Evaluating Defence Resource Management Effectiveness Through Adaptive Portfolio Selection

Оцінювання ефективності управління оборонними ресурсами на основі адаптивного портфельного підходу

Pavlo Makoshenets
PhD Student, e-mail: pavmamot@gmail.com, ORCID ID: https://orcid.org/0000-0002-6780-9934
Національний університет оборони України, м. Київ, Україна

Павло Макошенець
ад'юнкт, e-mail: pavmamot@gmail.com, ORCID ID: https://orcid.org/0000-0002-6780-9934
National Defence University of Ukraine, Kyiv, Ukraine

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Purpose. To develop and test a methodological approach to evaluating the effectiveness of defence resource allocation based on adaptive portfolio selection with Bayesian updating of programme implementation success estimates.

Method. The study employs multicriteria expert assessment, analysis of two sets of ten expert questionnaires, beta-binomial Bayesian updating, discrete optimisation through exhaustive enumeration of feasible portfolios, and sensitivity analysis.

Findings. For six hypothetical defence programmes, potential protective effects ranging from 23.50 to 100.00 conditional points and initial success indices ranging from 0.458 to 0.816 were determined. Based on simulated observations, success estimates were updated, and portfolio optimisation was performed under a budget constraint. The optimal portfolio composition changed from P1 + P5 + P6 to P2 + P3 + P4 + P5. The adaptive portfolio achieved an expected effect of 181.32 conditional points at an assumed cost of UAH 76 billion, exceeding the static portfolio's result by 61.9%.

Theoretical Implications. The study systematises a procedure integrating expert assessment, sequential updating of probabilistic estimates, and portfolio optimisation under resource constraints.

Practical Implications. The proposed approach can support evidence-based revisions of defence programme funding priorities as new information becomes available.

Originality/Value. The study advances portfolio selection procedures by integrating initial expert assessments with Bayesian updating and subsequent re-optimisation of programme portfolios.

Research Limitations. The findings are based on a hypothetical model, unverified expert data, and scenario-based assumptions. Further empirical validation is required.

Paper Type: Theoretical and methodological study with model-based validation.

Мета роботи. Розробити та апробувати методичний підхід до оцінювання результативності розподілу оборонних ресурсів на основі адаптивного портфельного відбору з баєсівським оновленням оцінок успішності реалізації програм.

Метод дослідження. Застосовано багатокритеріальне експертне оцінювання, аналіз двох наборів по десять анкет, бета-біноміальне баєсівське оновлення, дискретну оптимізацію шляхом повного перебору допустимих портфелів та аналіз чутливості.

Результати дослідження. Для шести умовних оборонних програм визначено потенційний захисний ефект у діапазоні 23,50–100,00 умовних балів і початкові індекси успішності 0,458–0,816. На основі модельних спостережень здійснено оновлення оцінок та оптимізацію портфеля за бюджетного обмеження. Оптимальний склад змінився з П1 + П5 + П6 на П2 + П3 + П4 + П5. Очікуваний ефект адаптивного портфеля становив 181,32 умовного бала за модельної вартості 76 млрд грн, що на 61,9 % перевищує результат статичного портфеля.

Теоретична цінність дослідження. Систематизовано процедуру інтеграції експертного оцінювання, послідовного оновлення імовірнісних характеристик та портфельної оптимізації в умовах ресурсних обмежень.

Практична цінність дослідження. Запропонований підхід може використовуватися для обґрунтування перегляду пріоритетів фінансування оборонних програм з урахуванням нової інформації.

Оригінальність дослідження. Удосконалено процедуру портфельного відбору шляхом поєднання початкових експертних оцінок з їх баєсівським оновленням та повторною оптимізацією складу програм.

Обмеження дослідження. Результати мають модельний характер, ґрунтуються на неверифікованих експертних даних і сценарних припущеннях та потребують емпіричної перевірки.

Тип статті: теоретико-методична з модельною апробацією.

Keywords: defence resources; programme portfolio; support of troops (forces); Bayesian updating; expert assessment; budget constraints; protective effect.

Ключові слова: оборонні ресурси; портфель програм; забезпечення військ (сил); баєсівське оновлення; експертне оцінювання; бюджетні обмеження; захисний ефект.

Introduction

The effective management of defence resources is particularly important during prolonged armed conflicts, when the demand for military capabilities, infrastructure protection, and logistical

resilience substantially exceeds available financial, material, and organisational resources. Under such conditions, defence planning requires not only the allocation of funding among established expenditure categories but also the selection of programmes capable of generating the greatest contribution to strategic and operational objectives within defined resource constraints.

The complexity of defence resource allocation arises from several interrelated factors. These include uncertainty regarding future threats, differences in programme implementation periods, technological and organisational risks, dependencies among defence capabilities, and the changing effectiveness of individual measures. Consequently, decisions based exclusively on initial programme assessments may become insufficiently justified when new information becomes available during implementation.

This problem is particularly relevant to programmes intended to protect military personnel, critical infrastructure, logistics facilities, and other essential elements of defence capability. Such programmes differ in their expected protective effects, implementation requirements, resource intensity, and sensitivity to changing operational conditions. Therefore, selecting programmes solely on the basis of their individual ratings or initial cost estimates does not necessarily produce the most effective combination within an available budget.

