effective economic process management, balanced development, and strategic planning to ensure optimal resource allocation, formulate state regulation strategies, and stimulate innovation activity. The use of such models allows for the identification of key development patterns in specific industries, forecasting their impact on macroeconomic indicators, and developing recommendations for enhancing their efficiency [3].

This study presents a universal methodology for industry differentiation using clustering models as a key component of modern decision support systems (DSS). The Ukrainian economy serves as a practical case study to demonstrate the effectiveness and adaptability of the proposed models.



1.1. Motivation

The analysis of Ukraine's economic development reveals significant structural imbalances in the real sector, as evidenced by numerous studies from international organizations and domestic analytical centers. According to a World Bank report [4], Ukraine experiences uneven industrial sector development, which negatively impacts the economy's competitiveness. The absence of an effective industry differentiation mechanism complicates strategic planning, economic risk forecasting, and investment resource allocation [5, 6].

Research findings from the National Bank of Ukraine (NBU) [7] indicate the need to improve the system for analyzing the sectoral structure of the economy to ensure its resilience to external shocks. Certain sectors demonstrate uneven growth rates, necessitating a differentiated approach to assess their condition and potential. An International Monetary Fund report [8] emphasizes the need to develop analytical models that allow for the effective evaluation of individual industry competitiveness and its role in macroeconomic stability.

Considering the current challenges of geopolitical instability, changes in global supply chains, and technological transformations, there is an urgent need to implement adaptive industry differentiation models. This will contribute to the development of effective state regulation strategies, enhance economic resilience, and create conditions for sustainable development in Ukraine [9, 10].

1.2. State of the Art

The basis of the differentiation process is determined by the data clustering method. The clustering method is a fundamental tool in analytical research that transforms large volumes of heterogeneous information into structured datasets [11]. Its primary advantage lies in the capability of the mathematical apparatus to effectively identify and group objects based on shared characteristics. This is achieved through the simultaneous analysis of multiple features, which facilitates the discovery of latent patterns and the organization of complex multidimensional data.

Cluster analysis facilitates sample set formation according to defined criteria by segmenting multidimensional space into homogeneous groups. A common approach to clustering involves using the Euclidean distance metric, which quantifies the similarity between objects based on specified parameters. Objects with minimal Euclidean distances are grouped into common clusters, thereby streamlining subsequent analyses and enhancing the large dataset processing efficiency.

Contemporary clustering algorithms are continually refined to address domain-specific challenges. One

such refinement is noise mitigation in density-based clustering analysis. The KR-DBSCAN algorithm, which leverages the concepts of the reverse nearest neighbor and influence space, was introduced by the following authors [12]. The main objects are identified through their nearest-reverse neighborhood, and the influence spaces of these objects are determined by computing the k -nearest neighborhood and the nearest-reverse neighborhood for each data point using the Euclidean distance as a metric. This approach effectively differentiates clusters with different densities. In contrast, [13] proposed an enhanced version of the DBSCAN algorithm that incorporates self-adaptive parameter determination, using only core points for grouping.

Beyond numerical data clustering, there are established text grouping methodologies using language models [14]. The input data for these clustering models comprised texts with varying cluster counts, including 4, 20, 17, and 109. A previous study [14] revealed that increasing dimensionality does not consistently improve clustering efficiency. Similar text clustering studies have been conducted using alternative models, such as BERT [15].

Clustering techniques also apply to grouping images. For instance, a ConvNet-based image segmentation method employing novel loss functions was presented in the following study [16]. The versatility of the method enables its application to diverse image types.

In addition to object grouping, the use of clustered data for decision-making is crucial. Classical Decision Support System (DSS) architectures comprise databases, mathematical models, and user dialog interfaces [17]. Decision-making necessitates the formulation of appropriate criteria. For example, [18] evaluated complex systems and made ranking-based selection decisions.

The adaptation of decision-making processes in critical infrastructure management was investigated in [19], with the advantage of real-time decision-maker state diagnostics. The robust operation of this system is a key feature, even under external perturbations. The distinction between the real and financial sectors is a key aspect of modern economic analysis, as evidenced by its integration and interdependence [20]. The deep integration of digital technologies with the real economy is viewed as a promising approach for sustained economic growth in this context [21].

The development of robust models for industry differentiation within the real economy is increasingly pertinent given the current state of scientific advancements. Critical tasks in the context of military exigencies include supporting strategically vital industries, ensuring their resilience to risks, diversifying production capabilities, and optimizing logistics and resource conservation [22]. In this context, the development of

effective models of industry differentiation will contribute to the formation of adaptive strategies to the changing external environment, based on the optimal combination of state economy management and market self-regulation mechanisms. This will, in turn, stimulate high value-added industries, drive economic restructuring, and establish the prerequisites for sustained economic growth and enhanced Ukrainian competitiveness in the global arena.

1.3. Objective and Approach

This article examines the **approach** to differentiating industries of the real economy sector as a key component of DSS in detail.

This research **aims** to develop and validate adaptive models for differentiating industries into clusters (groups) to enhance the effectiveness of decision-making systems, with an application to the real economy of Ukraine.

Achieving the goal involves the implementation of several tasks:

1. Creating a decision-making system model for clustering industries of Ukraine's real economy.
2. Performing software implementation of the created models and conducting an experiment.
3. Developing a DSS module for generating indicative tactical measures for the development of industries within Ukraine's real economy based on the results of cluster analysis.

The **novelty** of the conducted research lies in the development and substantiation of models for differentiating industries of Ukraine's real economy, integrated into DSS. For the first time, an adaptive approach to the classification of the industries of the real sector of the economy is proposed based on the analysis of their development indicators. This approach combines traditional clustering models (K-means, DBSCAN) and ensemble models with genetic algorithm optimization. The originality of the approach lies in the comprehensive integration of multi-criteria clustering and automated selection of management decisions based on machine learning models into the decision support system architecture, using the real sector of Ukraine's economy as an example. The scientific novelty of the proposed methodology is rooted in its universal applicability, a key feature that is not limited to the specific case of Ukraine's economy. The effectiveness and robustness of the proposed models will be mathematically validated in the "Results and Discussion" section using established metrics such as Silhouette Score and Davies-Bouldin Score. These calculations provide a quantitative basis to demonstrate that the clustering approach is highly effective and can be applied to diverse economic datasets

from various countries, thereby enhancing the research's global relevance and scientific value.

The **relevance** of this research is determined by several key factors. First, there is a need to optimize management decisions in the real sector of the economy to ensure its adaptability in conditions of uncertainty and global economic changes. Second, existing approaches to industry differentiation require improvement considering the structural transformations caused by wartime and post-war challenges. Third, the effective application of differentiation models will contribute to the formulation of indicative tactical measures to support economic development and will also underpin the processes of digitalization and the integration of Ukraine into global supply chains.

The implementation of the proposed models will increase the accuracy of forecasting economic dynamics, improve the quality of state regulation, and establish effective mechanisms for supporting the management decision-making process both at the industry level and across the economy as a whole.

