Intelligent Information Systems

UDC 331.5:519.876.5:004.89(477) **doi:** https://doi.org/10.20998/2522-9052.2026.1.11

Oleksandr Kushnerov[1], Anastasiia Niesheva[1], Viktoriia Shcherbachenko[1], Vladyslav Sokol[2], Khaliq Amiraslanov[3]

[1] Sumy State University, Sumy, Ukraine
[2] National Technical University “Kharkiv Polytechnic Institute”, Kharkiv, Ukraine
[3] Azerbaijan Technical University, Baku, Azerbaijan

NEURAL NETWORK MODELING AND FORECASTING OF IMBALANCES IN UKRAINE’S LABOR MARKET UNDER EXTREME CONDITIONS

Abstract. Relevance. The full-scale military invasion of the Russian Federation has caused unprecedented distortions in the labour market of Ukraine. These deformations are characterized by deep sectoral and territorial disproportions, which are caused by mass migration, mobilization, destruction of production, and changes in the structure of labor supply and demand. This causes an urgent need to develop tools to quantify and predict said deformations, which is essential for making informed decisions. **The purpose of this research** is to develop and test a complex technique based on neural network modelling (Long Short-Term. Memory – LSTM). This methodology aims to identify, assess, and forecast labour market deformations and imbalances in Ukraine, and includes the development of a system of criteria for their evaluation. **The research methodology** is based on an integrated approach that incorporates time series analysis, neural network forecasting (LSTM), methods for detecting structural shifts and anomalies (Isolation Forest), cluster analysis (K-Means), and determination of influencing factors (Random Forest). **The research presents** a developed system of criteria for assessing war-induced deformations, conducts a quantitative evaluation of sectoral disruptions resulting from the conflict, provides a forecast of imbalance dynamics, and identifies the most vulnerable sectors of the economy. **The conclusions** emphasise the scientific and practical significance of the developed methodology for monitoring the labour market, as well as for developing adaptive employment policies and programs to support the post-war recovery of the Ukrainian economy. They also demonstrate the potential of neural network models for analysing labour markets under extreme conditions нof uncertainty.

Keywords: labour market; war deformations; disproportions; neural network modelling; LSTM; forecasting; industry analysis; structural shifts; cluster analysis; influencing factors; system of criteria.

Introduction

The full-scale invasion of Ukraine by the Russian Federation, which began on February 24, 2022, caused not only a humanitarian catastrophe and large-scale destruction of infrastructure, estimated at hundreds of billions of dollars [1], but also deep, multifaceted deformations of the national labor market. These deformations are unprecedented in their scale and specificity for the modern history of both Ukraine and Europe. The general characteristics and forecasts of Ukraine's labor market are thoroughly analyzed in specialized reviews [2]. During the first months of the invasion, economic activity declined sharply. According to surveys, up to 75% of small businesses were forced to suspend activities, transport infrastructure stopped, and the mass movement of the population from dangerous regions led not so much to a jump in unemployment as to a record reduction in the labor force. As of the end of 2022, at least 5 million people have lost their jobs because of hostilities, and about 7 million Ukrainians have left the country. Analytical reports indicate significant difficulties in finding a career due to the war [3].

The impact of war manifests itself through a range of interconnected channels. In particular, the mass forced migration of the population (both internally displaced persons and refugees abroad) has led to significant regional imbalances in the labor force and changes in its demographic structure. The mobilization of a substantial portion of the working-age population, primarily men, into the ranks of the Ukrainian Armed Forces created an acute personnel shortage in several industries and professions where men were traditionally employed. The direct destruction of enterprises, particularly in the eastern and southern regions of the country, led to the loss of millions of jobs and a reduction in production capacity. The significant destruction of enterprise infrastructure is directly a result of hostilities [1]. This, in turn, has led to a dramatic change in the structure of labor supply and demand: there is an increase in demand in the military-industrial complex, logistics, recovery and relief services, and medicine, while in other sectors, especially those focused on the consumer market or exports, demand has decreased significantly. Restrictions on access to export markets generally hurt the market strength of labor at the firm level. Security factors, in particular, the impossibility or high risk of working in territories close to the war zone or in temporarily occupied territories, as well as constant psychological stress, significantly affect labor productivity and people's willingness to enter the labor market. General economic instability, high inflation, declining gross domestic product, and disruptions to supply chains further complicate the functioning of enterprises and negatively affect employment levels. The overall economic impact of the invasion is multifaceted and profound [4].

To illustrate the scale of changes, let's consider some key aggregate labor market indicators before and during the full-scale war, as presented in Table 1. These data were obtained by aggregating and comparing the average values for the relevant periods based on information from the State Statistics Service of Ukraine and the Open Data

Portal of Ukraine [5; 6]. The data from Table 1 shows a significant drop in both the number of registered unemployed and the number of vacancies in the war period compared to the pre-war period. Research on the labor market confirms its considerable transformation under the influence of hostilities [3, 7].

Table 1 – **Key aggregate indicators of the labor market of Ukraine before and during the full-scale war (averages)**

Indicator	Pre-war period (average)	Wartime period (average)	Change, % (estimated)
Number of unemployed (amount)	616734.33	151533.00	-75.4%
Number of vacancies (amount)	531953.67	93801.89	-82.4%
Imbalance (amount)	-84780.67	-57731.11	+31.9%
Tension (average)	4.28	3.49	-18.5%

Under conditions of high uncertainty and structural changes typical of wartime, traditional econometric models often prove to be inadequate [8, 9]. Classical trend forecasting tools, such as autoregressive models like ARIMA, can account for autocorrelations and short-term fluctuations over time but rely on the assumption of relative stability in structural relationships. Forecasting macroeconomic dynamics in wartime requires adaptation of existing models [10]. This has led to a growing interest in the application of machine learning (ML) techniques, particularly neural networks, for analyzing and predicting labor markets. Long Short-Term Memory (LSTM) architectures have demonstrated the capability to model complex temporal relationships and nonlinear processes, making them a promising tool for predicting economic indicators, such as inflation and recessions, under volatile conditions. [11, 12]. Some research highlights the advantages of hybrid models that combine LSTM with other approaches, such as hidden Markov models (HMMs), to enhance interpretability and accuracy, or with feature selection methods like LASSO [13]. At the same time, there are caveats that LSTMs are not always superior to simpler models in certain prediction problems, which emphasizes the need for careful validation and comparison of models [12]. Broader applications of machine learning in labor market analysis include predicting skills shortages, classifying vacancies, and analyzing labor mobility during crises using clustering [14, 15]. This justifies the use of methods such as K-Means and Random Forest in this research.

To quantify labor market distortions, it is essential to develop or adapt a system of criteria that accurately reflects these distortions [16, 17]. Despite the presence of a significant body of research on the impact of crises on labor markets and the use of modern modeling methods, there is a gap in comprehensive research that explicitly assesses the war deformations of the labor market in Ukraine [18]. Most existing analyses either focus on specific aspects, such as migration or unemployment, or employ traditional approaches that may not be sufficiently sensitive to the unique challenges posed by a full-scale war. No comprehensive models currently exist that integrate neural network modelling, other machine learning methods, and an adapted system of criteria for assessing deformations under conditions of extreme uncertainty and structural disruptions caused by hostilities and their direct and indirect consequences [19, 20].

Therefore, the **primary objective of this research** was to develop and validate a methodological approach using neural network modelling for the comprehensive assessment and forecasting of war-induced deformations and imbalances in Ukraine's labor market across various sectors, considering the unique conditions of wartime.

To achieve this, a series of tasks were established, including the development of a system of criteria for identifying and quantifying wartime labor market distortions, integrating indicators of imbalance, tension, structural changes and abnormal deviations; the conceptual justification of the impact of military factors on sectoral distortions of the labor market, in particular through the prism of changes in the labor supply function under the influence of non-monetary factors such as security and displacement; the adaptation and application of LSTM neural network models to forecast key indicators of the labor market by industry during wartime; the identification and analysis of war-induced industry deformations based on the developed criteria and modeling results, including LSTM, K-Means, Isolation Forest; as well as assessing the impact of key macroeconomic and specific military factors, using Random Forest algorithms, on the formation of imbalances.

