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# SUPPLY CHAIN MANAGEMENT USING EVOLUTIONARY ALGORITHMS

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**Supply Chain Management Using Evolutionary Algorithms**

*The era of digital transformation has made it possible to accumulate large amounts of data that can be used in the decision-making process, in particular in supply chain management. With the complication of the problems to be solved, classical optimization methods lose their effectiveness and do not allow to obtain a solution in an acceptable time, which creates the need to study another suitable tools, among which there are evolutionary algorithms that use the principles of biological evolution, allowing to obtain solutions close to optimal (or even exactly optimal) in an acceptable time. Evolutionary algorithms are part of a broader field in artificial intelligence that is evolutionary computing. The article allocates the characteristics of evolutionary algorithms that distinguish them from other algorithms of evolutionary computing, and analyzes the most popular evolutionary algorithms: genetic algorithm, genetic programming, evolutionary programming, evolutionary strategies and differential evolution, in particular, their features and areas of application in supply chain management. A comparative analysis is carried out and recommendations are provided for the selection of the appropriate algorithm, taking into account the characteristics of the problem, in particular, the structure of the solution (coding), the discreteness or continuity of variables, and the speed of getting into the local optimum. The available literature is analyzed and a list of the use of various evolutionary algorithms for the tasks of supply chain management is provided, in particular, in warehouse planning, transportation organization, work planning, etc. Since the effectiveness of the application of evolutionary algorithms depends not only on the choice of a specific algorithm, but also on the choice of parameters, their flexible configuration, etc., in future studies it is advisable to consider modifications of evolutionary algorithms, both hybrid and adaptive approaches.*

***Keywords:*** *evolutionary algorithms, supply chain management, genetic algorithms, genetic programming, evolutionary programming, evolutionary strategies, differential evolution.*

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***Скіцько В. І., Войніков М. Ю. Управління ланцюгами поставок із використанням еволюційних алгоритмів***

*Епоха цифрових трансформацій уможливила накопичення великих масивів даних, які можуть бути використані у процесі прийняття рішень, зокрема в управлінні ланцюгами поставок. При ускладненні розв'язуваних задач класичні оптимізаційні методи втрачають свою ефективність і не дозволяють отримати рішення за прийнятний час, що породжує потребу у дослідженні нових інструментів для їх вирішення, серед яких є й еволюційні алгоритми, що використовують принципи біологічної еволюції, дозволяючи отримати рішення, близькі до оптимального (або й точно оптимальні) за прийнятний час. Еволюційні алгоритми входять до ширшого напряму в штучному інтелекті – еволюційних обчислень. У статті виокремлено характеристики еволюційних алгоритмів, які вирізняють їх з-поміж інших алгоритмів еволюційних обчислень, і проаналізовано найпопулярніші еволюційні алгоритми: генетичний алгоритм, генетичне програмування, еволюційне програмування, еволюційні стратегії та диференціальну еволюцію, зокрема, їх особливості та сфери застосування в управлінні ланцюгами поставок. Проведено порівняльний аналіз і надано рекомендації щодо вибору відповідного алгоритму, зважаючи на характеристики задачі, зокрема, структуру рішення (кодування), дискретність чи неперервність змінних, швидкість потрапляння до локального оптимуму. Проаналізовано літературу та наведено перелік щодо використання різних еволюційних алгоритмів для задач управління ланцюгами поставок, зокрема, в складському плануванні, організації перевезень, планування робіт тощо. Оскільки ефективність застосування еволюційних алгоритмів залежить не лише від вибору конкретного алгоритму, а й від вибору параметрів, їх гнучкого налаштування тощо, у наступних дослідженнях доцільно розглянути модифікації еволюційних алгоритмів, гібридні й адаптивні підходи.*

*Ключові слова:* *еволюційні алгоритми, управління ланцюгами поставок, генетичні алгоритми, генетичне програмування, еволюційне програмування, еволюційні стратегії, диференціальна еволюція.*

*Рис.:* *2.* *Табл.:* *2.* *Бібл.:* *23.*

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**Introduction.** Under digital transformation conditions, effective management decision-making is achievable through various economic models and methods. These methods can be rooted in classic approaches or leverage cutting-edge techniques such as algorithms of collective intelligence and evolutionary algorithms.