The institutional framework for defence planning and portfolio management in Ukraine is established by relevant regulatory documents of the Ministry of Defence of Ukraine (Ministry of Defence of Ukraine, 2020, 2024). International approaches to portfolio management emphasise strategic alignment, the assessment of programme dependencies, risk management, and periodic revision of portfolio composition (International Organization for Standardization, 2022; European Commission, 2022; U.S. Department of Defense, 2023). Nevertheless, the implementation of these principles requires methodological instruments capable of incorporating new information into programme evaluation and subsequent resource allocation decisions.

Traditional multicriteria assessment enables decision-makers to compare programmes according to their strategic significance, expected outcomes, feasibility, and resource requirements. However, when the resulting scores remain unchanged throughout programme implementation, the selection process cannot adequately reflect changes in the likelihood of achieving planned results. This limitation becomes particularly significant in an uncertain environment, where initial assumptions may be contradicted by testing, inspections, monitoring activities, or intermediate implementation outcomes.

One possible methodological solution is to combine expert-based multicriteria assessment with Bayesian updating and discrete portfolio optimisation. Multicriteria assessment provides an initial representation of programme potential and implementation conditions. Bayesian updating offers a formal procedure for revising probabilistic estimates in response to new observations, while portfolio optimisation identifies the combination of programmes that maximises an explicitly defined objective under a common budget constraint.

However, integrating these methods requires several methodological precautions. In particular, expert scores cannot automatically be interpreted as statistically calibrated probabilities. Similarly, the simultaneous use of implementation probabilities and risk-adjustment coefficients may lead to double counting unless their meanings are clearly distinguished. The potential contribution of such an approach therefore depends on the transparency of its assumptions, the consistency of its calculations, and the explicit definition of its applicability limits.

The research problem addressed in this study is the insufficient formalisation of a reproducible procedure linking initial expert assessments, subsequent revisions of programme implementation estimates, and resource-constrained portfolio selection. The unresolved methodological issue concerns how updated information can systematically influence the composition of a defence programme portfolio rather than merely change the ratings of individual programmes.

The purpose of this study is to develop and test a methodological approach to evaluating defence resource allocation through adaptive portfolio selection with Bayesian updating of programme implementation success estimates.

To achieve this purpose, the study addresses the following objectives: to substantiate criteria for assessing potential protective effects; to process expert assessments of programme potential and implementation conditions; to establish initial success indices; to demonstrate their Bayesian updating using hypothetical monitoring observations; to determine feasible programme portfolios under a common budget constraint; and to assess the sensitivity of portfolio selection to changes in the assumed strength of prior information.

The study considers six hypothetical defence programmes representing different areas of protective capability development. Their selection provides a controlled numerical environment for demonstrating the proposed procedure without disclosing information about specific military facilities, operational plans, or actual defence appropriations.

The scientific contribution of the research lies in the methodological integration of expert assessment, sequential probabilistic updating, and repeated portfolio optimisation into a transparent decision-support procedure. Unlike fixed-score programme ranking, the proposed approach demonstrates how changes in assumed implementation success can alter the preferred combination of programmes under unchanged budget constraints.

The study is theoretical and methodological, supported by a model-based numerical illustration. Accordingly, its results demonstrate the properties of the proposed decision procedure rather than establish a causal relationship between adaptive portfolio management and actual defence outcomes.

Literature Review

The theoretical foundations of portfolio selection originate from research addressing the allocation of limited resources among competing alternatives. Markowitz (1952) established fundamental principles of portfolio analysis by considering the relationship between expected returns and risk. Although originally developed for financial assets, these principles influenced subsequent approaches to evaluating combinations of projects, programmes, and investment alternatives.

Archer and Ghasemzadeh (1999) developed an integrated framework for project portfolio selection that combines individual project evaluation with portfolio-level decision-making. Their approach demonstrates that the relative attractiveness of a project cannot be considered independently of financial constraints, organisational priorities, and the characteristics of other projects included in the portfolio.

For defence capability development, portfolio analysis has particular importance because programmes differ substantially in strategic value, technological complexity, implementation schedules, and operational dependencies. Davis et al. (2008) examined portfolio-analysis methods for assessing capability alternatives and demonstrated the importance of evaluating combinations of capabilities rather than isolated projects. Shafi et al. (2017) investigated multi-objective optimisation under uncertainty, providing a methodological basis for analysing competing planning objectives.

An additional dimension is introduced by systems-of-systems approaches. Davendralingam and DeLaurentis (2014) emphasised that the overall value of a portfolio depends not only on the characteristics of its individual elements but also on the interactions among them. This consideration is particularly relevant to defence programmes, where the effectiveness of engineering protection, early warning, electronic countermeasures, and logistical resilience may depend on their coordinated implementation.

Research on performance-based budgeting further establishes the importance of linking financial allocations to expected results. The OECD (2019) emphasised the role of performance information in budgetary decision-making. From this perspective, resource allocation should be

evaluated not merely through expenditure execution but also through the achievement of defined outcomes. Nevertheless, the practical application of performance-based budgeting requires sufficiently reliable indicators and an explicit understanding of the relationship between allocated resources and achieved results.

Institutional approaches to defence portfolio management are reflected in national and international regulatory frameworks. The European Commission (2022) considers portfolio management an instrument for aligning projects and programmes with strategic objectives. ISO 21504:2022 establishes general guidance for portfolio management, including the selection, prioritisation, monitoring, and adjustment of portfolio components (International Organization for Standardization, 2022).

In the defence sector, the U.S. Department of Defense (2023) provides a framework for capability portfolio management, emphasising the coordination of capability development and resource allocation. Comparative research by Tkach et al. (2024) identifies basic requirements for defence portfolio management in leading NATO member states, while McKernan et al. (2024) examine planning, programming, budgeting, and execution practices in allied and partner organisations.