The developed methodology can become the basis for creating more advanced decision-making support systems in the field of employment.

1. Theoretical and methodological foundations for the research of war-induced labor market deformations

War-induced deformations of the labor market are defined as profound, often sudden, and non-linear changes in the structure, functioning, and dynamics of the labor market. One effective method for detecting such changes is the application of machine learning techniques, particularly cluster analysis. This approach enables the grouping of economic sectors based on similarities in key labor market characteristics, such as the unemployment rate and the number of job openings. Fig. 1 visually illustrates this process by presenting the clustering results of sectors within the Ukrainian economy.

This graph illustrates the results of applying the K-Means clustering method to aggregated sectors of the Ukrainian economy, based on labor market indicators such as the number of unemployed and vacancies, for 2024. Each industry is represented as a point on a two-dimensional plane, created by reducing the dimensionality of the scaled features. The color of each point indicates the cluster to which the respective sector belongs. This grouping enables the identification of sectors facing similar challenges or trends, such as industries experiencing acute labor shortages or, conversely, an oversupply of workers. Identifying groups of industries with similar challenges enables the more effective adaptation of support and recovery strategies.

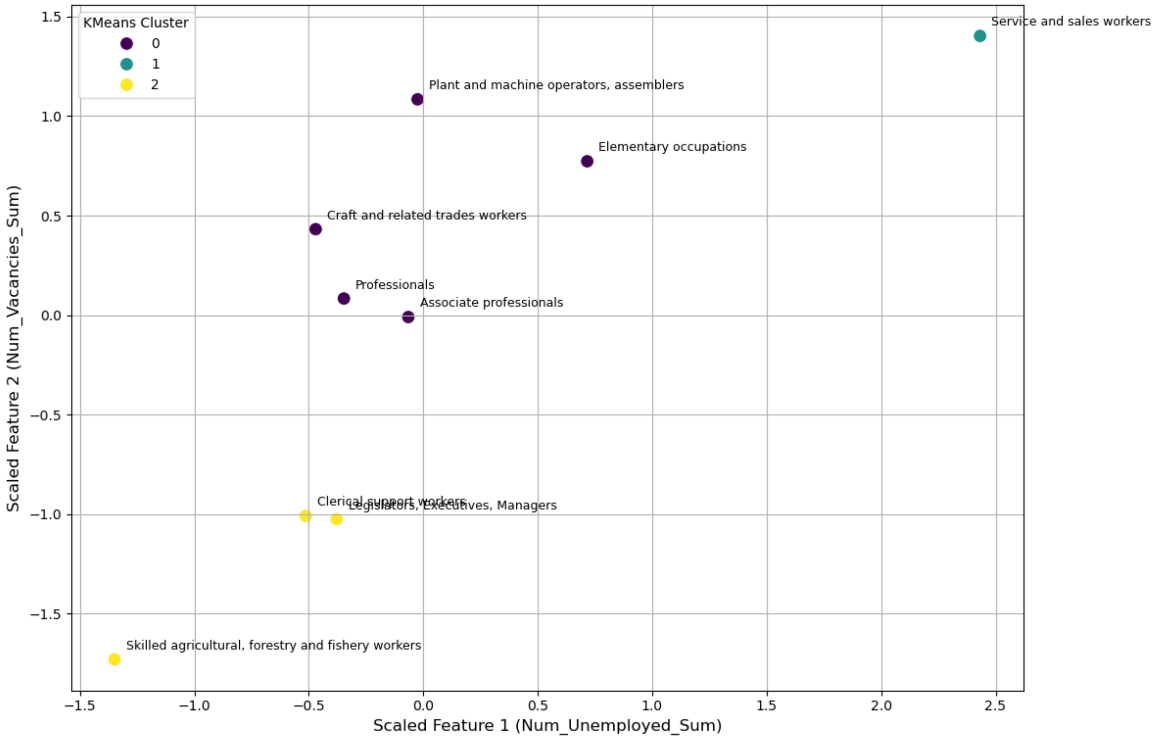

Fig. 1. Clustering of sectors in the Ukrainian economy based on labor market characteristics (based on K-Means analysis of scaled features, 2024)

In addition to structural ones, quantitative deformations, characterized by a sharp reduction or, in some cases, an increase in the level of employment and unemployment, as well as the number of vacancies and resumes, also exert a significant impact. The manifestations of these changes are clearly illustrated by the dynamics of the general imbalance, presented in Fig. 2, and the dynamics of the number of unemployed by industry, reflected in Fig. 3. Fig. 2 provides a detailed overview of the general aggregate trend of labor market imbalance in Ukraine, encompassing historical data, forecast values, and actual indicators for January to April 2025. The graph illustrates the historical dynamics of the overall total imbalance – i.e., the difference between vacancies and unemployment in all sectors – in the Ukrainian labor market since 2017. It also presents forecasted values for the period 2025–2030 generated by the LSTM model, alongside the actual aggregate imbalance recorded for January–April 2025. The blue line on the graph reflects significant fluctuations in historical data, including a pandemic-related drop in 2020 and a deeper drop in 2022 due to a full-scale invasion. The orange dotted line represents a forecast that indicates a gradual decrease in the negative imbalance. The red cross marks the actual figure for the first four months of 2025, enabling a comparison between the real situation and the model's projection.

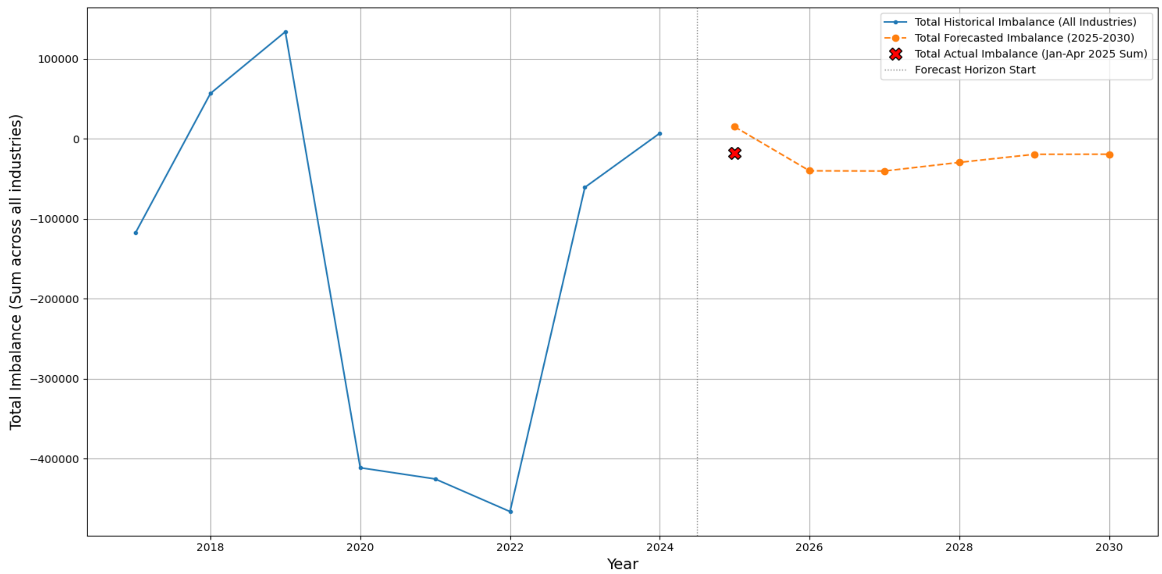

Fig. 2. General aggregate trend of imbalance in the labor market of Ukraine: historical data, forecast, and actual data for January-April 2025

Complementing the general picture of quantitative deformations, Fig. 3 provides a detailed overview of the unemployment dynamics across individual aggregate sectors of the Ukrainian economy for the period 2017–2024.

