Information and Prognostic System for the Analysis and Prediction of Conflict Actions

Leonid Hulianytskyi[1,†], Kostiantyn Boskin[1,*,†]

[1] *VM Glushkov Institute of Cybernetics of the National Academy of Sciences of Ukraine, Academician Glushkov Avenue, 40, Kyiv, 03187, Ukraine*

Abstract

The article describes a multifunctional information and prognostic system (MIPS) for analysis, forecasting, and decision support during conflict situations. It also proposes specific indicators to determine the characteristics of strike actions in Ukraine and their systematization. The focus is on the developed aggregated indicators, such as action power, action impact, and productivity over a given period, calculated based on weighted coefficients for various types of involved resources. The article outlines the requirements for systems of this kind, and the architecture of the MIPS as well as presents the research and implementation of a predictive mechanism using time series analysis for actions forecasting.

Keywords

Keywords: information and prognostic system, conflict situations, aggregated indicators, forecasting, open data, system architecture

1. Introduction

In the context of large-scale invasions, analyzing data and probabilistically forecasting the future course of the military situation gain significant importance. Open data, such as satellite imagery [1], sentiment analysis of social media data [2], OSINT analysis [3], and other information sources, provide valuable insights for understanding and predicting developments.

Combining these data with statistical models, time series analysis models, and artificial intelligence methods makes it possible to create predictive systems capable of prognosing the course of events over time and their potential consequences. Utilization of the gathered data utilization allows developers to create tailored decision support systems for comprehensive analysis and enhances the decision-making process.

Outputs of such forecasting models can be applied in areas such as supporting specialized decision-making, informing the public and the international community by presenting analytical data through a user-friendly interface, and forecasting specific events for a selected period.

This paper focuses on the approaches, aggregated mathematical indicators, and the multifunctional information and prognostic system (MIPS). It represents an integrated applied system for the intelligent analysis of available data, designed for use both as an information-analytical tool for displaying diverse input and aggregated data and as an instrumental decision-support tool based on the use of predictive models.

Information Technology and Implementation (IT&I-2024), November 20-21, 2024, Kyiv, Ukraine

* Corresponding author.

† These authors contributed equally.

leonhul.icyb@gmail.com (L. Hulianytskyi); kostiantyn.boskin@gmail.com (K. Boskin)

0000-0002-1379-4132 (L. Hulianytskyi); 0009-0002-7866-3886 (K. Boskin)

2. Review of relevant publications

Prognostic systems that rely on time series models, artificial intelligence models, and statistical methods find widespread use in practice. The contemporary application of deep machine learning techniques, in conjunction with the improved performance of user computers and the expansion of computational resources, has motivated researchers to experiment with a diverse array of models, resulting in a rise in the number of research initiatives. Forecasting the impact of conflicts from local to global levels and prediction of local events inside of the conflicts using open data sources stands out across other different applications.

Using open data from the Kaggle platform and the open-source Prophet model [4], researchers created a prognostic model capable of predicting potential personnel losses during a conflict [5]. Another study [6], that leverages geographical data from WikiLeaks and statistical models, demonstrated the ability to analyze and predict the intensity of combat in specific regions and the conditions of military units. Notably, image recognition and visual recognition techniques stand out in this area of research. Researchers assessed the extent and geography of building damage during the Syrian conflict by analyzing landscape changes using open Sentinel-1 satellite imagery [7].

Another prominent area of research involves forecasting conflict probabilities for specific regions. Using algorithms such as Random Forest and Naive Bayes, a study demonstrates how to predict the number of combat engagements in Africa [8] for a given time period. Also remarkable, the utilization of Markov Chains for modeling conflict intensity [9] based on open data, and the implementation of Recurrent Neural Networks for predicting future events using historical data, are explored in [10].

An equally important research direction is the prediction of future demographic trends in countries experiencing conflict. Time series analysis and statistical methods have been employed to suggest a potential correlation between the existence of conflict and the sex ratio (the number of males per N females born) [11].

As a result of the analysis of scientific literature, only a relatively small number of studies related to the current situation in Eastern Europe, particularly in Ukraine, have been identified in the field of building predictive models of the current conflict.

3. Tasks principles of construction, and functional blocks of the MIPS

3.1. Concept of the System, Tasks, and Objectives

The primary objective of the MIPS is to aggregate, visualize, analyze, and forecast data and events related to actions associated with the invasion of Ukraine over selected periods of time, primarily using open sources from the Internet. By "open sources," we refer to publicly available resources on the Internet, such as daily updated data (e.g., the currently available reports of 14 categories of losses), accessible news, and more.

From the system design perspective, the architecture of the MIPS is based on the principles of hierarchy and modularity. Researchers aimed to combine the advantages of integrated systems for processing various types of information objects with mathematical tools for time series forecasting, all within a sophisticated application system.

The formulation of the MIPS was directed by the following fundamental principles:

1. Creation of maximum convenience for users;
2. Integration of data analysis tasks into a unified technological process, taking into account specific interpretations and enabling decision-making based on the provided forecasts of event developments;
3. Provision of aggregated performance indicators for actions, allowing users to make timely decisions and enhancing the rationale behind those decisions;

4. Ensuring a high degree of reliability in the obtained results;
5. Flexibility, adaptability, modifiability, extensibility, and mobility of the system's software.

The MIPS is architecturally designed as a microservice-based client-server web system deployed in the cloud. The system's development incorporates years of experience in designing and building decision-support systems, user-facing web platforms, and software solutions that handle intensive, high-load computations.

The main design tasks of the system include:

1. Collection and analysis of open data related to the conflict in Ukraine.
2. Preparation of forecasts for specified periods and data visualization across the existing 14 categories of losses (including categories such as UAVs, Missiles, and Personnel).
3. Decision-support capabilities for professional users based on the prepared forecasts.
4. Expansion of the awareness level for general users through representative visualization of processed data and centralization of this information on the web system's pages.
5. Support for multiple languages, including translations into the most widely spoken languages globally.
6. Analysis of event intensity in specific regions.
7. Analysis of "action power," considering the specific types of resources used (e.g., particular types of UAVs).
8. Safety analysis of enterprises in certain territories based on statistical analysis.
9. Analysis of the "action coverage area."
10. Sentiment analysis to improve the accuracy of forecasting "air actions" and other exogenous events.
11. Forecasting using neural networks to identify patterns across multiple categories.