These studies establish the organisational and methodological importance of portfolio management. However, they do not eliminate the need for an explicit procedure connecting changes in programme implementation evidence with revisions of the preferred portfolio composition.

Another relevant area concerns strategic flexibility and portfolio risk management. Teller (2013) demonstrated the importance of integrating risk management into project portfolio processes. Kopmann et al. (2017) examined how project portfolio management contributes to the interaction between deliberate and emergent organisational strategies. Their findings support the view that effective portfolio management should accommodate both predefined strategic objectives and changing implementation conditions.

Nevertheless, risk-oriented approaches frequently rely on estimates established during initial programme evaluation. When these parameters remain fixed, the decision model may not adequately reflect newly identified uncertainties. A methodological distinction is therefore required between incorporating risk into an initial score and revising the underlying assessment after receiving additional evidence.

Bayesian statistical methods offer a theoretical foundation for such revisions. Bayes (1763) established the basis for updating probability estimates through new information. Subsequent developments in Bayesian decision theory provide a formal framework for combining prior information with observed evidence (Berger, 1985; Bernardo & Smith, 1994). Robert (2007) and Smith (2010) further developed approaches to decision-making under uncertainty and the use of updated probabilistic assessments.

For defence programme selection, Bayesian updating may be useful when implementation conditions change and observations become available during successive stages of a programme. However, its application requires a clear definition of the event being modelled, an appropriate probabilistic representation of prior information, and consistency between the assumed statistical model and the available observations.

In particular, a weighted expert score is not equivalent to an empirically established probability of implementation success. Interpreting such scores probabilistically requires additional calibration or explicitly stated modelling assumptions. Similarly, a beta-binomial model is appropriate only when the observations can reasonably be treated as comparable binary outcomes under the assumed probability structure.

These limitations are important because the apparent precision of posterior probability estimates does not independently establish their empirical validity. Therefore, Bayesian updating should be regarded as a formal mechanism for revising assumptions rather than as a substitute for reliable observations and independent model validation.

The assessment of protective programmes also requires consideration of the technical characteristics of engineering measures and their expected operational effects. Voloshchenko et al. (2023, 2025) examined the resistance of protective structures to explosive impacts. Bilyk and Kashuba (2024) investigated engineering protection measures against unmanned aerial threats, while Mykhailovskyi (2025) analysed the evolution of fortification and protective structures.

Further research by Loik et al. (2025) and Kotliarevskyi (2026) addresses passive engineering protection and the modelling of protective infrastructure. These studies indicate that the effectiveness of protective measures depends on specific technical configurations, threat characteristics, and operational conditions. Accordingly, a generalised evaluation of protective programmes must distinguish their potential contribution from the likelihood of successful implementation.

Legal and accounting considerations represent additional constraints. Zaiets and Sychova (2024) examined legal issues related to land use for fortification construction, while Sokolenko (2024) analysed accounting challenges associated with fortification facilities. These aspects demonstrate that programme selection cannot be determined exclusively by expected protective effects and financial costs. Legal feasibility, implementation requirements, and accounting obligations may constitute independent conditions for admitting a programme into the portfolio.

The reviewed literature therefore provides several complementary methodological foundations: multicriteria portfolio evaluation, defence capability planning, risk-oriented management, Bayesian decision theory, and the technical assessment of protective measures. However, these approaches address different components of the decision-making process and do not, by themselves, establish a unified procedure for adaptive resource-constrained selection.

The research gap addressed in this study concerns the operational integration of these components into a reproducible sequence in which initial expert assessments are separated from implementation success estimates, the latter are revised using new information, and portfolio composition is subsequently re-optimised under an unchanged or revised resource constraint.

The proposed methodology does not claim novelty in the individual mathematical techniques employed. Its intended contribution is the transparent integration of established methods for illustrating adaptive defence programme selection and identifying the conditions required for their subsequent empirical application.

Research Methodology

1. Research design and data

The study employs a theoretical and methodological research design supported by a numerical illustration involving six hypothetical defence programmes. The methodological framework combines multicriteria assessment, expert-based initial evaluation, Bayesian updating, discrete portfolio optimisation, and sensitivity analysis.

The object of the research is the allocation of defence resources among programmes aimed at enhancing the protection of military personnel and critical infrastructure. The subject of the research comprises methodological procedures for evaluating programme potential, updating implementation success estimates, and selecting a portfolio under resource constraints.

The source material includes a description of the proposed methodology and its calculation example, a collection of regulatory and scientific references, and two sets of ten expert questionnaires. The first set contains assessments of programme implementation success, while the second provides assessments of potential protective effects.

Information concerning the identities and qualifications of the experts, the questionnaire administration dates, and the independent verification of the datasets is unavailable. Consequently, the expert assessments are treated as supplied inputs to the model rather than as a statistically representative or independently validated empirical sample.

Six hypothetical programme alternatives were considered:

P1 — integrated active protection, early warning, and electronic countermeasures.

P2 — engineering protection of critical infrastructure facilities.

P3 — fortification measures and troop shelters.

P4 — camouflage, decoys, dispersion, and protective screens.

P5 — digital monitoring, accounting, and inspection.

P6 — resilience of logistics hubs and alternative supply routes.

These alternatives represent different functional areas of defence protection. Their characteristics are generalised, and the numerical parameters do not correspond to actual military facilities or approved defence appropriations.

The research procedure consists of five consecutive stages: assessment of potential protective effects; determination of initial implementation success indices; Bayesian updating based on hypothetical observations; adjustment of expected effects for criticality, urgency, synergy, and risk; and optimisation of portfolio composition within the available budget.