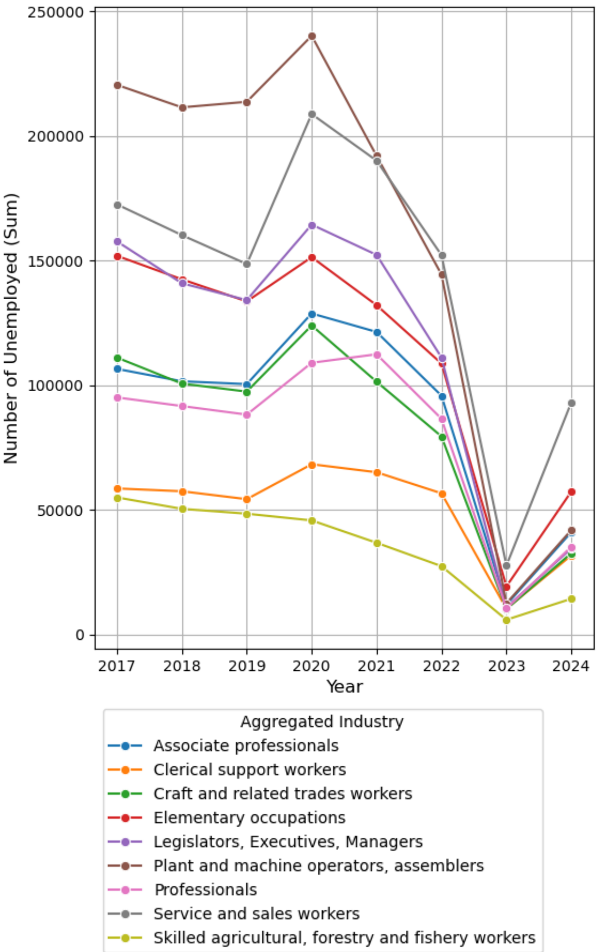

Fig. 3. Dynamics of unemployment across aggregate sectors of the Ukrainian economy (2017-2024)

This line graph illustrates changes in the total number of registered unemployed individuals across aggregate sectors of the Ukrainian economy from 2017 to 2024. Each line corresponds to a specific industry. As shown in the graph, most industries experienced a general decline in officially registered unemployment in 2022–2023. Most industries experienced a general decrease in officially registered unemployment in 2022–2023. In 2024, a moderate increase in unemployment can be observed in several sectors. This type of sectoral analysis enables the identification of industries that have been most affected or have undergone specific changes in the context of employment.

In addition to quantitative changes, the war also causes qualitative deformations of the labor market. These include the deterioration of working conditions, the growing mismatch between workers' skills and employers' requirements – the so-called skills mismatch – an increase in the share of informal and precarious employment, as well as the loss of human capital due to breaks in work, education, or migration [21–23]. The following necessary type is territorial deformations, which reflect the uneven impact on regional labor markets. This impact is due to factors such as proximity to war zones, temporary occupation, concentration of internally displaced persons, and destruction of infrastructure in specific regions [24].

The channels of the war's impact on the labor market can be divided into two main groups: direct and indirect. Direct channels include the physical destruction of enterprises, the loss of life and health of employees, mobilization, and forced displacement. Indirect channels include supply chain disruptions, inflationary processes, changes in the investment climate, deteriorations in business expectations, and psychological impacts on the workforce [25].

To quantitatively assess and qualitatively characterize war-induced labor market deformations, this research proposes a comprehensive system of criteria grounded in the analysis of available data and modeling outcomes. The system integrates quantitative indicators, results from cluster analysis, anomaly detection methods, and deviations identified through predictive modeling.

The first criterion – the level and structure of the imbalance of supply and demand – is evaluated through the absolute imbalance, designated as Imbalance_Sum, its dynamics, illustrated in Fig. 2, and the sectoral distribution shown in Fig. 4. Significant and stable negative values of this indicator indicate an excess of labor supply, positive ones indicate a shortage of personnel, and sharp changes indicate structural deformations.

The second criterion – tension in the labor market – is measured by the tension indicator designated as Tension_Mean. This definition aligns with the methodological approaches presented in previous research [20]. Very low values of this indicator indicate weak demand for labor, while high values indicate a labor shortage. Extreme values or sharp fluctuations are a sign of labor market distortion.

The third criterion – structural shifts in employment and unemployment – is examined by analyzing changes in the industry's share of overall unemployment, denoted as Industry_Share_Unemployed. This involves comparing the employment structure before and during the war, using data similar to that presented in Table 1, as well as interpreting the results of K-Means clustering, which identify groups of industries exhibiting similar patterns, as illustrated in Fig. 1.

The fourth criterion – abnormal dynamics of key indicators – is determined through the identification of abnormal values using the Isolation Forest method, as well as through the analysis of significant deviations of actual values from LSTM forecasts. Examples of such deviations can be seen in Fig. 5 and in the comparative data of estimates for 2025, which are based on exact data for January-April 2025.

The fifth criterion – a change in the rate of growth or decline in labor market indicators – considers the absolute and relative increases or decreases in the number of unemployed, specifically the Unemployed_Growth_Absolute and Unemployed_Growth_Relative indicators, as well as the number of vacancies. These variables are essential factors in the Random Forest model, as shown in Fig. 6. Abnormally high or low rates of change in indicators signify disruptions in the normal functioning of the labor. The fifth criterion, along with the overall importance of accounting for the war factor, is highlighted by the results of the factor significance analysis performed using the Random Forest model. These results are visualized in Fig. 6. The diagram presents the results of the feature importance analysis conducted using the Random Forest model. The purpose of this analysis was to identify the key determinants that influence the formation of labor market imbalances.

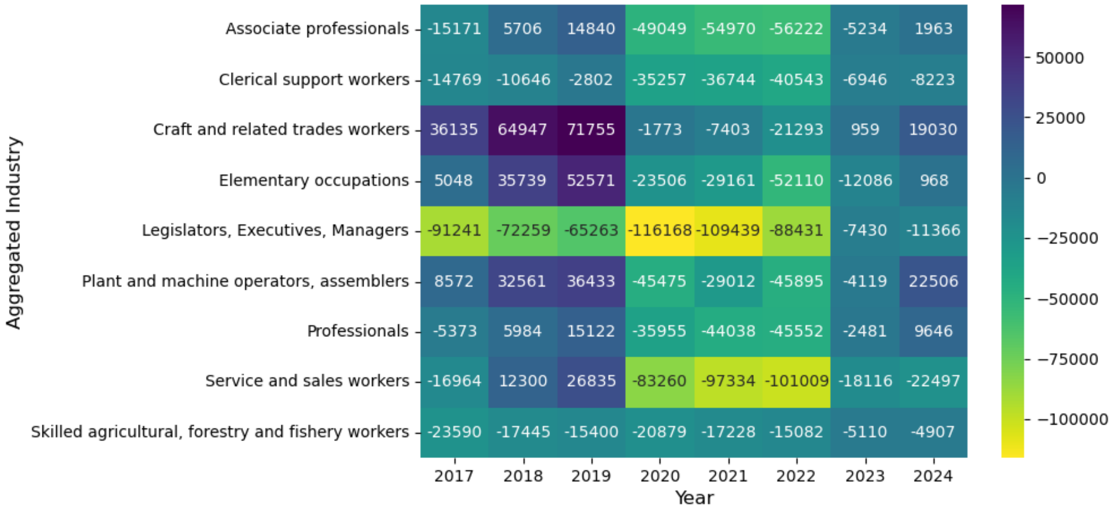

Fig. 4. Heat map of the total imbalance (the difference between vacancies and unemployed) by aggregate industries and years in Ukraine

