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MODELLING THE VULNERABILITY OF THE RUSSIAN FEDERATION'S MILITARY CAPABILITIES USING TOPSIS

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Abstract: *The present article proposes a quantitative model for assessing the vulnerability of the russian federation's military potential in 2022–2025, utilising multi-criteria decision-making methods. A comprehensive set of monthly data pertaining to 13 indicators was retrieved from publicly accessible sources. These indicators encompassed 12 categories of weapons and equipment losses, in addition to personnel losses. The retrieved data underwent a rigorous processing procedure, utilising the TOPSIS method within the PyMCDM library. Five objective weighting schemes are applied — uniform, entropy-based, standard deviation, coefficient of variation, and statistical dispersion — to reflect alternative views on the importance of indicators and to verify the reliability of the comprehensive vulnerability index. The data obtained using TOPSIS is subsequently scaled by the ratio of military expenditure to GDP to obtain a budget-adjusted vulnerability index that reflects both battlefield losses and financial stability. A sensitivity analysis of key indicators (UAVs, MLRS, missiles) reveals that the index remains stable when indicators are removed for most weighting methods, with only entropy weights demonstrating a more pronounced response to missile losses. The findings of the simulation scenarios for three prospective configurations of UAV stocks and defence budgets demonstrate a clear correlation between increased investment in unmanned systems and a larger share of the budget on the one hand, and significantly lower vulnerability on the other. In contrast, simultaneous reductions in UAVs and the budget lead to the highest levels of vulnerability. It is evident that the proposed index provides a transparent, policy-relevant instrument for the purpose of tracking structural military vulnerability over time. Furthermore, it has the capacity to stress test alternative force structures and funding scenarios, in addition to supporting evidence-based defence planning.*

Key words: *TOPSIS vulnerability modelling, objective weighting methods, military capability, defense budget, Russo-Ukrainian war.*

Артюшенко О., Асроров Ф., Терещенко Є., Тимошенко Д., Коваль О. Моделювання вразливості військового потенціалу рф методом TOPSIS. Соціально-економічні проблеми і держава. 2025. Вип. 2 (33). С. 166-180. URL: http://sepd.tntu.edu.ua/images/stories/pdf/2025/25aoocut.pdf

1. Statement of the Problem.

The full-scale invasion of Ukraine by russia has resulted in an accumulation of losses with regard to both personnel and equipment. In addition, there has been a rapid reorganisation of defence budgets and armed forces structures. An examination of open statistical data pertaining to losses, in conjunction with independent assessments, suggests that the russian federation has sustained comparable levels of casualties and damage to infrastructure as observed in major conflicts of the 20th century. Concurrently, the Kremlin has implemented an escalation in defence expenditures and a recalibration of its mobilisation strategy. In such circumstances, the assessment of both the magnitude of losses and their structural impact on military capabilities has become a pivotal task for defence analysts and planners.

Thus, deliberations concerning defence expenditure in Europe underscore that the efficacy of military expenditure is contingent upon the allocation of resources to pivotal domains of capability, as opposed to being solely dependent on the aggregate budgetary allocation. Recent studies of military sector efficiency demonstrate that, despite budgetary increases, significant discrepancies in capability can persist if investments fail to meet operational requirements. For Ukraine and its partners, this shift in focus entails a transition from the examination of overall russian expenditure and loss figures to the interrogation of structural vulnerability. This involves the identification of the components of capability that are most vulnerable, the investigation of how vulnerability changes over time, and the analysis of how it responds to alternative scenarios of resources and force structure.

Multi-criteria decision-making (MCDM) methods, in particular TOPSIS, offer a natural framework for constructing comprehensive vulnerability indices based on heterogeneous indicators. The TOPSIS method has been successfully applied to assess the vulnerability and resilience of systems in areas such as natural disaster risk management, infrastructure protection, and national security capability assessment. In such cases, it is necessary to combine numerous, often conflicting criteria into an interpreted ranking or time series. However, extant studies generally rely on a single weighting scheme and provide limited analysis of how alternative objective weights and indicator sets affect vulnerability scores. This is a critical issue when the underlying data are variable and partially uncertain, as in the case of wartime casualty statistics.

The present article addresses these gaps by developing a vulnerability index for the russian federation's military capabilities for 2022–2025 based on TOPSIS, constructed from monthly data on personnel and equipment losses and adjusted for the share of military expenditure in GDP. The model integrates 13 indicators and employs five objective weighting schemes – equal, entropy, standard deviation, coefficient of variation, and range-based variance – to explore how different perceptions of indicator importance shape the final vulnerability trajectories. Furthermore, the study conducts 'leave one out' sensitivity tests for key systems (UAVs, MLRS, missiles) and develops forward-looking scenarios that change UAV stocks and budget levels, thereby linking observed loss dynamics to forward-looking models of structural vulnerability

2. Analysis of recent research and publications.

Recent studies have confirmed the extensive utilisation of TOPSIS for quantitative vulnerability assessment in complex systems, including logistics, infrastructure, and security-sensitive areas. For instance, Xu employs TOPSIS within a comprehensive MCDM framework to evaluate vulnerability in emergency supply chains, thereby demonstrating the efficacy of multi-indicator vulnerability indices in identifying critical periods and vulnerable links in response networks (Xu, W., Lu, Y., & Proverbs, D., 2024). Peng develops a TOPSIS-based vulnerability assessment for cultural heritage sites, combining it with clustering to classify vulnerability levels (Peng, N., et al, 2024). This demonstrates the capacity of TOPSIS to transform heterogeneous risk indicators into a temporal vulnerability profile, which is methodologically analogous to the monthly index constructed in this study. In addition, recent reviews have emphasised the popularity of TOPSIS due to its geometric intuition, its capacity to manage benefit and cost criteria, and its ease of integration with other MCDM tools (Ahuja, H., et al, 2024; Atenidegbe, O. F., & Mogaji, K. A., 2023). However, these reviews have also cautioned about its sensitivity to weighting schemes and normalisation choices.

