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STOCHASTIC EFFICIENCY MODELING OF MULTIMODAL TRANSPORT SYSTEMS USING AN INTEGRATED PERFORMANCE INDICATOR AND MONTE CARLO SIMULATION

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The growing complexity and uncertainty of multimodal transport systems require the development of advanced methodological approaches for performance evaluation. This paper presents a structured analysis of contemporary research on multimodal transportation efficiency, focusing on deterministic, multi-criteria, and stochastic modeling approaches. The review reveals that deterministic models, although widely used, fail to adequately capture the inherent variability of logistics processes, leading to overly optimistic performance estimates. Multi-criteria approaches improve the comprehensiveness of evaluation but often remain limited by their deterministic nature and subjective weighting schemes.

This study proposes a novel stochastic framework for assessing the performance of multimodal transport systems based on an Integrated Performance Indicator (IPE) that simultaneously accounts for delivery time, transportation cost, and reliability.

The proposed approach formalizes the transport process as a stochastic dynamic system, where key parameters such as travel time, delays, and operational costs are modeled as random variables. To capture the inherent uncertainty, a Monte Carlo simulation method is employed, allowing the estimation of the probability distribution of the IPE rather than relying on deterministic point estimates. Additionally, a nonlinear extension is considered to account for the increased sensitivity of system performance to risk factors.Simulation results demonstrate that deterministic approaches tend to overestimate system efficiency, while stochastic modeling reveals a significant reduction in expected performance due to variability and risks.

The findings confirm that incorporating stochastic modeling and integrated performance metrics provides a more realistic and robust basis for decision-making in multimodal logistics. The proposed framework can be applied to route selection, risk management, and strategic planning of transport operations, particularly in environments characterized by high uncertainty and dynamic disruptions.

Key words: *multimodal transportation; logistics optimization; modeling; risk management; Integrated Performance Indicator.*

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Introduction. Modern research in the field of multimodal transport systems focuses on improving the efficiency of logistics processes in the context of the growing complexity of global supply chains [1–4]. The main approaches to assessing efficiency can be divided into deterministic, multi-criteria and stochastic.

Deterministic models, which are widely used in classical transport problems [5], are based on the use of average or fixed values of parameters, such as delivery time, transportation cost and infrastructure capacity. In particular, in [6] a cost minimization model is proposed taking into account time and environmental factors. However, such approaches are based on fixed parameters and do not take into account the randomness of the transport process, which leads to an overestimation of efficiency.

Despite the simplicity of implementation and interpretation, such approaches have a significant drawback - they do not take into account the uncertainty and random nature of logistics processes. As a result, the resulting estimates may be significantly overestimated and do not reflect the real conditions of the functioning of transport systems, especially in conditions of instability.

Analisys of recent studies and publications. Multi-criteria models are more flexible, as they allow taking into account several factors simultaneously. For example, in [7] a combined approach using DEA and multi-criteria optimization was used, which takes into account time, cost and environmental indicators. However, most of these models remain deterministic and do not integrate uncertainty into the evaluation process. A separate direction is research devoted to the use of stochastic models and simulation modeling methods, in particular the Monte Carlo method [8].

Such approaches allow taking into account the randomness of the parameters of the transport process, including delays, weather conditions and technical failures. However, in most works stochastic analysis is used mainly to assess individual indicators, such as delivery time or the risk of delay, without integrating into a single generalized efficiency criterion. In [9] a stochastic model of transportation planning using mixed nonlinear programming was proposed. Similarly, in [10] Monte Carlo was used to analyze routes and costs. Despite this, most studies apply stochastic analysis only to individual parameters (time or cost).

Modern research also actively uses algorithmic and intelligent methods. For example, in [11], an approach based on reinforcement learning is proposed to take into account time uncertainty. However, such methods are difficult to interpret and do not always provide transparency in decision-making. Another important direction is robust optimization. In [12], it is shown that taking into account uncertainty allows to increase the stability of decisions, although this may increase costs.

In addition, considerable attention is paid to the environmental aspects of transportation. In [13], route optimization is considered taking into account CO_2 emissions and energy factors. However, a literature review [14] confirms that most current approaches face scalability, complexity, and limited real-time applicability.

Considerable attention in modern research is paid to the digitalization of logistics systems [15, 16], including the use of information platforms, Internet of Things technologies, blockchain and artificial intelligence. These approaches are aimed at increasing transparency, coordination and speed of data processing in transport systems. However, in most cases there is no formalized mathematical model that would allow to quantitatively assess the impact of digital solutions on the efficiency of logistics processes.