The widespread use of digital technologies allows for the collection of large amounts of data, improving the efficiency of decision-making. The growing complexity of mathematical methods and models enables more accurate decisions using this extensive data. However, this complexity also increases computational demands, which impacts the time needed to find solutions. In this context, evolutionary algorithms have emerged as powerful tools for solving complex optimization problems in different fields, including supply chain management.

Evolutionary algorithms are optimization algorithms inspired by the principles of natural evolution, including selection, mutation, recombination, and survival of the fittest [1]. These algorithms work on a population of potential solutions, evolving them over multiple generations to find optimal or near-optimal solutions to complex problems. Evolutionary algorithms use mechanisms similar to biological evolution to iteratively improve a set of candidate solutions based on a defined fitness function.

This paper comprehensively examines evolutionary algorithms, encompassing genetic algorithms, genetic programming, evolutionary programming, evolution strategies, and differential evolution. It delves into their mechanisms, applications, and distinctive characteristics, emphasizing their significant contributions to evolutionary computation and their profound impact on supply chain management optimization. Through this exploration, we aim to illustrate how evolutionary algorithms can revolutionize decision-making processes and elevate supply chain management operations' efficiency and effectiveness in the digital transformation era, choosing the appropriate tools for solving problems.

**Analysis of recent publications.** Recent studies have extensively explored the application of evolutionary algorithms in supply chain management, highlighting their effectiveness in solving complex optimization problems. Genetic algorithms (GAs) have been widely used for route optimization, warehouse management, and scheduling tasks. For instance, the article [2] demonstrated that improved GAs could optimize logistics distribution routes more efficiently than traditional methods. The paper [3] applied GAs to warehouse layout optimization, achieving significant reductions in order-picking times. In the study [4] utilized GAs to enhance automated sorting systems, improving processing times and worker efficiency.

Genetic programming (GP) has been employed for demand forecasting and evolving heuristics for dynamic routing. The authors [5] used GP to develop heuristics for vehicle routing problems with time windows, enhancing real-time decision-making. In [6] GP is applied for stock market prediction, indicating its potential in demand forecasting within supply chain management. Evolutionary programming (EP) has proven effective in scenarios with many local optima. In the paper [7] EP is combined with artificial bee colony algorithms for optimal path planning in mobile robots, which can be adapted for warehouse automation. Evolution strategies (ES) focus on self-adaptive mutation rates and have been used in manufacturing optimization in numerous of studies. For instance, in [8] ES is utilized to optimize pull production systems, improving operational efficiency. The author [9] applied ES to the multiple traveling salesmen problem, enhancing route planning for multiple agents. Differential evolution (DE) has been applied to continuous optimization problems in supply chain management. In [10] a DE algorithm for sequencing and scheduling optimization is introduced, handling uncertainties effectively. The paper [11] proposes combined DE with particle swarm optimization to address stochastic location-inventory-delivery problems, optimizing strategic decisions in distribution networks.

These publications highlight the versatility and effectiveness of evolutionary algorithms in optimizing supply chain operations. However, there is a notable gap in research that aggregates these algorithms and provides recommendations for their application to specific problem types. Besides this, some authors have outlined various areas of evolutionary computation in general [1; 12; 13] categorization is required to clarify the distinctions between the different algorithms and their optimal use cases.

**Aim of the study and the methodology.** The study aims to explore the application of evolutionary algorithms in optimizing supply chain management processes. It focuses on demonstrating how various evolutionary algorithms, including genetic algorithms, genetic programming, evolutionary programming, evolution strategies, and differential evolution, can be utilized to enhance decision-making, improve operational efficiency, and solve complex optimization problems within supply chain management. Through this comparative analysis, the paper identifies the strengths, weaknesses, and applicability of evolutionary algorithms to different types of supply chain challenges, providing recommendations for their optimal use. Additionally, the study aims to draw distinctions between evolutionary computation and other algorithms, highlighting the unique characteristics that differentiate evolutionary algorithms from other approaches.