3.2. Challenges and their solutions

One of the principal responsibilities of the MIPS is to improve the accessibility of information on military events (actions) and adversary losses for both specialists and the general public. Researchers faced a few challenges, one of the most difficult was the collection and keeping the data up to date, since there is no official data update schedule

Based on observations, updates in open sources occur within the day following the date for which the data is provided. Since the system is cloud-based, researchers selected hours as the time interval, considering this optimal from the perspective of balancing resource usage and the number of requests to open sources.

Given the lack of information about the specific hour of the day when data updates occur in open sources, the "update" event can be considered a random variable. Therefore, the probability of data being updated at hour X can be modeled according to the normal distribution of variables. However, considering the need to obtain updated data as quickly as possible and after analyzing the complexity of implementation, the decision was made to approximate the distribution as uniform. This simplifies the initially complicated data update algorithm, as it is reasonable to assume that data can be refreshed hourly using a timer.

$$p(X = h_i) = 1/24, i \in 1, \dots ,24, \quad (1)$$

Where h_i – the random hour of the day, X – the sought-after hour during which data is updated in the sources.

Thus, it was decided to update the data hourly, as under this assumption the probability of updating the open data per hour h_i and h_{i+1} is equivalent leading to a fairly simple solution.

To achieve this, developers created a separate dedicated module responsible for data collection and synchronization. The update algorithm checks if new data is available and skips the forecast update procedure if no updates are found. The algorithm's flowchart appears in Fig 1.

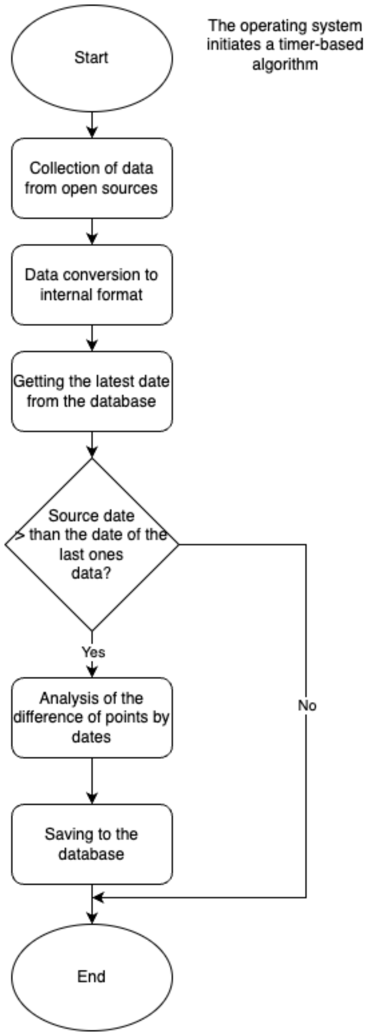

Figure 1: Data Synchronization Algorithm

3.3. Architecture and Technological Solutions

While designing the MIPS architecture, SOLID principles [12] were applied to ensure quality, maintain a clear separation of component responsibilities, and reduce defects in the long run.

As previously mentioned, the MIPS is a web platform consisting of a server-side component and a user interface presented as a web application. The server-side architecture follows the principles of hierarchy and modularity that uses a microservices approach [13]. The final server application is deployed in the cloud using containerization technology [14]. This decision was motivated by the fact that compared to monolithic architecture, microservice architecture is considered to be a more modern approach, offering greater flexibility and easier scalability [15].

The use of a microservices approach for the MIPS provides the following advantages:

- The ability to use different programming languages for various microservices (since there are no language restrictions for each microservice). This is beneficial for systems where certain components may perform resource-intensive computational operations.

- Flexibility in horizontally scaling the infrastructure as needed (since each service operates as an independent part of the system and can be deployed on a suitable server).
- More focused test coverage for specific functionalities (as they exist in separate services).

Use of the containerization in the MIPS has mitigated issues related to standardizing development and testing environments during cloud deployment.

As the primary language for implementing the server side it was decided to use Python. This decision dictated by few reasons, some of them are the fact that Python is a modern tool, convenient for designing server-side components [16], and for utilizing AI models and methods due to its extensive set of available tools and their ease of use [17]. The overall system architecture is presented in Figure 2.

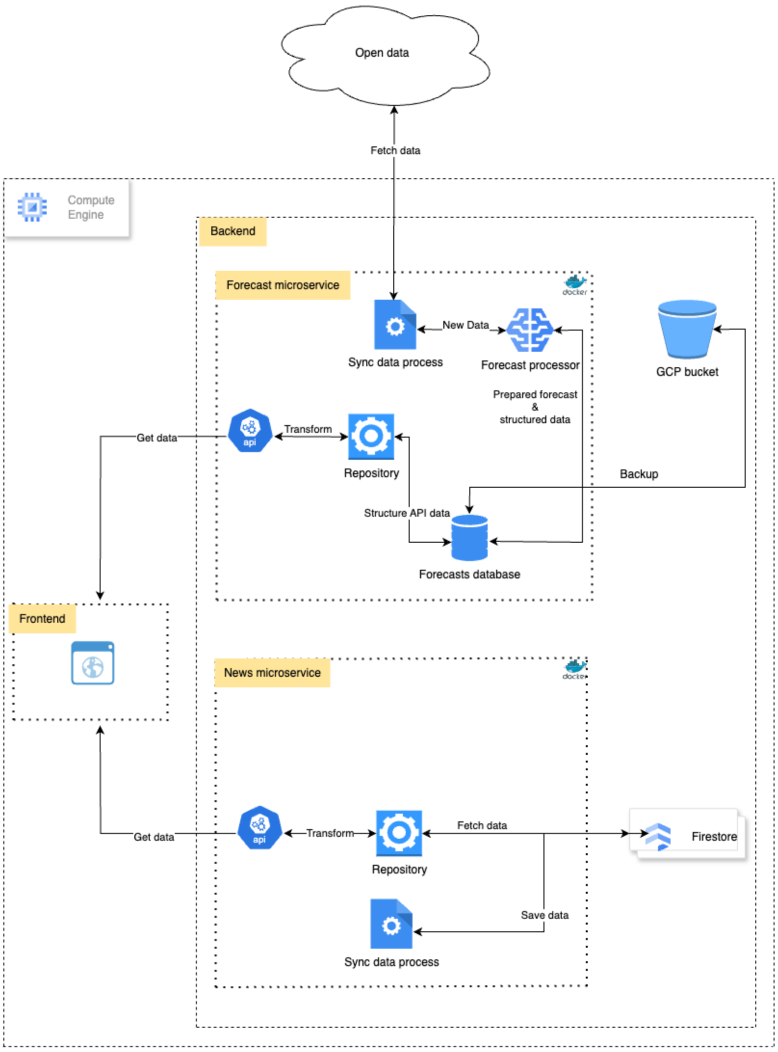

Figure 2: MIPS Architecture

PostgreSQL [18] was selected as the relational database for data storage since the MIPS requires both structured data and semi-structured data. Unstructured data includes raw information obtained from open sources. This data is processed and transformed into a format suitable for generating forecasts. The forecast itself is structured data produced as output and represented in the form of relational tables. The database schema consists of several unlinked tables, representing raw data for each specific category, along with separate tables where the processed forecasts are stored. Database schema presented in Figure 3.