It should be noted that multi-criteria optimization methods [17], including approaches based on Pareto analysis and weight functions [18], allow to simultaneously take into account several efficiency indicators, in particular time, cost, energy consumption and environmental factors. However, most of such models, such as those shown in [19, 20], consider the criteria in a deterministic formulation, which limits their applicability in real conditions. In addition, the choice of weight coefficients is often subjective, which reduces the objectivity of the results obtained.

Thus, the analysis of modern scientific approaches allows us to identify a number of unresolved problems. First, there is no universal indicator that would simultaneously take into account the time, economic and risk characteristics of multimodal transportation. Second, there is a gap between stochastic modeling methods and multi-criteria approaches to assessing efficiency. Third, the impact of digital logistics systems on the parameters of transport models in a formalized form remains insufficiently studied. In this regard, the development of an integrated approach that combines stochastic modeling, multi-criteria optimization and assessment of the impact of digital technologies is relevant.

Purpose and objectives of the study. The object of the study is the process of functioning of multimodal transport systems under conditions of uncertainty, characterized by variability of delivery time, transport costs and reliability of logistics operations.

The subject of the study is methods and models for assessing the efficiency of multimodal transportation, taking into account the stochastic nature of transport processes, as well as the impact of digital logistics solutions on their parameters.

The choice of research methods is based on the analysis of modern scientific approaches, which revealed the limitations of deterministic models, insufficient integration of multi-criteria and stochastic approaches, as well as the lack of formal consideration of the digitalization of logistics systems.

The aim of the research is to improve the efficiency of multimodal maritime transportation by developing an intelligent risk-based decision support system that combines stochastic modeling, multi-criteria optimization, and assessment of the impact of digital technologies.

To achieve the set goal, the following tasks have been formulated:

– construction of a formal model;

– development of a simulation apparatus;
– quantitative assessment of efficiency.

Main Section. Multimodal transportation is considered as a complex stochastic system in which different types of transport, infrastructure elements and information flows interact. In the conditions of modern logistics chains, such systems operate under the influence of numerous random factors, in particular delays, changes in speed, infrastructure overload and external risks, which is confirmed by modern research in the field of multimodal transportation [21, 22]. Risk modeling is carried out using probability distributions to describe delays, cargo losses, weather effects and technical failures [23]. The main tool is the Monte Carlo method [8], which is one of the key tools of stochastic modeling and has significant advantages over deterministic and classical analytical approaches, especially when studying complex logistics systems. This method allows for the explicit consideration of random factors by using probability distributions of parameters. Unlike deterministic models that give one fixed value, Monte Carlo allows you to obtain a distribution of possible outcomes, which is especially important for transport systems where delivery times are random, delays are stochastic, and costs vary under the influence of external factors. In addition, it allows you to estimate not only the average value, but also the variance, confidence intervals, and probabilities of achieving a certain result, since probabilistic approaches demonstrate greater resistance to errors and biases compared to deterministic models. It also allows you to determine which parameters have the greatest impact on the result and how changing one factor changes the entire system, because unlike deterministic models, where there are 1–3 scenarios, Monte Carlo allows you to analyze thousands of scenarios and obtain statistically sound decisions.

The primary advantages of Monte Carlo simulation, as outlined in [24–26], include its rigorous, comprehensive, and probabilistic nature. This approach is particularly well-suited for risk management and making complex decisions. It is highly valuable in analyses where precision is critical. Relying solely on deterministic methods for significant strategic decisions without accounting for uncertainty can be risky.

Therefore, according to [26] and [27], multimodal transportation can be represented as:

$$MM = \{S_1, S_2, \dots, S_n\}, \tag{1}$$

where S_i is transport segment (river, sea, road);
n is number of route segments.

Total delivery time is defined as the sum of the travel times of individual route segments:

$$T = \sum_{i=1}^{n} \left(\frac{L_i}{V_i} + \Delta_i\right), \tag{2}$$

where: L_i is length of the i-th route segment;
V_i is random speed;
Δ_i is random delay (port, weather, operational);
n is number of segments.

Speed is modeled as a normally distributed random variable:

$$V_i \sim N(\mu V_i, \sigma V_i). \tag{3}$$

where: μ is the mathematical expectation;
σ is the square deviation;
N is normal distribution law (Gaussian distribution).

The distributions of random variables Δ_i can be determined by the exponential distribution:

$$\Delta_i \sim Exp(\mu\Delta_i, \sigma\Delta_i) \tag{4}$$

The probability of a missed deadline is then determined by the formula:

$$P_{delay} = P(T_{total} > T_{max}). \tag{5}$$

where: T_{max} is maximum allowable delivery time;

T_{total} is the total delivery time. It can be determined by:

$$T_{total} = \sum_{i=1}^{n} T_i. \qquad (6)$$

Total transportation costs are determined:

$$C = C_{fuel} + C_{port} + C_{delay} + C_{risk}. \qquad (7)$$

where C_{fuel}, C_{port}, C_{delay}, C_{risk} these are fuel costs, port costs, time costs and unforeseen costs respectively.