2. Assessment of potential protective effects

The potential protective effect of programme j, denoted by B_j, is determined through multicriteria evaluation.

Four assessment criteria are used: relative reduction of expected losses or damage L_j; strategic significance S_j; coverage of priority facilities O_j; and reduction of capability gaps G_j.

Each criterion is assessed by ten experts using a scale from 0 to 10. The average criterion scores are normalised to the interval from 0 to 1.

The weighted potential protective effect is calculated as:

$$B_{\text{j}} = 100 \times (0{,}35L_{\text{j}} + 0{,}25S_{\text{j}} + 0{,}20O_{\text{j}} + 0{,}20G_{\text{j}}). \quad (1)$$

The weighting coefficients sum to one and represent the assumptions adopted for the numerical illustration. Their values reflect the author's assessment of the relative importance of the selected criteria rather than the results of an independently validated weighting procedure.

Although the Analytic Hierarchy Process proposed by Saaty (2008) could provide an additional basis for determining criterion weights, it was not applied in the present study.

Accordingly, B_j is interpreted as a normalised index of potential protective effect expressed in conditional points. It does not represent a directly measured reduction in casualties, infrastructure damage, or financial losses.

3. Determination of initial implementation success estimates

The initial implementation success index is calculated using six criteria reflecting the organisational, technical, and resource conditions of programme implementation.

These criteria include technical feasibility T_j, organisational readiness O'_j, resource availability R_j, confirmation of expected results through testing or practical experience BCE_j, risk manageability RM_j, and adaptability to changing conditions A_j.

Their respective weighting coefficients are 0.20, 0.15, 0.15, 0.25, 0.15, and 0.10.

For expert e, the weighted score of programme j is determined by:

$$S_{\text{je}} = 0{,}20T_{\text{je}} + 0{,}15O'_{\text{je}} + 0{,}15R_{\text{je}} + 0{,}25BCE_{\text{je}} + 0{,}15RM_{\text{je}} + 0{,}10A_{\text{je}}; \quad (2)$$

The initial success index is then calculated as:

$$p_{0\text{j}} = \left(\frac{1}{10}\right) \cdot \left(\frac{\Sigma_{\text{e}} S_{\text{je}}}{10}\right). \quad (3)$$

The resulting index ranges from 0 to 1.

This transformation provides a normalised representation of expert assessments. However, the resulting value should not automatically be interpreted as a statistically calibrated probability of programme implementation success.

For the purpose of the numerical illustration, p_{0j} is treated as a conditional initial estimate used to parameterise the Bayesian model. Its interpretation as a probability in real applications would require calibration against verified historical programme implementation data.

To characterise differences among individual expert assessments, the arithmetic mean and sample standard deviation are calculated for each programme. These statistics describe variability within the supplied questionnaires but do not establish the representativeness of the expert group.

4. Bayesian updating of implementation success estimates

To demonstrate adaptive revision of programme assessments, the initial success index is represented through a beta distribution:

$$p_j \sim \mathrm{Beta}(\alpha_{0j}, \beta_{0j}). \quad (4)$$

where the initial distribution parameters are defined as:

$$\alpha_{0j} = n_0 p_{0j}, \qquad \beta_{0j} = n_0(1 - p_{0j}). \quad (5)$$

The parameter n_0 represents the assumed strength of prior information. In the baseline scenario, $n_0 = 10$.

After observing s_j positive outcomes and f_j negative outcomes, the posterior distribution becomes:

$$p_j \mid s_j, f_j \sim \mathrm{Beta}(\alpha_{0j} + s_j, \beta_{0j} + f_j). \quad (6)$$

The posterior mean is calculated as:

$$p_j(t) = \frac{n_0 p_{0j} + s_j}{n_0 + s_j + f_j}. \quad (7)$$

The model assumes that the observations are comparable binary outcomes associated with a common definition of implementation success and are sufficiently independent for the beta-binomial formulation.

In this study, the numbers of positive and negative observations are hypothetical scenario parameters. They do not represent independently verified monitoring records or documented outcomes of actual defence programmes.

Consequently, the posterior estimates illustrate how new evidence would influence the model under the adopted assumptions. They should not be interpreted as empirically validated probabilities of successful programme implementation.

The uncertainty of the posterior estimates is characterised through conditional 95% Bayesian credible intervals derived from the corresponding beta distributions.

5. Adjustment of expected programme effects

The expected protective effect of each programme is adjusted to account for its estimated implementation success, criticality, urgency, synergy, and risk.

The adjusted effect is defined as:

$$E_j(t) = B_j \cdot p_j(t) \cdot K_{\mathrm{crit},j} \cdot K_{\mathrm{urg},j} \cdot K_{\mathrm{syn},j} \cdot K_{\mathrm{risk},j}. \quad (8)$$

Here, B_j denotes the potential protective effect; $p_j(t)$ is the updated implementation success estimate; $K_{\mathrm{crit},j}$ is the criticality coefficient; $K_{\mathrm{urg},j}$ is the urgency coefficient; $K_{\mathrm{syn},j}$ is the programme-specific synergy adjustment; and $K_{\mathrm{risk},j}$ is the risk coefficient.

The latter is calculated as:

$$K_{\mathrm{risk},j} = 1 - q_j \cdot i_j. \quad (9)$$

where B_j denotes the assumed probability of a critical risk event and i_j represents its normalised impact severity.