The methodology of the study involves a comprehensive literature review and analysis of recent research publications on the use of evolutionary algorithms in supply chain management. The study includes the development of a comparative framework to assess the effectiveness of each algorithm based on problem characteristics like solution structure, local optima, and data type (continuous or discrete). Additionally, case studies from existing literature are analyzed to demonstrate the practical applications and results achieved with these algorithms in real-world supply chain problems.

**Main results.** Evolutionary algorithms (EAs) are a subset of evolutionary computation. Evolutionary computation is a subfield of artificial intelligence, including algorithms inspired by natural evolution and biological processes [1; 12]. These algorithms, such as evolutionary algorithms, swarm intelligence, and artificial immune systems (see Fig. 1), use mechanisms like selection, mutation, and recombination to solve complex optimization and search problems. Evolutionary computation aims to find high-quality solutions in large and dynamic search spaces by mimicking biological evolution.

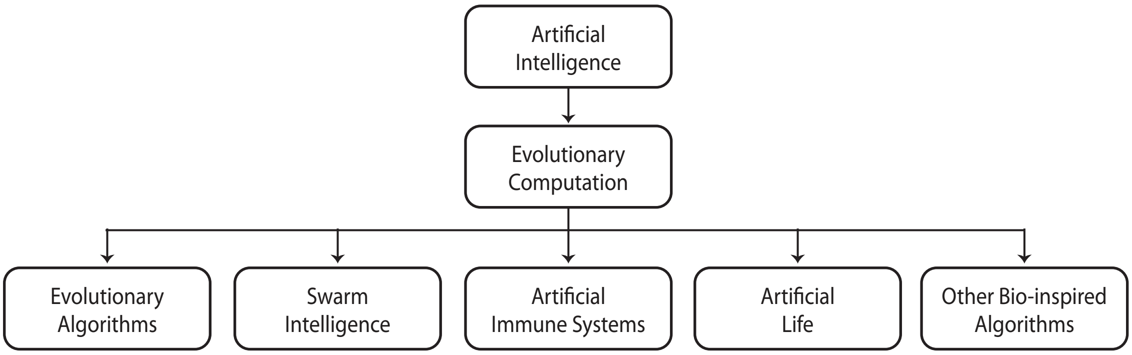


**Fig. 1. Evolutionary computation fields**

*Source:* developed by the authors based on [1; 13]

The figure showcases the diverse branches of evolutionary computation, each offering a distinct approach inspired by biological processes to craft algorithms for solving optimization problems:

- Evolutionary algorithms draw inspiration from natural selection, mutation, and recombination to evolve solutions to optimization problems [12];
- Swarm Intelligence mirrors the collective behavior of decentralized, self-organized systems, emulating the social behavior of organisms like birds or ants to solve optimization problems [1; 13];
- Artificial Immune Systems harness principles from the adaptive immune system, including immune response and memory, to detect and solve complex problems [14];
- Artificial Life algorithms aim to replicate biological processes in artificial systems by studying and simulating life-like behaviors to solve problems;
- Other Bio-inspired Algorithms draw inspiration from various biological strategies, such as bacteria's foraging behavior [15].

These algorithms are categorized under evolutionary computation due to their shared characteristics, which we explore in the next section.

Evolutionary algorithms. An evolutionary algorithm is a type of population-based metaheuristic optimization algorithm within evolutionary computation, inspired by biological evolution and using mechanisms such as reproduction, mutation, recombination, and selection, where candidate solutions act as individuals in a population, with their quality determined by a fitness function and evolved through repeated application of these operators.

Evolutionary algorithms share common characteristics with other evolutionary computation algorithms, placing them in a specific branch. The following are the distinct traits of evolutionary algorithms that differentiate them from other subfields of evolutionary computation [1; 13]:

1. Genetic operators: They employ specific genetic operators such as mutation and crossover to create new candidate solutions;
2. Selection mechanism: EAs rely on a selection process that imitates natural selection, where the fittest individuals are chosen for reproduction;
3. Population-based approach: They work with a population of solutions that evolve over generations;
4. Fitness-based evolution: Individuals are evaluated based on a fitness function that is used to evaluate how well a particular solution or individual in the population performs relative to the problem being solved;
5. Generational replacement: Each generation is replaced by the next, leading to the population evolving towards better solutions over time.