The selection of objective weights is paramount for the establishment of data-driven vulnerability indices. A comparative analysis conducted by Mukhametzyanov et al. demonstrates that entropy, standard deviation, and related dispersion-based methods can produce significantly different weight vectors (Mukhametzyanov, I., 2021). This suggests that these methods may be conceptually misused if applied mechanically. The analysis therefore suggests the use of multiple objective schemes and comparison of their results rather than reliance on a single method. Recent methodological developments have also proposed hybrid objective weighting approaches, such as the IQRBOW-E method, which combines interquartile range with entropy using a tunable parameter to improve reliability in the presence of outliers and data irregularities. Babaei et al. present novel weighting methods based on variance and deviation from the mean, and compare these with classical Shannon entropy (Babaei, H., Mohammadi, S., & Ghaneai, H., 2025). The authors illustrate how sensitivity to weight variability can amplify critical but unstable criteria in decision-making models. The present works serve to corroborate the concepts outlined in this article, wherein levels, entropies, standard deviations, coefficients of variation, and range-based weights are applied to a uniform set of loss data, with the objective of ascertaining the impact of alternative objective concepts of 'importance' on the vulnerability index (Erbey, A., Fidan, Ü., & Gündüz, C., 2025).

An increasing number of literature sources emphasise the necessity for a systematic assessment of the sensitivity of MCDM results, particularly in conditions of changing weights and sets of indicators. Nabavi et al. propose a structured system for assessing the sensitivity of multi-criteria methods, emphasising that weights based on standard deviation are particularly useful for identifying targets whose variability leads to instability in the ranking (Gómez-Castro, F. I., & Rico-Ramírez, V., 2025). Ogunnusi's analysis corroborates the efficacy of the TOPSIS-based decision-making tool by examining the alterations in ranking when the weights of criteria or alternatives are modified (Ogunnusi, M., Omotayo, T., & Akponeware, A., 2025). He further asserts that a stable ranking with reasonable fluctuations is a prerequisite for its utilisation in policy. Concurrently, industry applications of TOPSIS, such as the assessment of natural disaster risks, infrastructure and defence capabilities, frequently integrate TOPSIS with scenario analysis to explore 'what if' changes in key indicators. This corresponds to the utilisation of 'leave one out' tests and predictive scenarios for UAV configurations and budgets in this study. Considering the context, the present article contributes by integrating five objective weighting methods, explicit 'leave one out' tests for indicators, and budget-aware scenario modelling into a unified TOPSIS framework adapted to military vulnerability.

3. Task Formulation.

The purpose of this study is to construct and analyse a multi-criteria vulnerability index of the russian federation's military potential for 2022–2025, considering the budget, using the TOPSIS method and objective weighting schemes.

Research objectives:

The objectives of the study are as follows:

1. To create a monthly data array on the losses of russian military personnel and equipment, as well as defence budget indicators for 2022–2025. In addition, the study will select 13 relevant criteria for assessing vulnerability.

2. The TOPSIS method is to be applied with five objective weighting schemes (equal,

entropy, standard deviation, coefficient of variation, and variance) to obtain a comprehensive vulnerability index over time.

3. The TOPSIS-based index is to be adapted to consider the share of military expenditure in GDP, thereby obtaining a budget-scaled indicator of military vulnerability.

4. A sensitivity analysis, incorporating 'leave one out' tests for key indicators (UAVs, MLRS, missiles), should be conducted to assess the index's robustness to changes in criteria and weights.

5. A scenario analysis should be conducted for alternative future configurations of UAV losses and defence budgets. The impact of these configurations on the vulnerability index should then be assessed.

4. Main Research Results.

The following section will verify the hypothesis: “Losses of weapons and military equipment affect rf's military capabilities, considering the size of the military budget”.

First, we must develop and apply a comprehensive military capability vulnerability index to assess the structural vulnerability of the rf’s military capabilities between 2022 and 2025, based on its losses during the war. The study introduces a multifactorial sensitivity–adaptability model that quantitatively measures a country’s economic sensitivity to losses of personnel, weapons and equipment in the military. The model integrates 12 armament and equipment indicators and one personnel indicator, applying five weighting methods (uniform, entropy, standard deviation, statistical dispersion and coefficient of variation) combined through the TOPSIS method within a PyMCDM Python framework. The rf's military budget acts as a contextual scaling variable, calibrating the overall vulnerability index against fiscal resilience.

During our research, we use objective weighting methods. The first method we use is Uniform (Equal) Weights. This method played a key role in our modelling, providing a simple, transparent and reproducible weighting structure for all criteria (military capability indicators) in the TOPSIS-based vulnerability index. [5].

Let x_{ij} denote the performance of alternative i under criterion j.

$$w_j = \frac{1}{n}, \tag{1}$$

where n=number of criteria.

