# МАТЕМАТИКАНЫ ОҚЫТУ ӘДІСТЕМЕСІ

# МЕТОДИКА ПРЕПОДАВАНИЯ МАТЕМАТИКИ

# METHODS OF TEACHING MATHEMATICS

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## APPLIED ORIENTATION OF TEACHING STOCHASTIC METHODS TO ENGINEERING STUDENTS

*Abstract*

The application of stochastic techniques as a tool for enhancing the quality of the technical specialties' educational process is investigated in this paper. Particularly relevant in the framework of fast technical and digitalization advancements, these approaches enable the modeling of complicated industrial processes and solving of problems under conditions of uncertainty. The research emphasizes the development of strategies for instructing stochastic procedures inside educational curricula designed to cultivate technical specialists. The primary objective of this study is to enhance students' analytical thinking, forecasting, and decision-making skills in unconventional situations, thereby allowing educational processes to align with the requirements of contemporary industrial sectors. The scientific and pragmatic relevance of the research is found in the fact that stochastic approaches enable the combination of theoretical knowledge with practical skills, therefore facilitating the training of highly qualified experts ready to operate in dynamic and complex systems. The study approach called for theoretical modeling, data analysis, and investigation of real-world examples. By means of production scenario modeling, the outcomes were acquired, therefore highlighting the efficiency of stochastic methods in addressing practical issues. The results of the research suggest that using stochastic approaches helps students to acquire their data analysis, process management under uncertainty, and modern digital tool application abilities. The approach significantly helps to create adaptable learning environments meant to solve industrial challenges. The practical relevance of the research findings is in their usefulness for the creation of educational programs meant to equip graduates fulfilling the criteria of digital transformation and modern industries.

**Keywords:** stochastic methods, Monte Carlo method, Markov processes, applied problems, technical specialties.

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## ТЕХНИКАЛЫҚ МАМАНДЫҚТАРДЫҢ СТУДЕНТТЕРІНЕ СТОХАСТИКАЛЫҚ ӘДІСТЕРДІ ОҚЫТУДЫҢ ҚОЛДАНБАЛЫ БАҒЫТЫ

*Аңдатпа*

Мақалада техникалық мамандықтарда білім беру үдерісінің сапасын арттыру құралы ретінде стохастикалық әдістерді қолдану қарастырылады. Бұл әдістер күрделі өндірістік процестерді модельдеуге және белгісіздік жағдайларында мәселелерді шешуге мүмкіндік береді, бұл технологиялар мен цифрландырудың қарқынды дамуы жағдайында ерекше маңызды. Зерттеу техникалық мамандарды дайындау үшін білім беру бағдарламаларына стохастикалық әдістерді оқытудың әдістемелік тәсілдерін әзірлеуге бағытталған. Жұмыстың негізгі идеясы – студенттердің аналитикалық ойлау, болжау және стандартты емес жағдайларда шешім қабылдау дағдыларын қалыптастыру арқылы білім беру үдерістерін қазіргі заманғы өнеркәсіп салаларының талаптарына бейімдеу. Зерттеудің ғылыми және практикалық маңыздылығы стохастикалық әдістер теориялық білімді практикалық дағдылармен үйлестіруге мүмкіндік беретінімен ерекшеленеді, бұл күрделі және динамикалық жүйелер жағдайында жұмыс істей алатын жоғары білікті мамандарды даярлауға ықпал етеді. Зерттеу әдіснамасында теориялық модельдеу, деректерді талдау және практикалық кейстерді зерттеу қолданылды. Нәтижелер өндірістік жағдайларды модельдеу негізінде алынған, бұл стохастикалық тәсілдердің нақты мәселелерді шешудегі тиімділігін көрсетеді. Зерттеу нәтижелері стохастикалық әдістерді қолдану студенттердің деректерді талдау, белгісіздік жағдайларында процестерді басқару және заманауи цифрлық құралдарды пайдалану дағдыларын дамытуға ықпал ететінін растайды. Жұмыс білім беру жүйесін өндірістік міндеттерді шешуге бағытталған адаптивті жүйелерді дамытуға елеулі үлес қосады. Зерттеу нәтижелерінің практикалық маңыздылығы оның нәтижелерін цифрлық трансформацияның және қазіргі заманғы индустриялардың талаптарына жауап беретін түлектерді дайындайтын білім беру бағдарламаларын әзірлеу кезінде қолдану мүмкіндігінде жатыр.