Each evolutionary algorithm shares common characteristics, yet each also exhibits distinct differences. Let us examine the most popular evolutionary algorithms – genetic algorithms, genetic programming, evolutionary programming, evolution strategies, and differential evolution (see Fig. 2) – by analyzing their mechanisms, applications, and unique characteristics to provide a comprehensive understanding of their individual contributions to the field of evolutionary computation.

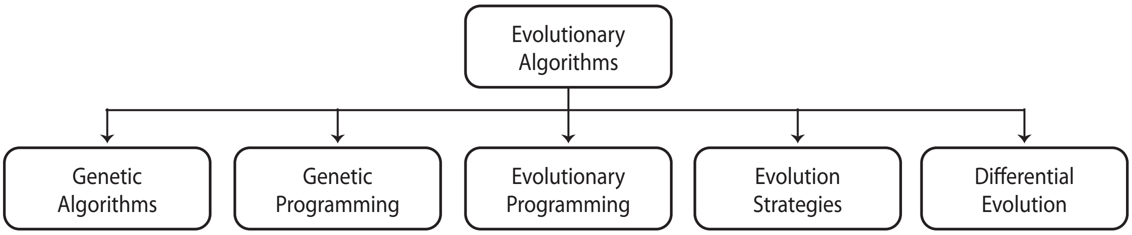


**Fig. 2. Evolutionary algorithms**

*Source:* developed by the authors based on [1; 12; 16; 17]

*Genetic algorithms* are a type of evolutionary algorithm where candidate solutions, known as chromosomes, are represented as vectors of decision variables, with each variable, or gene, representing a value, or allele, to be optimized [1]. Traditionally, GAs used binary strings to encode real values through multiple binary symbols, but modern implementations often use real-value encoding.

The algorithm progresses through generations, utilizing selection, crossover, and mutation operators to evolve the population of solutions. The fitness of each chromosome is evaluated, and the best-performing individuals are selected for reproduction, ensuring that advantageous traits propagate through subsequent generations. GAs are widely used in optimization, machine learning, and scheduling applications.

*Genetic programming* extends the concept of genetic algorithms to evolve programs or symbolic expressions instead of fixed-length character strings [16; 17]. In GP, individuals in the population are compositions of primitive functions and terminals appropriate to the problem domain. These compositions can be visualized as rooted, point-labeled trees, where internal nodes represent functions and leaf nodes represent terminals (inputs or constants).

The goal of GP is to find computer programs of varying sizes and shapes that solve a given problem by recursively composing available primitive functions and terminals. This approach is particularly useful for problems where the solution structure needs to be flexible and dynamic, such as symbolic regression, automatic code generation, and machine learning model development.

*Evolutionary programming* is a paradigm within evolutionary computation similar to genetic programming but focused on evolving the parameters of fixed-structure programs or models [17]. Unlike genetic algorithms, EP does not use crossover operators to create offspring. Instead, it relies on mutation and selection processes. In EP, the selection is stochastic, often involving tournaments where an individual competes against a user-defined number of other individuals, with weaker ones being eliminated.

This approach is efficient for optimization problems with many local optima, as it allows for a diverse set of solutions to be explored simultaneously. EP's robustness and simplicity suit various applications, from control systems to machine learning.

*Evolution strategies* are evolutionary algorithms that focus on the self-adaptive nature of mutation rates. Schwefel, Rechenberg, and Bienert introduced them in the 1960s. ES aims to optimize real-valued parameters using deterministic selection mechanisms [2; 12]. Unlike genetic algorithms, which heavily rely on crossover, ES primarily uses mutation to generate new solutions.