We get the expected value:

$$E(C) = \frac{1}{N}\sum_{k=1}^{N} C(k). \qquad (8)$$

Reliability is defined as the probability of meeting the delivery deadline:

$$R = P(T \leq T_{crit}), \qquad (9)$$

where T_{crit} – maximum allowable delivery time.

Construction of a formal model. There is a methodology for multi-criteria optimization of maritime transport under conditions of uncertainty of the external environment [10]. Also, many researchers determine that the most rational way to solve transport problems under conditions of uncertainty is multi-criteria optimization. in which there is a vessel loading, delivery duration, transition speed, load on the main engine, fuel consumption, deviation from the route, transportation cost [10–13].

We propose to introduce an Integrated Performance indicator of Efficiency (IPE), which is a multi-criteria optimization parameter that combine s time efficiency, economic efficiency, risk resistance and reliability for multimodal transportation. The integral efficiency index (IPE) is defined as the weighted sum of the normalized utility functions of delivery time, transportation cost and route reliability and can be determined by the formula:

$$IPE(U_T, U_C, U_R, U_N) = w_T \cdot U_T + w_C \cdot U_C + w_R \cdot U_R + w_N \cdot U_N, \qquad (10)$$

where $U_T = \frac{T_{ref}}{T_{total}}$ is delivery time, $U_C = \frac{C_{ref}}{C}$ is cost, $U_R = R = 1 - P_{delay}$, is route reliability; $U_N = \frac{NPV}{NPV_{ref}}$ is economic efficiency; T_{total} is expected delivery time; C is expected cost. T_{ref}, C_{ref} – base (initial) values of delivery time and cost, respectively; w_T, w_C, w_R w_N is weighting factors.

$$w_T + w_C + w_R + w_N = 1, \qquad (11)$$

Normalization is carried out relative to the baseline scenario T_{ref}, C_{ref}, which ensures the dimensionlessness of the indicator and the possibility of comparing alternative logistics solutions.

An integral indicator of the efficiency of a multimodal logistics system is proposed, which simultaneously takes into account the time, economic and risk characteristics of transportation, as well as the investment feasibility of digitalization.

Based on the calculation of the Saati matrix for 4 elements, the following values of weight coefficients were obtained $w_T = 0{,}34$, $w_C = 0{,}29$, $w_R = 0{,}20$, $w_N = 0{,}17$ to constrain the objective function:

$$\max_{U} IPE(U) \qquad (12)$$

Where $U = (U_T, U_C, U_R, U_N)$ is logistics parameters. For $C(U) \leq C_{max}$, $T(U) \leq T_{max}$, $R(U) \leq R_{max}$. IPE application area summarized in a table 1.

Table 1 – Interpretation of IPE

IPE	***Interpretation***
> 0.8	Highly efficient system
0.5 – 0.8	Acceptable
< 0.5	Inefficient

The IPE evaluation criterion is defined as:

$$\Delta IPE = IPE_{SN} - IPE_{base}, \quad (13)$$

where IPE_{SN} is integral indicator of effectiveness from the implementation of solutions.

IPE_{base} is ntegral indicator of the effectiveness of the basic model.

If ΔІПЕ > 0 – the solutions are effective, the implementation of the appropriate management policy is considered appropriate.

Let's take into account the military situation as a risk function, then $w_R = f(R)$,, the result of IPE calculations is shown in Fig. 1