**Түйін сөздер:** стохастикалық әдістер, Монте-Карло әдісі, марков процестері, қолданбалы есептер, техникалық мамандықтар.

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**ПРИКЛАДНАЯ НАПРАВЛЕННОСТЬ ОБУЧЕНИЯ СТОХАСТИЧЕСКИМ МЕТОДАМ СТУДЕНТОВ ТЕХНИЧЕСКИХ СПЕЦИАЛЬНОСТЕЙ**

*Аннотация*

В статье исследуется применение стохастических методов как инструмента для повышения качества образовательного процесса технических специальностей. Особенно актуальными эти подходы становятся в условиях стремительных технических и цифровых преобразований, так как они позволяют моделировать сложные промышленные процессы и решать задачи в условиях неопределенности. Исследование сосредоточено на разработке методик преподавания стохастических методов в образовательных программах, направленных на подготовку технических специалистов. Основной целью работы является развитие у студентов аналитического мышления, навыков прогнозирования и принятия решений в нестандартных ситуациях, что позволяет адаптировать образовательный процесс под требования современных отраслей промышленности. Научная и практическая значимость исследования заключается в том, что стохастические подходы способствуют объединению теоретических знаний с практическими навыками, тем самым обеспечивая подготовку высококвалифицированных специалистов, готовых работать в динамичных и сложных системах. В рамках исследования использовались теоретическое моделирование, анализ данных и изучение реальных примеров. Путем моделирования производственных сценариев были получены результаты, подтверждающие эффективность стохастических методов в решении практических задач. Результаты исследования показывают, что применение стохастических методов помогает студентам приобретать навыки анализа данных, управления процессами в условиях неопределенности и использования современных цифровых инструментов. Подход значительно способствует созданию адаптируемых учебных сред, направленных на решение задач промышленного сектора. Практическая значимость результатов исследования заключается в их применимости для разработки образовательных программ, нацеленных на подготовку выпускников, соответствующих критериям цифровой трансформации и современных отраслей промышленности.

**Ключевые слова:** стохастические методы, метод Монте-Карло, марковские процессы, прикладные задачи, технические специальности.

## Main provisions

The major objectives of the research are to investigate methodological approaches to their use and to find the relevance of stochastic techniques in the technical education process. Markov processes and the Monte Carlo approach were applied to fit instructional materials for industrial environments. These approaches were seen as efficient instruments for addressing mathematical problems and simulating complicated systems. The goal of this research aimed to offer a thorough investigation of stochastic technique use in the educational process.

## Introduction

Modern technical education is absolutely essential in the environment of industrial globalization, digital transformation, and technological uncertainty to provide professionals with the necessary skills to operate successfully. Students in practical industrial environments have to gain not just academic knowledge but also skills in data analysis, forecasting, and management due of the complexity of industrial processes and the rapid development of technology. Sometimes conventional teaching methods are insufficient for properly preparing students to manage the complexity of modern industrial processes and may not be able to control changing surroundings.

Derived from probabilistic models, stochastic approaches find tremendous use in engineering for data analysis and process optimization. Sheldon M. Ross's work [1] carefully investigates the fundamental concepts and instruments of stochastic processes. Moreover addressed in the monograph [2] by András Prékopa are other applications for stochastic optimization methods. These studies offer the theoretical framework for the use of stochastic methods spanning several domains; yet, there is still a great gap in particular direction for their implementation inside the educational system. Recently, stochastic approaches added into the learning process have drawn interest. The work of Haldar and Mahadevan highlights the managing of engineering design uncertainty by use of stochastic methods [3]. Although this research demonstrate the effectiveness of stochastic approaches in engineering, careful strategies for their methodical use in educational settings still lack.