The criticality, urgency, and synergy coefficients are assigned according to the scenario assumptions. They are not independent empirical estimates.

An important methodological limitation is that the implementation success estimate and the risk coefficient may partially reflect the same adverse events. Therefore, practical application requires a clear distinction between the probability of programme non-completion and the potential reduction in protective effect conditional on completion.

Similarly, the fixed synergy coefficient is used as a simplifying programme-level adjustment. It does not explicitly model interactions among programmes or changes in their combined effects under different portfolio compositions.

6. Portfolio optimisation under budget constraints

The portfolio selection problem is formulated as a discrete optimisation model.

Let $x_j \in \{0,1\}$ indicate whether programme j is included in the selected portfolio. Let C_j denote its assumed annual cost, and H represent the available annual budget.

The objective function is:

$$\max Z = \sum_{j=1}^{6} E_j\,(t)x_j. \tag{10}$$

subject to the budget constraint:

$$\sum_{j=1}^{6} C_j\,x_j \le H. \tag{11}$$

with:

$$x_j \in \{0,1\}, \qquad j = 1,\dots,6. \tag{12}$$

The baseline numerical illustration assumes an annual budget of UAH 80 billion.

The respective programme costs are set at UAH 50, 32, 24, 12, 8, and 20 billion for P1–P6.

These values are hypothetical scenario parameters rather than actual government appropriations.

Because the model includes six binary decision variables, all $2^6 = 64$ possible portfolio combinations can be evaluated through exhaustive enumeration. Combinations exceeding the available budget are excluded, and the feasible portfolio with the highest expected adjusted protective effect is selected.

The resource efficiency index is calculated as:

$$PI = \frac{\sum_{j=1}^{6} E_j\,(t)x_j}{\sum_{j=1}^{6} C_j\,x_j}. \tag{13}$$

provided that the total portfolio cost is greater than zero.

This index characterises the expected protective effect per unit of expenditure. However, it is used as an additional evaluation indicator rather than as the portfolio optimisation objective.

7. Comparison of management scenarios

Three portfolio selection scenarios are considered to illustrate differences between fixed and adaptive decisions.

The first scenario represents a traditional selection approach with the predetermined composition P1 + P6.

The second scenario represents a static portfolio selected using initial programme success estimates. Its composition is P1 + P5 + P6.

The third scenario represents an adaptive selection procedure in which programme success estimates are updated and portfolio optimisation is repeated.

For comparability, all three portfolios are evaluated using the same posterior programme parameters. The traditional and static portfolio compositions remain unchanged, whereas the adaptive portfolio may be revised.

This comparison demonstrates the influence of updated information on portfolio selection within the formulated mathematical model. It does not constitute an empirical evaluation of actual defence management systems.

8. Sensitivity analysis and methodological limitations

Sensitivity analysis is conducted to evaluate how changes in the assumed strength of prior information affect posterior estimates and the resulting portfolio selection.

Four values of the prior strength parameter are examined:

$$n_0 \in \{5,\ 10,\ 20,\ 50\}. \qquad (14)$$

For each value, posterior programme estimates are recalculated, adjusted protective effects are determined, and the portfolio optimisation problem is solved again.

All other model parameters remain unchanged. Therefore, the analysis evaluates sensitivity specifically to prior strength rather than to the full range of uncertainties associated with programme costs, criterion weights, risk coefficients, and programme interactions.

The methodology is subject to several limitations. First, the expert datasets have not been independently verified. Second, the initial success indices have not been calibrated against observed implementation frequencies. Third, the monitoring observations, programme costs, and adjustment coefficients are hypothetical. Fourth, interdependencies among programmes are represented only indirectly through fixed coefficients.

These limitations restrict the interpretation of the numerical results to methodological illustration.

Further empirical application would require validated programme data, operational definitions of monitoring outcomes, calibrated probability estimates, and explicit modelling of dependencies and implementation constraints.

The proposed framework should therefore be considered a decision-support methodology for evaluating alternative allocations of defence resources rather than a validated predictive model of actual defence programme effectiveness.

Results

1. Summary of the primary expert questionnaires

The primary expert assessment involved ten questionnaires for each of six hypothetical defence programmes (P1–P6). Table 2 reports the weighted mean success scores, sample standard deviations (SDs), and resulting initial success indices (p_0j). The indices were computed from unrounded scores and are presented to four decimal places to preserve the precision used in subsequent calculations.

Table 2. Expert assessment of initial programme success (*n* = 10)

Programme	Mean score	SD, points	p_0j
P1	8.160	0.122	0.8160
P2	5.560	0.100	0.5560
P3	6.025	0.121	0.6025
P4	4.575	0.123	0.4575
P5	4.970	0.113	0.4970
P6	5.975	0.129	0.5975

Source: Author's processing of ten expert questionnaires per programme.

P1 received the highest initial assessment, whereas P4 and P5 received the lowest. The relatively small SDs indicate limited dispersion among the ten responses in this particular assessment; they do not, however, establish the representativeness of the expert sample or validate the estimates against observed implementation outcomes.

A separate expert assessment was used to calculate the potential protective effect on the basis of four criteria (L, S, O, and G). Table 3 presents their aggregate scores, the corresponding baseline effect B, and the between-expert dispersion of B.

Table 3. Potential protective effect and between-expert variability

Code	L	S	O	G	B, points	SD(B)
P1	1.00	1.00	1.00	1.00	100.00	0.00
P2	0.70	0.85	0.70	0.60	71.75	6.84
P3	0.75	0.70	0.65	0.55	67.75	6.58
P4	0.45	0.35	0.40	0.25	37.50	7.94
P5	0.15	0.25	0.30	0.30	23.50	4.14
P6	0.60	0.65	0.55	0.55	59.25	6.49

Source: Author's calculations based on ten questionnaires assessing the baseline protective effect.

