UDC 004.8
DOI https://doi.org/10.32782/2663-5941/2025.3.2/39

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SURVEY OF APPLICATION OF THE KOLMOGOROV-ARNOLD NETWORKS TO TRANSPORTATION NETWORK INTERDICTION GAMES

This paper is dedicated to the analysis of transportation network interdiction, which examines the mechanisms by which an adversary with limited resources can disable or degrade connections within a network, as well as the defender's response in rerouting flows to maintain system efficiency.

The evolution of interdiction methods is presented–from classical bilevel optimization approaches employing mixed-integer programming, Benders decomposition, cutting-plane methods, and heuristics to contemporary algorithms that leverage large-scale data analysis.

A classification of machine-learning methods for interdiction is provided, namely:

1. Reinforcement learning, which involves training agents through interaction with a simulated environment.

2. Adversarial and multi-agent learning, which employs self-play and online no-regret algorithms to develop robust strategies.

3. Imitation learning and inverse reinforcement learning, which rely on analyzing demonstrations or actual adversary trajectories.

4. Evolutionary algorithms combined with neural approximators, which offer scalable solutions at the expense of strict theoretical guarantees.

Theoretical foundations of Kolmogorov–Arnold Networks (KANs) are revealed, showing how, based on the universal approximation theorem, they approximate multivariate functions via a sequence of learned univariate mappings. Initial applications of KANs in transportation tasks–such as traffic flow optimization and power-grid state estimation–are analyzed, and the potential for modeling defender responses using a compact, interpretable architecture is identified.

It is determined that, for further advancement in this field, the following key challenges must be addressed:

1. Embedding bilevel decision logic into differentiable models.

2. Handling graph-structured inputs without sacrificing approximation properties.

3. Generating representative, "adversarial" training datasets.

4. Developing rigorous evaluation protocols and determining performance bounds.

A research roadmap is proposed that integrates optimization and learning approaches, prioritizes reproducibility on both synthetic and real datasets, and seeks to balance computational efficiency with model transparency. This survey establishes a foundation for the development of effective and interpretable interdiction strategies in transportation and other critical infrastructure networks.

Key words: *transportation networks, network interdiction, Kolmogorov-Arnold networks, neural network training, performance evaluation, comparative analysis, mathematical optimization.*

Statement of the problem. Network interdiction games model an attacker-defender scenario on a network, where one agent attempts to disrupt or block network routes while the other tries to maintain efficient connectivity. Formally, a network (e.g., a road network or supply chain) is given on which an operator (defender) seeks to perform an optimally efficient action, such as sending flow, finding the shortest path, or servicing demands. An interdictor (attacker) moves first by incapacitating or degrading some network elements (nodes or links) within a limited budget of attacks [1]. Then the operator routes flow or traffic in the damaged network attempting to minimize the loss (e.g., finds the quickest remaining route, or maximizes the throughput that can still be delivered). This sequential play defines a Stackelberg game: the attacker anticipates the defender's best response when choosing what to attack [1]. Depending on the context, the defender's "action" can be passive (simply the outcome of an optimization like shortest path) or active (e.g., allocating defensive resources or fortifications before the attack, leading to a tri-level game [1], although we focus on the bilevel case here).

These models have critical relevance in logistics, as they help identify weak links in supply chains and transportation networks and devise strategies to improve network resilience [2]. In a typical formulation (often a Stackelberg game), an *interdictor* (leader) with limited resources chooses a set of network arcs or nodes to disable or degrade. Then, an *evader* (follower) finds its optimal path through the remaining network [2]. The interdictor's goal is to maximize the cost or length of the evader's route (e.g., lengthening the shortest path) while the evader seeks to minimize it, producing a two-level optimization problem. Classic analysis usually assumes perfect rationality and complete information, but these assumptions are often unrealistic in practice [3]. Moreover, solving such interdiction problems is usually computationally hard: even restricted versions (like selecting k arcs to remove) are NP-hard, making exact solvers impractical on large networks [2]. These challenges have spurred research into AI agent training methods that learn effective interdiction strategies through simulations and theoretical models.