The **structure of the paper** is as follows:

In Section 1, "Introduction," the relevance and problems of differentiating the industries of the real sector of Ukraine's economy are examined in the context of strategic management. The main challenges and opportunities for using industry differentiation models in modern DSS are analyzed. A review of scientific research and applied solutions related to existing clustering algorithms is conducted.

Section 2, "Materials and Methods of Research," based on an analytical review, formalized approaches to modeling industry differentiation are presented. The selection of methodological approaches, including multi-criteria analysis, data clustering, and machine learning for building integrated models of management decision support, is substantiated. Figure 1 shows the overall research flow, serving as a methodological roadmap.

Section 3, "Results and Discussion," the results of clustering the industries of Ukraine's real economy using three researched models: K-means, DBSCAN, and the Ensemble model. Each model was evaluated in terms of its effectiveness and ability to provide reliable classifications. Based on a comparative analysis, the selection of the most optimal model for DSS application is justified. Figure 2 shows a detailed, multi-layered architecture of the DSS, compared with classical solutions. The automated selection of strategic scenarios using the Decision Tree Classifier is the final section.

In the final section, "Conclusions," the obtained results are summarized, and the main conclusions regarding the application of models for differentiating the industries of the real economy in strategic management processes are described. The prospects for further research, particularly toward integrating the developed

models with modern information platforms for economic forecasting and state regulation, are outlined.

2. Materials and methods of research

The input sample contains production volumes, structured by real economy industries [23] G1, G2, G3, ..., Gn in dynamics over the years T1, T2, T3, ..., Tn. Since the input data can vary in different ranges, appropriate normalization and analysis methods are required for their processing. Based on this sample, the clustering of industries of the real economy will be carried out by constructing differentiation models, which will be integrated into the DSS to optimize the management of the development of Ukraine's economy. The production volumes of enterprises by real economy industries are differentiated as follows (Table 1). Note that the input data cover the pre-war period, namely 2015-2021. This is due to the following. Firstly, the need to ensure the objectivity and representativeness of the data should be considered. Production volume data before the start of the war reflect the real economy's stable state, formed on the basis of long-term macro- and microeconomic trends. This allows for the correct clustering of industries and identification of their development patterns without the influence of war distortions. Second, there is a need to avoid extreme distortions. Military actions

have significantly affected production activities in most sectors of the economy, causing enterprises to be shut down, logistics chains to be displaced, sales markets to be reduced, and investment flows to change. The inclusion of such data in the initial sample could distort the clustering structure and complicate the construction of relevant models. Third, this study aims to form a basic model for analyzing changes in the environment. Utilizing pre-war data enables the creation of a reference (benchmark) model for industry differentiation, which will subsequently allow for assessing the scale and nature of changes resulting from the war, identifying affected and promising sectors of the real economy, and developing indicative tactical measures to support development.

Thus, the use of pre-war production volumes as basic input data is a scientifically sound approach that contributes to more accurate modeling, comparative analysis, and the development of effective mechanisms for managing Ukraine's economic development.

The decision-making system used the input sample, which considered the issues of creating clustering models.

The process of researching clustering models was conducted in three stages. The first stage involved the use of the classical clustering models.

Table 1

Research input data, billion UAH

Industry	Year						
	2015	2016	2017	2018	2019	2020	2021
Defense	73.6	70.2	67	63.9	60.9	57.8	54.7
Fuel and energy complex	392.7	381.4	370.1	358.8	347.5	326.1	324.9
Transport industry	118.4	116	111.7	107.4	103.1	98.8	94.5
Enterprises providing placement and storage of material assets of the state reserve	2.2	2.1	2	1.9	1.8	1.7	1.6
Agro-industrial complex	23.6	22.8	22.1	22.9	20.2	19.5	18.8
Telecommunications and communications sphere	12.5	11.7	10.9	10.1	5.3	5	4.2
Aviation and rocket and space industry	22.7	22.5	20.1	19.5	21.3	22.1	22.7
Engineering industry	50	48.3	46.6	44.9	43.2	41.5	39.9
Metallurgical complex	139.2	130.9	122.6	114.3	106	97.7	90.4
Chemical complex	15.21	14.66	14.11	13.56	13.01	12.46	11.99
Scientific activity	2.61	2.52	2.43	2.34	2.25	2.16	2.07
Sphere of standardization, metrology and certification	1.5	1.4	1.3	1.2	1.1	1	0.9
Hydrometeorological activity	1.7	1.6	1.5	1.4	1.3	1.2	1.1
Building materials industry	33.3	32.2	31.1	30	28.9	27.8	26.7
Financial and budgetary sphere	16.2	15.7	15.2	14.7	14.2	13.7	13.2
Food industry	1.6	1.5	1.9	1.8	1.7	1.85	1.9
Light industry	14.8	14.3	13.8	13.3	12.8	12.3	11.8
Printing	0.52	0.53	0.55	0.42	0.5	0.53	0.51
Geological exploration industry	-	-	-	0,18	0.19	0.2	0.19
Amount	922.34	890.31	854.99	822.6	785.25	743.4	722.06

The studied sample was used to create K-means and DBSCAN clustering models, which involved determining the number of clusters using the Within-Cluster Sum of Squares metric. Notably, DBSCAN [24, 25] performs density-based spatial clustering of applications with noise. It identifies high-density core samples and expands clusters from these.

The number of clusters was searched in the range [1, 19] with a step of 1. K-means had a hyperparameter `random_state=42` to obtain consistent results after each model run. The DBSCAN model had hyperparameters `eps=1.5`, `min_samples=2`. The control of the number of clusters was performed using the `value_counts()` tool, and the quality criteria of the constructed models were `silhouette_score` calculated by formula [26]:

$$c(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \quad (1)$$

where $a(i)$ – the average distance between point i and all other points within the same cluster;

$b(i)$ – the smallest average distance between point i and all points in any other cluster.

Davies-Bouldin score is calculated by formula [27]:

$$DBI = \frac{1}{N} \sum_{i=1}^N \max_{j \neq i} \frac{S(i) + S(j)}{D(i, j)}, \quad (2)$$

where N – the number of clusters;

$S(i)$ – the scatter;

$D(i, j)$ – distance between the centroids of clusters i and j .

Note that the closer the `silhouette_score` coefficient is to 1.0, the better the model, and the opposite is true for `davies_bouldin_score`.

To investigate the accuracy of industry grouping, combined object clustering methods are considered.

The second stage of the research involved the application of K-means [25] and Agglomerative Clustering [28] to group objects into clusters based on their similarity. Data points are iteratively merged based on their proximity until a single large cluster is formed in the agglomerative approach.

K-means and Agglomerative Clustering were integrated into an ensemble (ensemble clustering) using a voting principle [29], where the search for optimal parameters was conducted via a genetic algorithm. The "ward" linkage method was employed to minimize the within-cluster variance in the agglomerative process. The combined use of K-means and Agglomerative Clustering allows for the aggregation of multiple clustering

models to achieve an enhanced outcome the ensemble clustering.