P1 attained the maximum score for every criterion in all ten questionnaires, resulting in $SD(B) = 0$. This outcome should be interpreted with caution because the bounded assessment scale may exhibit a ceiling effect. Dispersion was greater for P2–P6, indicating more disagreement about their potential protective effect. Based on the primary questionnaires, the recalculated values are $B_2 = 71.75$, $B_3 = 67.75$, and $B_6 = 59.25$ points; the unrounded initial success scores of P1 and P5 are 8.160 and 4.970, respectively. All subsequent computations use these underlying values without intermediate rounding.

2. Bayesian updating and risk-adjusted programme effects

To illustrate sequential information updating, positive (s_j) and negative (f_j) outcomes were specified for each hypothetical programme. These outcomes are model inputs, not independently documented implementation results. With prior strength $n_0 = 10$, the posterior mean success estimate was calculated as $p_j(t) = (n_0 p_{0j} + s_j)/(n_0 + s_j + f_j)$. Equal-tailed 95% posterior credible intervals were obtained from the corresponding beta distributions. These intervals quantify uncertainty conditional on the stipulated prior and observations, rather than empirical uncertainty about real-world programme effectiveness.

Table 4. Bayesian updates based on hypothetical observations

Code	$p_0 j$	s_j	f_j	$p_j(t)$	95% credible interval
P1	0.8160	4	12	0.468	0.284–0.657
P2	0.5560	14	4	0.699	0.520–0.850
P3	0.6025	18	5	0.728	0.567–0.863
P4	0.4575	16	3	0.709	0.535–0.857
P5	0.4970	18	4	0.718	0.553–0.857
P6	0.5975	8	6	0.582	0.384–0.767

Source: Author's calculations. Success and failure counts are assumed scenario observations; displayed posterior summaries are rounded only for reporting.

Under the specified model evidence, P1 exhibits the largest downward revision, from 0.8160 to approximately 0.468, as its scenario contains four positive and twelve negative outcomes.

Conversely, P3 increases from 0.6025 to approximately 0.728, and P4 from 0.4575 to approximately 0.709. The example demonstrates that the ranking implied by the initial expert assessment can change after probabilistic updating. It does not establish that the same revisions would occur with observed programme data.

The updated probabilities were combined with baseline protective effects and programme-specific criticality, urgency, synergy-adjustment and risk coefficients to calculate expected adjusted effects $E_j(t)$. In the adopted model, $K_{risk,j} = 1 - q_j i_j$, where q_j is the assumed probability of a specified risk event and i_j its proportional impact. The resulting risk coefficient is a model adjustment, not an independently estimated causal effect. Model costs and all coefficients are reported in Table 5.

Table 5. Programme costs and scenario adjustment coefficients

Code	C, UAH bn	K_{crit}	K_{urg}	K_{syn}	q	i	K_{risk}
P1	50	1.30	1.20	1.10	0.55	0.60	0.6700
P2	32	1.25	1.15	1.05	0.35	0.45	0.8425
P3	24	1.20	1.20	1.00	0.30	0.35	0.8950
P4	12	1.10	1.15	1.10	0.20	0.25	0.9500
P5	8	1.00	1.05	1.15	0.25	0.30	0.9250
P6	20	1.15	1.10	1.05	0.35	0.40	0.8600

Source: Scenario assumptions. Risk coefficients are computed as 1 − qi; additional digits are retained where needed for reproducibility.

The adjusted effect was obtained from $E_j(t) = B_j p_j(t) K_{crit}$, $K_{urg,j} K_{syn,j} K_{risk,j}$. Resource efficiency, $RE_j(t)$, was calculated as $E_j(t)/C_j$, in adjusted-effect points per UAH billion. Table 6 contains the consistently labelled P1–P6 results.

Table 6. Expected adjusted effect and programme-level resource efficiency

Code	$B_{,points}$	$p_j(t)$	$E_j(t)$, points	RE_j, $_{points}$/UAH bn
P1	100.00	0.468	53.77	1.08
P2	71.75	0.699	63.74	1.99
P3	67.75	0.728	63.57	2.65
P4	37.50	0.709	35.17	2.93
P5	23.50	0.718	18.84	2.36
P6	59.25	0.582	39.41	1.97

Source: Author's calculations from Tables 3–5; computations use unrounded posterior means and coefficient values.

P4 has the highest programme-level resource efficiency (approximately 2.93 points per UAH billion), whereas P1 has the lowest (approximately 1.08). However, selecting programmes solely by RE_j does not necessarily maximise total adjusted protective effect under a fixed budget. The coefficient $K_{syn,j}$ adjusts each programme individually; it does not explicitly represent pairwise or higher-order interactions among programmes. Consequently, any claim about portfolio-level synergy would require additional interaction terms and supporting assumptions.

3. Comparison of portfolio compositions

With six binary decisions, the model contains $2^6 = 64$ possible portfolios, including the empty portfolio. A full enumeration was conducted subject to the assumed annual budget ceiling of UAH 80 billion. Maximising the total effect under initial success estimates selects P1 + P5 + P6, costing

UAH 78 billion and yielding approximately 147.30 adjusted-effect points on the a priori basis. After Bayesian updating, the optimal composition changes to P2 + P3 + P4 + P5, costing UAH 76 billion and yielding 181.32 points on the posterior basis.