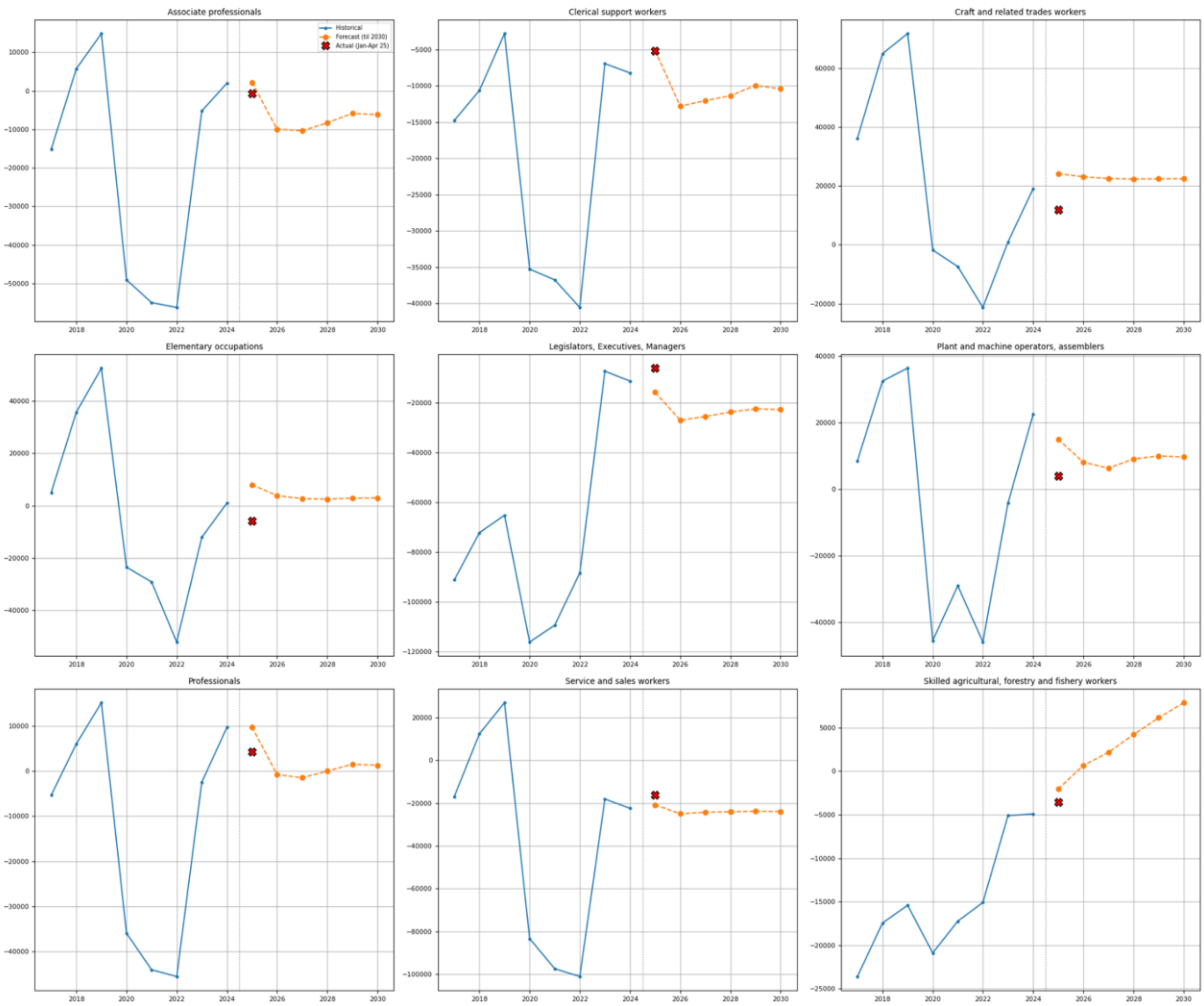

Fig. 5. Comparison of forecast and actual values of imbalance in the labor market across aggregate industries of Ukraine (validation of the forecast for 2025)

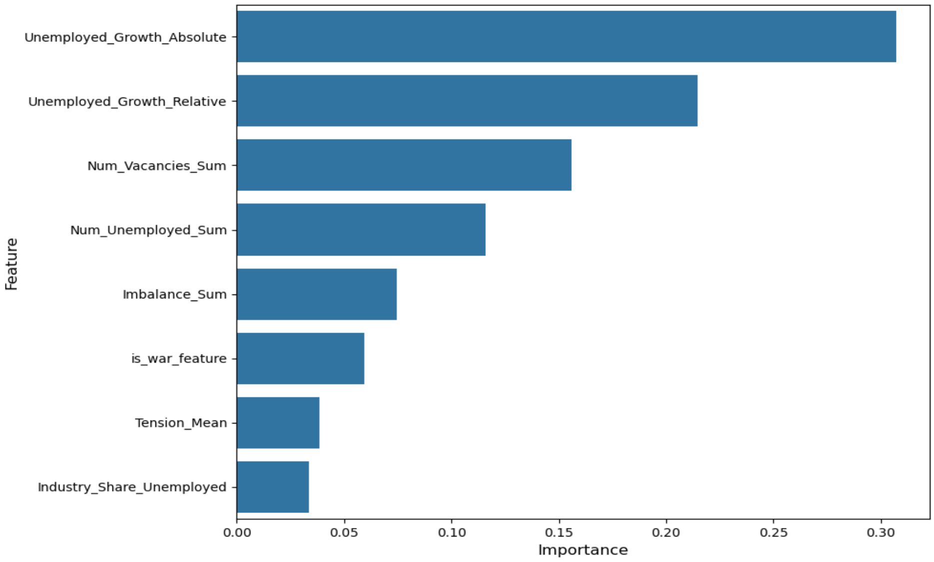

Fig. 6. The importance of factors for modeling labor market deformations (based on the results from the RandomForest Classifier)

Most likely, the target variable was either cluster membership or the level of imbalance. As can be seen from the diagram, the most significant factors were the absolute increase in the number of unemployed, designated as Unemployed_Growth_Absolute, and the relative increase in the number of unemployed, i.e., Unemployed_Growth_Relative. Additionally, the total number of vacancies (Num_Vacancies_Sum) and the total number of unemployed (Num_Unemployed_Sum) exert a significant impact. Notably, the is_war_feature variable also exhibits a significant impact, confirming the hypothesis that the war serves as an independent and critical factor in modeling labor market distortions.

Classical labor supply models typically consider an individual's decision to participate in the labor force as a function of the wage rate (w) and non-working income ($I_{non-labor}y$). This can be represented as:

$$L_s = f(w, I_{non-labor}),$$

where L_s is the labor supply.

However, under conditions of war and extreme crises, non-monetary factors assume a significantly greater, and sometimes decisive, role. For the conceptual justification of these changes, it is proposed to consider a modified function of labor supply, which incorporates an additional variable - a generalized "factor of war risks and deformations", denoted as R:

$$L_s = f(w, R, I_{non-labor}).$$

This factor R may aggregate the influence of components such as security, territorial, migration, psychological, and institutional factors. It is expected that the partial derivative of labor supply with respect to factor R will be negative, $\left(\frac{\partial L_s}{\partial R} < 0\right)$, meaning that an increase in war-related risks and associated deformations leads to a decrease in labor supply at any given wage level. The task of forecasting labor market indicators $Y_t = (Y_{1t}, Y_{2t}, \dots, Y_{mt})$ under wartime influences $X_t = (X_{1t}, \dots, X_{nt})$ can be formulated as a search for the mapping of F:

$$\hat{Y}_{t+\tau} = F(Y_t, Y_{t-1}, \dots; X_t, X_{t-1}, \dots),$$

where $\hat{Y}_{t+\tau}$ are the predicted values of the vector of indicators for τ periods ahead. In this research, the LSTM neural network architecture serves as an approximation of this complex nonlinear mapping of F.

2. Data and methods of neural network modeling of imbalances

The empirical base of this research is formed based on data obtained from official sources, specifically the State Statistics Service of Ukraine [5] and the Open Data Portal of Ukraine [6]. Primary data, including information on the year of observation, occupation name, occupation code, aggregated and detailed industry, number of unemployed, and number of vacancies by specific professions and industries, were aggregated for this research. Based on this raw data, key indicators were calculated for the aggregated sectors of the Ukrainian economy, hereafter referred to as Aggregated_Industry. These indicators include:

- Year – year of observation;
- Aggregated_Industry – aggregate sector of the economy;
- Num_Unemployed_Sum – the total number of unemployed, presumably officially registered, by the aggregate industry;
- Num_Vacancies_Sum – the total number of vacancies in the aggregated industry;
- Imbalance_Sum – estimated imbalance, defined as: Num_Vacancies_Sum - Num_Unemployed_Sum;
- Tension_Mean – average tension in the labor market;
- Industry_Share_Unemployed – the share of the aggregate industry in the total number of unemployed;
- Unemployed_Growth_Relative – relative increase in the number of unemployed;
- Unemployed_Growth_Absolute is the absolute increase in the number of unemployed.