Further studies have stressed how stochastic approaches should be applied during the learning process [4,5]. Examining difficult systems using these methods will enable pupils to develop professionally more ready. Many current studies neglected practical relevance in favor of theoretical models. The present publication attempts to offer methodological rules and explore the possibilities of stochastic approaches for technical education. Review present methods, modify stochastic models for education, and evaluate how these changes impact students' analytical and practical skills are the key objectives. Stochastic techniques are supposed to increase students' capacities in data analysis, forecasting, and decision-making under uncertainty, therefore enabling their successful assimilation into practical industrial environments. This work presents a comprehensive understanding of the opportunities for adding stochastic techniques into instructional activities by means of real-world case studies, industrial situation modeling, and theoretical analysis.

## Research methodology

In engineering sciences, often employed stochastic models and methods contributed to develop methodological approaches. By means of mathematical modeling and probabilistic tools, these methods allow efficient management of systems affected by stochastic fluctuations and uncertainty. Stochastic methods are a collection of mathematical and computational techniques designed to address random or uncertain factors in issues. Mostly different from others are stochastic approaches in their use of probabilistic models to facilitate decision-making in uncertain surroundings and help to clarify events. These approaches help with optimization, forecasting, modeling difficult systems, data analysis [6,7] and other areas.

1. The Monte Carlo method is a mathematical computational tool based on probability and random numbers. It is used for the modeling and analysis of systems that incorporate stochastic elements or provide challenges in solving intricate mathematical models. Especially in instances where a perfect analytical solution is unattainable, the Monte Carlo method facilitates the approximation of solutions to several problems. This method fundamentally produces a substantial quantity of random numbers for computational purposes. These figures represent the stochastic processes of actual systems. Each computation is regarded as a "experiment," and the average of the outcomes gives an approximate value for the quantity being assessed [7,8].

2. Markov processes are mathematical models of random systems where the probability of transitioning to the next state depends only on the current state and is independent of all previous states. These processes are used to analyze systems undergoing dynamic changes, such as predicting equipment failures or modeling the flow of requests in service systems.

In the field of education, Markov processes have been utilized to model sequences of events characteristic of real industrial processes [7,9]. A Markov chain is a stochastic process where the probability of transitioning to the next state depends only on the current state. In other words, past states have no influence on this transition probability. This characteristic is known as the Markov property [7,3].

*Key Concepts:* Set of States: $S = \{s_1, s_2, ..., s_n\}$

Time Scale: time can be either discrete $(t = 0,1,2...)$ or continuous $(t \in R)$.

Transition Probability:

For discrete time: $P(X_{t+1} = s_j \mid X_t = s_i) = p_{ij}$.

For continuous time, the transition rate $q_{ij}$ is used.

*Discrete Markov Chain*

Transition probabilities between states are described by the matrix P, where $p_{ij}$ represents the probability of transition from state i to state j.

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix}.$$

*Conditions:*

1. $0 \le p_{ij} \le 1$ for all i, j..
2. The sum of each row equals 1: $\sum_{j=1}^{n} p_{ij} = 1$

If $\pi_t$ - represents the probability distribution at step t, then the probability distribution after n steps is given by: $\pi_{t+n} = \pi_t P^n$,

Here $P^n$ – is the n-th power of the transition probability matrix P.

*Stationary Distribution*

A stationary distribution π satisfies the following equation: $\pi = \pi P$,

Where: $\pi = \{\pi_1, \pi_2, ..., \pi_n\}$ and $\sum_{i=1}^{n} \pi_i = 1$

*Continuous-Time Markov Chain*

In continuous-time Markov chains, the transition probabilities are described using the generator matrix *Q*, where $q_{ij}$ – represents the transition rate from state i to state j. The transition rates $q_{ij}$ are defined as:

$q_{ij} = \lim\limits_{\Delta t \to 0} \dfrac{P_{ij}(\Delta t) - \delta_{ij}}{\Delta t}$, where $\delta_{ij}$ – Kronecker Delta Symbol ($\delta_{ij} = 1$, if *i=j*, or $\delta_{ij} = 0$).

Properties of the Generator Matrix *Q*:

1. $q_{ij} \ge 0$ for $i \ne j$ 2. $q_{ii} = -\sum_{i \ne j} q_{ij}$

*Task 1.* The company wants to evaluate the probability that its web server can handle incoming requests within a specified time interval ($t_{\max}$). The number of requests (N) varies depending on the time of day, ranging from 100 to 1,000. The processing time for each request (t) is a random variable with a mean and standard deviation (mean processing time is approximately μ=0.02 seconds, and standard deviation is σ=0.005 seconds). The total time required to process all requests is $t_{total} = \sum_{i=1}^{N} t_i$. Determine the probability that, $t_{total} \le t_{\max}$ under the given conditions.