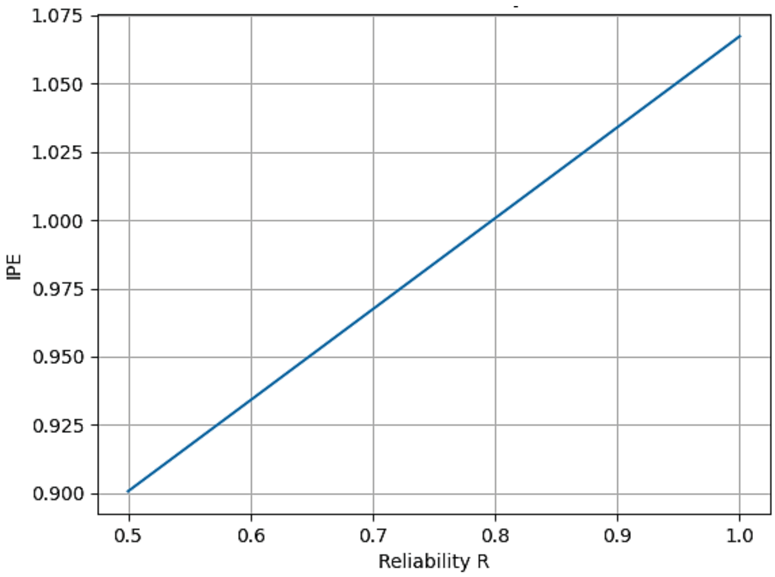

Figure 1 – Graph of the dependence of the integral efficiency indicator $IPE = f(R)$ on reliability

As shown in Fig. 1, the integral efficiency indicator has a monotonic dependence on the probability of delays. The increase in risk leads to a proportional decrease in the efficiency of the logistics system. It is determined that the critical zone is the value P_{delay}>0.4, at which the system loses its economic feasibility. Instead, in the range of 0.05–0.25, an optimal balance between costs, time and reliability of transportation is ensured. at $R \approx$ 0.8→ $IPE \approx 1$ (balance point).

Areas of application of the integral efficiency indicator (IPE):

– route selection;
– transportation optimization;
– ETA planning;
– carrier selection;
– transshipment planning;
– fleet management;
– investments in digitalization;
– selection of logistics corridors;
– port efficiency assessment;
– route instability;
– military risks;
– alternative corridors (Danube, Black Sea, etc.).

Criteria efficiency limits:

If $w_T \gg w_C, w_R$ – then the system is based more on speed and it is possible to ignore costs.

If $P_{delay} \to 0.5$ – the IPE indicator becomes unstable, at $0.7 < R < 0.98$ – IPE is effective and the system is stable, outside this range – the system is risky.

Development of a simulation apparatus. Taking into account the uncertainty of the parameters of the transport process, the integral efficiency indicator is considered as a random variabl:

$$IPE = IPE(T, C, R). \quad (14)$$

For its evaluation, the Monte Carlo method was used, which is one of the key tools of stochastic modeling and has significant advantages over deterministic and classical analytical approaches, especially when studying complex logistics systems. The main advantage of the Monte Carlo method is the ability to explicitly take into account random factors by using probability distributions of parameters.

Unlike deterministic models that give one fixed value, Monte Carlo allows you to obtain a distribution of possible results [24]. This is especially important for transport systems where: delivery time is random, delays are stochastic in nature, and costs change under the influence of external factors. Therefore, the Monte Carlo method provides a more realistic and justified assessment of the efficiency of multimodal transportation, which is critically important in dynamic and unstable logistics environments.

Accordingly, in each iteration we will simulate random values of speed and delays, and then calculate the delivery time, transportation cost, and reliability index. The total delay is defined as:

$$P_{delay\_h} = \frac{1}{N}\sum_{k=1}^{N} I({T_{total}}^{k} > T_{max}) \quad (15)$$

where N is number of simulations; I is indicator function.

The code Monte Carlo algorithm is given showen in Figure 2.

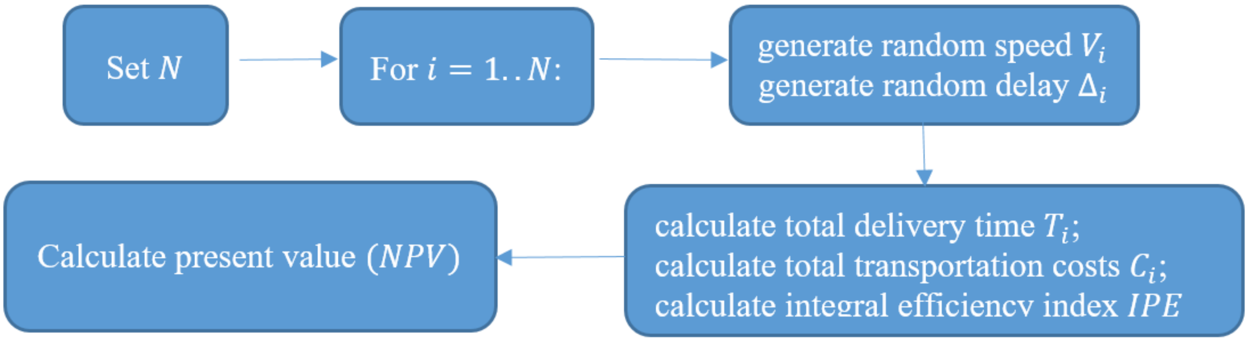

Figure 2 – Monte Carlo algorithm

Calculate for each iteration the time of passage of the i-th segment:

$$T_i = \frac{L_1}{V_{1,i}} + \Delta_{1,i} + \frac{L_2}{V_{2,i}} + \Delta_{2,i} \quad (16)$$