In ES, the population adjusts its mutation strength dynamically, learning to fine-tune the mutation rates without external control. Selection in ES is usually deterministic, with only the best-performing individuals being chosen for the next generation, similar to animal or plant breeding. This method is particularly suitable for continuous optimization problems where parameter fine-tuning is crucial.

*Differential evolution* draws inspiration from the self-organization principles of the Nelder-Mead simplex search method [1]. In DE, a population of candidate solutions is maintained, and new solutions are created by combining existing ones using a specific formula. The mutation operator in DE involves selecting two existing search points, calculating their vector difference, scaling it by a constant factor (F), and adding this to a third randomly selected search point. The resulting mutated vector is then combined with another search point using a crossover operator, and the resulting trial vector is evaluated against the target vector. If the trial vector has a higher fitness, it replaces the target vector.

DE's unique approach to mutation and crossover makes it highly effective for continuous optimization problems, providing a robust and efficient means of exploring complex search spaces.

To facilitate a comprehensive comparison, we have consolidated each evolutionary algorithm's key features and characteristics into a single table (see Table 1). This table highlights the differences in representation, selection mechanisms, variation operators, application domains, and core attributes among the described algorithms. By examining these distinctions side by side, we can better understand each algorithm's unique strengths and suitable application scenarios.

In real-world applications, it is crucial to identify the problem characteristics to select the most suitable algorithm. Key considerations include:

- Solution Structure Flexibility: determine if the problem requires a flexible or dynamic solution structure;

Table 1

**Comparison of evolutionary algorithms**

| | Genetic algorithms | Genetic programming | Evolutionary programming | Evolution strategies | Differential evolution |
|---|---|---|---|---|---|
| Solution structure | Fixed-length or variable-length encoded binary strings (in classic approach). | Hierarchical compositions of functions and terminals (trees). | Like GA but more commonly with non-binary encoding. | Like GA but more commonly with non-binary encoding. | Like GA but more commonly with non-binary encoding. |
| Selection | Stochastic, often using fitness-based selection. | Stochastic, often using fitness-based selection. | Stochastic, often using tournament selection. | Deterministic, selecting top-performing individuals. | Fitness-based selection, replacing target vectors if trial vectors are better. |
| Variation operators | Crossover, mutation. | Crossover, mutation. | Mutation. | Mutation with self-adaptive mutation rates. | Mutation based on vector differences, crossover. |
| Domain | Optimization, machine learning, scheduling, etc. | Symbolic regression, automatic code generation, machine learning. | Control systems, optimization with many local optima. | Continuous optimization problems. | Continuous optimization problems, engineering design. |
| Core attributes | ▪ Uses populations of chromosomes;<br>▪ Applies natural selection principles;<br>▪ Fitness evaluated to guide selection. | ▪ Evolves programs or expressions;<br>▪ Suitable for problems needing flexible solution structures;<br>▪ Uses tree structures to represent solutions. | ▪ No crossover; relies on mutation and stochastic selection;<br>▪ Effective for problems with many local optima;<br>▪ Competes against other individuals in tournaments. | ▪ Self-adaptive mutation rates;<br>▪ Deterministic selection similar to breeding;<br>▪ Dynamically adjusts mutation strength. | ▪ Mutation based on vector differences from the population;<br>▪ Combines existing solutions to explore new solutions;<br>▪ Efficient in exploring complex search spaces. |

*Source:* developed by the authors based on [1; 2; 12; 16; 17]

- Local Optima: identify if the problem has many local optima that must be avoided. Use heuristic methods to assess the presence of local optima or test various algorithms on sample data to identify local optima issues;
- Parameter Adjustment: evaluate whether the problem requires frequent adjustments to parameters, such as mutation rates, which can be determined empirically;
- Continuous vs. Discrete: determine whether the variables are continuous or discrete. Select algorithms suited for the variable type (e.g., gradient methods for continuous, greedy algorithms for discrete).

As an initial step, it is essential to thoroughly understand the problem's domain and clearly define the problem and its requirements. Based on these key considerations, the following table provides a general recommendation for matching problem characteristics with appropriate algorithms (see Table 2).