The proposed model structure incorporates the normalization of the real sector industries' scores using Standard Scaler, implemented through `scaler.fit_transform(df)`.

Subsequently, a genetic algorithm is configured to address hybrid computation tasks, specifically the creation of a population, selection, crossover, and mutation, governed by the `population_size` and `num_generations` parameters [30]. The genetic algorithm's output scores are used to construct ensembles, facilitated by the `BaseEstimator` and `ClusterMixin` parameters from `sklearn.base`. The performance of the algorithm was evaluated using the `silhouette_score` and `davies_bouldin_score` metrics. These quality metrics remain consistent across all research stages, as their performance is compared.

Single-parameter clustering serves an illustrative purpose. Therefore, the third stage of the research involved the utilization of the first criterion, as described in the preceding stages, and a second criterion, i.e., the value of the change in the number of enterprises strategically significant for Ukraine's economy and security over a 6-year period (Table 2).

Consequently, the input data comprised two matrices of 19x6 and 19x7 dimensions. The average value of the data over n years was determined separately for each criterion to facilitate graphical interpretation. The defined dataset was then consolidated into a feature matrix. Given the varying data magnitudes, normalization was performed using the `MinMaxScaling` method within the range [0, 1]. The elbow method was used to determine the optimal number of clusters, followed by the application of K-means clustering [32]. The clustering results are recorded in Table 3.

To examine the correlation between industries with similar characteristics, we constructed graphs of dependencies between industries. This facilitated the establishment of cluster-based decision-making conditions. The decision tree classifier was employed for the automation and visualization of decision-making based on the experimentally formed conditions. Thus, a decision-making module is proposed. The operational scheme is as follows: clustering is performed based on one or two criteria, the results are analyzed (statistical analysis), and decisions are made according to the established conditions. The decision-making process is automated using a classifier that operates based on the four defined conditions.

The Python programming language was chosen with a standardized package of libraries, including `pandas`, `numpy`, and `sklearn`. The `scipy.cluster.hierarchy` library was used to study the hierarchical structure of clusters.

Table 2

Research input data (number of enterprises strategically significant for the economy and security), units [31]

Industry	Year					
	2015	2016	2018	2019	2020	2021
Defense	73	73	75	76	76	76
Fuel and energy complex	27	27	26	27	28	28
Transport industry	51	51	52	51	51	51
Enterprises providing placement and storage of material assets of the state reserve	24	24	24	24	24	24
Agro-industrial complex	6	6	6	6	6	5
Telecommunications and communications sphere	43	43	44	14	14	14
Aviation and rocket and space industry	15	15	14	14	14	15
Engineering industry	6	6	5	5	5	5
Metallurgical complex	8	8	8	7	7	7
Chemical complex	8	8	8	7	7	7
Scientific activity	31	31	36	34	34	35
Sphere of standardization, metrology and certification	6	6	6	5	5	5
Hydrometeorological activity	1	1	1	1	1	1
Building materials industry	2	2	2	2	2	2
Financial and budgetary sphere	4	4	4	4	3	3
Food industry	1	1	1	1	1	1
Light industry	1	1	1	1	1	1
Printing industry	1	1	1	1	1	1
Geological exploration industry	0	0	6	6	6	4
Amount	308	308	320	286	286	285

Table 3

Statistics of the economic sector industry clusters

Industry name	Change in number of enterprises	Production volume	Normalized variable	Normalized volume
Name	Variable 1	Variable 2	Variable 3	Variable 4

A Raspberry Pi 5 single-board computer with 8 GB RAM was used for research flexibility. This research technique will increase decision-making efficiency.

To clearly demonstrate the methodological substantiation and implementation of the integrated models for management decision support, the overall research process, which links the multi-criteria analysis, data clustering, and machine learning into a unified system, is visualized as a structured flow (see Figure 1).

This structured implementation ensures the study's methodological coherence, combining data acquisition (Tables 1 and 2), model optimization (Stages 1 and 2), and automated decision-making based on multi-criteria differentiation (Stage 3) into a unified framework for effective economic governance.

3. Results and Discussion

The DSS architecture, designed to translate complex analytical results into executable policy recommendations, comprises the following core components that fully realize the research methodology. Figure 2 provides a comprehensive, multi-layered model of the system's operational structure. The overall architecture is visually detailed.

The structural components of the DSS are as follows:

1. Data accumulation module. Collect input data (e.g., production volumes and enterprise counts), clustering outcomes, and formulate decision rules. The module uses an SQLite database to receive and perform standard data procedures (create, delete, update, and rename).

2. Data processing module. Handles necessary data cleaning procedures, such as normalization and processing of missing values, ensuring data quality for subsequent analysis.

3. The assessment grouping module (clustering module). Employs comparative clustering algorithms, including K-means, DBSCAN, agglomerative clustering, and a genetic algorithm-optimized ensemble clustering model.

4. Module for data analysis. Performs a comprehensive analysis of key indicators (production volumes and enterprise counts) and provides a graphical interpretation of the clustering results.

5. Decision-making module. Executes strategic decisions based on the four proposed conditions using the integrated decision tree classifier.