Figure 3: MIPS DB schema

The user-facing web component (front-end) was implemented using HTML, CSS, and JavaScript. React [19] and Next.js [20] were chosen as the primary frameworks for the web portion of the system. This choice is justified by the potential need to expand the system with pages for each specific day since the start of the invasion. Next.js addresses this requirement by efficiently handling "page loading with required data," which minimizes server load and significantly improves the performance of the user interface.

3.4. Architecture and Technological Solutions

The MIPS interface is designed in a minimalist style [21] as a dashboard. Presenting the interface as a dashboard allows for the organization of a large amount of important information on a single page. The main goal of this user interface is to convey data to the user in the most accessible visual format possible, utilizing data visualization. Graphically represented data is much easier to interpret and understand, which, according to researchers, is particularly useful for general users interested in processed statistics. From a system analysis perspective, the MIPS presents semi-structured data in a structured format, enabling additional capabilities such as forecasting, trend analysis, and more.

The main MIPS interface consists of several components: a widget that provides a summary of data with an option to select the period (latest updates in the database, shown in Figure 4), graphical widgets for data aggregation by category and year in the form of bar and pie charts, and a prognostic widget that allows forecasting for the upcoming week.

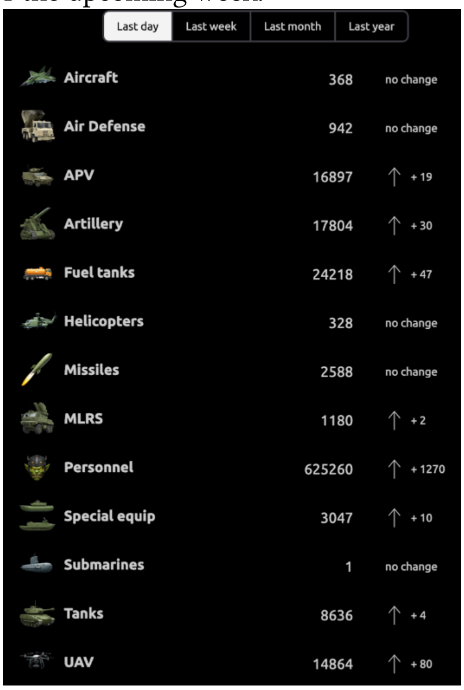

Figure 4: Data Summary Widget with Period Switching Capability

The central element of the interface is the graphical representation, allowing users to view both the available data and the forecast for each of the accessible categories (Figure 5). The graph for each category consists of two parts: the green line represents interpolated open data for each day, while the yellow line shows the forecast prepared using statistical models for the next 7 days. This type of visualization is valuable as it provides a broader view of the situation while utilizing the maximum amount of available data.

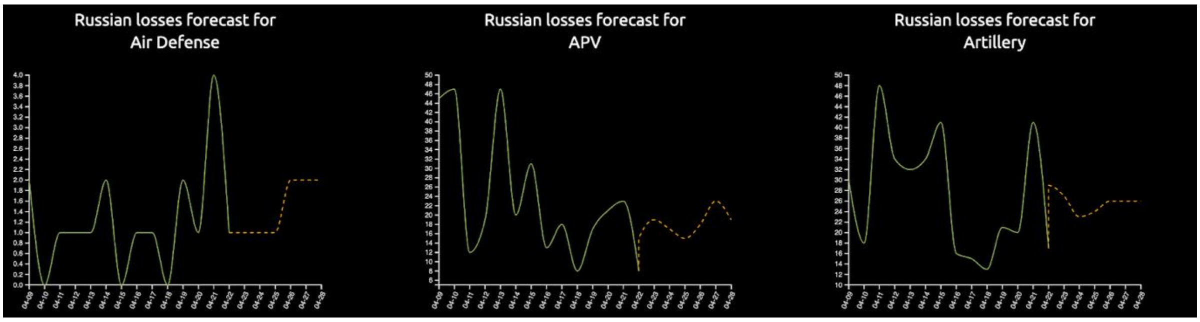

Figure 5: Forecast Display

Data aggregation is a separate component within the overall interface. This component focuses on the analysis of equipment units. The data aggregation section consists of two widgets: a pie chart for comparing losses by year across categories, and a bar chart for category analysis by year. Both widgets are useful for analysis from different perspectives and for examining specific situations. Examples are shown in Figure 6.