Using equal weights as part of the TOPSIS modelling process enables transparent, fair and replicable quantitative assessments of military capability vulnerability. This supports both rigorous academic analysis and practical policy communication.

Next, we use entropy weights. These provide an objective, data-driven measure of criterion importance based on the degree of informational diversity or dispersion in our dataset. Thus, the first step is to normalise our dataset:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=n}^{m} x_{ij}}, \tag{2}$$

where p_{ij} is the normalized value (proportion) of criterion j for alternative (or observation) i;

x_{ij} is the original value of criterion j for alternative (or observation) i.

In our military capability modelling, this is the loss count for a specific type of equipment or variable in a given period; $\sum_{i=n}^{m} x_{ij}$ is the sum of all observed values of criterion j across alternatives or all time periods under consideration (from observation n to m). This denominator provides the basis for normalization; n and m is the range of the summation, typically from the first to the last observation or alternative considered.

Then we need to calculate the entropy. The formula below represents the entropy value (E_j) for criterion j, which is fundamental to calculating entropy weights in multi-criteria decision analysis:

$$E_j = -k \sum_{i=n}^{m} p_{ij} \ln\left(p_{ij}\right), k = \frac{1}{\ln m}, \tag{3}$$

where E_j is the entropy measure for criterion j, reflecting the information content or disorder within that criterion across all observations;

k is a normalization constant to ensure the entropy value ranges between 0 and 1, calculated as $k = \frac{1}{\ln m}$ where m is the total number of observations;

p_{ij} is the normalized value (proportion) of criterion j for observation i, previously calculated as the share of x_{ij} in the total for criterion j;

ln (p_{ij}) is the natural logarithm of the proportion.

Next formula calculates the entropy weight (w_j) for criterion j—a fundamental step in the entropy-based weighting method used in our modelling:

$$w_j = \frac{1-E_j}{\sum_{j=1}^{n}\left(1-E_j\right)}, \tag{4}$$

where w_j is the normalized weight assigned to criterion j;

E_j is the entropy value for criterion j;

n is the total number of criteria.

Using entropy weights in our modelling added a layer of data-driven prioritization, allowing our vulnerability index to dynamically reflect which military losses or budget changes are most "informative" or critical in real operational terms [6]. This strengthens both the analytical power and policy relevance of our findings.

Next we use Standard Deviation Method. This method determines the weights of the criteria in terms of their standard deviations, which assigns small weights to criteria, if it has similar criteria values across alternatives [7].

Standard Deviation of Criterion j (σ_j):

$$w_j = \frac{\sigma_j}{\sum_{j=1}^{n} \sigma_j}, \tag{5}$$

where σ_j is the standard deviation for criterion j;

x_{ij} is the observed value of criterion j for alternative (or time point) i;

$\bar{x}_j$ is the mean value of criterion j across all m observations;

m is the total number of observations.

Standard Deviation Weight for Criterion j (w_j):

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}\left(x_{ij}-\bar{x}_j\right)^2}{m}}, \tag{6}$$

where w_j is the normalized weight of criterion j, ensuring that the sum of weights for all n criteria is equal to 1;

σ_j is the standard deviation of criterion j.

The employment of standard deviation as a weighting method was instrumental in enhancing the efficacy of our modelling. This approach entailed the allocation of greater weight to volatile and variable military loss indicators, thereby acknowledging their elevated influence on overall vulnerability. This approach complements other weighting methods and enhances the robustness and interpretability of our quantitative vulnerability index.

In the subsequent stage of the analysis, the coefficient of variation is utilised. The Coefficient of Variation (hereinafter—CV) is a measure of variability that is standardized, thus balancing out the effects of scale and mean differences among criteria:

$$w_j = \frac{CV_j}{\sum_{j=1}^{n} CV_j} \tag{7}$$

$$CV_j = \frac{\sigma_j}{\bar{x}_j}, \tag{8}$$

where w_j is the normalized weight assigned to criterion j, reflecting its relative importance in the analysis;

CV_j is the coefficient of variation for criterion j, calculated as the ratio of the standard deviation (σ_j) to the mean ($\bar{x}_j$) of criterion j;

σ_j is the standard deviation for criterion j, measuring the spread or variability of observations;

$\bar{x}_j$ is the mean (average) value of criterion j over all observations.

The employment of the coefficient of variation enhanced the vulnerability modelling by introducing an objective, normalised measure of indicator dispersion. This enabled the model to reflect not only the extent to which military capabilities vary, but also the significance of these variations relative to their typical levels. Consequently, this enhanced the accuracy of risk assessments and the relevance of policies.

Furthermore, statistical dispersion was utilised as the objective weighting method. The primary function of the CV in the military capability assessment was to quantify the relative variability of each indicator. This measure facilitates the identification of capabilities that exhibit larger fluctuations relative to their mean, thereby highlighting their importance or risk in dynamic situations.

$$w_j = \frac{R_j}{\sum_{j=1}^{n} R_j} \tag{9}$$

$$R_j = \max(x_{ij}) - \min(x_{ij}), \tag{10}$$

where R_j is the range of criterion j across all observations; max (x_{ij}) is the maximum value observed for criterion j;

w_j is the normalized weight for criterion j based on its range.

In the following section, it is essential to acknowledge the employment of the TOPSIS method in our military capability vulnerability assessment. This method is a widely recognised, robust, and practical multi-criteria decision-making (MCDM) technique. It is particularly well-suited to the comparison of complex alternatives evaluated across multiple diverse criteria.

Normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \tag{11}$$

where r_{ij} is the normalized (vector normalized) value of criterion j for alternative i;
x_{ij} is the original value of criterion j for alternative i;
m is the total number of alternatives.

Weighted normalization:

$$v_{ij} = w_j \times r_{ij}, \tag{12}$$

where v_{ij} is the weighted and normalized value of criterion j for alternative i. This is the final value that enters the decision matrix for further steps in TOPSIS. w_j is the weight assigned to criterion j, determined by methods like equal weights, entropy, standard deviation, coefficient of variation, or statistical dispersion. r_{ij} is the normalized value of criterion j for alternative i, calculated via vector normalization.

Determine ideal solutions:

$$A^+ = \{\max(v_{ij}) \big| j \in J_{benefit}; \min(v_{ij}) \big| j \in J_{cost}\} \tag{13}$$

$$A^- = \{\min(v_{ij}) \big| j \in J_{benefit}; \max(v_{ij}) \big| j \in J_{cost}\}, \tag{14}$$

where v_{ij} is weighted and normalized value for criterion j and alternative i;
$J_{benefit}$ is the set of criteria for which higher values are preferable;
J_{cost} is the set of criteria for which lower values are preferable;
max (v_{ij}) is the highest value of v_{ij} for criterion j across all alternatives;
min (v_{ij}) is the lowest value of v_{ij} for criterion j across all alternatives.

Separation measures:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^+\right)^2} \tag{15}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^-\right)^2}, \tag{16}$$

where S_i^+ is the Euclidean distance from alternative i to the positive ideal solution (A^+), across all criteria j;
S_i^- is the Euclidean distance from alternative i to the negative ideal solution (A^-), across all criteria j;
v_{ij} is the weighted, normalized value of criterion j for alternative i;
A_j^+ and A_j^- are positive and negative ideal values for criterion j, respectively;
n: is the total number of criteria.

Closeness Coefficient and Ranking:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}, \tag{17}$$

where CC_i is the closeness coefficient for alternative (e.g., month, unit, or scenario) i;
S_i^+ is the Euclidean distance from alternative i to the positive ideal solution (A^+), representing the “best” possible state;
S_i^- is the Euclidean distance from alternative i to the negative ideal solution (A^-), representing the “worst” possible state.

Subsequently, an integration with the military budget must be performed. Each vulnerability index $V_i$can be adjusted for fiscal resilience. This formula adjusts the final vulnerability index based on the proportion of military budget to GDP (military expenditures), providing an economically normalized capability index:

$$V_i^* = V_i \times \frac{1}{B_i/GDP} \tag{18}$$

where V_i^* is the adjusted vulnerability index for period (or alternative) i, scaled for economic context;

V_i is the original TOPSIS-based vulnerability index (closeness coefficient) for period i before economic adjustment;

B_i is the value of the military budget for period i;

GDP is a Gross Domestic Product, representing the total economic output;

B_i/GDP (military expenditures) is the share of military budget in GDP for period i;

$\frac{1}{B_i/\text{GDP}}$ is the inverse of the budget-to-GDP ratio, used to scale the vulnerability index.

Tye formula above rescales the military vulnerability score by how much of the national economy is allocated to defense.

The formula for V_i—military capability vulnerability index—is the TOPSIS closeness coefficient:

$$V_i = CC_i = \frac{S_i^-}{S_i^+ + S_i^-}, \tag{19}$$

where V_i is the original TOPSIS-based vulnerability index for alternative i;

S_i^+ is the Euclidean distance from alternative i to the positive ideal solution (best capability scenario);

S_i^- is the Euclidean distance from alternative i to the negative ideal solution (worst capability scenario).

Thus, V_i quantifies how close each alternative is to the ideal solution—higher values indicate lower vulnerability (closer to best-case), while lower values indicate greater vulnerability (closer to worst-case). So, V_i is calculated directly with the TOPSIS closeness coefficient formula above and then used for further transformations or scaling, as in military expenditures adjustment [8].

As previously indicated, Python has been identified as the primary language of choice for our modelling process. The PyMCDM Framework is utilised for the implementation of the TOPSIS method. The system also facilitates the execution of structured, mathematical decision analysis with multiple metrics or indicators. Furthermore, the system incorporates automated weighting and ranking functions.

In the subsequent phase of the procedure, we proceeded with the importation of weighting modules, including both Entropy_Weights and Equal_Weights. These functions are predefined objective weighting functions (Entropy for information-theoretic weighting; Equal for uniform baseline). Furthermore, we defined our custom weight functions to complement the model: The third factor is referred to as 'std_weights', which is an abbreviation for 'standard deviation'. The fourth factor is referred to as 'cv_weights', which is an abbreviation for 'coefficient of variation'. The fifth factor is referred to as 'dispersion_weights', which is an abbreviation for 'range or spread-based'.

The extraction of features for modelling purposes results in a modelling matrix comprising 44 periods (months) × 13 indicators, facilitating the implementation of objective weighting and the execution of the TOPSIS analysis (see Figure 1).