Analysis of recent research and publications. Several comprehensive surveys have been published on transportation network interdiction, including Smith and Song (2020), who review a broad range of bilevel optimization models and solution techniques; Brown et al. (2019), which focuses on mixed-integer programming and decomposition methods; and Zhang and Li (2021), which examines machine-learning–based heuristics. These works systematically cover reinforcement learning, adversarial/multi-agent frameworks, imitation learning, and evolutionary or heuristic approaches, yet none of them mention Kolmogorov–Arnold Networks (KANs) as a potential modeling paradigm. Consequently, there is a gap in existing literature regarding the application of KANs to network interdiction, despite their ability to approximate complex multivariate defender-response functions via learned univariate mappings.

Task statement. This survey aims to trace the evolution of transportation network interdiction methodologies – from classical bilevel optimization techniques to modern AI-driven approaches – and to identify open challenges hindering further progress.

The current study is focused on reinforcement learning, adversarial (multi-agent) learning, imitation learning, and other relevant methodologies. Specifically, the objectives are to:

- Categorize existing interdiction approaches, contrasting operations-research methods with machine-learning frameworks, and summarize their respective strengths and limitations.
- Highlight the theoretical foundations and initial applications of Kolmogorov – Arnold Networks (KANs) in related transportation domains.
- Identify critical research gaps, including embedding bilevel decision logic into differentiable models, handling graph-structured inputs without losing approximation power, generating representative adversarial training datasets, and establishing rigorous evaluation protocols.

Propose a research roadmap that integrates optimization and learning approaches, emphasizes reproducibility on both synthetic and real-world datasets, and balances computational efficiency with model interpretability.

Outline of the main material of the study. Formulation of the problem

A rigorous mathematical formulation for the **network interdiction game** is typically expressed as a **Stackelberg (leader-follower) bilevel optimization problem** [6].

Consider a transportation network modeled as a directed graph $G = (V, E)$ where V is the set of nodes (vertices). E is the set of arcs (edges), with each arc $(i, j) \in E$ having associated parameters (e.g., capacity, cost, or travel time).

An attacker aims to degrade the network by **interdicting** (attacking/removing or partially disabling) a subset of arcs, subject to resource or budgetary constraints. The defender subsequently routes traffic or flow optimally through the network to minimize operational costs or maximize efficiency given the interdicted network.

The attacker (leader) chooses binary interdiction decisions:

$$x_{ij} = \begin{cases} 1, if\ arc\,(i, j)\, is\, interdicted\,(disabled\, or\, degraded) \\ 0, otherwise \end{cases}$$

The defender (follower) chooses continuous routing decisions:

$$f_{ij} \geq 0\left(flow\, on\, arc\,(i, j)\, after\, interdiction\right)$$

The attacker selects arcs to interdict to maximize damage to the defender. Formally, the attacker solves the following problem:

$$\max_x Z\left(x, f^*(x)\right)$$

subject to interdiction budget constraints:

$$\sum_{(i,j)\in E} c_{ij}^a x_{ij} \leq B$$

where:

1. $Z\left(x, f^{*}(x)\right)$ is the damage (loss) function defined by the attacker (e.g., total increase in travel time or total flow reduction), dependent upon the defender's optimal response $f^{*}(x)$.
2. c_{ij}^{a} is the cost of interdicting arc (i, j).
3. B is the attacker's budget (limited resources for attacks).

Follower's Problem (Defender)

Given the interdicted arcs (decision x), the defender solves an inner-level optimization problem, typically to minimize their operational costs, or equivalently, to maintain optimal network efficiency:

$$f^{*}(x) \in arg \min_{j} C(f, x)$$

subject to network constraints: Flow conservation at each node $k \in V \backslash\{s, t\}$ (where s is source and t is sink):

$$\sum_{(i,k)\in E} f_{ik} - \sum_{(k,j)\in E} f_{kj} = 0, \forall k \in V\{s,t\}$$

Capacity constraints on arcs, adjusted for interdictions:

$$0 \le f_{ij} \le c_{ij}\left(1 - x_{ij}\right), \forall (i,j) \in E$$

where:

1. $C(f, x)$ is the defender's cost function, typically given by total transportation costs or total travel time.
2. c_{ij} is the original capacity of the arc (i, j) before interdiction.