Costs:

$$C_i = f(T_i) \quad (17)$$

$$R_i = 1(T_i < T_{crit}) \quad (18)$$

The integral efficiency indicator is used as the objective function of the stochastic multi-criteria optimization problem of multimodal transportation.

$$IPE(U) = w_T \cdot \frac{T_{ref}}{T_i} + w_C \cdot \frac{C_{ref}}{C_i} + w_R \cdot R_i + w_N \cdot \frac{NPV}{NPV_{ref}} \quad (19)$$

Optimization is carried out by means of multiple Monte-Carlo simulation of possible configurations of the logistics system with the subsequent search for the configuration that provides the maximum value of the integral efficiency criterion.

Simulation result. Let's calculate for the base scenario, parameters: $T_{ref} = 60\ hours$, $C_{ref} = 3000€, NVP_{ref} = 7800000€$.
For an alternative scenario, we assume: $T = 55\ hours,\ C = 2700€,\ R = 0.82,\ NPV = 8800000€$.
Calculation:

$$w_T = 0.34, w_C = 0.29, w_R = 0.2, w_N = 0.17$$

$$R = 1 - 0.18 = 0.82$$

$$IPE(U) = 0.34 \cdot \frac{60}{55} + 0.29 \cdot \frac{3000}{2700} + 0.2 \cdot 0.82 + 0.17 \cdot \frac{8.8}{7.8} + =$$

$$= 0.34 \cdot 1.091 + 0.29 \cdot 1.111 + 0.2 \cdot 0.82 + 0.17 \cdot 1.13 =$$

$$= 0.371 + 0.3223 + 0.246 + 0.164 = 1.021$$

$$IPE > 1\ , \Delta IPE = +0.11\%$$

With equal weight coefficients, $IPE = 1.021$ was obtained, which indicates an increase in the efficiency of the system compared to the basic variant. IPE has a monotonic dependence on the reliability of the route. An increase in the R indicator leads to a proportional increase in the efficiency of the logistics system.

Calculations considering the Monte Carlo distribution will be based on uncertainty of risk occurrence.

Simulation results ($N = 1000$) showed: $IPE = 0.52$.

The results shown in Fig. 3 show that IPE drops when we start to consider risks. Therefore, the real system is much less efficient due to uncertainty, since delays "eat" efficiency and speed variation has a critical impact.

The obtained distribution demonstrates that even with favorable average parameters, the system is characterized by a decrease in efficiency due to the influence of stochastic factors.

This confirms the need to consider risks when evaluating logistics decisions.

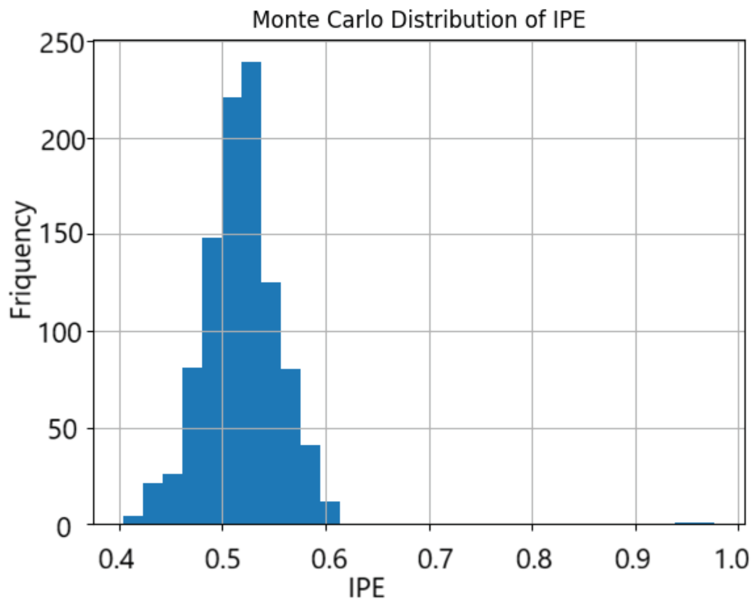

Figure 3 – Distribution of IPE depending on the frequency of risk occurrence

The integral performance indicator correlates with financial results, in particular with net present value (NPV), where the growth of IPE corresponds to the increase in the economic feasibility of logistics solutions: $NPV = f(IPE)$,

The adopted basic values and parameters for modeling are presented in the table 2.