*Methodological Guidelines for Solving the Problem*

a) Algorithm and Application of the Monte Carlo Method:

1. Identifying the Given Data

Number of requests (N) is a random variable in the range [100,1000].

Processing time for each request (t) follows a normal distribution with a mean μ and standard deviation σ. Total processing time for all requests: $t_{total} = \sum_{i=1}^{N} t_i$

2. Simulation

Perform M iterations (e.g., M=10,000). In each iteration:

Randomly select the number of requests (N).

Randomly generate the processing time for each request (t).

Calculate the total processing time $t_{total}$.

3. Condition Check

If $t_{total} \le t_{\max}$ the simulation is considered successful.

4. Calculate the Result

Estimate the probability using the number of successful simulations:

$$P_{success} = \frac{SuccessCount}{M}$$

b) Flowchart

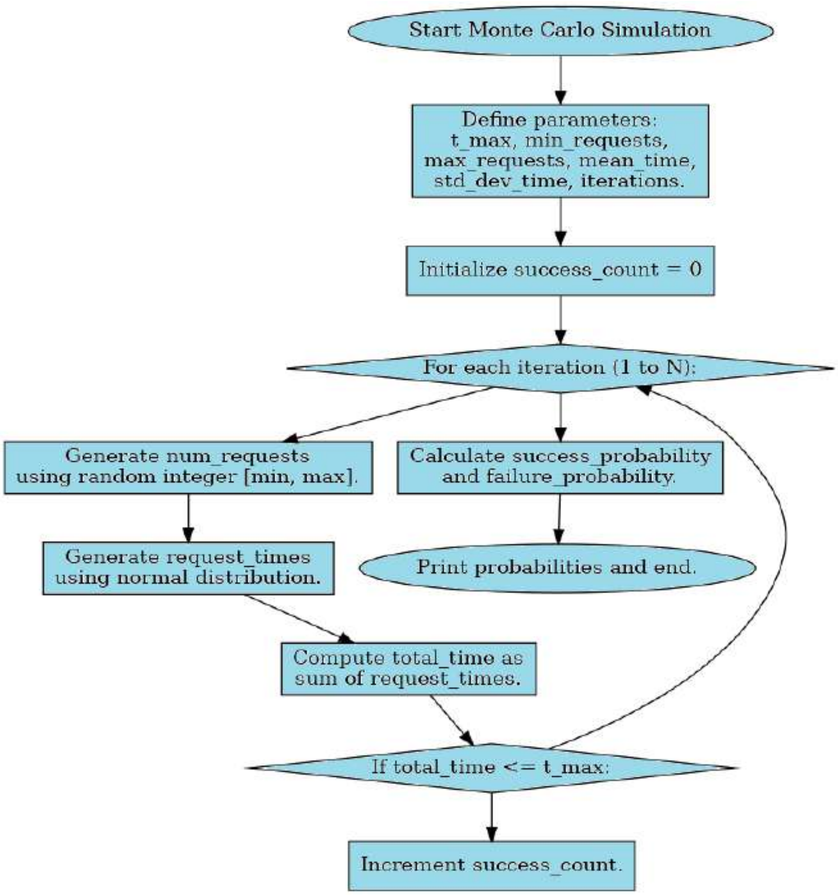


*Figure 1. Flowchart for Solving the Problem*

c) Solution in Python Program:

```
import numpy as np

# Parameters
t_max = 5  # Maximum time (seconds)
min_requests = 100  # Minimum number of requests
max_requests = 1000  # Maximum number of requests
mean_time = 0.02  # Average processing time per request (seconds)
std_dev_time = 0.005  # Standard deviation (seconds)
iterations = 10000  # Number of iterations

# Results
success_count = 0

# Monte Carlo Simulation
for _ in range(iterations):
    # Number of requests
    num_requests = np.random.randint(min_requests, max_requests + 1)
    # Processing time for each request
    request_times = np.random.normal(mean_time, std_dev_time, num_requests)
    # Total processing time
    total_time = np.sum(request_times)

    # Check condition
    if total_time <= t_max:
        success_count += 1

# Calculate results
success_probability = success_count / iterations
failure_probability = 1 - success_probability

print(f"Probability of successful processing: {success_probability:.2%}")
print(f"Probability of failed processing: {failure_probability:.2%}")
```

```
Probability of successful processing: 16.83%
Probability of failed processing: 83.17%

=== Code Execution Successful ===
```