For an internally consistent comparison, Table 7 evaluates the traditional, fixed a priori-optimal, and re-optimised adaptive compositions using the same posterior success estimates. PI is defined as the ratio of total adjusted effect to total cost for each nonempty portfolio.

Table 7. Portfolio comparison using a common posterior assessment

Approach	Composition	Cost, UAH bn	$E, points$	PI
Traditional (fixed)	P1 + P6	70	93.18	1.33
Static (prior-optimal, fixed)	P1 + P5 + P6	78	112.02	1.44
Adaptive (posterior-optimal)	P2 + P3 + P4 + P5	76	181.32	2.39

Source: Author's calculations. All three rows use posterior probabilities; only the adaptive approach reselects its programme composition.

Relative to the traditional fixed portfolio, the adaptive composition produces approximately 94.6% more modelled adjusted effect; relative to the fixed a priori-optimal portfolio, the difference is approximately 61.9%. The respective PI values are 1.33, 1.44, and 2.39 points per UAH billion. These contrasts quantify differences between scenario outcomes within the specified optimisation model. They are not experimentally identified causal impacts of adaptive portfolio management and should not be extrapolated to operational programmes without empirical validation.

4. Sensitivity to prior-information strength

A one-parameter sensitivity analysis tested the strength of the beta prior at $n_0 \in \{5, 10, 20, 50\}$, holding all other inputs constant. A larger value of n_0 assigns greater relative weight to the initial expert assessment, so the same new observations induce smaller posterior revisions. The resulting portfolio solutions and effects are presented in Table 8.

Table 8. Sensitivity of the optimal portfolio to prior strength

n_0	$p_1(t)$	Optimal portfolio	E, points
5	0.385	P2 + P3 + P4 + P5	189.78
10	0.468	P2 + P3 + P4 + P5	181.32
20	0.564	P2 + P3 + P4 + P5	170.76
50	0.679	P2 + P3 + P4 + P5	157.20

Source: Author's calculations using the same hypothetical observations, baseline effects, costs, and adjustment coefficients.

The optimal composition remains P2 + P3 + P4 + P5 under each of the four prior-strength settings, although the estimated total effect decreases from 189.78 to 157.20 points as n_0 increases. Thus, the selected composition is stable with respect to the tested values of this single parameter. This is a limited robustness result: it does not address simultaneous uncertainty in criterion weights, costs, the assumed observations, risk parameters, or interactions between programmes. Future applications should examine these factors jointly, consider out-of-sample evidence, and explicitly estimate portfolio-level dependencies where relevant.

Discussion

The findings of this study are consistent with the argument advanced by Davis et al. (2008) that defense capability planning requires the evaluation of integrated capability portfolios rather than individual projects in isolation. The strategic prioritization principles outlined by the European

Commission (2022) also emphasize the importance of considering strategic significance, interdependencies, and resource constraints. These considerations are reflected in the multi-criteria assessment framework employed in the proposed approach. Its principal methodological contribution is the integration of Bayesian updating into portfolio optimization, allowing newly available information to influence not only the assessment of individual programmes but also the composition of the selected portfolio.

The results demonstrate that changes in estimated implementation success probabilities can substantially affect portfolio selection. In particular, the reassessment of programme P1 illustrates how an initially high expert evaluation may be revised downward following the incorporation of additional observations. Consequently, a programme initially regarded as a priority may become less attractive than alternative investments. However, a reduction in the estimated probability of successful implementation should not automatically result in programme termination. Strategically indispensable programmes may require alternative management responses, including phased implementation, scope reduction, additional testing, modifications to contractual arrangements, or the development of contingency options. Therefore, the proposed approach should be regarded as a decision-support instrument rather than a substitute for managerial judgment and institutional responsibility.

These findings are also relevant to the portfolio risk management principles discussed by Teller (2013), who emphasizes the integration of risk considerations into portfolio-level decision-making. Nevertheless, the proposed model requires a clearer distinction between implementation success probability and risk-adjustment factors. If the probability estimate and the risk coefficient incorporate the same underlying events or consequences, their simultaneous application may lead to double counting of risk and an unjustified reduction in expected programme effects. Accordingly, practical implementation requires a standardized risk classification system, explicit definitions of risk indicators, and a transparent specification of causal relationships between risk events, implementation outcomes, and expected protective effects.

Another methodological limitation concerns the representation of programme interdependencies. The programme-specific synergy coefficient $K_{\mathrm{syn},j}$ reflects an assumed adjustment to the expected effect of an individual programme. However, it does not explicitly describe how programme value changes depending on the inclusion or exclusion of other programmes within the portfolio. Therefore, the current formulation should not be interpreted as a comprehensive model of inter-programme synergy. Further development could incorporate interaction terms, compatibility constraints, or conditional effects to account for complementarities and dependencies between programmes.

The empirical foundation of the study also imposes important limitations on the interpretation of its results. Although the two sets of ten expert questionnaires provide the numerical inputs required to demonstrate the proposed methodology, the available information is insufficient to independently verify respondent selection, expert qualifications, survey conditions, and the timing of data collection. Furthermore, the uniformly maximum evaluations assigned to programme P1 across all protective-effect criteria suggest a potential ceiling effect, which may reduce the discriminatory capacity of the assessment scale.

The assumed programme costs, adjustment coefficients, and model observations are not derived from independently verified implementation records. Consequently, the numerical experiment should be interpreted as a methodological demonstration of the proposed approach rather than empirical evidence of the actual effectiveness of defense expenditure. The identified differences between traditional, static, and adaptive portfolio configurations demonstrate the consequences of alternative decision rules under specified assumptions, but they do not establish the superiority of adaptive management in operational practice.