Table 2 – Parameters for simulation

Parameter	***Value***
Transportation volume, t/year	120000
Base transportation cost, EUR/t	65
Annual costs, EUR	7800000
Discount rate	0,1
Delay before implementation, %	24,12
Delay after implementation, %	8,6
Cargo losses before implementation, %	3
Cargo losses after implementation, %	1
Project period, years	5
Number of Monte Carlo iterations	500

The formulation of the optimization problem can be reduced to $\max_{R,M}(R, M)$ on condition

$$T_{total} \leq T_{max}, C \leq C_{max}, P_{delay} \leq \varepsilon \quad (20)$$

where M – management policy (digital architecture).

A Python program was developed for modeling. Therefore, to normalize the pairwise comparison matrix, the following weighting coefficients were obtained:

$$w_T = 0.34, \ \ w_C = 0.29, \ w_R = 0.2, w_N = 0.17.$$

The initial parameter input screen and part of the code are shown in Fig. 4

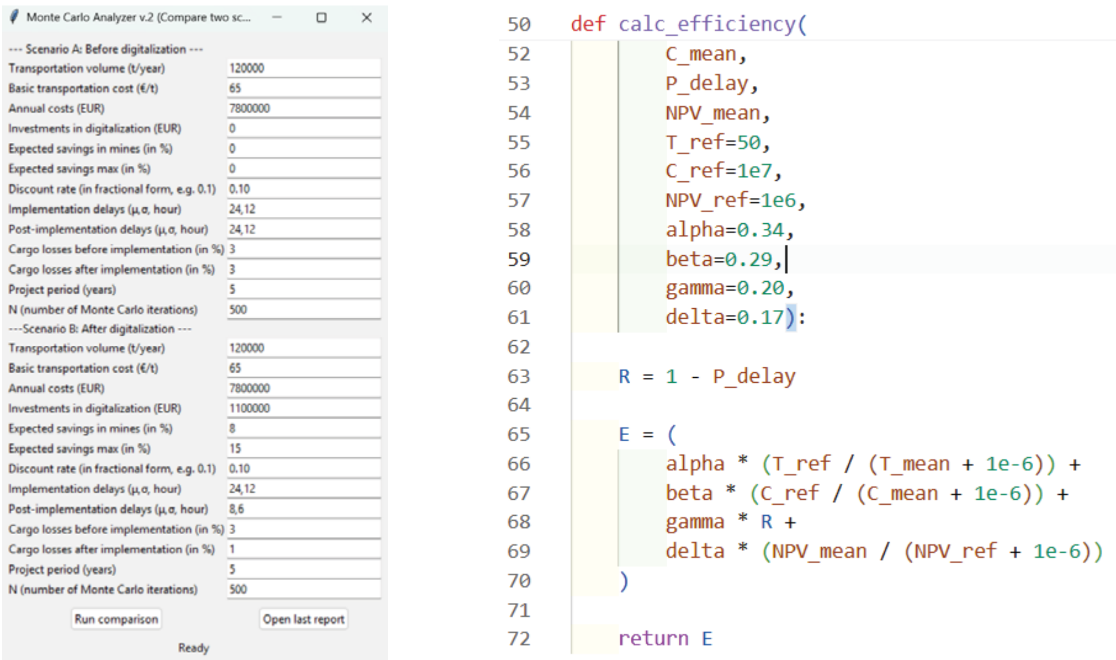

Figure 4 – The initial parameter input screen and part of the code of programm

Monte Carlo simulation is implemented by repeatedly generating random scenarios of the functioning of a multimodal transport system. In each iteration, the following are randomly generated: time delays; economic effect of digitalization; extreme logistics events; freight losses; total logistics costs. To generate random variables, the following are used: normal distribution – for modeling standard delays; uniform distribution – for estimating the range of savings; binomial mechanism – for generating extreme risk events. The part of the code where random variable generation is implemented is shown in Fig. 5.

```python
    for i in range(N):

        saving = np.random.uniform(save_min, save_max)

        delay_before = np.random.normal(mu_no, sigma_no)
        delay_after = np.random.normal(mu_with, sigma_with)

        delay_before = max(delay_before, 0)
        delay_after = max(delay_after, 0)

        # extreme events
        if np.random.rand() < p_extreme:
            delay_before += np.random.uniform(48, 120)

        if np.random.rand() < p_extreme * 0.5:
            delay_after += np.random.uniform(24, 72)

        total_time = delay_after

        cost_before = (
            transport_base +
            delay_before * 1000 +
            loss_before * transport_base
        )

        cost_after = (
            transport_base * (1 - saving) +
            delay_after * 1000 +
            loss_after * transport_base
        )

        annual_saving = cost_before - cost_after

        npv = (
            np.sum([
                annual saving / ((1 + r) ** t)
                for t in range(1, T_proj + 1)
            ])
            - I
        )

        npv_results.append(npv)
        time_results.append(total_time)
        cost_results.append(cost_after)

    npv_results = np.array(npv_results)
    time_results = np.array(time_results)
    cost_results = np.array(cost_results)

    delay_prob = np.mean(time_results > np.mean(time_results))

    summary = {
        "npv_results": npv_results,
        "time_results": time_results,
        "cost_results": cost_results,

        "mean_npv": np.mean(npv_results),
        "std_npv": np.std(npv_results),

        "mean_time": np.mean(time_results),
        "mean_cost": np.mean(cost_results),

        "delay_prob": delay_prob,

        "p_positive": np.mean(npv_results > 0)
    }

    return summary
```