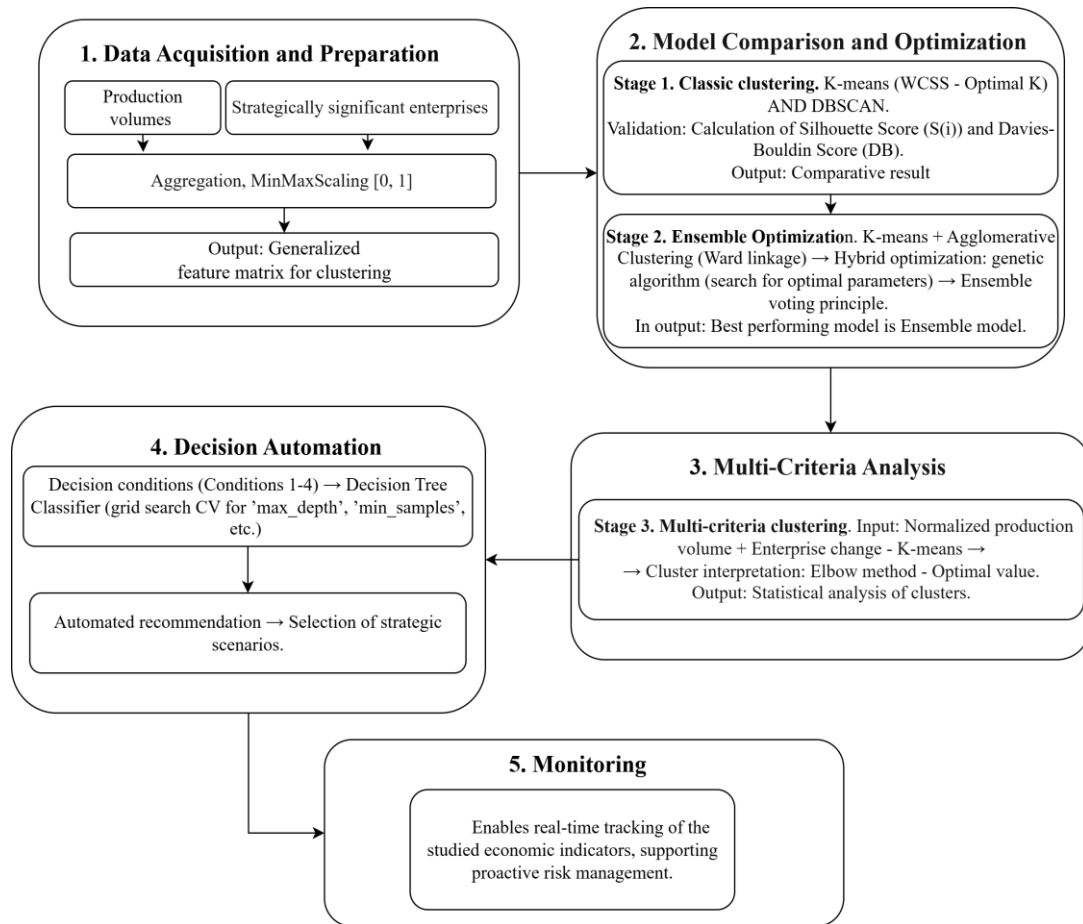


Fig. 1. Research process flow for the development of integrated management decision support models

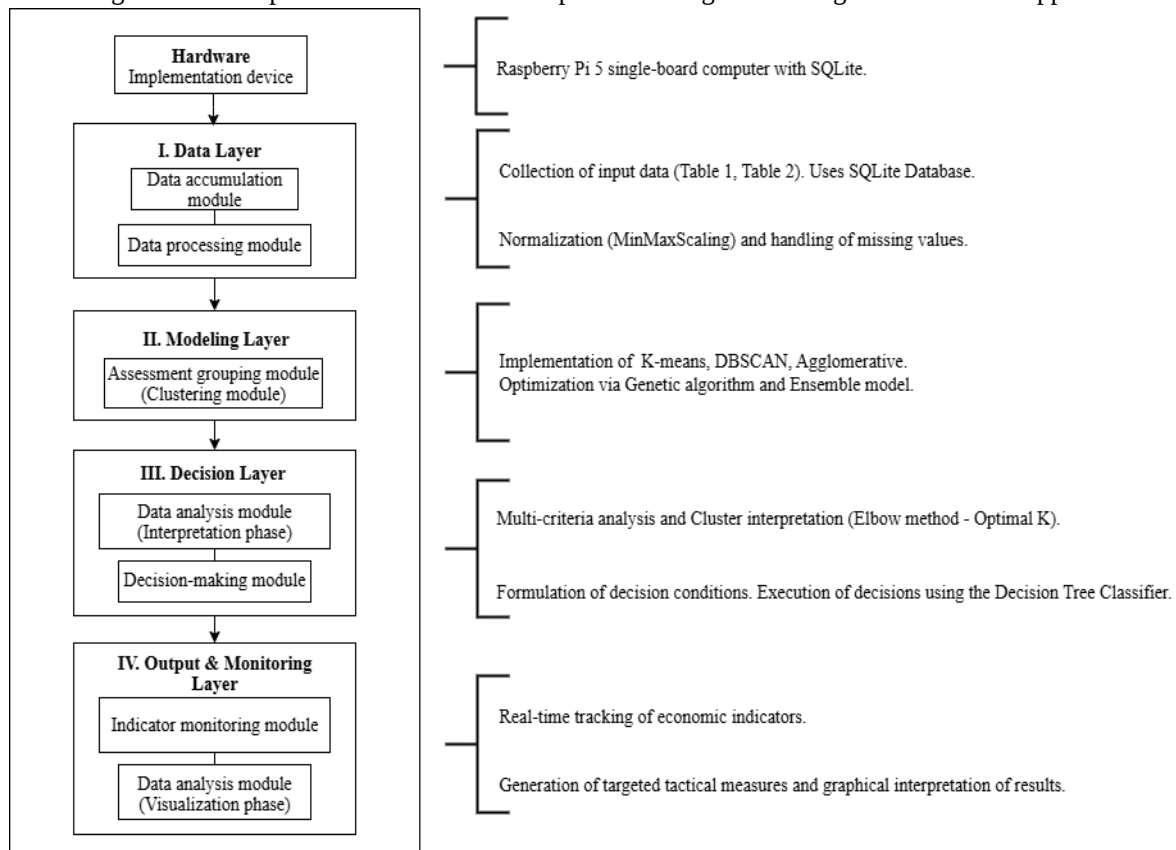


Fig. 2. Detailed multi-layered DSS architecture for industry differentiation

6. The indicator monitoring module. Real-time tracking of the studied economic indicators supports proactive risk management.

The hardware implementation device for the decision-making system is a single-board Raspberry Pi 5 computer with SQLite.

The proposed architecture significantly extends the capabilities of classical DSS solutions [33, 34], making it suitable for adaptive governance. Traditional systems often rely on static models and descriptive reporting, whereas our approach is hybrid and prescriptive. The key differentiator is the direct integration of machine learning algorithms (ensemble clustering and decision tree classification) into the decision-making pipeline. This allows the system to move beyond information support to the automated selection of targeted strategic scenarios, which is critical for managing the real sector during periods of high economic uncertainty and aligns with the journal's profile on advanced analytical systems.

Let us consider the process of investigating the first two stages. The DSS in real sector economic management is built on a multi-layered architecture [33, 34] and includes the following key stages: data clustering, results analysis, and management decision development and implementation.

The data clustering and analysis module functions according to the defined research methodology. The grouping of real sector industries by production level is carried out based on multidimensional analysis, which allows for the identification of structural risks, vulnerable sectors, and potential growth points. The module's output parameters are cluster values, which characterize the state of industries in defined economic conditions.

The DSS module generates indicative tactical measures using the clustering results. Based on the obtained assessments, tactical measures for the stabilization or development of industries are selected in accordance with the formed cluster model.

The proposed system contributes to risk minimization in the real sector. The proposed approach minimizes management risks by identifying groups of industries with similar development characteristics, which enables the early detection of industries with an elevated level of structural or economic risks [35]. Based on the clustering results, preliminary recommendations are formulated regarding adaptive responses to the challenges of economic development, tailored to the specific features of each cluster, thereby minimizing the likelihood of adopting ineffective or risky decisions. For example, the DSS can proactively flag a cluster of industries with declining production volumes and a decreasing number of enterprises as high-risk sectors by identifying them. This early warning, powered by the clustering model, allows policymakers to avoid broad, ineffective policies and instead implement targeted support measures, such as providing preferential loans or tax breaks, specifically to those at-risk clusters. This proactive, data-driven strategy directly contributes to risk reduction by preventing economic downturns in vulnerable sectors.