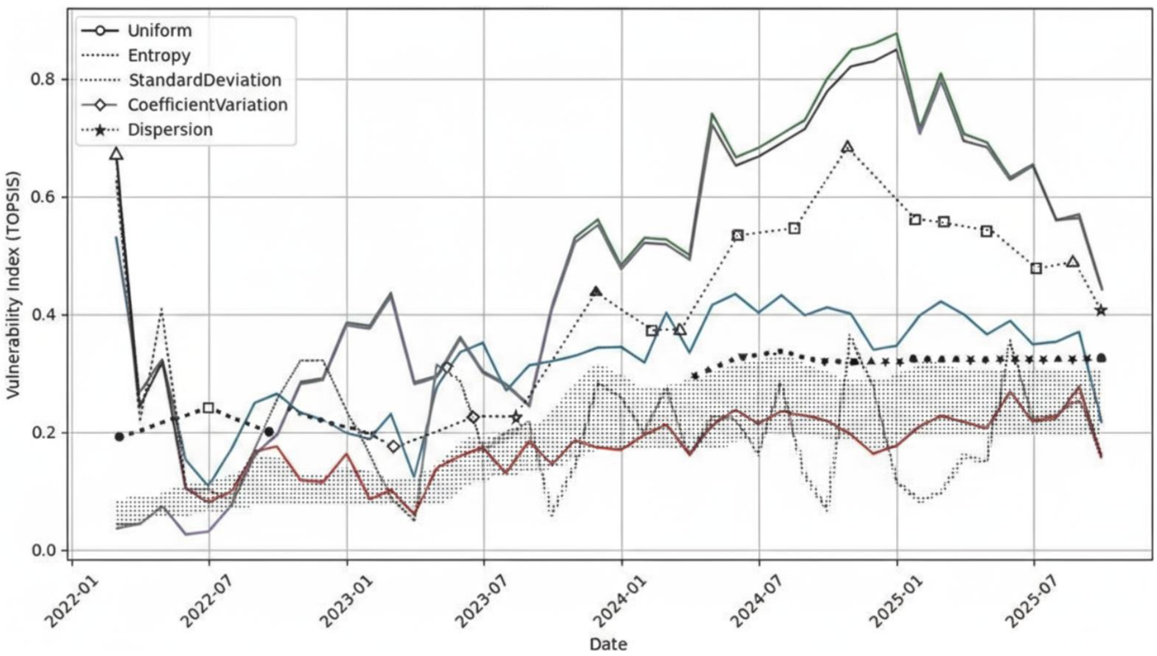

Figure 1. Military Capability Index over time (monthly, 01.2022—10.2025)
Source: compiled based on [8]

The military capability vulnerability index for each period has been visualised using TOPSIS and five different objective weighting methods. As illustrated in Figure 1 above, each curve represents a distinct weighting strategy, demonstrating the influence of weight selection on the assessment of vulnerability over time.

The subsequent stage of the process is the incorporation of military budget scaling (Fig. 2). In order to utilise the military budget as a scaling factor, it is necessary to adjust the vulnerability index for each period by dividing the TOPSIS scores for each period by the corresponding military budget.

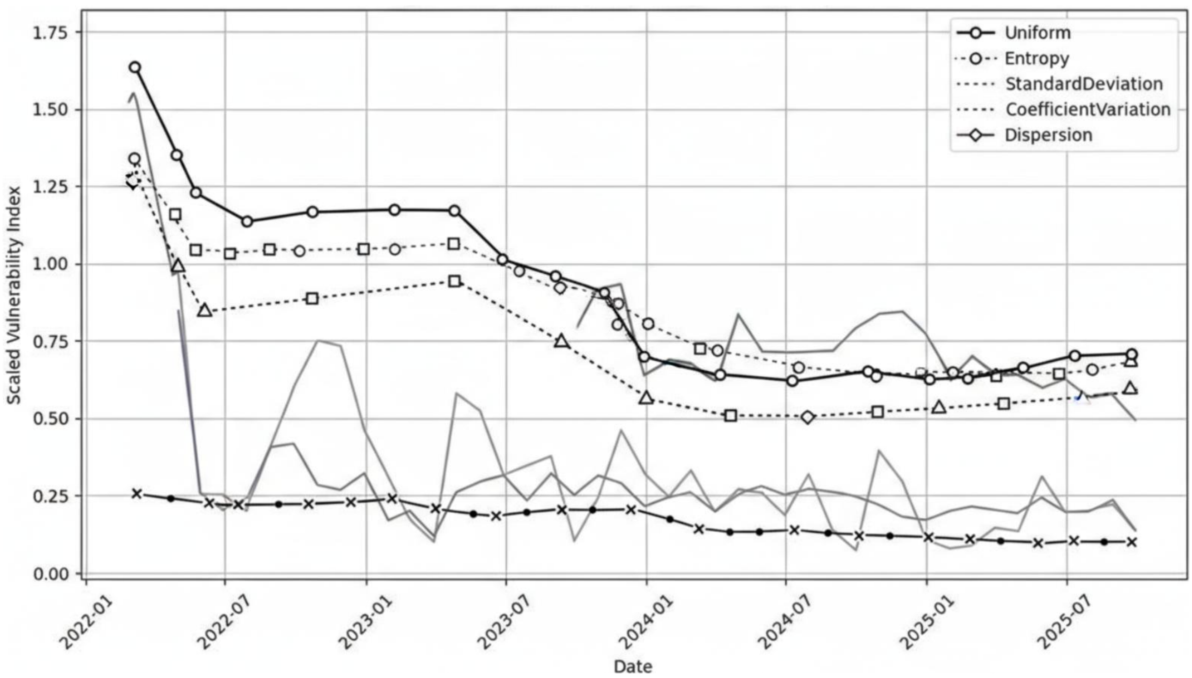

Figure 2. Budget-Scaled Military Capability Vulnerability Index (monthly, 01.2022—10.2025)
Source: compiled based on [8]