Figure 5 – The part of the code where random variable generation

Each iteration generates a separate scenario for the development of the logistics system, after which the integral efficiency indicators and net present value (NPV) are calculated.

1000 Monte-Carlo iterations were performed within the framework of the study, which allowed obtaining a statistically representative distribution of possible results.

A comparison of two scenarios is envisaged:

A (initial state) and *B* (state of the system after the implementation of risk assessment digitalization systems).

After modeling, the calculation results obtained are given in the table 3.

Table 3 – Simulation results

Scenario	***Mean NPV (million €)***	***Median NPV (million €)***	***P(NPV>0)***	***Std dev (million €)***
Before	0.88	0.52	57.60%	3.94
After	8.73	8.18	99.00%	3.93

Graphs comparing the results are shown in Fig. 3.

$$IPE_A = 0.43, IPE_B = 0.53$$

$$\Delta IPE = 0.12 \approx 12\%$$

Probability of negative $NPV_A = 42.40\%$, $NPV_B = 1\%$.

Quantitative assessment of efficiency. The *IPE* distribution for scenario *B* is shifted towards higher values and is characterized by lower variability (Fig.6). This indicates an increase in the average level of efficiency (Fig. 7 and Fig. 8); a reduction in the risk of inefficient implementations and a stabilization of the logistics process.