The complete **bilevel Stackelberg interdiction game** formulation is expressed as:

$$\max_{x} Z\left(x, f^{*}(x)\right)$$

subject to:

$$\sum_{(i,j)\in E} c_{ij}^{a} x_{ij} \le B, x_{ij} \in \{0,1\}$$

and

$$f^{*}(x) \in arg \min_{j} C(f, x)$$

subject to:

1. Flow conservation:

$$\sum_{(i,k)\in E} f_{ik} - \sum_{(k,j)\in E} f_{kj} = 0, \forall k \in V\{s,t\}$$

2. Arc capacities (post-interdiction):

$$0 \le f_{ij} \le c_{ij}\left(1 - x_{ij}\right), \forall (i,j) \in E$$

Interpretation

Leader (Attacker): Moves first and strategically selects arcs to disrupt, considering how the follower will optimally respond.

Follower (Defender): Moves second, optimally redistributing traffic or flow on the network given the damage caused by the leader.

Transportation systems provide many practical cases of network interdiction games. Consider a highway network where an attacker aims to maximize congestion by disabling a few critical interchanges while the traffic authority reroutes vehicles to minimize total delay. This can be cast as an interdiction game in which the attacker removes network capacity and the defender solves a traffic assignment or flow minimization problem [7]. Similar models appear in the analysis of terrorist threats to transit systems, freight network resilience against disruptions, and smuggler interception on transportation corridors [3]. A common objective for the interdictor is to inflict maximum damage (e.g., maximize travel time or flow loss), while the defender's aim is typically to minimize that damage – yielding a zero-sum or leader-follower optimization framework [7].

Solving network interdiction problems optimally is generally **computationally hard**. Even with moderate network sizes, the bilevel formulation becomes large and non-convex. Traditional methods reformulate or relax the problem into single-level models. For example, one can replace the defender's linear program (like a max flow) with its dual and embed it into the attacker's problem, resulting in a single-level but still combinatorial formulation [8]. Exact algorithms often use cutting planes, branch-and-bound, or Benders decomposition (row generation) to search the attack space efficiently [8]. Despite these advances, the curse of dimensionality remains: as networks grow or as the attacker's budget increases, the number of possible attack combinations explodes. Smith and Song (2020) note that modern research is pushing into interdiction models with probabilistic and dynamic elements, which further increase complexity [6]. In such settings, exact solution methods can become prohibitively slow, and even heuristic or MILP solvers struggle to provide timely solutions [9]. This is problematic for transportation agencies that have to analyze worst-case disruption scenarios or identify vulnerabilities in large-scale networks (e.g., a national highway system).

Thus, exact solutions are challenging for large-scale networks, motivating the development of advanced approximate solution techniques [10] including potentially promising methods like Kolmogorov-Arnold Networks.

Publication Selection

The identification and curation of relevant literature constitute the initial phase of this survey [4]. We combine an automated controlled snowball-sampling procedure [5] with manual screening and citation-network exploration to ensure both breadth and relevance.

Inclusion and Exclusion Criteria

We defined explicit inclusion and exclusion criteria for selecting publications to ensure a high-quality and relevant literature base.

Inclusion Criteria: We focused on peer-reviewed research articles (including conference papers and journal articles) and credible systematic literature reviews published roughly in the last 10 years (2015–2025). We included studies explicitly addressing the application of AI (e.g., machine learning, deep learning, evolutionary algorithms, knowledge-based systems) to software testing or quality control. Also, we included older seminal works if they were highly cited and foundational to the field (to provide historical context or definitions). We limited sources to English-language publications from reputable venues in software engineering and AI. For tools or industry solutions, official documentation or whitepapers (software manuals) were considered if they provided technical details.

To assemble a focused yet comprehensive body of work, we established explicit criteria. We included peer-reviewed journal articles and conference papers–published between 2010 and 2025–that directly address transportation network interdiction or closely related topics (e.g., logistics, supply-chain resilience). These works encompass both classical optimization techniques, such as bilevel programming, mixed-integer programming, and decomposition algorithms, and modern AI methods, including reinforcement learning, graph neural networks, and Kolmogorov–Arnold Networks. Additionally, we considered highly cited, pre-2010 publications that introduced foundational concepts in interdiction game theory or network security. All included studies are in English and originate from recognized operations-research and AI venues. Conversely, we excluded papers that discuss network flow or routing without an interdiction component, focus solely on defender-only optimization, or address AI system testing rather than using AI for interdiction. Non-peer-reviewed sources (e.g., blogs or opinion pieces) were omitted unless they provided critical methodological details, and purely theoretical works without computational or empirical evaluation were likewise set aside.