Critical for research is the binary feature is_war_feature. It marks the periods following the onset of the full-scale invasion, taking the value 1 for the period after February 24, 2022, and 0 for the period before this date. To validate and test the predictive capacity of the developed models, data reflecting the actual state of the labor market for January to April 2025 are used. These data were also obtained through the processing of raw data for the corresponding period. It is essential to note that the analysis is conducted at the level of aggregated industries. This represents a limitation of the research, driven by the unavailability of sufficiently detailed regional data at the time of the research. The data preprocessing stage was comprehensive and involved several key operations: aggregation of primary data, calculation of derived indicators, processing of missing values, standardization of numerical features, creation of lag variables for time series, and identification of anomalies using the Isolation Forest method. Importantly, the results of some of these algorithms were used as additional features in further modeling. These are KMeans_Cluster – the cluster number to which the industry is assigned based on the results of cluster analysis – and Anomaly_IsoForest – a binary feature indicating an observational anomaly for a particular sector, detected by the Isolation Forest method.

The choice of the architecture of recurrent neural networks of the Long Short-Term Memory (LSTM) type for predicting indicators of labor market disparities is justified by their proven ability to model long-term dependencies in time series effectively. LSTM networks demonstrate high efficiency when working with unstable, non-linear series, which is characteristic of economic indicators in crisis periods. A significant advantage of LSTM is also the ability to take into account multiple input factors, including the previously mentioned feature is_war_feature. Research results in related fields also confirm the benefits of using LSTM models for similar forecasting tasks [11–13, 26, 27].

The architecture of the LSTM models used in this research presumably included a sequence of LSTM layers, fully cohesive layers known as Dense, and Dropout layers for regularization. Model training was carried out using the Adam optimizer and the Mean Squared Error, or MSE, loss function. Graphs of the loss function for different industries, as will be shown in Fig. 7, demonstrate the convergence of models during training. Notably, the training was conducted individually for each aggregated industry, allowing for the specific characteristics of each to be taken into account.

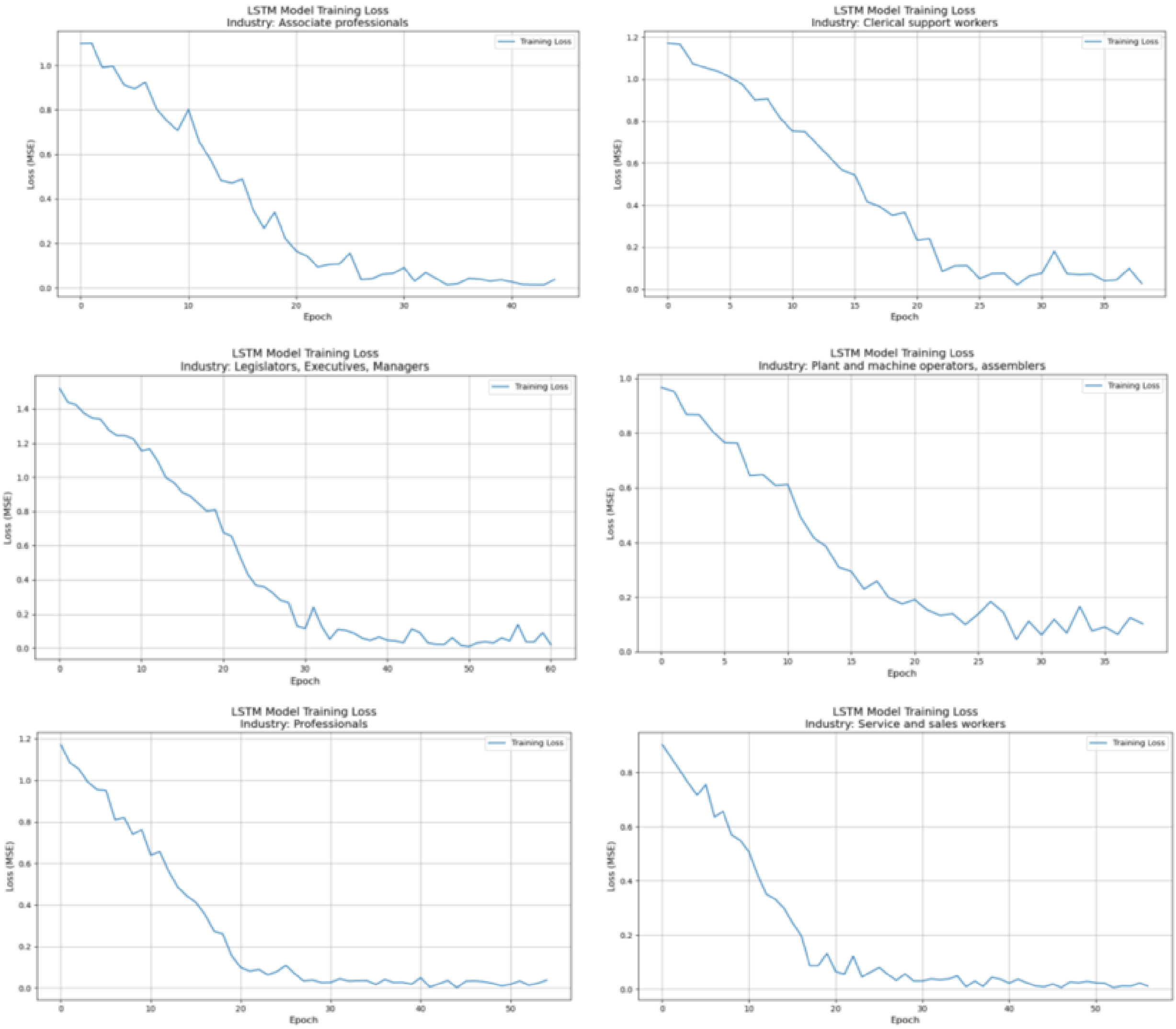

Fig. 7. Loss graphs (MSE) of training LSTM models for various aggregate sectors of the Ukrainian economy

Validation of the developed models was performed using a deferred data sample. A comparison of forecasts with actual data for different industries was presented earlier in Fig. 5. The obtained forecasts are used to assess the depth of war deformations. This is achieved by comparing forecasted values with actual data from the wartime period; in particular, an analysis is conducted of the discrepancies between the 2025 forecasts and the actual imbalance recorded for January–April 2025.

As mentioned earlier, the training of LSTM models was carried out individually for each industry, and their convergence was controlled using the loss function. Fig. 7 illustrates the dynamics of the loss function (MSE) during training of these models for various aggregate industries. This figure presents a set of individual graphs, each illustrating the dynamics of the loss function – Mean Squared Error, or MSE – for the corresponding aggregate sector of the Ukrainian economy during the training of LSTM models. The X-axis on each graph represents the training epochs, while the Y-axis shows the values of the loss function. A decreasing and subsequently stabilizing loss curve for each sector indicates that the model is successfully learning, with its parameters being optimized to minimize prediction error on the training data. Reaching a plateau on the loss graph is a crucial indicator of the model's learning process converging.

In addition to LSTM forecasting, several assistive machine learning methods were employed to analyze wartime fluctuations in the labor market further.

K-Means (Cluster Analysis). This method was used to classify economic sectors based on the similarity of their labor market characteristics under wartime conditions, relying on relevant indicators [14].

Random Forest (Feature Importance Determination). This method was used to identify the key factors that most affect the indicators of disparities. The results of the feature importance analysis were visualized earlier in Fig. 6. This method helps to determine which aspects of the labor market or external factors, including the is_war_feature variable, are the most significant drivers of labor market distortions.

Isolation Forest (Anomaly Detection). The Isolation Forest method was used to identify industries or time periods with extreme values of indicators. Such extreme values can signal the presence of acute deformations or the impact of unique economic shocks. The quality indicators of the classification models used, namely RandomForest and XGBoost, are presented in Table 3.

Table 3 – **Quality indicators of classification models**

Model	Accuracy	F1_Macro
RandomForest	0.9473684210526315	0.9641025641025642
XGBoost	1.0	1.0

The data presented in Table 3 indicate a high accuracy of the employed classification models, confirming the reliability of the results obtained using them.