This table offers a general guideline for selecting algorithms based on specific problem characteristics. However, it is not intended to be a definitive rule, as each evolutionary algorithm employs unique mechanisms that may be more or

Table 2

**Algorithms matching specific problem characteristics**

| Problem Characteristic | Preferable algorithm |
|---|---|
| Solution structure | GP |
| Local optima | EP |
| Parameter adjustment | ES |
| Continuous variables | ES, DE |
| Discrete variables | GA, GP, EP |

*Source:* developed by the authors

less effective depending on the specific context. Therefore, it is crucial to analyze evolutionary algorithms within the specific context of supply chain management, considering its unique challenges and requirements.

Supply chain management involves the planning, implementing, and controlling the efficient flow and storage of goods, services, and information from the point of origin to the point of consumption. As supply chains become increasingly complex, the need for advanced optimization techniques becomes paramount. This chapter explores the diverse applications of evolutionary algorithms in supply chain management, demonstrating their effectiveness in improving operational efficiency, reducing costs, and enhancing service quality. Each type of evolutionary algorithm will be reviewed, along with the specific supply chain management problems they can solve, highlighting their unique strengths and applications.

*Genetic algorithms*, with their practical adaptability, are a valuable tool for addressing a wide array of real-world supply chain management challenges. These include but are not limited to route optimization, warehouse optimization, fleet management, inventory management, and job scheduling. The extensive body of literature on the application of genetic algorithms in supply chain management underscores their practicality and effectiveness:

- Logistics Distribution Route Optimization: Genetic algorithms are highly effective in optimizing logistics distribution routes by creating efficient delivery plans and minimizing the time to find optimal routes. [2] demonstrated that an improved GA could find optimal routes faster than traditional methods;
- Warehouse Layout Optimization: Genetic algorithms optimize product placement and warehouse order picking routes. [3] showed significant reductions in order-picking times using GAs;
- Fleet Management: GAs can optimize vehicle routing for perishable goods, addressing cost minimization and quality preservation. [18] applied GAs to vehicle routing problems with time windows and quality constraints;
- Inventory Management: Genetic algorithms help optimize inventory levels within supply chains, minimizing total supply chain costs. [19] used GAs to determine optimal stock levels;
- Job Scheduling: GAs solve scheduling problems in manufacturing systems, finding optimal or near-optimal solutions for complex scheduling issues. [20] discussed using GAs for advanced manufacturing scheduling;
- Automated Sorting Systems: Genetic algorithms optimize warehouse shipment and sorting processes, improving processing times and worker efficiency. [4] used GAs to optimize worker numbers and sorting times.

*Genetic programming* is valuable for problems that require a flexible and dynamic solution structure, such as symbolic regression, automatic code generation, and the development of machine learning models. In supply chain management, genetic programming can automatically evolve heuristics for any heuristics-solvable problem or evolve predictions through symbolic regression, such as demand forecasting. Examples of genetic programming being used in modern literature include:

- Dynamic Vehicle Routing: GP evolves heuristics for dynamic vehicle routing problems, handling real-time decision-making for route adjustments. [5] showed GP's effectiveness in evolving heuristics for vehicle routing with time windows;
- Demand Prediction Models: GP creates models for predicting product demand, aiding inventory management. [6] used multi-gene symbolic regression GP for stock market prediction, highlighting its potential in demand forecasting.

*Evolutionary programming* can be used for the same problems as GA, but it is especially effective when the problem has many local optima. Due to the use of mutation operator only and specific selection method, it may apply to fewer problems; however, in some cases, it can still prove to be efficient, such as in the following paper:

- Shortest Route Planning: EP, combined with artificial bee colony algorithms, optimizes path planning for mobile robots. [7] showed improved path planning performance using EP.