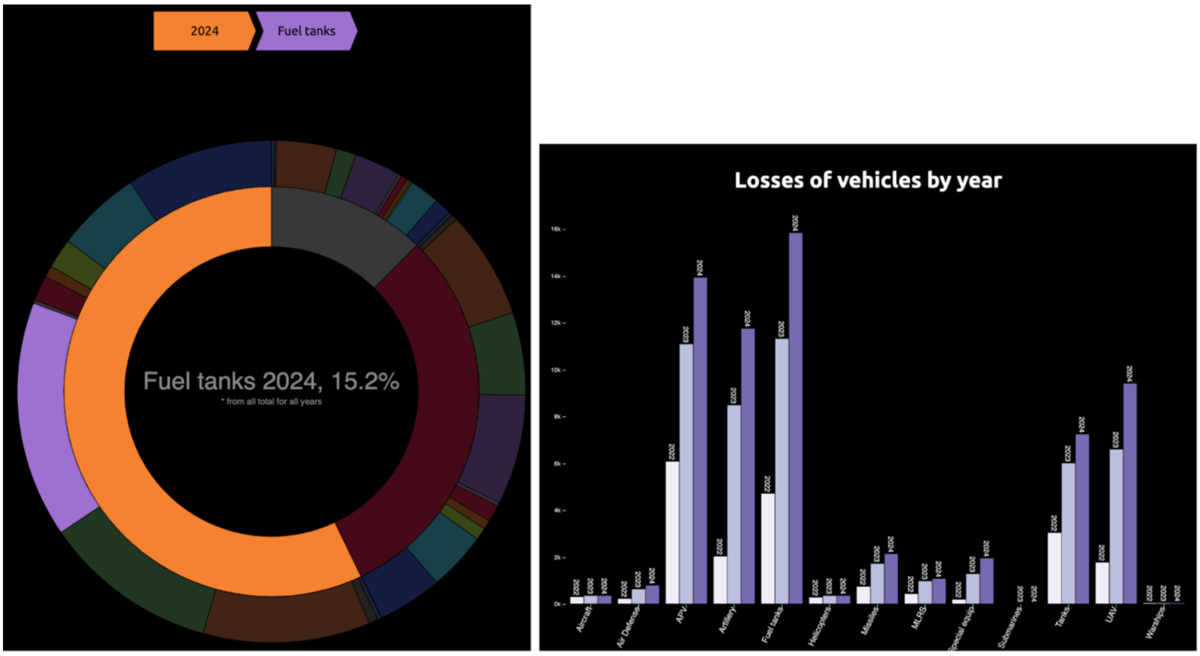

Figure 6: Data aggregation widgets

The data aggregation widgets are helpful when it comes to the long-term analysis (year-over-year comparison) or comparisons between different categories.

4. Mathematical framework

Since the primary goal of the MIPS is aggregation, visualization, analysis, and forecasting, specific concepts are proposed for comparing categories and evaluating the impact of various factors.

4.1. Metrics and Coefficients

During the analysis of data related to the outcomes of "actions" involving various means and their identified consequences, the introduction of specific indicators is proposed. An "action" refers to a particular set of actions and means employed by the adversary. To assess these actions, researchers suggest a hierarchical system of characteristics and indicators, forming the basis for two aggregated indicators: action power $PA(d)$, action impact $IA(d)$ and one integral indicator $E(V,p)$ – performance effectiveness over a selected period of time p based on the vehicle count V used during the action.

$PA(d)$ and $IA(d)$, as indicators characterizing a specific action, can serve as a basis for solving the challenges of forecasting future actions.

$PA(d)$ characterizes the quantity and quality of the means involved during the action, while $IA(d)$ – impacts that are characterized by the action. The formation of aggregated indicators is carried out by utilizing lower-level indicators, taking into account both their weight coefficients and their position in the hierarchy.

4.2. Action power

The action power is determined based on three main subcategories (Air Vehicles, Land Vehicles, Water Vehicles), each of which consists of its own subcategories and unit subtypes. A basic example of the hierarchical calculation scheme for this indicator is presented PA(d) is shown in Figure 7.

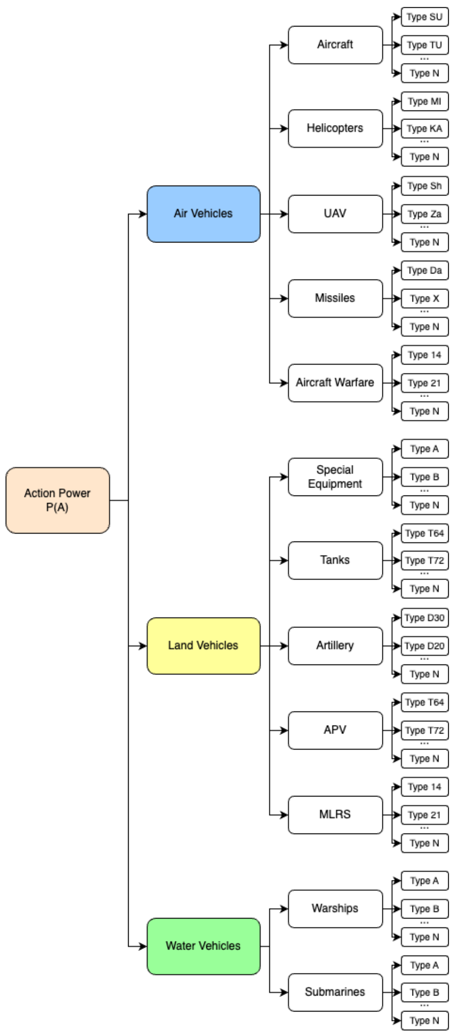

Figure 7: Hierarchical Clustering of Action Power

The power of an action is determined by the number of units of each type involved in the action, considering the weight coefficient of each subtype belonging to the higher-level type.

Let's define these sets as follows. Let's assume that V_{air} is a set of air units, in this case, V_{air} can be represented as the next set of categories:

$$V_{air} = \{Aircraft, Helicopters, UAV, Missiles, Aircraft\ Warfare\} \quad (2)$$

Using the example of subcategories, we will examine how a category is defined by the types of units:

$$Aircraft = TypeSU, TypeTU, \ldots, TypeN, UAV = TypeSh, TypeZa, \ldots \quad (3)$$

In a manner like $\boldsymbol{V_{air}}$, $\boldsymbol{V_{land}}$ and $\boldsymbol{V_{water}}$ are defined, each consisting of their respective subtypes.

$PA(d)$ – This is the total power of the action, calculated by summing the contributions of each set and its subsets, considering their weight coefficients, for the chosen date d. In this case $P(d,t)$ – represents the power of the action for each subtype t for the date d. Therefore $PA(d)$ can be defined by the following formula:

$$PA(d) = \sum_{v \in V_{air}} \sum_{t \in v} P(d,t) \cdot w(t) + \sum_{v \in V_{land}} \sum_{t \in v} P(d,t) \cdot w(t) + \sum_{v \in V_{water}} \sum_{t \in v} P(d,t) \cdot w(t) \quad (4)$$

where v represents the exact category of units (Tanks, MLRS), t – respective subtype (Type Sh, Type X), d – date, $w(t)$ – corresponding weight coefficients. Generalized $PA(d)$ sums the power of the action for each subtype in each category for the transportation units in the proposed domains V_{air}, V_{land}, V_{water}.

Separately, it is proposed to distinguish the concept of the **action power of an uncontrolled air action**. The power of an uncontrolled air action can be defined as the number of units of various types of UAVs or Missiles involved during the air action.

Let M – represent the set of units from the Missiles category, and U - UAV. An uncontrolled air action for a day d can be defined as:

$$PUA(d) = M(d) \cup U(d) \quad (5)$$

then, the power of an uncontrolled air action on a day d can be calculated as follows:

$$PUA(d) = \sum_{v \in \{M \cup U\}} \sum_{t \in v} P(d,t) \cdot w(t). \quad (6)$$

where both $P(d,t)$ and $w(t)$ have the same definition as for $PA(d)$ but respecting the fact there are dedicated categories (Missiles, UAV)

4.3. Action Impact

Researchers propose to introduce the concept of the action's impact. The impact of an action $IA(d)$ can be characterized as an integer value representing the action's power $PA(d)$ on a ten-point scale for the next branches b – civil infrastructure C, military infrastructure M, industrial infrastructure I, logistics L, and environment (ecology) M, assuming action's day d.