Publication Selection Method

Our selection unfolded in three stages. First, we performed keyword searches–using terms such as "transportation network interdiction", "bilevel network games", and "network interdiction learning" – across Scopus, Web of Science, and Google Scholar. An initial screening of titles and abstracts yielded approximately fifty candidate papers. Second, we applied the controlled snowball-sampling method of Dobrovolskyi and Keberle [5], tracing both forward and backward citations to capture seminal works while avoiding terminological drift; this refined our pool to about thirty-five publications. Finally, we obtained full texts (where available) and conducted a detailed manual review, verifying each against our inclusion/exclusion criteria, extracting key methodological details–such as network models, evaluation metrics, and principal findings–and discarding those that failed to meet our standards.

Analysis of collected publications

Kolmogorov-Arnold Networks

Kolmogorov-Arnold Networks are a novel class of neural networks grounded in a 1957 theorem by A.N. Kolmogorov (extended by V. Arnold), which states that any continuous function of several variables can be represented as a finite composition of one-dimensional functions [11]. Traditional neural networks achieve universal approximation by layering fixed non-linear activations; in contrast, KANs implement the Kolmogorov-Arnold construction directly. Each hidden "layer" in a KAN applies *learnable* transformations on each input dimension rather than a fixed activation across all neurons [12]. For example, instead of a weight w_{ij} multiplying input x_j KAN would apply a learned spline function $f_{ij}\left(x_j\right)$ input connection. These learned univariate functions serve as customized activations that can adapt their shape to the data. As a result, KANs can capture complex nonlinear relationships with a compact architecture.

One immediate advantage of KANs is **flexibility**. The network can mold its activation functions to fit intricate patterns, which is beneficial for highly nonlinear domains like traffic flow or infrastructure failure cascades. Another advantage is potential **interpretability**: the learned activation functions on each edge can be inspected and, in some cases, have been shown to correlate with meaningful physical relationships [hollosi2024detection]. Indeed, KANs have been used to rediscover mathematical or physical laws from data, highlighting their ability to reveal the structure behind the patterns they learn [12]. Furthermore, variants like *Convolutional KANs* integrate spline-based activations into CNN architectures to reduce parameter counts while maintaining accuracy [12]. In image classification tasks (e.g. MNIST), such convolutional KANs matched traditional CNN performance using fewer resources [12]. This efficiency is attributed to KAN's capacity to approximate functions with fewer neurons by using richer neuron-wise activations. KANs are particularly effective at modeling high-dimensional datasets with intricate interdependencies. For example, in hyperspectral image classification and time-series forecasting, they have achieved leading results by accurately representing both spatial and temporal correlations [14]. All these traits suggest that KANs could be well-suited to model the complexity of transportation networks under attack, where system behavior (e.g., total travel time, flow distribution) is a highly nonlinear function of which components are disrupted.

However, KANs are not universally superior to conventional networks in every scenario. A comprehensive empirical study by Bodner *et al.* (2024) found that when controlling for model size and FLOPs, standard MLPs still outperformed KANs on most machine learning benchmarks except those involving symbolic function representation [13]. These findings underline that while KANs offer a powerful representational framework, they also introduce new challenges.

Applying Kolmogorov-Arnold networks to network interdiction is a cutting-edge idea that has only begun to be explored. Because KANs themselves have gained attention mainly in the past few years, there are not that many direct studies on using KANs for interdiction games. Recent advances along two parallel lines of inquiry provide valuable guidance. The first involves employing machine-learning methods–including neural networks–to augment or even replace conventional solvers in network interdiction tasks. The second focuses on the successful deployment of KAN models in a variety of transportation-focused problems. Together, these developments imply that KANs may be particularly well-suited to address the challenges posed by interdiction games in transportation networks.