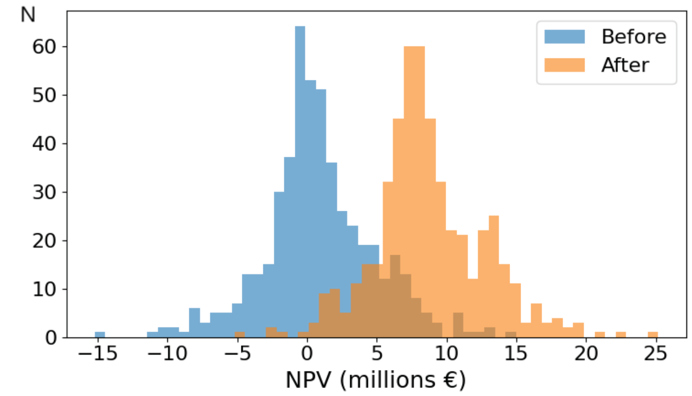

Figure 6 – Comparison of distributions NPV_A i NPV_B

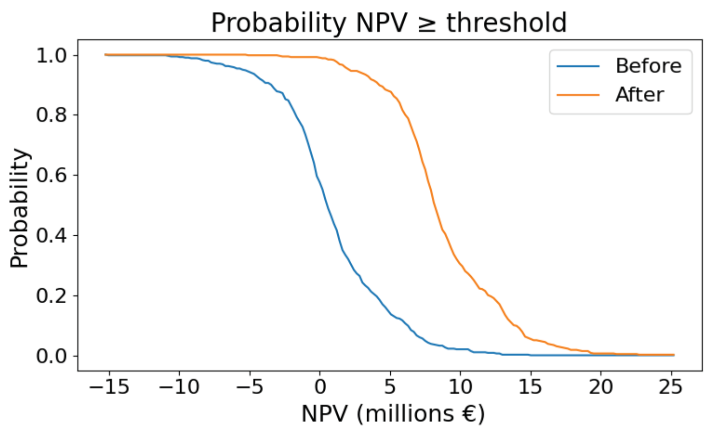

Figure 7 – Probability dependence NPV_A i NPV_B depending on costs

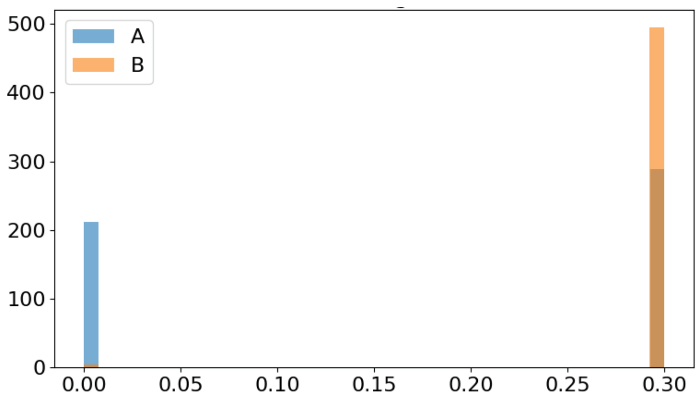

Figure 8 – Distribution of the integral indicator for the options *A* and *B*

Scenario *B* demonstrates a higher expected economic benefit compared to *A* – the implementation of digital solutions is economically feasible according to average estimates.

Implementation reduces the probability of losses (negative *NPV*).

Conclusions. The integral efficiency indicator is a generalized criterion for evaluating multimodal transportation, which combines time, economic and risk characteristics into a single function. Its application allows not only to compare alternative logistics solutions, but also to formalize the task of optimizing routes under uncertainty. Unlike classical approaches, the proposed indicator takes into account the stochastic nature of transport processes, which makes it suitable for practical use in modern conditions of instability of logistics systems.

The constructed mathematical model allows taking into account the random nature of key parameters of the transport process, in particular delivery time, delays and transportation costs. The results of simulation modeling showed that different management policies can significantly differ in terms of the "cost-risk" ratio.

The improvement of the integral indicator by 11% was due to the fact that the coordination of multimodal transportation allowed: to reduce unproductive downtime; to reduce transshipment costs; to reduce operating costs; to optimize the use of ship batches. This ensured a decrease in total logistics costs and an increase in net discounted income (NPV).

this was implemented by reducing and reducing additional delays in the event of crisis situations. As a result, the dispersion of the transport process decreased and its stability increased.

The proposed integral performance indicator allows for a comprehensive assessment of alternative logistics solutions and to justify the choice of the optimal management architecture for early risk detection; delay prediction; route reservation; adaptive transportation replanning.

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Жищинський Ю. С. Шарко О. В. СТОХАСТИЧНЕ МОДЕЛЮВАННЯ ЕФЕКТИВНОСТІ МУЛЬТИМОДАЛЬНИХ ТРАНСПОРТНИХ СИСТЕМ З ВИКОРИСТАННЯМ ІНТЕГРОВАНОГО ПОКАЗНИКА ЕФЕКТИВНОСТІ ТА МОДЕЛЮВАННЯ МЕТОДОМ МОНТЕ-КАРЛО

Зростаюча складність та невизначеність мультимодальних транспортних систем вимагають розробки передових методологічних підходів до оцінки ефективності. У цій статті представлено структурований аналіз сучасних досліджень ефективності мультимодальних перевезень, зосереджуючись на детермінованих, багатокритеріальних та стохастичних підходах моделювання. Огляд показує, що детерміновані моделі, хоча й широко використовуються, не враховують належним чином притаманну мінливість логістичних процесів, що призводить до надмірно оптимістичних

оцінок ефективності. Багатокритеріальні підходи покращують повноту оцінки, але часто залишаються обмеженими своєю детермінованою природою та суб'єктивними схемами зважування.
Запропоновано нову стохастичну структуру для оцінки ефективності мультимодальних транспортних систем на основі Інтегрованого показника ефективності (IPE), який одночасно враховує час доставки, вартість транспортування та надійність.
Запропонований підхід формалізує транспортний процес як стохастичну динамічну систему, де ключові параметри, такі як час подорожі, затримки та експлуатаційні витрати, моделюються як випадкові величини. Для врахування невід'ємної невизначеності використовується метод моделювання Монте-Карло, що дозволяє оцінити розподіл ймовірностей IPE, а не покладатися на детерміновані точкові оцінки. Результати моделювання показують, що детерміновані підходи схильні переоцінювати ефективність системи, тоді як стохастичне моделювання виявляє значне зниження очікуваної ефективності через мінливість та ризики.
Результати підтверджують, що поєднання стохастичного моделювання та інтегрованих показників ефективності забезпечує більш реалістичну та надійну основу для прийняття рішень у мультимодальній логістиці. Запропонована структура може бути застосована для вибору маршруту, управління ризиками та стратегічного планування транспортних операцій, особливо в середовищах, що характеризуються високою невизначеністю та динамічними збоями.
Ключові слова: *мультимодальні перевезення; оптимізація логістики; моделювання; управління ризиками; інтегральний показник.*

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