*Figure 2. Solution in the Python Program*

d) Result:

As a result of the simulation, the probability of successful processing is calculated. This indicator allows assessing the server's ability to handle the load.

*Task 2.* The time to download a file of size F=500F = 500F=500 MB from a server depends on the download speed S, which is determined by a normal distribution (μ=10 MB/sec, σ=2 MB/sec). Perform M=10,000 simulations and calculate the mean download time of the file along with the 95% confidence interval.

*Methodological Guidelines for Solving the Problem*

a) Algorithm and Application of the Monte Carlo Method

1. Identifying the Given Data:

F – file size (MB), μ,σ – mean and standard deviation of the download speed,

M – number of simulations.

2. Simulation

A loop is created to repeat M times.

At each iteration, the download speed (S) is randomly selected based on the normal distribution.

If S≤0, the download speed is set to S=0.1 (to avoid errors).

The download time is calculated using the following formula: $T = \frac{F}{S}$.

3. Calculating the Results

Mean download time: $T_{mean} = \frac{1}{M}\sum_{i=1}^{M} T_i$ .

Confidence interval: $CI = T_{mean} \pm z\frac{\sigma_T}{\sqrt{M}}$

where *z*=1.96 (for a 95% confidence level).

b) Flowchart

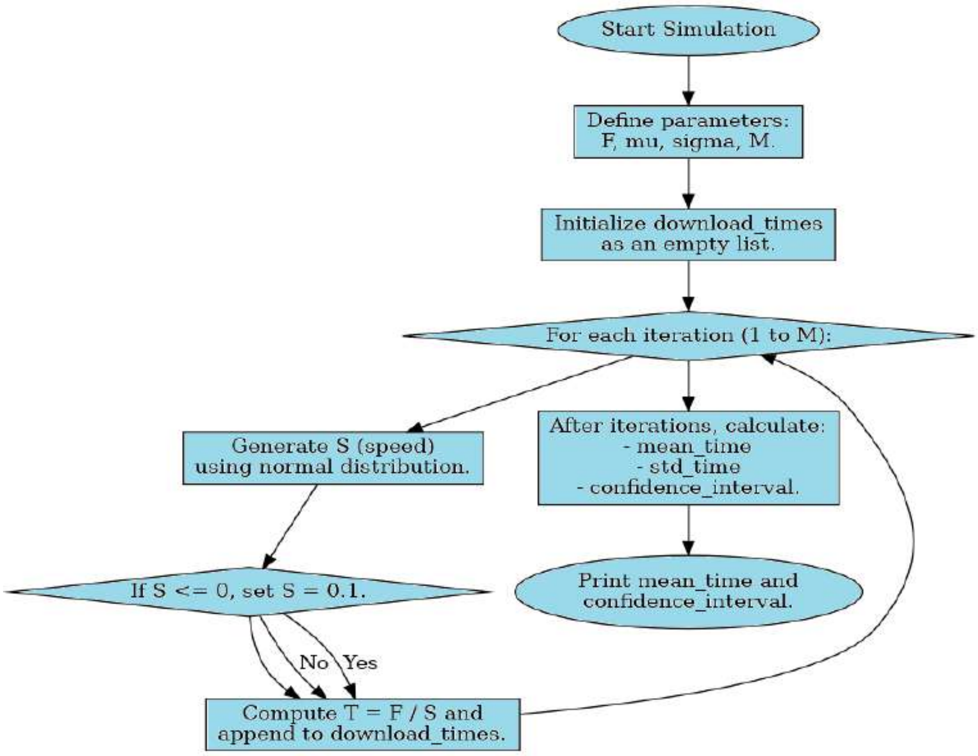


*Figure 3. Flowchart for Solving the Problem*

c) Solution in the Python Program:

```
import numpy as np

# Input Data
F = 500  # File size (MB)
mu = 10  # Average download speed (MB/sec)
sigma = 2  # Standard deviation of download speed (MB/sec)
M = 10000  # Number of simulations

# Simulation results
download_times = []

for _ in range(M):
    # Generate download speed based on normal distribution
    S = np.random.normal(mu, sigma)
    # If the speed is below 0, set it to 0.1
    if S <= 0:
        S = 0.1
    # Calculate download time
    T = F / S
    download_times.append(T)

# Calculate results
mean_time = np.mean(download_times)  # Average download time
std_time = np.std(download_times)  # Standard deviation
confidence_interval = (
    mean_time - 1.96 * std_time / np.sqrt(M),
    mean_time + 1.96 * std_time / np.sqrt(M),
)

print(f"Average download time: {mean_time:.2f} seconds")
```

```
Average download time: 52.06 seconds
Confidence interval: [51.83, 52.30] seconds

=== Code Execution Successful ===
```

*Figure 4. Solution in the Python Program*

d) Result

Mean Download Time ($T_{mean}$): The average time required to download the file.

Confidence Interval (CI): Indicates that with 95% probability, the download time will fall within this interval.