Let $Level(b,d)$ be the level of impact indicator for an action on a branch b, $w(b,d)$ – importance weight coefficient, defined based on the expert opinion. The level of impact can be evaluated on an interval scale from 1 to 10. The overall impact of the action can be calculated by summing the weighted impact levels for each branch.

$$IA(d) = \sum_{b \in \{C,M,E,L,I\}} Level(b,d) \cdot w(b,d) \tag{7}$$

where b – branch, $w(b,d)$ – the importance weight coefficient (if the importance is the same, the coefficient is identical for all domains), $Level(b,d)$ – level of impact, for branch b, for the day d. The values on the ten-point scale correspond to one of three proposed levels of impact: low, medium, and high. For visualization purposes, a gradient from green to red is suggested to enhance the presentation of information. An example of the hierarchical calculation scheme for the indicator $IA(d)$ is shown in Figure 8.

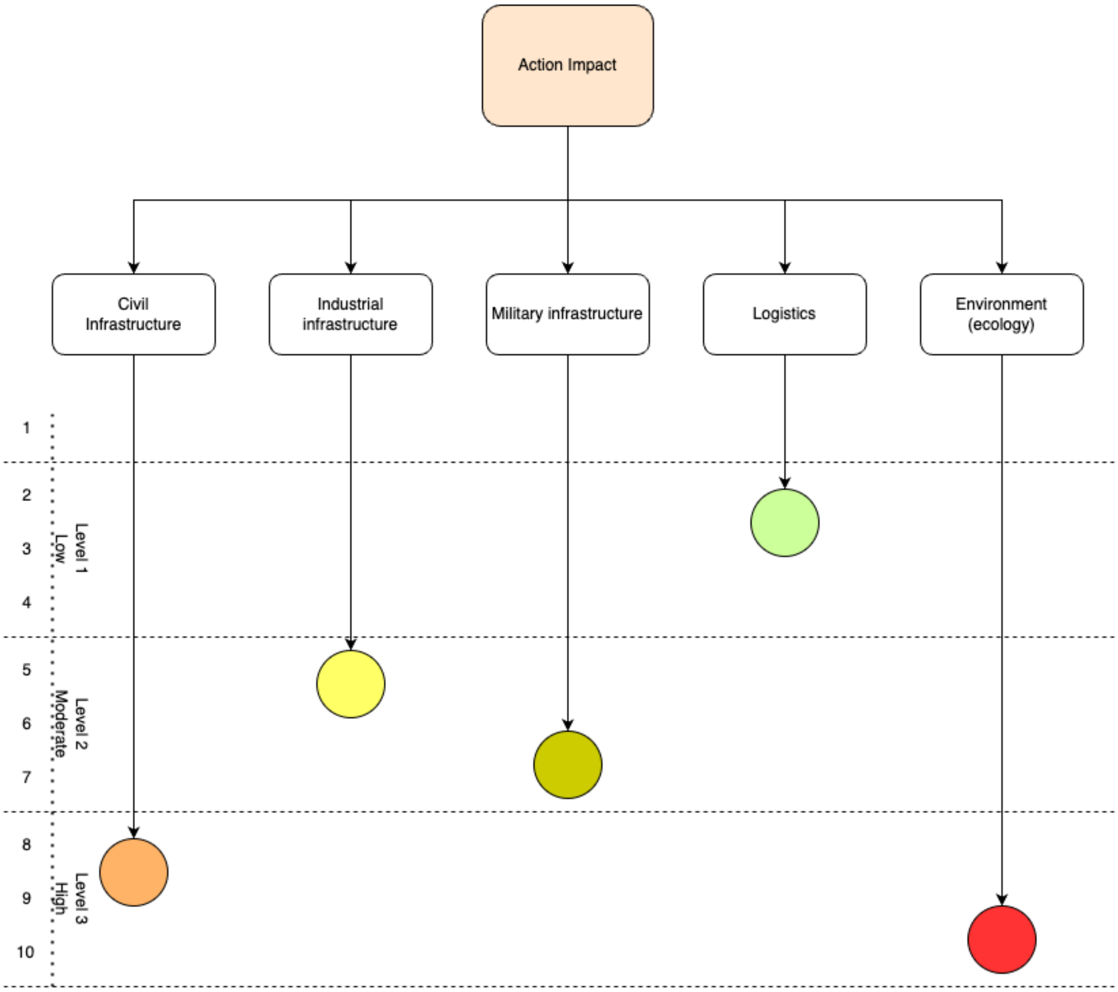

Figure 8: Visualization of the action impact indicator.

The proposed visualization allows easy comparison of the impacts of actions against each other and simplifies the influence analysis at the specific domains.

4.4. Performance Effectiveness

Performance effectiveness is an integral coefficient that characterizes the total number of critically damaged armored vehicles over a selected period. The primary purpose of measuring performance effectiveness is to compare the effectiveness of defensive actions across different periods. According to the researcher's opinion, annual metric is probably the most appropriate way of measurement.

Let's define $C = \{n1, .., n_K\}$ – set of all possible categories, K – their count and V_n – is the set of all affected units of equipment within a specific category where $n \in C$, p – period. Let's introduce $E(V, p)$ – performance effectiveness over period p. Then the total number of all affected units of equipment V will be the sum of the units from all categories over the period p :

$$E(V, p) = \sum_{n=1}^{N} V_n(p)\,,\ n \in C \tag{8}$$

Using the proposed formula, we can calculate the current performance in annual equivalents for the years 2022, 2023, and partially for 2024, with the aim of identifying trends and conducting a more representative analysis. The results of this measurement are displayed in the pie chart widget of the MIPS and in the computational experiment.

While the MIPS provides measurement and visualization of annual performance effectiveness, this parameter can also be utilized for other time intervals to enable more granular analysis. One can consider that the annual performance effectiveness consists of the sum of monthly performance effectiveness.

$$E(V, \text{year}) = \sum_{m=1}^{12} E(V, m) \tag{9}$$

where $E(V, m)$ – effectiveness per month m, where m =1,...,12.