A further issue concerns the interpretation of expert assessments as prior probabilities.

Transforming an average expert rating into the initial probability p_{0j} requires appropriate calibration, since an assessment of seven points on a ten-point scale does not necessarily correspond to a 70% probability of successful implementation. Without empirical validation, such a transformation remains a modeling assumption. The use of the beta-binomial model also presupposes binary observations generated under an appropriately specified probability model. Combining heterogeneous evidence, such as implementation delays, technical test results, and financing milestones, without a consistent measurement framework may distort posterior estimates.

Future applications should therefore distinguish between indicators of intermediate programme readiness and indicators of actual protective outcomes. Where observations differ in reliability, timing, or substantive meaning, hierarchical Bayesian models or other explicitly justified evidence-integration approaches may be more appropriate. In addition, predictive performance should be evaluated using independent observations or out-of-sample validation procedures. Such measures would strengthen the empirical reliability and reproducibility of the proposed methodology.

For practical implementation, the findings support the establishment of a standardized portfolio information system containing programme profiles, baseline assessments, resource requirements, risk indicators, monitoring evidence, and documented management decisions. Periodic reassessment procedures should be defined in advance, together with responsibilities for data collection, validation, and approval. Programme managers, financial units, and technical departments should have clearly assigned responsibilities for maintaining cost, performance, and risk information.

Particular attention should be given to the institutional and regulatory conditions governing defense infrastructure and fortification programmes. Legal, land-use, procurement, and accounting requirements should be incorporated as explicit feasibility constraints rather than treated solely as additional evaluation criteria. This distinction is important because regulatory non-compliance cannot necessarily be compensated for by a high expected protective effect (Cabinet of Ministers of Ukraine, 2023; Zaiets & Sychova, 2024; Sokolenko, 2024).

The sensitivity analysis provides additional insight into the stability of the proposed decision-making approach. Across the four examined values of prior information strength, n_0, the composition of the optimal portfolio remained unchanged, while its expected adjusted effect varied. This finding indicates that the selected portfolio is stable with respect to the examined changes in this particular parameter. However, it does not establish overall model robustness, since uncertainty in expert weights, programme costs, risk coefficients, budget levels, and inter-programme dependencies was not comprehensively investigated.

Overall, the numerical experiment demonstrates how Bayesian updating can be integrated with multi-criteria assessment and constrained portfolio optimization to support the reassessment of defense resource allocation priorities. The results illustrate the potential decision-making value of incorporating new information into portfolio selection. Nevertheless, they do not constitute a statistical test of differences in the actual effectiveness of alternative management systems.

Further research should focus on empirical validation using observed programme implementation data, calibration of expert-derived probabilities, explicit modeling of programme interdependencies, and comprehensive sensitivity and uncertainty analyses. Comparative evaluation across actual planning and funding cycles would also be necessary to determine whether the proposed approach improves resource allocation outcomes under operational conditions.

Conclusions

The study developed and demonstrated a methodological approach to evaluating and selecting defense programmes under budget constraints by integrating multi-criteria assessment, expert-based prior estimates, Bayesian probability updating, and portfolio optimization. The proposed approach provides

a structured and reproducible procedure for revising programme priorities as new information becomes available. Its principal methodological contribution lies in linking the updating of implementation success estimates directly to the reassessment of portfolio composition, rather than limiting the use of new evidence to adjustments of individual programme ratings.

The numerical experiment involving six conditional defense programmes and two sets of ten expert questionnaires produced potential protective-effect scores ranging from 23.50 to 100.00 points and initial implementation success indices ranging from 0.4575 to 0.8160. Following Bayesian updating based on assumed observations, the estimated success probability of programme P1 decreased from 0.8160 to approximately 0.468, whereas that of P3 increased from 0.6025 to approximately 0.728. These changes altered the optimal portfolio composition from P1 + P5 + P6 under the initial estimates to P2 + P3 + P4 + P5 under the updated estimates.

Under the common posterior evaluation framework and an annual budget limit of UAH 80 billion, the adaptive portfolio achieved an expected adjusted protective effect of 181.32 points at an assumed cost of UAH 76 billion. By comparison, retaining the initially optimal portfolio resulted in 112.02 points at an assumed cost of UAH 78 billion. Thus, the adaptive configuration produced a 61.9% higher expected effect within the specified model scenario while requiring fewer financial resources. The sensitivity analysis further demonstrated that the selected adaptive portfolio remained unchanged across the examined values of prior information strength, although its expected effect varied.

These findings illustrate the potential value of systematically incorporating new evidence into defense resource allocation decisions. However, the numerical results depend on assumed implementation observations, programme costs, expert assessments, and adjustment coefficients. Therefore, the estimated improvement should not be interpreted as empirical confirmation of the superiority of adaptive portfolio management under actual operational conditions.

Further research should focus on calibrating expert-derived prior probabilities against observed implementation outcomes, validating the assumptions underlying Bayesian updating, explicitly modeling inter-programme dependencies and risk interactions, and extending sensitivity analysis to programme costs, evaluation weights, and budget constraints. Empirical testing using verified longitudinal data on defense programme implementation is also necessary to assess predictive accuracy and practical decision-making effectiveness.

Subject to such validation, the proposed approach may serve as a methodological foundation for transparent, evidence-informed, and adaptive portfolio management in defense resource allocation.

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