As previously mentioned, the budget-scaled Military Capability Vulnerability Index has been calculated and visualised (see Figure 2) for all periods and weighting methods. The incorporation of each curve into the assessment now incorporates the military budget, thereby providing a more economically contextualized evaluation. It is important to note that each TOPSIS vulnerability index is divided by the corresponding monthly military budget. This process produces a scaled index that reflects fiscal resilience. The curves are indicative of periods in which capability losses are high relative to budget, thus signalling greater vulnerability. The budget-scaling mechanism facilitates the identification of not only raw losses, but also periods during which resources may be in short supply.

The subsequent stage of the research is to perform interpretation and sensitivity analysis. The scaled vulnerability index is a metric that demonstrates fluctuations in military capability losses relative to the military budget over time. Peaks in the curve indicate periods in which losses were particularly high relative to the available budget, revealing moments of heightened vulnerability.

The Uniform and Entropy methods have been observed to demonstrate more moderate or stable trends, as they distribute weights more evenly or information-theoretically among criteria. The Standard Deviation and Dispersion methods frequently generate higher and more volatile peaks, as they amplify the influence of indicators with higher variability or range. The Coefficient of Variation produces lower, more smoothed curves, as it balances both the mean and the dispersion.

A thorough examination of the critical periods reveals that there is a conspicuous surge in activity in early 2022 and during the 2024–2025 period, evident across all methodologies. It can be hypothesised that these correspond to months which have been subject to considerable losses or relatively diminished budgets. This would signify critical vulnerabilities for the RF's military during those phases.

It appears that elevated index values may serve as an indication of potential stress on military logistics and resource allocation, suggesting instances where operational or fiscal exhaustion risks may escalate. Lower values are indicative of periods of enhanced sustainability.

As part of the sensitivity analysis, the same TOPSIS model was run using five distinct weighting methods. This comparative sensitivity analysis is presented in Table 1 below.

Table 1. The comparative sensitivity analysis

Weighting Method	Index Volatility	Implications
Uniform	Moderate/Flat	All indicators treated equally; les responsive to major shifts
Entropy	Moderate/Responsive	More sensitive to rare or information-rich losses
Std. Deviation	High	Prioritizes volatile indicators; detects shocks/surges well
Coefficient Variation	Smoothed	Normalizes for mean; less jumpy; good for persistent changes
Dispersion	High/Punctuated	Amplifies range; sharp jumps reflect extreme events

Source: compiled based on [8]

In the end we need to provide a test to assess model stability by removing several indicators and recalculating the index to see how much results change. It consist a process of altering indicator values artificially to observe effect size on the final index. We are going to proceed the “leave-one-out” procedure for “UAVs” “MLRS” and “Missiles”.

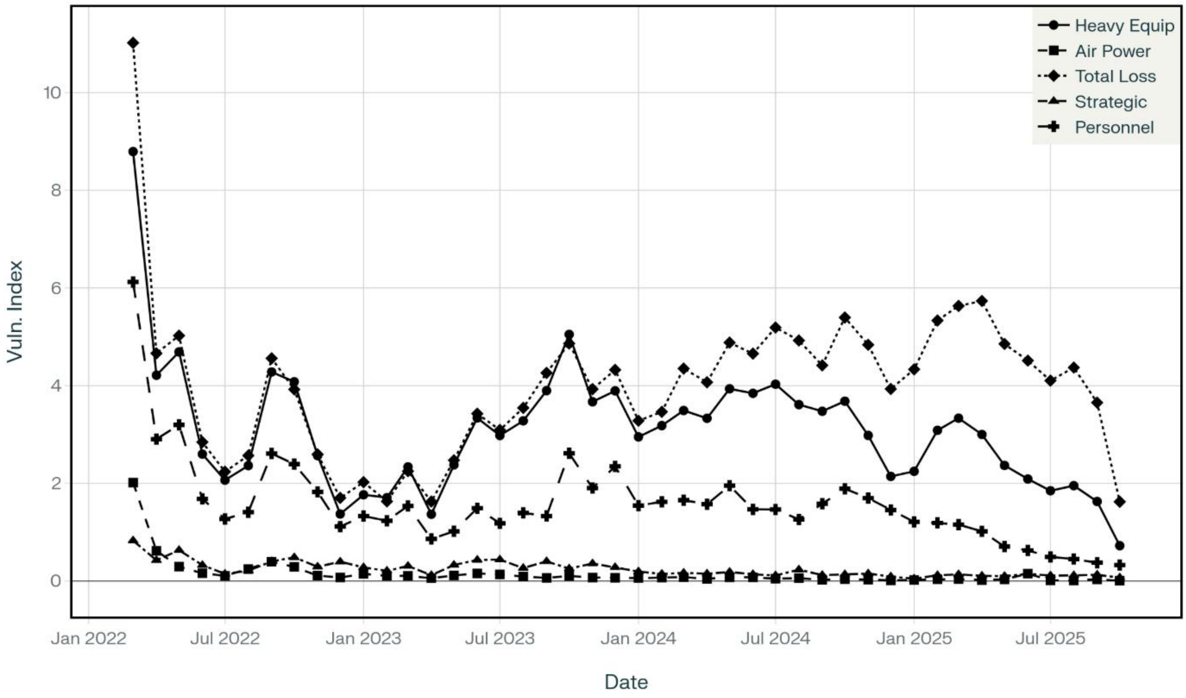

Figure 3. Budget-Scaled Vulnerability Index (Indicator Sensitivity)
Source: compiled based on [8]

As demonstrated in Figure 3, the sensitivity analysis for UAVs, MLRS, and missiles indicates that the budget-scaled vulnerability index curves maintain a high degree of consistency with the curves for the full indicator set across all weighting methods.