4.5. Prognostic Mechanism

The core of the prognostic mechanism is based on the SARIMAX model, with coefficient selection performed for each data category. The choice of this model is justified by its ability to account for exogenous factors in addition to seasonal factors, unlike the SARIMA model [22].

Researchers note that both exogenous factors and seasonality appear in the data that the prognostic mechanism of such a system must handle. To illustrate the importance of this, we examine several examples of real categories. For the Missiles category, we can identify a seasonality of approximately 7 months between peaks of actions, where the count of units at these peaks remains relatively similar, forming a specific pattern visible even without the application of data processing techniques like differentiation of moving to the logarithmic scale. However, the most recent period (September 2024) reveals certain changes in seasonality (Figure 9).

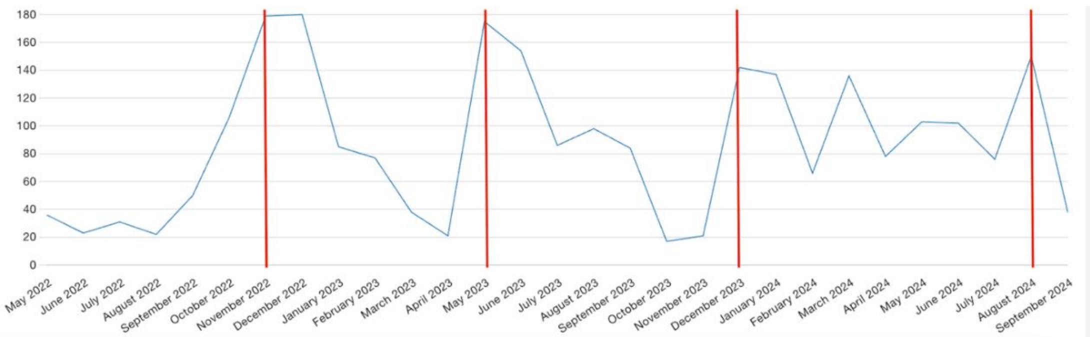

Figure 9: Seasonality example in the Missiles Category

Another example — the Fuel Tanks category — we can identify a trend and some distinct seasonality. During the autumn and winter periods, we observe consistency in the Fuel Tanks category, while activity in this category increases during other seasons. So, the seasonality is similar to that of the Missiles category, but in this case, we also see a clear trend (Figure 10).

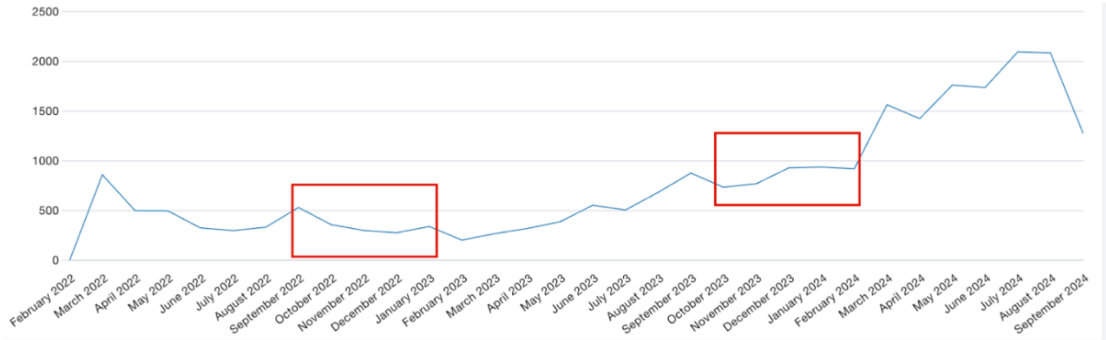

Figure 10: Seasonality in the Fuel Tanks Category

It is reasonable to consider the choice of a model that supports seasonality. The data analysis also revealed that the data, particularly in the Missiles category, exhibits exogenous characteristics. For instance, the provided graphs show a peak in March 2024, which is atypical. Therefore, it is essential to incorporate the exogeneity factor into the mathematical framework, making the SARIMAX model a justified choice in this case.

As of the time of writing the paper researchers are also considering alternative ways to organize the core of the mathematical mechanism. Since the data consists of multiple categories, we can treat it as multidimensional data and utilize a mathematical framework that operates with multidimensional time series with the assumption that different variables may correlate over time. For example, Bayesian Neural Networks (BNN) allow for a more detailed probabilistic interpretation of these relationships by examining the distribution of model parameters and their effects and correlations. This approach enables the identification of interdependencies among various parameters [23]. In the context of the MIPS tasks, using such a neural network would allow for analyzing interdependencies between categories and provide additional useful functionality.

5. Experimental research

Since the available open data currently lacks granular information segmented by subtype category, the experimental research was conducted using data from individual grouped categories. For instance, while information about specific types of UAVs is missing, the total number of UAVs is consistently available in the open data.

5.1. Action Power

Using the available data, we will calculate the power of some uncontrolled air actions in 2024, which will include both UAV types and Missile types. Table 1 displays the MIPS data for the period from January 1 to January 2, 2024, for two categories – UAVs and Missiles.

Table 1
MIPS Data for the Period January 1, 2024 – January 2, 2024, for the Categories UAV and Missiles

Timestamp	Count	Type
2024-01-01 00:00:00	0	Missiles
2024-01-01 00:00:00	66	UAV
2024-01-02 00:00:00	1	Missiles
2024-01-02 00:00:00	53	UAV

Each tuple contains the following data:

- Timestamp: Date and time of the event (specifically, the start of the day).

- Count: Number of units used in the corresponding category (UAV or Missiles).
- Type: Category (UAV or Missiles).

For example, on January 1, 2024, during the uncontrolled air action, no Missiles were involved, but 66 UAVs were deployed.

According to the results, we can see that uncontrolled air actions occurred during the interval from January 1 to January 2 and from January 2 to January 3. Since data on subtypes is not available at the moment, we will assume that the coefficient $w(t) = 1$, establishes the parity in impact between the categories. According to the proposed formula for calculating uncontrolled air actions, the value $PUA(01-02)$, is equal to 66, since in total there were 66 units used:

$$PUA(d) = \sum_{v\in\{M\cup U\}} \sum_{t\in v} P(d,t)\cdot w(t) = PUA(01-02) = 0\cdot 1 + 66\cdot 1 = 66 \quad (10)$$

Similarly, we can calculate $PUA(02-03)$ and obtain a result of 54 (53 + 1):

$$PUA(d) = \sum_{v\in\{M\cup U\}} \sum_{t\in v} P(d,t)\cdot w(t) = PUA(02-03) = 53\cdot 1 + 1\cdot 1 = 54 \quad (11)$$

5.2. Performance Effectiveness

To calculate the performance effectiveness for each year (2022, 2023, and the first 9 months of 2024), we will use the available data at the time of the experiment. Using the following formula, we will compute the annual performance for 2022, considering all units of equipment:

$$E(V, \text{year}) = \sum_{m=1}^{12} E(V,m) \quad (12)$$

Thus, the annual performance for 2022, 2023, and 2024 appears as follows:

$E(V, 2022 = 19{,}668)$; $E(V, 2022) = 48{,}614$; $E(V, 2022) = 95{,}78$.