The strength of the proposed methodological approach lies precisely in the integration of the machine learning methods. Specifically, LSTM models provide forecasts of key indicators, K-Means clusters industries based on similar characteristics, Random Forest identifies the most important influencing factors, and Isolation Forest detects statistically significant unique anomalies. This comprehensive approach not only enables the identification of existing problems and the prediction of their future development but also facilitates a deeper understanding of the nature and specifics of wartime deformations in the Ukrainian labor market.

3. Assessment and forecast of war deformations of the labor market of Ukraine

Based on the theoretical and methodological foundations outlined above, a comprehensive system of criteria was developed to assess wartime labor market deformations. This system integrates quantitative indicators, results from cluster analysis, anomaly detection methods, and predictive deviations, enabling not only the identification of changes but also their interpretation within the context of wartime impacts.

The main criteria include:

– the level and structure of the imbalance of supply and demand;

– tensions in the labor market;

– structural shifts in employment and unemployment;

– abnormal dynamics of key indicators;

– a change in the rate of growth or a fall in indicators.

Applying this system to specific industries allows for the identification of the most vulnerable market segments and the characteristic types of deformations affecting them.

The analysis of sectoral deformations reveals significant heterogeneity in the war's impact across different sectors of Ukraine's economy.

The heatmap of aggregate imbalances by industry and year, previously presented in Fig. 4, vividly illustrates this varied picture.

The dynamics of the number of unemployed across aggregate industries, illustrated in Fig. 3, show that after a sharp drop in the number of registered unemployed in all sectors during 2022-2023, there is an inevitable increase in this indicator across most sectors in 2024.

The results of K-Means clustering, as visualized in Fig. 1 and detailed in Table 4 (average: a – Num_Unemployed_Sum; b – Num_Vacancies_Sum; c – Imbalance_Sum; d – Tension_Mean), enable the identification of three main groups of industries with similar labor market characteristics as of 2024.

Table 4 – **Characteristics of industry clusters according to the results of K-Means analysis (data for 2024)**

Cluster	Industry	a	b	c	d
0	"Associate professionals", "Craft and related trades workers", "Elementary occupations", "Plant and machine operators, assemblers", "Professionals"	38219	51089	12870	1.83
1	"Service and sales workers"	93174	70677	-22497	4.86
2	"Clerical support workers", "Legislators, Executives, Managers", "Skilled agricultural, forestry and fishery workers"	26892	18727	-8165	2.60

Cluster 0 brings together industries with a relatively moderate number of unemployed and vacancies, but with a pronounced positive imbalance.

Cluster 1 is represented by a single, yet huge industry: "Service and sales workers." This sector is characterized by the highest numbers of both unemployed individuals and job vacancies, yet it exhibits a significant negative imbalance.

Cluster 2 comprises industries with a relatively low number of vacancies and a moderate number of unemployed individuals, resulting in a negative imbalance.

Such a significant decline in registered unemployment, amounting to 75.4% – appears counterintuitive against the backdrop of the economic crisis and extensive destruction caused by the war. This is likely attributable to methodological peculiarities in data collection, mass migration both within the country and abroad, the mobilization of a substantial portion of the working-age population, as well as a possible shift of some employment into the informal sector of the economy [21, 23].

Forecasting labor market dynamics during the war is highly challenging due to the high level of uncertainty and the high likelihood of sudden structural changes. Nevertheless, the LSTM models used in this research demonstrated their ability to capture complex dependencies and adapt to changes. Sectoral imbalance forecasts, as presented in Fig. 5, also exhibit diverse dynamics. For some industries – for example, "Craft and related trades workers", "Plant and machine operators, assemblers" and "Professionals" – a positive imbalance is predicted to persist or even intensify, indicating a shortage of personnel. For other industries, such as "Service and sales workers" or "Legislators, Executives, Managers", a negative imbalance is predicted to persist, although with a noticeable tendency toward a decrease in its absolute value during the forecast period. The analysis of the accuracy of short-term forecasts, detailed in Table 5, shows significant deviations for some industries.

Table 5 – **Comparison of the projected annual imbalance (model 2025) with the actual aggregate imbalance (January-April 2025) by industry**

Aggregated industry	Projected imbalance 2025 (annual model)	Actual imbalance January-April 2025 (amount)	Difference (Forecast - Fact)
Associate professionals	2176.71	-671	2847.71
Clerical support workers	-5156.23	-5145	-11.23
Craft and related trades workers	24120.18	11951	12169.18
Elementary occupations	8030.64	-5795	13825.64
Legislators, Executives, Managers	-15871.67	-6182	-9689.67
Plant and machine operators, assemblers	15044.82	3984	11060.82
Professionals	9715.56	4200	5515.56
Service and sales workers	-20839.81	-16234	-4605.81
Skilled agricultural, forestry and fishery workers	-2047.48	-3578	1530.52

The analysis of the factors' importance, conducted using the Random Forest model, enabled the identification of key determinants of labor market imbalances. Visualization of these results was presented earlier in Fig. 6, and the numerical importance values are given in Table 6.

Table 6 – **Importance of Features for Modeling Labor Market Deformations (Random Forest)**

Factor	Importance
Unemployed_Growth_Absolute	0.307442
Unemployed_Growth_Relative	0.214792
Num_Vacancies_Sum	0.155926
Num_Unemployed_Sum	0.115837
Imbalance_Sum	0.074533
is_war_feature	0.059298
Tension_Mean	0.038667
Industry_Share_Unemployed	0.033504

According to the data in Table 6, the most significant factors are the absolute and relative growth in the number of unemployed, as well as the total number of vacancies and the number of registered unemployed. It is noteworthy that the feature, is_war_feature, with an importance of 5.9%, confirms its independent and statistically significant impact on the simulated processes. A smaller, yet still substantial, impact is observed from indicators such as labor market tension and the share of a specific industry in the overall unemployment structure. It is important to note that the is_war_feature variable may influence the labor market both directly and indirectly, particularly through its effect on the values of other key indicators mentioned above.

The use of the Isolation Forest method enabled the identification of two industries with anomalous indicators in 2024: the "Service and sales workers" sector and the "Skilled agricultural, forestry and fishery workers" sector. The anomaly observed in the first sector likely highlights the extreme nature of challenges in this critical segment of the labor market. In the case of the second sector, its anomaly may be linked to a low number of vacancies or sharp fluctuations in other key indicators.

4. Discussion of the results and their implications

The research results indicate the presence of deep and multi-dimensional deformations in Ukraine's labor market, which were caused by the full-scale war. There is significant sectoral heterogeneity in the reaction of various economic sectors to war shocks. Thus, some industries, particularly "Craft and related trades workers" and "Plant and machine operators, assemblers," belonging to Cluster 0, exhibit signs of personnel shortages. This may be due to the growing demand in the military-industrial complex and the construction sector, which are involved in the recovery processes, as well as the outflow of skilled workers resulting from mobilization or migration.

In contrast, the largest sector of the labor market – "Service and sales workers", which forms Cluster 1 – is characterized by a significant negative imbalance, despite the high number of available vacancies. This situation may indicate a structural mismatch between the candidates' existing skills and the needs of employers, high staff turnover, or generally unattractive working conditions in this sector. Industries included in Cluster 2 – for example, "Clerical support workers" and "Legislators, Executives, Managers" – also demonstrate an excess of labor supply over demand [8]. The specificity of the Ukrainian context lies, in particular, in the significant role of the IT sector, which falls under the categories of "Professionals" or "Associate professionals". This sector was able to partially adapt to the war conditions thanks to the vast opportunities for remote work.

The integration of results obtained using the K-Means and Isolation Forest methods, along with an examination of deviations in LSTM forecasts, provided an opportunity to form a multidimensional picture of the current state of the labor market. However, it is essential to emphasize that the effectiveness of the proposed system of criteria largely depends on the quality and completeness of the input data available for analysis.

The LSTM models used have demonstrated their ability to generate forecasts under conditions of high uncertainty. At the same time, the accuracy of the obtained forecasts varies depending on the specific industry and the selected time horizon, as illustrated earlier in Fig. 2, Fig. 5, and Table 5. Compared to other research that used LSTM networks for economic forecasting under crisis conditions, the results obtained in this work are fully comparable in terms of the task complexity addressed (see, for example, [11–13]). Further improvements of the developed models may include the use of more complex neural network architectures, the addition of new exogenous variables that better reflect the specifics of wartime conditions, or the use of hybrid approaches to modeling.