The analysis of the optimal number of clusters using the K-means algorithm, evaluated using the Within-Cluster Sum of Squares (WCSS) metric, showed that the most appropriate division is into three clusters. This is confirmed by the visualization of the calculation results in Figure 3.

Having selected the specified number of clusters, the corresponding models were constructed. The results of using the genetic algorithm allowed us to obtain the following results: Best Parameters after Genetic Algorithm Optimization: ({'n_clusters': 2}, {'n_clusters': 7, 'linkage': 'ward'}) Best Fitness: 1.4491. As we can see, for K-means, the optimal number of clusters is 2, and for Agglomerative Clustering with the Ward method, it is 7, with a Best Fitness of 1.4491. As evident from the obtained Best Fitness value of 1.4491, Ward's method yielded the lowest within-cluster error.

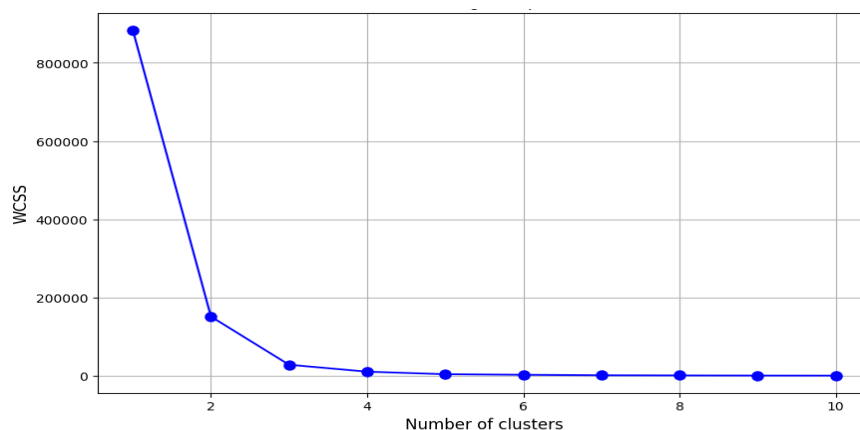


Fig. 3. Results of substantiating the number of clusters of real economy industries using the WCSS metric for K-means

The results of building clustering models and their comparative analysis according to the silhouette_score and davies_bouldin_score criteria are presented in Table 4.

As shown in Table 4, according to the silhouette_score criterion, DBSCAN and the Ensemble model have an advantage with a value of 0.8387, whereas the other model has a value of 0.7183. This high score, which approaches the optimal value of 1.0, is a direct computational proof that these models produce well-separated and dense clusters.

Similarly, according to the Davies-Bouldin Score criterion, the Ensemble model or DBSCAN models have an advantage, since their value is 0.0777, which is closer to the optimal value of 0.0 compared to K-means with 0.2779. This low score further confirms the effectiveness of these models in creating distinct and well-defined clusters with minimal similarity.

These quantitative results demonstrate that the chosen machine learning algorithms are highly efficient for differentiating economic sectors. Their performance is not dependent on the specific characteristics of the Ukrainian economy, which underscores the proposed methodology's universal applicability for analyzing similar datasets in other countries.

Figure 4 shows a graphical interpretation of the clustering results 4.

The graphical interpretation of the three clustering model results shows that most assessments are in the range [0, 1], indicating the first cluster, whereas other values are the second cluster.

Figure 5 shows the hierarchical cluster structure for the Ensemble model. A combination of several algorithms facilitates the creation of an ensemble approach and reduces the impact of their individual limitations on the overall model quality.

As shown in Figure 5, the real economy industries' clusters form two main groups, each of which contains subgroups. The fuel and energy complex stands out among other industries due to its unique characteristics, which determine its clustering structure. The remaining industries form the second group, which is divided into subgroups according to similar economic parameters.

The clustering results of Ukraine's real economy industries enable the development of preliminary recommendations regarding support measures for clusters of the real economy industries, adapted to each cluster's specific features. Figure 5 shows two clusters. The first cluster includes the fuel and energy complex, a strategically important industry with significant growth potential. Accordingly, the support proposals for the cluster of critically important industries and industries with high growth potential may include the following management decisions: infrastructure strengthening, development of export potential (including facilitating access to international markets through export credit mechanisms, establishing trade offices, and logistics hubs) [36, 37], and digitalization and automation of production processes [38].

Table 4

Comparative analysis of clustering models based on silhouette_score, davies_bouldin_score criteria

First research stage		
Investigated clustering model	silhouette_score value	davies_bouldin_score value
K-means	0.7183	0.2779
DBSCAN	0.8387	0.0777
Second research stage		
Investigated clustering model	silhouette_score value	davies_bouldin_score value
Ensemble model	0.8387	0.0777