*Task 3.* The network load over time can exist in three states: Low, Medium, and High. The probability of staying in the Low Load state is 70%, transitioning to the Medium Load state is 25%, and transitioning to the High Load state is 5%. For the Medium Load state, the probability of staying is 50%, transitioning to the Low Load state is 30%, and transitioning to the High Load state is 20%. In the High Load state, the probability of staying is 30%, transitioning to the Low Load state is 40%, and transitioning to the Medium Load state is 30%. If the network initially starts in the Low Load state, determine the probability of being in each state after 5 transitions.

*Methodological Guidelines for Solving the Problem*

This problem is based on the transition probabilities of Markov processes. The states of the network transition from one state to another over time, and these transition probabilities are described by a matrix.

a) Constructing the Transition Probability Matrix:

Based on the given probabilities, we construct the transition matrix:

$$P = \begin{pmatrix} 0.7 & 0.25 & 0.05 \\ 0.3 & 0.5 & 0.2 \\ 0.4 & 0.3 & 0.3 \end{pmatrix}$$

This matrix represents the following:

First row: The probabilities of transitioning from the Low Load state to other states.

Second row: The probabilities of transitioning from the Medium Load state to other states.

Third row: The probabilities of transitioning from the High Load state to other states.

b) Determining the Initial State:

It is known that the network initially starts in the Low Load state. Therefore, the initial probability vector is: $\pi = (1,0,0)$

This vector indicates that the network is exclusively in the Low Load state.

c) Calculating the State After 5 Transitions:

To determine the probabilities of the network being in each state after 5 transitions:

$$\pi_5 = \pi P^5 .$$

Here, $P^5$ – is the transition matrix raised to the 5th power.

$\pi_5 = (P(Low), P(Medium), P(High))$

$$\pi_5 = \begin{pmatrix} 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} 0.7 & 0.25 & 0.05 \\ 0.3 & 0.5 & 0.2 \\ 0.4 & 0.3 & 0.3 \end{pmatrix}^5 = \begin{pmatrix} 0.525 & 0.341 & 0.134 \end{pmatrix}$$

d) Result:

The probabilities after 5 transitions are: $\begin{pmatrix} 0.525 & 0.341 & 0.134 \end{pmatrix}$

*Task 4.* In an online store, user actions are described by three states: Browse, Add to Cart, and Exit. A user can transition from one state to another, with the following transition probabilities:

In the Browse state, the probability of staying in Browse is 60%, transitioning to Add to Cart is 30%, and transitioning to Exit is 10%.

In the Add to Cart state, the probability of staying in Add to Cart is 50%, returning to Browse is 20%, and transitioning to Exit is 30%.

In the Exit state, the probability of staying in Exit is 50%, and transitioning back to Browse is 50%.

If the user initially starts in the Browse state, determine the probabilities of being in each state after 6 transitions.