This research has several limitations that are important to consider when interpreting the results obtained. The most significant limitation is the problems associated with collecting and maintaining the quality of official statistics during wartime. Official data on registered unemployment likely do not provide a complete and accurate picture of the labor market's state. In addition, the lack of sufficiently detailed regional data limits the possibility of conducting an in-depth territorial analysis. The aggregation of industry data used in the research can also hide critical intra-industry differences and specificities. It should also be remembered that any economic and mathematical modelling is inevitably based on certain assumptions and simplifications of reality. The choice of a specific architecture for LSTM networks, a set of factors for the Random Forest model, as well as clustering parameters – all these factors can inevitably affect the research results.

Additionally, it is impossible to fully formalize and include all aspects of the war's impact in quantitative models. Such elements include, for example, the psychological state of the population, the dynamics of changes in the informal sector of the economy, the exact level of destruction of specific enterprises, and many other factors that are difficult to quantify. The current situation on the labour market and in Ukraine's economy is highly dynamic. It largely depends on the further course of hostilities, the volume and regularity of international aid, as well as on many other unpredictable factors. All this significantly complicates long-term forecasting and necessitates the constant updating of both the models themselves and the input data used for their training and validation. Further research on war-induced deformations of Ukraine’s labor market can develop along the following promising directions:

– modelling migration flows and assessing their quantitative impact on the structure of labor supply and demand;

– assessment of the effectiveness of specific state policy measures aimed at supporting employment and adapting the labor market to new conditions;

– using more complex neural network architectures or developing hybrid models to improve prediction accuracy.

Conclusions

The research enabled the development and successful testing of a comprehensive methodological approach to analyzing and forecasting labor market imbalances in Ukraine amid unprecedented military developments. The developed system of criteria, which integrates quantitative indicators, the results of cluster analysis, methods for detecting anomalies and neural network forecasts, made it possible to quantify industry deformations. It was also likely to identify the most vulnerable sectors of the economy and the key factors that determine the current dynamics of the labor market.

Neural network modelling using the LSTM architecture has demonstrated its significant potential for predicting key labor market indicators even in conditions of high uncertainty and deep structural fractures caused by the war. At the same time, the accuracy of the forecasts obtained and the urgent need to constantly update the models, considering the dynamically changing situation, remain relevant challenges for further research. The use of assistive machine learning methods – specifically K-Means, Random Forest, and Isolation Forest – significantly complemented the analysis capabilities. These methods enabled the classification of industries based on their characteristic types of deformations, the determination of the importance of various influencing factors, and the identification of statistically significant anomalous phenomena.

A deep understanding of the nature, extent, and specifics of war-induced labor market deformations is critically essential for minimizing their negative long-term consequences and ensuring the country’s sustainable development in the future. Continued scientific research and ongoing monitoring of the current labor market situation are crucial for effectively addressing the complex challenges facing the Ukrainian labor market in today’s environment.

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.

Use of artificial intelligence

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

Acknowledgements

The research was carried out with funds from the budget of the Ministry of Education and Science of Ukraine on the topic of the research project "Modelling educational transformations in wartime to preserve the intellectual capital and innovative potential of Ukraine" (0123U100114).

References

1. (2024), *$155 billion – The total amount of damages caused to Ukraine's infrastructure due to the war, as of January 2024*, KSE, Kyiv, available at: https://kse.ua/about-the-school/news/155-billion-the-total-amount-of-damages-caused-to-ukraine-s-infrastructure-due-to-the-war-as-of-january-2024/
2. Atamaniuk, R., Klymenko, I., Melnychuk, L., Kravets, I. and Yarmak, T. (2024), "The impact of mass migration on the demographic situation and the labor market in Ukraine", *Multidisciplinary Reviews*, vol. 7, issue 10, e2024196, doi: https://doi.org/10.31893/multirev.2024196
3. (2025), *Finding a job in Ukraine: How the war affected the labor market*, The Institute of Analytics and Advocacy, IAA, available at: https://iaa.org.ua/en/articles/znajty-robotu-v-ukrayini-yak-vijna-vplynula-na-rynok-praczi/
4. Misini, S. and Tosuni, G. (2023), "An analysis of the impact of external shocks on the economic performance index of the European union countries: the case of the russian invasion of Ukraine", *Journal of Governance and Regulation*, vol. 12, issue 4, (Special Issue), pp. 315–325, doi: https://doi.org/10.22495/jgrv12i4siart11
5. (2025), *Indices of industrial production in Ukraine for 2015-2025*, State Statistics Service of Ukraine, Kyiv, available at: https://www.ukrstat.gov.ua/
6. (2025), *Survey of enterprises on labor statistics*, Open Data Portal, Datasets, available at: https://data.gov.ua/dataset
7. Braun, S. T., and Stuhler, J. (2023), *Exposure to War and Its Labor Market Consequences over the Life Cycle*, IZA Discussion Papers, No. 16040. Institute of Labor Economics (IZA), 15 p., available at: https://docs.iza.org/dp16040.pdf
8. Zambrana, M. (2025), "The challenge of rebuilding the economy and the labour market in post-war Syria", *Equal Times*, 1 April 2025, available at: https://www.equaltimes.org/the-challenge-of-rebuilding-the
9. Fedorovich, O., Kosenko, V., Lutai, L. and Zamirets, I. (2022), "Methods and models of research of investment attractiveness and competitiveness of project-oriented enterprise in the process of creating innovative high-tech", *Innovative Technologies and Scientific Solutions for Industries*, vol. 3 (21), pp. 51–59, doi: https://doi.org/10.30837/ITSSI.2022.21.051
10. Dobrovolska, O., Kolotilina, O., and Ostapenko, M. (2024), "Forecasting Macroeconomic Dynamics in Ukraine: The Impact of a Full-Scale War", *SocioEconomic Challenges*, vol. 8(3), pp. 211–237, doi: https://doi.org/10.61093/sec.8(3).211-237.2024
11. Chung, S. (2023), "Inside the black box: Neural network-based real-time prediction of US recessions", *arXiv*, doi: https://doi.org/10.48550/arXiv.2310.17571
12. Rygh, T., Vaage, C., Westgaard, S., and Lange, P. E. D. (2025), "Inflation Forecasting: LSTM Networks vs. Traditional Models for Accurate Predictions", *Journal of Risk and Financial Management*, vol. 18 (7), doi: https://doi.org/10.3390/jrfm18070365
13. Sivakumar, G. (2025), "HMM-LSTM Fusion Model for Economic Forecasting", *arXiv*, arXiv:2501.02002, doi: https://doi.org/10.48550/arXiv.2501.02002
14. Kuchuk, H., Mozhaiev, O., Tiulieniev, S., Mozhaiev, M., Kuchuk, N., Tymoshchyk, L., Onishchenko, Yu., Tulupov, V., Bykova, T. and Roh, V. (2025), "Devising a method for forming a stable mobile cluster of the internet of things fog layer", *Eastern-European Journal of Enterprise Technologies*, 2025, vol. 1, no. 4(133), pp. 6–14, doi: https://doi.org/10.15587/1729-4061.2025.322263
15. Kuchuk, H., Mozhaiev, O., Kuchuk, N., Tiulieniev, S., Mozhaiev, M., Gnusov, Y., Tsuranov, M., Bykova, T., Klivets, S., and Kuleshov, A. (2024), "Devising a method for the virtual clustering of the Internet of Things edge environment", *Eastern-European Journal of Enterprise Technologies*, vol. 1, no. 9 (127), pp. 60–71, doi: https://doi.org/10.15587/1729-4061.2024.298431
16. Giupponi, G., and Machin, S. (2024), "Labour market inequality", *Oxford Open Economics*, vol. 3, issue Supplement_1, pp. i884–i905, doi: https://doi.org/10.1093/ooec/odad039
17. Rezanov, B., and Kuchuk, H. (2023), "Model of elemental data flow distribution in the Internet of Things supporting Fog platform", *Innovative Technologies and Scientific Solutions for Industries*, vol. 2023(3), pp. 88–97, doi: https://doi.org/10.30837/ITSSI.2023.25.088
18. Sarsenbaev, B., Rakhimboev, M., Aytmuratova, U., Kaypnazarova, G. and Shamshetova, D. (2025), "Econometrical modeling of dynamic processes of labor market development", *Aip Conference Proceedings*, vol. 3331, is. 1, 040019, doi: https://doi.org/10.1063/5.0305894
19. Kashkevich, S., Kuchuk, H., Plekhova, G., Davydov, V., Yefymenko, O. and Beketov, Y. (2024), "The development of methods of learning artificial neural networks of intelligent decision-making support systems", *Information and Control Systems Modelling and Optimizations*, pp. 102–137, doi: https://doi.org/10.15587/978-617-8360-04-7.CH4
20. Kovalenko, A., Kuchuk, H., Kuchuk, N. and Kostolny, J. (2021), "Horizontal scaling method for a hyperconverged network", *2021 International Conference on Information and Digital Technologies* (IDT), Zilina, Slovakia, doi: https://doi.org/10.1109/IDT52577.2021.9497534
21. Sokolovskyi, I. (2023), "Ukraine's Labor Market After a Year and a Half of Full-Scale War: Prestandard Employment and Digitalization", *Sociology: Theory, Methods, Marketing*, vol. 4, pp. 89–106, doi: https://doi.org/10.15407/sociology2023.04.89
22. Kuchuk, H., Chumachenko, I., Marchenko, N., Kuchuk, N. and Lysytsia, D. (2025), "Method for calculating the number of IOT sensors in environmental monitoring systems", *Advanced Information Systems*, vol. 9, no. 3, pp. 66–32, doi: https://doi.org/10.20998/2522-9052.2025.3.08