Whilst interpreting the multi-indicator sensitivity results, emphasis is placed on several aspects:

1. In the context of model robustness, the dashed lines (after omitting UAVs, MLRS, or missiles) demonstrate a high degree of correlation with the solid, full-indicator lines. This finding indicates that no individual indicator (UAVs, MLRS, or missiles) exerts a disproportionate influence on the composite vulnerability index. The model's structural integrity and reliability are retained even when these critical capabilities are excluded one at a time.

2. In the context of the Weighting Method Comparison, it was found that all weighting strategies (Uniform, Entropy, Standard Deviation, Coefficient Variation, Dispersion) displayed similar levels of robustness. The removal of individual indicators did not induce major changes in the index time series. This finding lends further support to the hypothesis that results are not contingent upon a specific weighting choice or indicator, thereby promoting generalizability and objectivity.

In order to systematically summarise and compare the results of the "leave-one-out" sensitivity analysis for "Tank," "UAVs," "MLRS," and "Missiles," it is necessary to compile the full vulnerability index time series for each exclusion scenario. This involves the calculation of summary statistics, including the mean, maximum absolute difference, and standard deviation, for each method or scenario (see Table 2).

Table 2. The comparative sensitivity analysis

Indicator	Uniform	Entropy	Standard Deviation	Coefficient of Variation	Dispersion
UAVs	0.019706	0.001899	0.019672	0.017995	0.029654
MLRS	0.019403	0.000147	0.000004	0.005657	0.000006
Missiles	0.029513	0.174062	0.000011	0.015346	0.000013

Source: compiled based on [8]

Finally, a scenario analysis is performed. In order to accomplish this objective, it is necessary to set the objective—to define the timeframe for the subsequent 12 months, commencing from the most recent date recorded in the 'df' dataframe (Python).

The following observations can be made with regard to the past year:

- There has been a doubling of UAVs;
- There has been a halving of missiles;
- There has been a doubling of the budget over the past two years.

It is imperative that the current status quo with regard to UAVs is maintained. Simultaneously, there is a necessity to reduce the number of missiles by half, and to increase the budget by 10% over the course of the next two years.

It is imperative to reduce the number of UAVs by half over the past year, and to reduce the number of missiles and budget by half over the past two years.

In order to inspect and compare the vulnerability index for all months where scenario modifications apply, and to visually analyse divergence for Scenarios 1, 2, and 3, it is necessary to inspect modified months and to apply scenario changes to existing data. Prior to the implementation of scenario modifications, it is imperative to explicitly cast the relevant columns as "float" to avert potential "dtype" conflicts and subsequent errors.

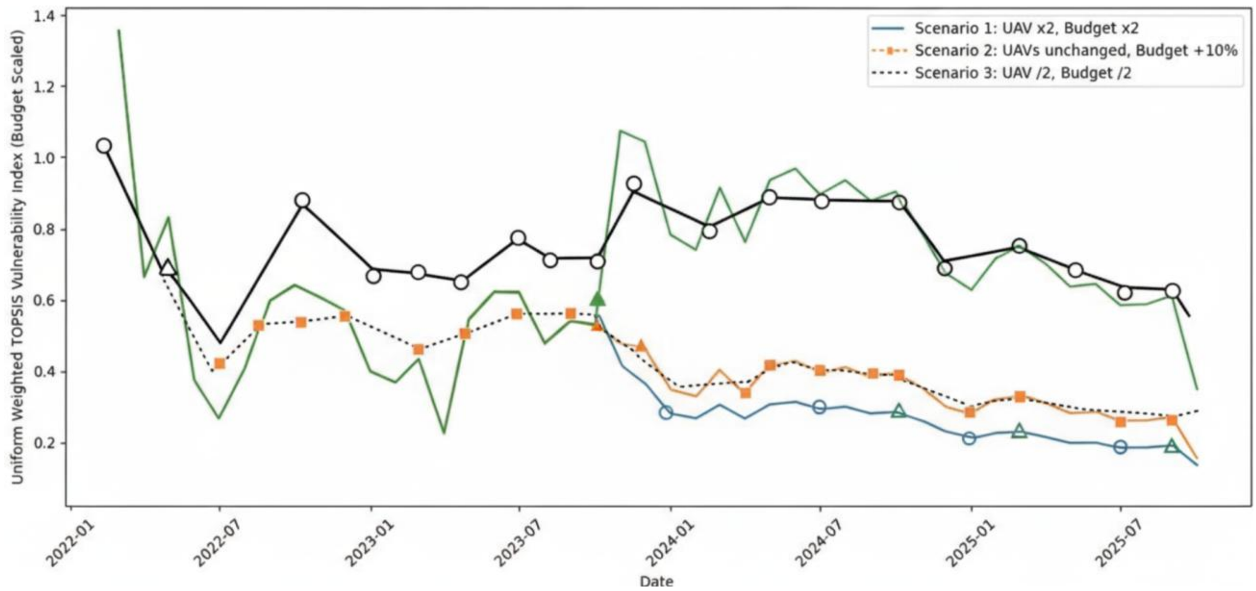

Figure 4. Vulnerability Index Comparison: Scenario Modelling

Source: compiled based on [8]

As demonstrated in the results section of Figure 4, the plot now accurately displays the divergence between the scenarios.