KANs in Transportation and Network Optimization

Initial deployments of KAN architectures in transportation applications demonstrate their effectiveness in handling complex network challenges, suggesting they may be well suited for interdiction scenarios. A very recent example is the use of KANs for traffic flow optimization. Zhang *et al.* (2025) proposed a hybrid model combining KANs with graph convolutional networks (TrafficKAN-GCN) to optimize urban traffic signal timings [9]. By embedding a KAN into a graph-based architecture, they aimed to capture complex nonlinear flow responses to control measures. While this work is at the preprint stage, it reflects a broader trend of integrating KANs into graph and network problems. Indeed, KANs have also been tested in power systems for *state estimation*, where interpretability and accuracy are crucial [15]. In all these cases, KANs provided an advantage when the problem involved learning a complicated mapping (e.g., from sensor readings or control actions to outcomes) that classical models struggled with.

Bridging the Fronts: The convergence of these research fronts – ML-assisted interdiction and KAN-enabled transport models – points to a strong opportunity at their intersection. We have seen that neural approaches can handle large-scale interdiction problems faster than traditional methods [10], and that KANs can capture complex system behaviors in transportation contexts with high fidelity [12]. Therefore, it is anticipated that applying Kolmogorov-Arnold networks to network interdiction games in transportation will bring significant advances. In the next section, we identify these anticipated benefits in detail, discussing how KAN's characteristics align with the needs of interdiction problems. We then analyze the challenges that must be addressed to realize these benefits.

AI-Based Approaches to Network Interdiction

Methods from machine learning and artificial intelligence have been employed to overcome the scalability and uncertainty challenges of classical interdiction solvers. In the last decade, the literature on AI-driven interdiction can be grouped into four main categories:

Reinforcement Learning

Reinforcement learning frames interdiction as a sequential decision-making process in a simulated environment [2]. Recent studies model the shortest-path interdiction problem as a Markov decision process and train deep RL agents–often using pointer networks–to select edges to disable. These agents learn policies that maximize a reward signal (e.g., the evader's path length), achieving near-optimal interdiction sets on large instances where mixed-integer solvers become intractable [16].

Adversarial and Multi-Agent Learning

Adversarial learning approaches explicitly account for the strategic interaction between interdictor and evader. Online no-regret algorithms update the defender's strategy against adaptive opponents, with provable sublinear regret bounds even when the evader adjusts tactics over time. Self-play RL schemes co-train attacker and defender agents, driving both toward equilibrium policies that generalize across network topologies [17].

Imitation and Inverse Reinforcement Learning

When demonstrations of expert or observed behavior are available, imitation learning and inverse RL can infer an opponent model. In one dynamic local interdiction study, human-generated evader trajectories were used to learn a reward function via IRL; this model then informed the interdictor's policy, which was further refined online through RL, yielding higher interdiction accuracy than [18].

Evolutionary and Heuristic Methods with Neural Approximators

Genetic algorithms and other population-based heuristics have long been applied to interdiction, identifying near-optimal link-removal sets on large networks. More recently, graph neural networks have been trained on MILP-derived solutions–termed "Network Interdiction Goes Neural" – to predict effective interdiction decisions in real time, outperforming greedy heuristics and matching solver quality at a fraction of the runtime [9].

By consolidating these paradigms into a single overview, we highlight how AI techniques–ranging from trial-and-error learning to expert modeling and hybrid heuristics–provide scalable, adaptable alternatives to exact optimization in network interdiction contexts.

Gaps and challenges

Integrating Kolmogorov-Arnold networks into network interdiction games is at its very beginning stage. It raises unique issues at the intersection of game theory, graph data, and deep learning.

- This survey has traced the evolution of transportation network interdiction–from its origins in bilevel optimization and mixed-integer programming to the latest trends in data-driven and learning-based methods. Classical solution techniques such as Benders decomposition, cutting-plane algorithms, and heuristic search continue to provide rigorous foundations and provable guarantees, yet they often struggle with scalability on large, realistic networks. In parallel, machine-learning paradigms–including reinforcement learning, adversarial and multi-agent frameworks, imitation and inverse reinforcement learning, as well as evolutionary algorithms augmented by neural approximators–have demonstrated remarkable flexibility and speed, albeit sometimes at the cost of formal optimality bounds.

A central theme of this review is the promise of Kolmogorov–Arnold Networks (KANs). By approximating multivariate defender-response functions via learned univariate mappings, KANs offer a compact architecture with the potential for greater interpretability than conventional deep-learning models. Early applications in traffic flow optimization and power-grid state estimation suggest that KANs can capture complex nonlinear behaviors in networked systems. Yet the direct application of KANs to interdiction games remains nascent.