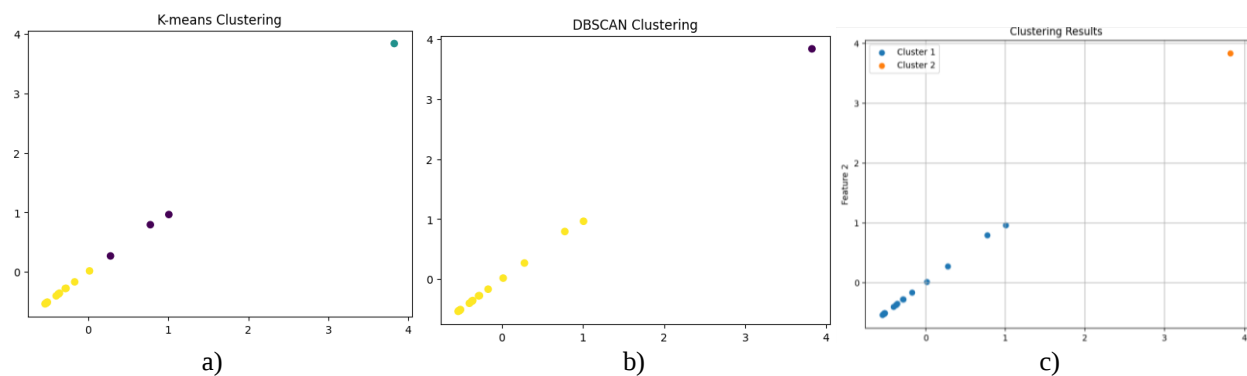


Fig. 4. Results of clustering models: a) K-means, b) DBSCAN, c) Ensemble model

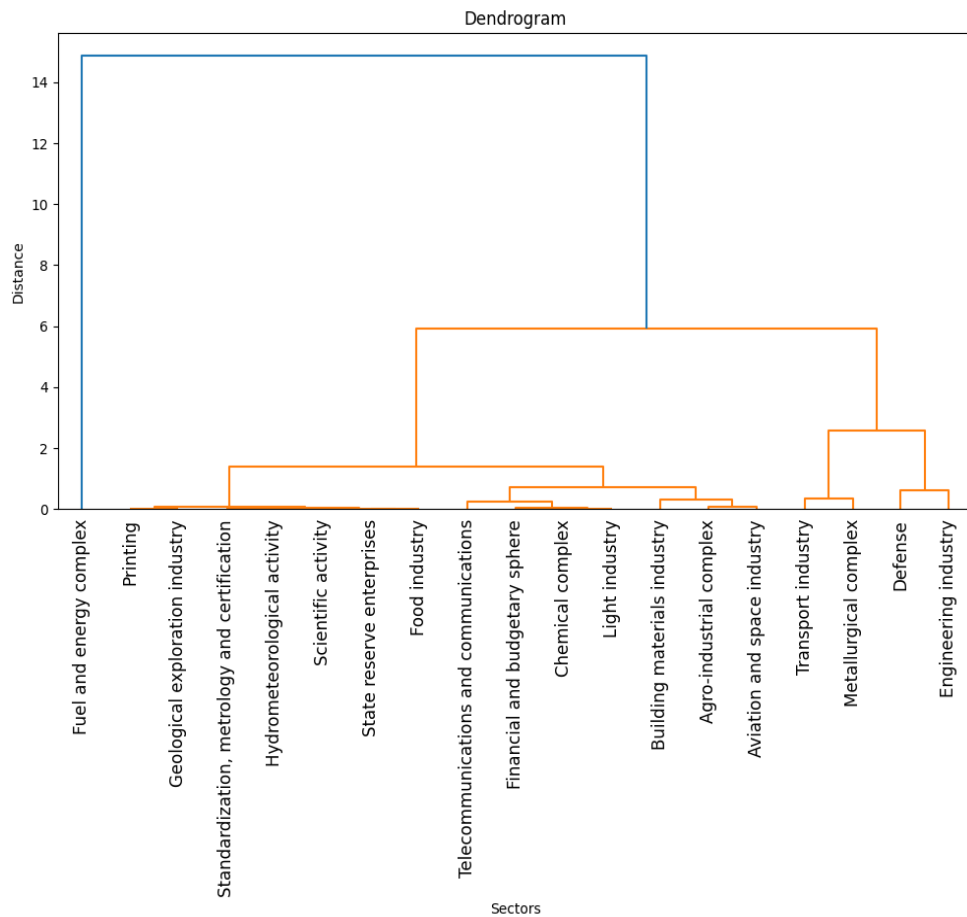


Fig. 5. Hierarchical structure of clusters of real economy industries

The second cluster includes industries that require structural restructuring and recovery in the post-war period. The potential support proposals for this cluster of Ukraine's real economy industries will include the following decisions: production diversification, i.e., state stimulation of the reorientation of enterprises operating in sectors with low productivity or significant losses; creating favorable conditions for public-private partnerships to modernize outdated enterprises [39]; and production capacity reconstruction, namely, the development of targeted infrastructure recovery programs, demining territories, and rebuilding enterprises.

The third stage of the research involved the use of two clustering criteria. The elbow method revealed that the optimal number of clusters is 4. Figure 6 shows the clustering results obtained using K-means tools.

The quality of the clustering was confirmed by the following clustering quality metrics: Silhouette Score 0.6, Davies-Bouldin Score 0.3516. Thus, 4 clusters were obtained, and a detailed analysis of the results is presented in Table 5. Let us consider the obtained generalized results.

Cluster 0. Industries with a high number of enterprises (approximately 100) and a high production volume. Cluster 0 includes 13 industries. The average

change in the number of enterprises is 4.6, the average production volume is 21.46 billion UAH, the minimum production volume is 0.19 billion UAH, and the maximum production volume is 114.44 billion UAH (Table 5).

Cluster 1. Industries with low values for both indicators. Cluster 1 includes 2 industries. The average change in the number of enterprises is 63, the average production volume is 85.57 billion UAH, the minimum production volume is 64.01 billion UAH, and the maximum production volume is 107.13 billion UAH.

Cluster 2. Average values. Cluster 2 includes 1 industry. The average change in the number of enterprises is 27.2, and the average production volume is 357.36 billion UAH.

Cluster 3. Industries with a high change in the number of enterprises but a low production volume (or vice versa). Cluster 3 includes 3 industries. The average change in the number of enterprises is 28.7, the average production volume is 4.26 billion UAH, the minimum production volume is 1.9 billion UAH, and the maximum production volume is 8.53 billion UAH.

To establish decision-making conditions, we use the identified clusters.