*Methodological Guidelines for Solving the Problem*

a) Constructing the Transition Probability Matrix:

Based on the given probabilities, we construct the transition matrix. This matrix represents the following:

$$P = \begin{pmatrix} 0.6 & 0.3 & 0.1 \\ 0.2 & 0.5 & 0.3 \\ 0.5 & 0 & 0.5 \end{pmatrix}.$$

his matrix is read as follows:

First row: The probabilities of transitioning from the "Browse" state to other states (Browse→Browse, Browse→Add to Cart, Browse→Exit).

Second row: The probabilities of transitioning from the "Add to Cart" state to other states (Add to Cart→Browse, Add to Cart→Add to Cart, Add to Cart→Exit).

Third row: The probabilities of transitioning from the "Exit" state to other states (Exit→Browse, Exit→Add to Cart, Exit→Exit).

b) Determining the Initial State:

Since the user initially starts in the "Browse" state, the initial probability vector is: $\pi = (1,0,0$ This vector indicates that the user is exclusively in the "Browse" state.

c) Calculating the State After 6 Transitions

To determine the probabilities after 6 transitions: $\pi_6 = \pi P^6$

$$\pi_6 = \begin{pmatrix} 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} 0.6 & 0.3 & 0.1 \\ 0.2 & 0.5 & 0.3 \\ 0.5 & 0 & 0.5 \end{pmatrix}^6 = \begin{pmatrix} 0.462 & 0.277 & 0.261 \end{pmatrix}$$

d) Result:

The probabilities of being in each state after 6 transitions: $\begin{pmatrix} 0.525 & 0.341 & 0.134 \end{pmatrix}$

**Results of the study**

Stochastic methods, including Markov processes and the Monte Carlo method, are extensively applied in the IT industry for modeling complex systems and decision-making processes. Teaching these techniques helps students develop the ability to solve real-world problems. To this end, a pedagogical experiment aimed at solving IT-related problems using Markov processes and the Monte Carlo method was conducted at Almaty University of Energy and Communications in October-November 2024. The study involved two groups: the ISk-23-1a control group and the ISk-23-1b experimental group. The control group followed traditional teaching methods, while the experimental group was introduced to new methods. These new methods focused on solving real IT problems through the application of stochastic techniques. To assess the knowledge of both groups, control tasks were performed before and after the experiment. During the experiment, students were given a set of 4 problems focused on applying Markov processes and the Monte Carlo method. These tasks were designed to develop skills in data modeling and analysis for the IT sector. The students' responses were recorded in terms of the percentage of correct and incorrect answers. To evaluate progress, the initial results of the control and experimental groups were provided (Table 1).

*Table 1. Initial Results of the Experiment*

| *Task* | *Control group (Correct %)* | *Control group (Incorrect %)* | *Experimental group (Correct %)* | *Experimental group (Incorrect %)* |
|---|---|---|---|---|
| *1* | *55* | *45* | *48* | *52* |
| *2* | *51* | *49* | *53* | *47* |
| *3* | *48* | *52* | *46* | *54* |
| *4* | *47* | *53* | *48* | *52* |
| *Average* | *50,25* | *49,75* | *48,75* | *51,25* |

After conducting the experimental work, the final results of the control group and the experimental group were presented to monitor the outcomes (Table 2).

*Table 2. Final Results of the Experiment*

| Task | Control group (Correct %) | Control group (Incorrect %) | Experimental group (Correct %) | Experimental group (Incorrect %) |
|---|---|---|---|---|
| 1 | 55 | 45 | 67 | 33 |
| 2 | 51 | 49 | 65 | 35 |
| 3 | 53 | 47 | 60 | 40 |
| 4 | 47 | 53 | 70 | 30 |
| Average | 51,5 | 48,5 | 65,5 | 34,5 |

A chart was created (Figure 5) to compare the initial and final results of the experimental group for each task, based on the results of the conducted summative assessment.