Based on the results, we can say that, as of the time of writing this article, 2024 was 1.97 times more productive than 2023. Below is a graphical comparison of productivity based on the available data (Figure 11).

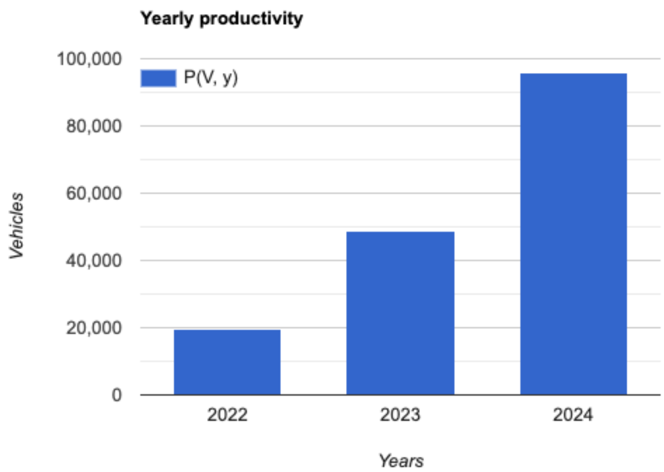

Figure 11: Results of the SARIMAX Predictive Model, Category MISSILES

5.3. Forecast Modelling

To determine the appropriate coefficients for the SARIMAX model capable of predicting the future power of potential uncontrolled air actions researches conducted an experiment. Let's examine the forecasting results using the SARIMAX models for the categories UAV and MISSILES (Figures 12 and 13, Table 2, Table 3).

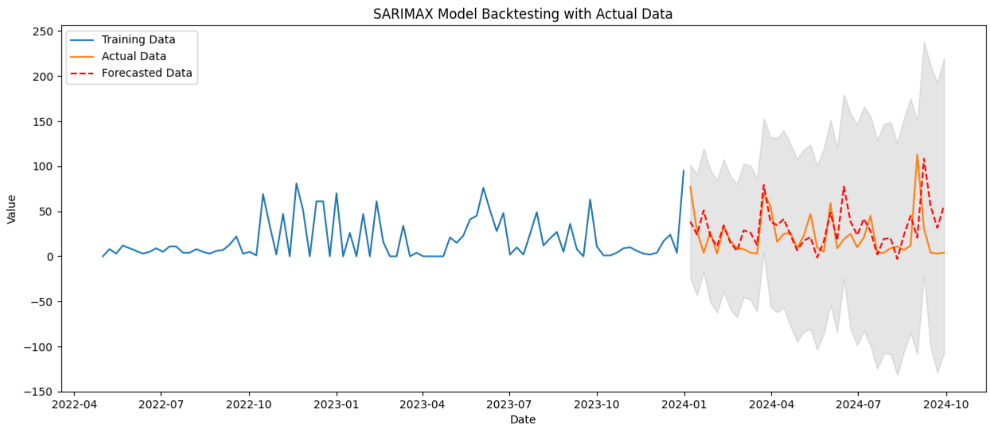

Figure 12: Forecast Results of the SARIMAX Model, Category MISSILES

Table 2

Coefficients of the SARIMAX Model for the Category MISSILES

Dep. Variable	Value	No. Observations	88
Model	SARIMAX(6, 1, 2)x(2, 2, 2, 12)	Log Likelihood	-163.342
Date	Mon, 30 Sep 2024	AIC	352.683
Time	20:53:20	BIC	372.138
Sample	05-01-2022 - 12-31-2023	HQIC	359.229

This table provides the technical specifications and quality assessments of the SARIMAX model used for forecasting the MISSILES category. The following notations have been used here:

- **Dep. Variable:** The dependent variable being forecasted (not specified, but this could be the number of units of equipment or similar data).
- **No. Observations:** The number of observations is 88, indicating the volume of historical data used to train the model.
- **Model:** Parameters of the SARIMAX model: (6, 1, 2) the ARIMA part that defines autoregression, differencing, and moving average; (2, 2, 2, 12) — the seasonal component of the model with a periodicity of 12 (year).
- **Log Likelihood:** The logarithm of the model's likelihood (-163.342), which indicates how well the model fits the data; higher values indicate better fit.
- **AIC (Akaike Information Criterion):** 352.683 — a metric that considers model fit quality and complexity. Lower values indicate a better model.
- **BIC (Bayesian Information Criterion):** 372.138 — similar to AIC but with a stricter penalty for model complexity.
- **HQIC (Hannan-Quinn Information Criterion):** 359.229 — another criterion for model evaluation.
- **Sample:** The time frame for the data used to train the model (January 5, 2022 - December 31, 2023).

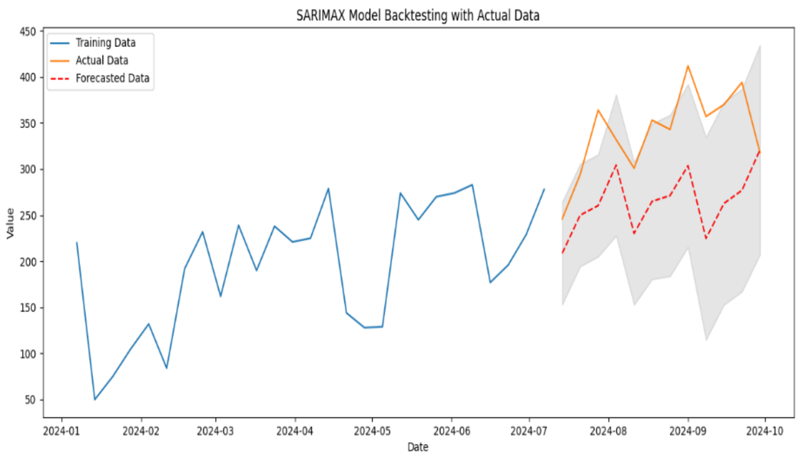

Figure 13: Forecast Results of the SARIMAX Model, Category UAV

Table 3
Coefficients of the SARIMAX Model for the Category UAV

Dep. Variable	Value	No. Observations	88
Model	SARIMAX(2, 1, 9)x(1, 1, [], 4)	Log Likelihood	-60.231
Date	Mon, 30 Sep 2024	AIC	146.461
Time	21:19:40	BIC	152.765
Sample	01-07-2024	HQIC	144.127

6. Conclusions

Hierarchical aggregated indicators have been proposed for assessing the designated type of actions, evaluating their effectiveness and power based on various categories of data. The indicators introduced include the action power $PA(d)$, impact of action $IA(d)$, performance effectiveness $E(V,p)$.