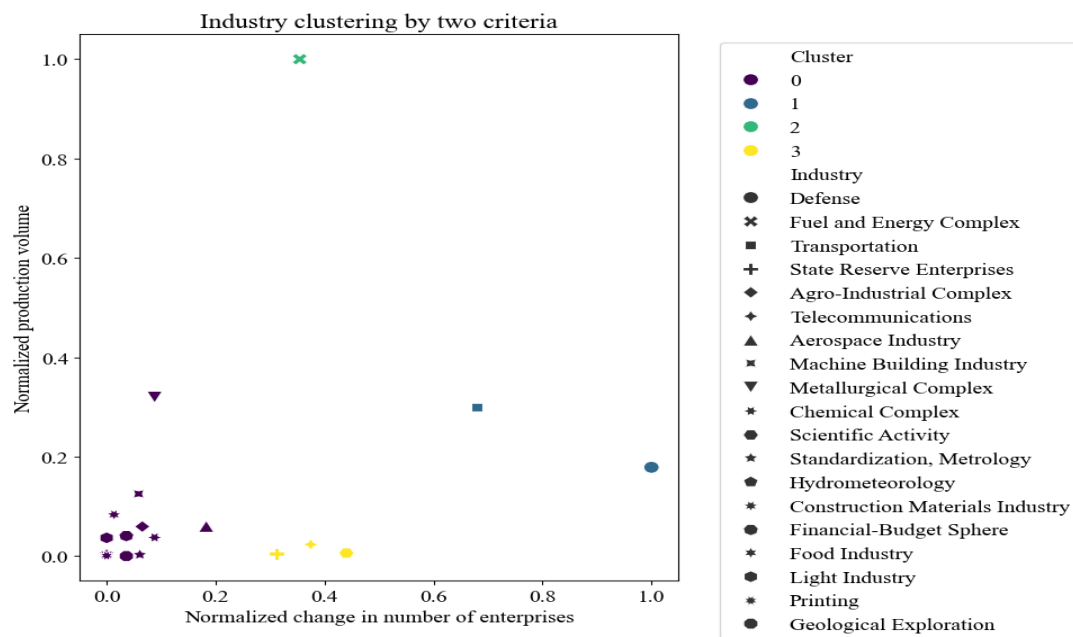


Fig. 6. Clustering results of economic sector industries based on two criteria

Table 5

Statistics of the economic sector industry clusters

Industry name	Change in number of enterprises	Production volume	Normalized variable	Normalized volume
Cluster 0				
Metallurgical complex	7.5	114.44	0.088	0.320
Engineering industry	5.3	44.91	0.059	0.125
Building materials industry	2.0	30.00	0.014	0.083
Aviation and rocket and space industry	14.5	21.56	0.183	0.060
Agro-industrial complex	5.8	21.41	0.065	0.059
Financial and budgetary sphere	3.7	14.7	0.036	0.041
Chemical complex	7.5	13.57	0.088	0.037
Light industry	1.0	13.3	0	0.037
Food industry	1.0	1.75	0	0.004
Hydrometeorological activity	1.0	1.4	0	0.003
Sphere of standardization, metrology and certification	5.5	1.2	0.061	0.003
Printing industry	1.0	0.51	0	0.001
Geological exploration industry	3.7	0.19	0.036	0
Cluster 1				
Transport industry	51.2	107.13	0.679	0.299
Defense	74.8	64.01	1.000	0.179
Cluster 2				
Fuel and energy complex	27.2	357.36	0.354	1.000
Cluster 3				
Telecommunications and communications sphere	28.7	8.53	0.375	0.023
Scientific activity	33.5	2.34	0.440	0.006
Enterprises providing placement and storage of material assets of the state reserve	24.0	1.90	0.312	0.005

Condition 1 (Cluster 0). If the production volume is greater than 100 billion UAH and a stable number of

enterprises is observed, production support is recommended.

Condition 2 (Cluster 1). If low indicators of production volume and number of enterprises are observed, conducting an audit of the enterprises is recommended.

Condition 3 (Cluster 2). If an average production volume (20-100 billion UAH) and a moderate change in the number of enterprises are observed, investors should be attracted.

Condition 4 (Cluster 3). If anomalies are observed, the causes of the anomalies should be analyzed.

For the automation and visualization of decision-making, we will create a Decision Tree Classifier based on the formed conditions (see Figure 7). The classifier involves selecting parameters 'max_depth': [2, 3, 4, 5], 'min_samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2, 4] using Grid Search CV. The optimal solution is graphically presented, showing the condition, class distribution, and dominant class.

The automated decision-making system, built using the Decision Tree Classifier, ensures the detection of anomalies and unstable trends in the structure of the economy in real time. This allows for the timely identification of critical changes in industry development dynamics and the prompt adjustment of management decisions.

Based on pre-war data, the developed models serve a crucial role as a benchmark model for the Ukrainian economy. While the current and post-war economic structure will inevitably differ, the pre-war data provides a stable, representative baseline against which future changes can be measured. Decision support systems specialists can use this model in the following ways. First, for the quantitative assessment of structural changes, analysts can quantify the deviation from the pre-war benchmark by applying the same clus-

tering methodology to current or future economic data. This allows for a precise identification of which industries have experienced the most significant distortions and the emergence of new growth clusters.

Second, the model facilitates the development of differentiated post-war strategies for targeted policy formulation. For example, industries that fell from a high-growth cluster (e.g., Cluster 2) into a low-volume cluster (e.g., Cluster 0) can be identified as requiring immediate state support. In contrast, industries that maintained their positions may be prioritized for attracting private investment.

Third, for universal application for stable economies, for DSS specialists in "peaceful" economies, the model provides a ready-to-use framework for analyzing their current economic structure, identifying high-risk and high-potential sectors, and optimizing management decisions. This demonstrates the value of the model beyond the specific context of Ukraine's challenges.

This approach validates the proposed methodology by transforming a perceived data limitation into a powerful analytical tool for assessing change and planning future development.

A decision tree structurally demonstrates the decision-making process, in which the conditions are checked.

Thus, the integration of clustering and decision-making models into the decision support system architecture enhances the validity of management decisions and ensures their adaptability to external environment changes. The proposed approach promotes proactive risk management and increases the economy's resilience [40].

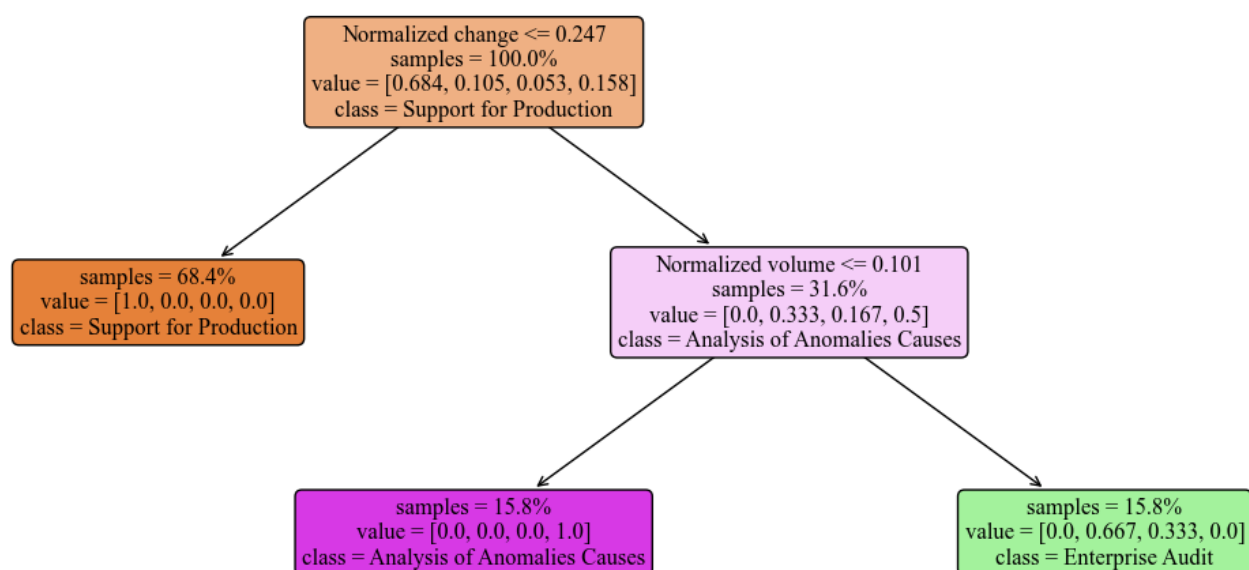


Fig. 7. Decision tree for decision-making based on formed conditions with optimal parameters
{'max_depth': 2, 'min_samples_leaf': 1, 'min_samples_split': 2}

4. Conclusions

This study explores the problem of using adaptive models to differentiate real economy industries in the context of developing effective state regulation strategies. The DSS architecture is described in detail, which includes a module for interactive analysis of cluster structures, an automated system for selecting strategic industry development scenarios, and tools for real-time monitoring of economic indicators. A model for clustering real sector industries based on machine learning and multifactor analysis is proposed. The task of developing a clustering model for the DSS was solved using the Ensemble model algorithm. Experimental clustering models were developed and tested as a result of the research, allowing the determination of the optimal number of clusters based on Silhouette Score and Davies-Bouldin Score metrics. A comparative analysis of the effectiveness of K-means, DBSCAN, and combined ensemble model algorithms was performed. Indicative directions for tactical measures to support individual clusters are proposed based on the conducted clustering of Ukraine's real economy industries.