23. Dotsenko, N., Chumachenko, I., Galkin, A., Kuchuk, H. and Chumachenko, D. (2023), "Modeling the Transformation of Configuration Management Processes in a Multi-Project Environment", *Sustainability (Switzerland)*, Vol. 15(19), 14308, doi: https://doi.org/10.3390/su151914308
24. Vyshnovetska, S. V., Vyshnovetskyi, V. M., Dyban, M. P., Kmetyk K. V. and, Chernous S. M. (2024), "Legal regulation of labour relations in the conditions of martial law in Ukraine", *Work Organisation, Labour & Globalisation*, vol. 18, issue 2, pp. 219–244, doi: https://doi.org/10.13169/workorgalaboglob.18.2.219
25. Trubnik, T., Popliuiko, Y., Galitsyna, O., Ivanenko, O. and Mazur, M. (2024), "Statistical Analysis of Inflationary Processes' Impact on Economic Development: Trends, Mechanisms and Models", *Economic Affairs New Delhi*, vol. 69, is. 1, pp. 715–724, doi: https://doi.org/10.46852/0424-2513.2.2024.32
26. Yaloveha, V., Hlavcheva, D., Podorozhniak, A. and Kuchuk, H. (2019), "Fire hazard research of forest areas based on the use of convolutional and capsule neural networks", *2019 IEEE 2nd Ukraine Conference on Electrical and Computer Engineering, UKRCON 2019 – Proceedings*, DOI: http://dx.doi.org/10.1109/UKRCON.2019.8879867
27. Yurtsever, M. (2023), "Unemployment rate forecasting: LSTM-GRU hybrid approach", *Journal for Labour Market Research*, vol. 57, article 18, doi: https://doi.org/10.1186/s12651-023-00345-8

Received (Надійшла) 04.10.2025
Accepted for publication (Прийнята до друку) 07.01.2026

ABOUT THE AUTHORS / ВІДОМОСТІ ПРО АВТОРІВ

Кушнерьов Олександр Сергійович – доктор філософії, старший викладач кафедри економічної кібернетики, Сумський державний університет, Суми, Україна;
Oleksandr Kushnerov – PhD, Senior Lecturer, Department of Economic Cybernetics, Sumy State University, Sumy, Ukraine;
e-mail: o.kushnerov@biem.sumdu.edu.ua; ORCID Author ID: https://orcid.org/0000-0001-8253-5698;
Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=58318301800.

Нєшева Анастасія Дмитрівна – асистент кафедри управління імені Олега Балацького, Сумський державний університет, Суми, Україна;
Anastasiia Niesheva – assistant of Oleg Balatsky Department of Management, Sumy State University, Sumy, Ukraine;
e-mail: a.niesheva@biem.sumdu.edu.ua; ORCID Author ID: https://orcid.org/0000-0003-0399-201X.
Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=60041047700.

Щербаченко Вікторія Олексіївна – кандидат економічних наук, доцент, старший викладач кафедри міжнародних економічних відносин, Сумський державний університет, Суми, Україна;
Viktoriia Shcherbachenko – Candidate of Economic Sciences, Associate Professor, Senior Lecturer, International Economic Relations Department, Sumy State University, Sumy, Ukraine;
e-mail: v.shcherbachenko@biem.sumdu.edu.ua; ORCID Author ID: https://orcid.org/0000-0002-4570-3389;
Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=57210744891.

Сокол Владислав Євгенович – кандидат технічних наук, докторант кафедри кібербезпеки, Національний технічний університет «Харківський політехнічний інститут», Харків, Україна;
Vladyslav Sokol – Candidate of Technical Sciences, Doctoral Student of Cybersecurity Department, National Technical University "Kharkiv Polytechnic Institute", Kharkiv, Ukraine;
e-mail: vladyslav.sokol@gmail.com; ORCID Author ID: https://orcid.org/0009-0009-9446-2049;
Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=56290096700 .

Амірасланов Халіг Велі огли – старший викладач кафедри комп'ютерних технологій Азербайджанського технічного університету; Баку, Азербайджан;
Khaliq Amiraslanov – Senior Lecturer, Department of Computer Technologies, Azerbaijan Technical University, Baku, Azerbaijan;
e-mail: xaliq763@gmail.com; ORCID Author ID: https://orcid.org/0009-0003-4801-2270.

Нейромережеве моделювання та прогнозування диспропорцій на ринку праці України в екстремальних умовах

О. С. Кушнерьов, А. Д. Нєшева, В. О. Щербаченко, В. Є. Сокол, Х. В. Амірасланов

Анотація. Актуальність. Повномасштабне військове вторгнення Російської Федерації спричинило безпрецедентні деформації на ринку праці України. Ці деформації характеризуються глибокими галузевими та територіальними диспропорціями, які зумовлені масовою міграцією, мобілізацією, руйнуванням виробництв та зміною структури попиту і пропозиції робочої сили. Це викликає нагальну потребу в розробці інструментів для кількісної оцінки та прогнозування зазначених деформацій, що є важливим для прийняття обґрунтованих рішень. **Метою цього дослідження** є розробка й апробація комплексної методики, заснованої на нейромережевому моделюванні (Long Short-Term Memory – LSTM). Ця методика спрямована на ідентифікацію, оцінку та прогнозування воєнних деформацій і диспропорцій на ринку праці України, а також включає розробку системи критеріїв для їхньої оцінки. **Методологія дослідження** базується на інтегрованому підході, що охоплює аналіз часових рядів, нейромережеве прогнозування (LSTM), методи виявлення структурних зсувів та аномалій (Isolation Forest), кластерний аналіз (K-Means) і визначення факторів впливу (Random Forest). **У результаті дослідження** представлено розроблену систему критеріїв для оцінки воєнних деформацій, здійснено кількісну оцінку галузевих деформацій, спричинених війною, надано прогноз динаміки диспропорцій та ідентифіковано найбільш вразливі галузі. **Висновки** підкреслюють наукову та практичну значущість розробленої методики для моніторингу ринку праці, розробки адаптивних політик зайнятості й програм післявоєнного відновлення економіки України. Також вони демонструють потенціал нейромережевих моделей для аналізу ринків праці в умовах екстремальної невизначеності.

Ключові слова: ринок праці; воєнні деформації; диспропорції; нейромережеве моделювання; LSTM; прогнозування; галузевий аналіз; структурні зрушення; кластерний аналіз; фактори впливу; система критеріїв.