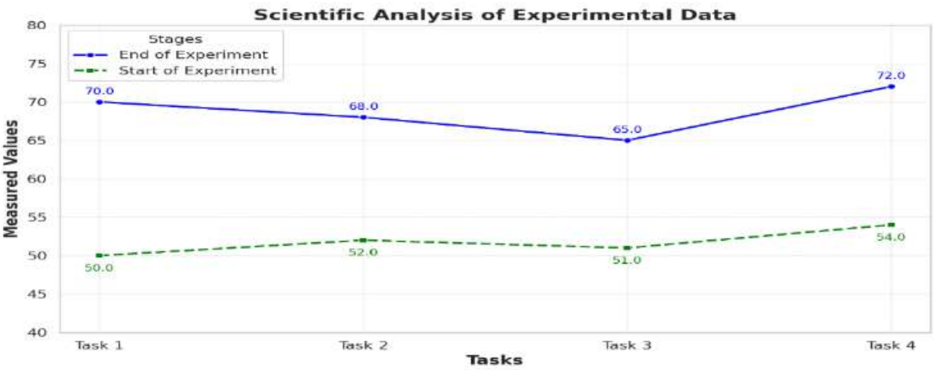


*Figure 5. Comparison of Results Chart*

The experimental group achieved an average result of 65.5%, which was notably higher than the control group's result of 51.5%. Students in the experimental group showed better performance when solving real IT problems. Mastery of these methods greatly improved their analytical thinking and problem-solving skills. The application of new methods reinforced their theoretical knowledge and enhanced their ability to solve practical tasks. The widespread use of these methods plays a key role in preparing future IT professionals and contributes to the improvement of their professional competencies.

**Discussion**

Modern studies demonstrate the efficiency of applying stochastic approaches in teaching technical fields. These techniques are absolutely important for developing analytical abilities, managing under uncertainty, and modeling complicated systems. For instance, high efficiency is shown by assessing system dependability and modeling real-world manufacturing scenarios with Markov processes and the Monte Carlo approach. In their study, Haldar and Mahadevan underlined the major part stochastic methods play in engineering reliability calculations [3]. Through random number modeling, the Monte Carlo approach lets one assess the efficiency of information systems and manufacturing. When complicated mathematical models or analytical solutions are absent, this approach is especially helpful. Walrand J. showed in his studies the great effectiveness of the Monte Carlo technique in production process optimization [10]. Technical systems are modeled using markov processes rather extensively. These techniques let one project the future condition of a system depending just on its present state. Markov processes, for instance, are especially good in estimating the equipment failure risk in manufacturing processes. In their study, Russell and Norvig underlined the need of this approach in evaluating manufacturing and service systems [11]. Using stochastic techniques helps students acquire the analytical ability required to address practical production issues. For example, assignments involving network operation optimization and server load prediction enable students improve their analytical skills. We have designed a set of activities aiming at promoting students' analytical thinking, problem-solving skills, and decision-making abilities under uncertainty using stochastic approaches in the teaching of technical disciplines based on the examination of scientific and methodological works. This system comprises tasks meant to leverage stochastic approaches in real-world production scenarios as well as puzzles and exercises for implementing stochastic models. For instance, we discuss such chores in the part on "Research Methodology" in our paper.

**Conclusion**

The application of stochastic methods in technical disciplines' education determines very much how students' analytical thinking, process modeling, and problem-solving abilities develop. Simulated real-world production situations allow students to blend their academic knowledge with practical skills by means of methodological approaches proposed in the research. The results of the experimental study revealed that applying stochastic methods enhanced the academic performance of the students. Particularly activities based on Markov processes and Monte Carlo methods significantly raised students' capacity to interpret data and under uncertainty make decisions. By allowing a greater understanding of the course content than by traditional teaching approaches, these techniques help students to use their knowledge to solve practical production problems. The practical importance of stochastic methods should be particularly emphasized. They provide the foundation for solving critical tasks such as evaluating the reliability of complex systems, optimizing production processes, and predicting the load of information systems. For example, the Monte Carlo method increases the ability to model random processes in systems, while Markov processes enable forecasting and analysis of system states. These methods prepare students to tackle problems arising in real-world situations and enhance their professional competencies. Incorporating stochastic approaches into the classroom improves not just students' practical skills but also helps them to meet the demands of the modern job market. Methodically teaching these techniques helps the educational process to match the new standards of technological development. Future development of the system of tasks based on stochastic techniques should be focused on their implementation in educational practice.

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