The results of this study, while based on the Ukrainian economy, provide a robust framework for developing adaptive management strategies in any country. The multi-factor clustering models and their quantitative validation using Silhouette Score and Davies-Bouldin Score demonstrate that the methodology is not dependent on specific national data. Specialists in Decision Support Systems in various countries can use our proposed architecture and algorithms to:

1. Identify key sectors of their economies based on a multi-criteria analysis.
2. Develop adaptive policies and tactical measures tailored to each industry cluster's specific needs.
3. Enhance the economic system's stability and resilience despite internal and external changes.

Future Research Development: The presented proposals should be legitimately considered as initial guidelines for tactical management decisions and require further in-depth verification based on an expanded multi-factor analysis and the inclusion of additional economic indicators. The computational validation performed in this study, using established clustering metrics, demonstrated the high efficiency and universal applicability of the proposed models. Future research by the authors, based on the differentiation of real economy industries, will focus on studying the specifics of decision-making using artificial intelligence. This will increase the speed of creating a management strategy for each selected cluster and increase their adaptability to changing environmental conditions, thereby solidifying the relevance of our quantitatively verified approach.

Contributions of authors: analytical review and analysis of information sources – **Alina Hlushko**; statement of the problem and formulation of the research purpose – **Alina Hlushko**; development of research methodology and software implementation of the proposed methods – **Oleksandr Laktionov, Alina Yanko, Oleksandr Isaiev**; calculations and description of the result – **Alina Hlushko**; analysis of results and formation of research conclusions – **Alina Yanko**; writing – original draft preparation, writing – review and editing – **Alina Yanko**.

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

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This research was conducted without financial support.

Data Availability

Data will be made available upon reasonable request.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence technologies in their work.

All authors have read and agreed to the publication of the final version of this manuscript.

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МОДЕЛІ ДИФЕРЕНЦІАЦІЇ ГАЛУЗЕЙ ДЛЯ СИСТЕМ ПІДТРИМКИ ПРИЙНЯТТЯ РІШЕНЬ НА ПРИКЛАДІ ЕКОНОМІКИ УКРАЇНИ

А. Д. Глушко, О. І. Лактіонов, А. С. Янко, О. Д. Ісасє

Стаття присвячена дослідженню проблеми використання адаптивних моделей диференціації галузей реального сектора економіки як ключового компонента сучасних систем підтримки прийняття рішень (СППР). Предметом дослідження є моделі диференціації галузей реального сектору економіки України для інтеграції в системи підтримки прийняття рішень з метою оптимізації державного управління. Метою дослідження є розробка та валідація адаптивних моделей диференціації галузей на кластери (групи) для підвищення ефективності систем прийняття рішень із застосуванням до реального сектору економіки України. Об'єктом дослідження виступає процес галузевої диференціації, що дозволяє визначити структурні особливості та закономірності функціонування економічних секторів. У ході дослідження запропоновано архітектуру СППР, що інтегрує багатofакторний аналіз та алгоритми машинного навчання для автоматизованого

вибору стратегічних сценаріїв. Для кластеризації використано показники обсягів виробництва та кількості стратегічно важливих підприємств України за довоєнний період (2015–2021 рр.), які слугують еталонною (бенчмарк) моделлю для порівняльного аналізу. Проведено порівняльну оцінку ефективності класичних алгоритмів K-means, DBSCAN та ансамблевого методу (Ensemble model) із кількісною перевіркою результатів за метриками Silhouette Score та Davies-Bouldin Score. Емпіричний аналіз засвідчив, що моделі DBSCAN та Ensemble model забезпечують найвищу якість кластеризації (Silhouette Score 0,8387; Davies-Bouldin Score 0,0777), формуючи надійне групування економічних секторів. На основі отриманих результатів розроблено модуль СППР для формування індикативних тактичних заходів підтримки, зокрема інфраструктурного зміцнення високопотенційних кластерів та структурної реорганізації вразливих. Висновки. Розроблені моделі формують універсальну методологічну основу, придатну для використання у різних країнах, зокрема в країнах з «мирною» економікою. Результати дослідження можуть бути використані фахівцями СППР для ідентифікації ключових секторів економіки, розробки адаптивних політик та підвищення стійкості і конкурентоспроможності економічних систем у динамічному середовищі.

Ключові слова: кластеризація; управління економікою; державна політика; ансамблева модель; цифрові рішення; адаптивна стратегія; система підтримки прийняття рішень.

Глушко Аліна Дмитрівна – канд. екон. наук, доц. каф. фінансів, банківського бізнесу та оподаткування, Національний університет «Полтавська політехніка імені Юрія Кондратюка», Полтава, Україна.

Лактіонов Олександр Ігорович – канд. техн. наук, доц. каф. автоматики, електроніки та телекомунікацій, Національний університет «Полтавська політехніка імені Юрія Кондратюка», Полтава, Україна.

Янко Аліна Сергіївна – канд. техн. наук, доц., доц. каф. комп'ютерних та інформаційних технологій і систем, Національний університет «Полтавська політехніка імені Юрія Кондратюка», Полтава, Україна.

Ісаєв Олександр Дмитрович – асп. каф. комп'ютерних та інформаційних технологій і систем спеціальності 122 «Комп'ютерні науки», Національний університет «Полтавська політехніка імені Юрія Кондратюка», Полтава, Україна.

Alina Hlushko – PhD (Economic Sciences), Associate Professor at the Department of Finance, Banking and Taxation, National University «Yuri Kondratyuk Poltava Polytechnic», Poltava, Ukraine, e-mail: glushk.alina@gmail.com, ORCID: 0000-0002-4086-1513, Scopus Author ID: 57202627340.

Oleksandr Laktionov – PhD (Technical Sciences), Associate Professor at the Department of Automation, Electronics and Telecommunications, National University «Yuri Kondratyuk Poltava Polytechnic», Poltava, Ukraine, e-mail: itm.olaktionov@nupp.edu.ua, ORCID: 0000-0002-5230-524X, Scopus Author ID: 57210360300.

Alina Yanko – PhD (Technical Sciences), Associate Professor, Associate Professor at the Department of Computer and Information Technologies and Systems, National University «Yuri Kondratyuk Poltava Polytechnic», Poltava, Ukraine, e-mail: al9_yanko@ukr.net, ORCID: 0000-0003-2876-9316, Scopus Author ID: 57094953000.

Oleksandr Isaiev – PhD Student of the Department of Computer and Information Technologies and Systems, specialty 122 "Computer Science", National University «Yuri Kondratyuk Poltava Polytechnic», Poltava, Ukraine, e-mail: smartov_alex@ukr.net, ORCID: 0009-0008-3228-2512.