The tasks and principles for building information and analytical tools to support decision-making in the analysis and forecasting of the designated type of actions have been examined. Time series that characterize the dynamics of actions have been analyzed, which justified the use of the implemented mathematical forecasting tools to address the challenges of this type.

The proposed mathematical framework serves as the foundation for creating an original software information and forecasting system, the MIPS, designed for aggregating, visualizing, analyzing, and forecasting data and events related to the specified actions.

A computational experiment demonstrated both the practical applicability of the current version of the system and its potential for future development and implementation.

The proposed MIPS system can be used as an intelligent component of integrated systems for analyzing data on the current socio-economic situation and predicting its development [24].

Future plans for the system include the following areas: aggregating data from various types of information sources (analytical websites, government websites, expert opinions, social networks), integrating additional databases and knowledge bases, improving existing and developing new models in scope of mathematical framework, analytical instruments, and information technologies for analyzing diverse types of data.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] Coscieme, L., Sutton, P. C., Anderson, S., Liu, Q., & Elvidge, C. D. (2017). Dark times: nighttime satellite imagery as a detector of regional disparity and the geography of conflict. GIScience & Remote Sensing, 54(1), 118-139.

[2] Zimbra, D., Abbasi, A., Zeng, D., & Chen, H. (2018). The state-of-the-art in Twitter sentiment analysis: A review and benchmark evaluation. ACM Transactions on Management Information Systems (TMIS), 9(2), 1-29.

[3] Williams, H. J., & Blum, I. (2018). Defining second generation open source intelligence (OSINT) for the defense enterprise. Santa Monica: Rand Corporation.

[4] Taylor SJ, Letham B. 2017. Forecasting at scale. PeerJ Preprints 5:e3190v2 https://doi.org/10.7287/peerj.preprints.3190v2

[5] Tanim, S. A., Khan, M., Prity, F. S., Tanvir, K., & Raju, V. (2023). An in-Depth Analysis of Military Casualties: Predicting Russian Losses in the Russia-Ukraine Conflict.1. Obendorf, H. (2009).

[6] Zammit-Mangion, A., Dewar, M., Kadirkamanathan, V., & Sanguinetti, G. (2012). Point process modelling of the Afghan War Diary. Proceedings of the National Academy of Sciences, 109(31), 12414-12419.

[7] Braun, A. (2018). Assessment of building damage in Raqqa during the Syrian civil war using time-series of radar satellite imagery. GI_Forum, 1(1), 228-242.

[8] Perry, C. (2013). Machine learning and conflict prediction: a use case. Stability: International Journal of Security and Development, 2(3), 56.

[9] Schrodt, P. A. (2006). Forecasting conflict in the Balkans using hidden Markov models. In Programming for peace: Computer-aided methods for international conflict resolution and prevention (pp. 161-184). Dordrecht: Springer Netherlands.

[10] Malone, I. (2022). Recurrent neural networks for conflict forecasting. International Interactions, 48(4), 614-632.

[11] Graffelman, J., & Hoekstra, R. F. (2000). A statistical analysis of the effect of warfare on the human secondary sex ratio. Human Biology, 433-445.

[12] Obendorf, H. (2009). Minimalism: designing simplicity. Springer Science & Business Media.

[13] Singh, H., & Hassan, S. I. (2015). Effect of solid design principles on quality of software: An empirical assessment. International Journal of Scientific & Engineering Research, 6(4), 1321-1324.

[14] Al-Debagy, O., & Martinek, P. (2018, November). A comparative review of microservices and monolithic architectures. In 2018 IEEE 18th International Symposium on Computational Intelligence and Informatics (CINTI) (pp. 000149-000154). IEEE.

[15] Vaño, R., Lacalle, I., Sowiński, P., S-Julián, R., & Palau, C. E. (2023). Cloud-native workload orchestration at the edge: A deployment review and future directions. *Sensors*, *23*(4), 2215.

[16] De Lauretis, L. (2019, October). From monolithic architecture to microservices architecture. In 2019 IEEE International Symposium on Software Reliability Engineering Workshops (ISSREW) (pp. 93-96). IEEE.

[17] Jindal, A., Emani, K. V., Daum, M., Poppe, O., Haynes, B., Pavlenko, A., ... & Patel, H. (2021, February). Magpie: Python at Speed and Scale using Cloud Backends. In CIDR.

[18] Raschka, S., Patterson, J., & Nolet, C. (2020). Machine learning in python: Main developments and technology trends in data science, machine learning, and artificial intelligence. Information, 11(4), 193.

[19] Douglas, K., & Douglas, S. (2003). PostgreSQL: a comprehensive guide to building, programming, and administering PostgresSQL databases. SAMS publishing.

[20] Aggarwal, S. (2018). Modern web-development using reactjs. International Journal of Recent Research Aspects, 5(1), 133-137.
[21] Lazuardy, M. F. S., & Anggraini, D. (2022). Modern front end web architectures with react. js and next. js. Research Journal of Advanced Engineering and Science, 7(1), 132-141.
[22] Alharbi, F. R., & Csala, D. (2022). A seasonal autoregressive integrated moving average with exogenous factors (SARIMAX) forecasting model-based time series approach. Inventions, 7(4), 94.
[23] Izmailov, P., Vikram, S., Hoffman, M. D., & Wilson, A. G. G. (2021, July). What are Bayesian neural network posteriors really like?. In International conference on machine learning (pp. 4629-4640). PMLR.
[24] Hulianytskyi L., Malyshko S. (2016), Big Data in Information Analytical System "NEWSCAPE". In: Data Stream Mining&Processing. Proc. of the 2016 IEEE First International Conference on Data Stream Mining&Processing (23-27 August 2016, Lviv, Ukraine). Lviv, 2016: 382–386.