*Evolution strategies* are primarily used for the same problems as genetic algorithms. They are particularly effective when it is necessary to adjust mutation rates during the execution due to the nature of the problem. This need arises because solutions may be more similar at certain execution stages and more diverse at others. The following studies utilize evolution strategies to address supply chain management problems:

- Manufacture Planning: ES optimizes production systems by determining optimal kanban sizes and production trigger values. [8] illustrated ES's application in optimizing pull production systems;
- Multiple Salesmen Problem: ES solves multiple traveling salesmen problems, optimizing routes for multiple salespeople. [9] demonstrated ES's superior performance in solving these problems compared to other algorithms;
- Colored Balanced Traveling Salesman Problem: ES, with tailor-made mutation operators, effectively solves the colored balanced traveling salesman problem (CBTSP). [21] showed that their ES approach surpasses the results of novel genetic algorithms for CBTSP in shorter amounts of time.

*Differential evolution* can also be used to solve problems typically addressed with genetic algorithms. However, the nature of differential evolution provides advantages for non-differentiable specific problems. Differential evolution has been applied in the following studies:

- Distribution Network Optimization: DE addresses stochastic location-inventory-delivery problems, optimizing strategic, tactical, and operational decisions. [11] combined DE with particle swarm optimization for effective network optimization;

- Delivery Scheduling: DE solves sequencing and scheduling optimization problems, adapting to discrete variables. [10] introduced a novel solution encoding mechanism for DE in scheduling;

- Supply Chain Optimization: DE, combined with chaotic sequences, optimizes integrated production-inventory-distribution systems. [22] showed DE's efficiency in supply chain optimization;
- Warehouse Allocation: DE determines optimal warehouse locations, minimizing transportation costs. [23] applied DE for warehouse location optimization using geographic information systems.

The following texts highlight the different ways evolutionary algorithms are utilized in logistics and supply chain management and demonstrate how these algorithms effectively optimize complex processes and enhance overall efficiency. Many of these problems have been extensively researched, showcasing the robustness and adaptability of evolutionary algorithms in real-world scenarios.

As the field continues to evolve, integrating these algorithms with emerging technologies such as artificial intelligence, machine learning, and big data analytics is expected to enhance their effectiveness further. These advancements will enable even more precise and efficient optimization of supply chain processes, ultimately leading to more resilient, agile, and sustainable supply chains. The ongoing research and development in this area promise significant improvements in operational efficiency, cost reduction, and service quality, cementing the role of evolutionary algorithms as indispensable tools in modern supply chain management.

**Conclusions.** Evolutionary algorithms are powerful and versatile tools for addressing various supply chain management problems. Their ability to manage complex, multi-objective optimization tasks and adaptability to numerous applications makes them invaluable in logistics and supply chain management. The research and practical implementations reviewed in this paper demonstrate the effectiveness of EAs in optimizing routes, managing inventories, scheduling tasks, and improving overall operational efficiency.

Evolutionary algorithms are used extensively in supply chain management, including route optimization, warehouse optimization, fleet management, inventory management, job scheduling, and other dynamic and flexible problem-solving.

Genetic algorithms, evolutionary programming, evolution strategies, and differential evolution can all solve practically the same set of problems. However, each algorithm's effectiveness depends on the specific problem's nature, including potential solutions, search space, and other criteria. Genetic programming, on the other hand, is different from the others and is particularly useful for creating regression models, tuning the heuristics of algorithms, and other structure-related problems.

It is essential to address several challenges and future directions for evolutionary algorithms in supply chain management. One main challenge is the computational cost, especially for large-scale problems. One way to mitigate this issue is by developing hybrid approaches that combine EAs with other optimization techniques. Additionally, premature convergence to suboptimal solutions is a concern. Adaptive mechanisms that adjust algorithm parameters dynamically can help maintain diversity in the solution population and avoid premature convergence.

Furthermore, the scalability of EAs to handle increasingly large and complex logistics networks requires further research. Exploring parallel and distributed computing techniques could enhance their scalability. Lastly, developing EAs capable of real-time decision-making and adaptation to changing conditions in logistics networks is an important area for future research, enabling more responsive and resilient logistics operations.

In summary, evolutionary algorithms have significantly contributed to optimizing logistics and supply chain management. EAs' ability to handle complex optimization tasks and adaptability to various applications make them indispensable tools in the digital transformation era. However, addressing challenges such as computational cost and premature convergence will enhance their effectiveness and applicability in real-world supply chain management scenarios.

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