From our analysis, four key research challenges emerge:

1. Bilevel Logic Embedding
2. Translating the sequential attacker–defender structure into a differentiable learning paradigm, without losing theoretical rigor.
3. Graph-Structured Input Handling
4. Extending KAN theory to accommodate networks' combinatorial topology, while preserving universal approximation guarantees.
5. Adversarial and Diverse Data Generation
6. Designing training datasets that reflect realistic, stochastic interdiction scenarios and adversarial variations.
7. Evaluation Protocols and Performance Guarantees
8. Developing standardized benchmarks, reproducible evaluation procedures, and methods to quantify approximation gaps or regret.

Addressing these challenges will require concerted efforts across optimization theory, graph-based learning, and robust machine-learning methodology. We foresee that hybrid frameworks–combining KAN-driven approximators with local optimization refinements–could deliver both high performance and verifiable guarantees. Moreover, establishing open datasets and shared evaluation platforms will be critical to drive reproducible progress.

In summary, while classical and modern AI-based methods each contribute valuable strengths, integrating KANs into transportation interdiction promises a new balance between computational efficiency, modeling fidelity, and interpretability. As research advances along the identified directions, we expect to see the emergence of more transparent, scalable, and reliable interdiction strategies applicable not only to road and logistics networks, but also to other critical infrastructures such as power grids and communication systems.

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Пасічник В.В., Добровольський Г.А. ЗАСТОСУВАННЯ МЕРЕЖ КОЛМОГОРОВА–АРНОЛЬДА ДО ІГОР ІНТЕРДИЦІЇ ТРАНСПОРТНИХ МЕРЕЖ

Стаття присвячена аналізу інтердиції транспортних мереж, що передбачає дослідження механізмів, за допомогою яких противник із обмеженими ресурсами може виводити з ладу або послаблювати зв'язки в мережі, а також реакцію захисника, який перенаправляє потоки для збереження ефективності системи.

У статті розкрито еволюцію методів інтердиції – від класичних бівертикальних оптимізаційних підходів із застосуванням змішаного цілочисельного програмування, декомпозиції Бендерса, методів розрізів та евристик до сучасних алгоритмів, що спираються на аналіз великих обсягів даних.

Розкрито класифікацію методів машинного навчання для інтердиції, а саме:

1. Навчання з підкріпленням, яке навчає агентів через взаємодію з імітованим середовищем;

2. Протидійне та багато-агентне навчання, що використовує навчання через гру з самим собою та онлайн-алгоритми без жалю для формування стабільних стратегій;

3. Імітаційне навчання та зворотне навчання з підкріпленням, які вивчають поведінку противника на основі демонстрацій або реальних траєкторій;

4. Еволюційні алгоритми у поєднанні з нейронними апроксиматорами, що забезпечують масштабованість рішень за рахунок відсутності суворих теоретичних гарантій.

Розкрито теоретичні засади мереж Колмогорова–Арнольда (KAN), які на основі універсальної теореми апроксимують багатовимірні функції через послідовність вивчених одновимірних відображень, та проаналізовано їхні початкові застосування в транспортних завданнях (зокрема оптимізація дорожнього руху та оцінка стану енергомереж). Визначено можливості використання KAN для моделювання реакції захисника в компактній та інтерпретованій архітектурі

З'ясовано, що для подальшого розвитку даної галузі необхідно вирішити такі ключові виклики:

1. Вбудування бівертикальної логіки в диференційовані моделі;

2. Обробка граф-структурованих вхідних даних без втрати апроксимаційних властивостей;

3. Генерація репрезентативних, «протидійних» наборів даних для навчання;

4. Розробка строгих протоколів оцінки та визначення меж продуктивності.

Запропоновано дослідницьку дорожню карту, що поєднує оптимізаційні й навчальні підходи, надає пріоритет відтворюваності результатів на синтетичних і реальних даних та прагне збалансувати обчислювальну ефективність із прозорістю моделей. Цей огляд створює основу для розробки ефективних і зрозумілих стратегій інтердиції в транспортних та інших критично важливих інфраструктурних мережах.

Ключові слова: *транспортні мережі, інтердикція мереж, мережі Колмогорова–Арнольда, навчання нейронних мереж, оцінка ефективності, порівняльний аналіз, математична оптимізація.*