1. In the context of the initial scenario, characterised by an augmentation in both Unmanned Aerial Vehicles and budgetary resources, the vulnerability is at its lowest point.

2. In the context of Scenario 2, characterised by an absence of modifications to UAVs and a budgetary increase of 10%, there is a moderate vulnerability that is accompanied by a slight improvement.

3. In the third scenario, the number of UAVs is reduced by half, and the budget is also reduced by half. This scenario demonstrates the highest level of vulnerability, which is indicative of compounded losses and constrained resource.

5. Conclusions.

It is possible to draw the following conclusions based on the modelling results, scenario analysis and robustness checks. The implementation of MCDM, specifically the TOPSIS approach, enables structured, quantitative assessment of military capability vulnerability across multiple loss indicators and over time. The utilisation of five objective weighting schemes – uniform, entropy, standard deviation, coefficient of variation, and statistical dispersion – demonstrates that the majority of weighting methods yield robust, consistent vulnerability time series and are not unduly sensitive to single indicator exclusion, thereby supporting the generalisability of the results. Sensitivity analysis, or 'leave-one-out' as it is also known, has been used to confirm that omitting UAVs, MLRS, or missiles generally produces minimal shifts in composite vulnerability index values (well below 0.03 for most methods). The exception to this is entropy weighting with missiles, which suggests heightened responsiveness to information-rich indicators under entropy schemes. Entropy, conversely, evinces a high degree of robustness.

The application of scenario analysis to the modification of recent periods for key indicators and budget has revealed clear policy-relevant trends.

The first scenario is characterised by an increase in both the number of UAVs and the military budget, resulting in a doubling of both variables. The lowest vulnerability is indicative of an enhanced operational resilience, owing to the augmentation of resources and the duplication of UAVs.

In the second scenario, the configuration of UAVs remains unaltered, while the budget is augmented by a proportion of 10%. The moderate vulnerability is shown to engender a modest improvement in comparison with the baseline.

In the third scenario, the number of UAVs is reduced by half, and the budget is also halved. This results in the highest level of vulnerability, indicating significant compounded risks and resource constraints under adverse conditions.

The scaling of budgets (i.e. the integration of defence spending as a percentage of GDP) offers a more nuanced interpretation, enabling the contextualisation of periods of heightened vulnerability by resource adequacy and fiscal resilience. Peaks in the scaled index serve to highlight moments of operational or fiscal stress, thus suggesting resource allocation bottlenecks and elevated risk.

The general structure and stability of the vulnerability index suggest that the composite metric is a valuable, policy-relevant tool for defence capability analysis, scenario planning, and resource management, supporting transparent evidence-based decisions even under conflicting pressures or rapidly changing operational environments.

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МОДЕЛЮВАННЯ ВРАЗЛИВОСТІ ВІЙСЬКОВОГО ПОТЕНЦІАЛУ РФ МЕТОДОМ TOPSIS

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Анотація: *У даній статті розроблено кількісну модель для оцінки вразливості військового потенціалу російської федерації у 2022–2025 роках з використанням методів багатокритеріального прийняття рішень. Помісячні дані із 13 показників (12 категорій втрат озброєння та обладнання плюс втрати особового складу) отримані з відкритих джерел і оброблені за допомогою методу TOPSIS, реалізованого в бібліотеці PyMCDM. Застосовуються п'ять об'єктивних схем зважування — рівномірна, на основі ентропії, стандартного відхилення, коефіцієнта варіації та статистичної дисперсії — для відображення альтернативних уявлень про важливість показників та перевірки надійності комплексного індексу вразливості. Отримані за допомогою TOPSIS дані додатково масштабуються за співвідношенням військових витрат до ВВП, щоб отримати скоригований на бюджет показник вразливості, який відображає як втрати на полі бою, так і фінансову стійкість. Аналіз чутливості щодо ключових показників (БПЛА, РСЗВ, ракети) показує, що індекс залишається стабільним при видаленні показників для більшості методів зважування, і лише ентропійні ваги сильніше реагують на втрати ракет. Моделювання сценаріїв для трьох перспективних конфігурацій запасів БПЛА та оборонних бюджетів демонструє, що більші інвестиції в безпілотні системи та більша частка бюджету пов'язані зі значно нижчою вразливістю, тоді як одночасне скорочення БПЛА та бюджету призводить до найвищих рівнів вразливості. Таким чином, запропонований індекс пропонує прозорий, політично релевантний інструмент для відстеження структурної військової вразливості в часі, стрес-тестування альтернативних сценаріїв структури сил та фінансування, а також підтримки планування оборони на основі фактичних даних.*

Ключові слова: *TOPSIS, методи об'єктивного зважування, військові спроможності, оборонний бюджет, російсько-українська війна.*

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://sepd.tntu.edu.ua/images/stories/pdf/2025/25aoocut.pdf

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