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A Comprehensive Review of Highway Emergency Facility Locating Models and Algorithms

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Abstract

This review paper aims to provide a comprehensive overview of existing research on highway emergency facility locating models and algorithms. The paper discusses the significance of effective emergency management in highway systems, outlines the primary objectives of emergency facility location, and presents a taxonomy of optimization models and algorithms. Furthermore, the paper concludes with recommendations for future research directions and potential applications.

Keywords

Highway emergency, locating models, OR algorithms, future directions.

1. Introduction

Highway emergency response planning[1] is a critical aspect of transportation and public safety management. Efficient and effective emergency response systems play a vital role in mitigating the impact of various types of emergencies, such as traffic accidents, natural disasters, and hazardous material spills. These emergencies can cause significant disruptions to transportation networks, lead to substantial economic losses, and, most importantly, pose a threat to human life. The primary goal of highway emergency response planning is to ensure the timely and adequate provision of emergency services, such as medical assistance, firefighting, and hazardous material containment, to minimize the adverse effects of emergencies on society.

An essential component of highway emergency response planning is the strategic decisions related to the location of emergency facilities. Emergency facility location decisions involve determining the optimal placement of facilities, such as hospitals, fire stations, and hazardous material response centers, to maximize their accessibility and coverage[2-5]. The optimization of these decisions is crucial for ensuring the prompt and effective response to emergencies and the efficient utilization of available resources.

Over the past several decades, numerous mathematical models and optimization algorithms have been developed to address the complex and challenging problems of emergency facility location. These models and algorithms have been applied in various emergency response contexts and have contributed to significant improvements in the efficiency and effectiveness of emergency response systems. However, as the scale and complexity of transportation networks continue to grow, and the frequency and severity of emergencies continue to increase

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due to factors such as urbanization, climate change, and technological advancements, new challenges and opportunities are emerging in the field of highway emergency facility locating.

In this review paper, we provide an extensive overview of the state-of-the-art models, algorithms, and methods in the field of highway emergency facility locating. We also provide recommendations for future research directions and applications to contribute to the continued advancement of the field.

2. Taxonomy of Optimization Models and Algorithms

2.1. Emergency Facility Location Models

In this section, we provide a further extended discussion of the four primary categories of emergency facility location models: deterministic, probabilistic, robust, and dynamic models. These models play a critical role in determining the optimal location of emergency facilities, ensuring timely response and efficient resource allocation during crisis situations.

Table 1 Taxonomy of optimization models

Emergency facility location models		References
Deterministic models	MCLM	Ansari et al. (2022)
	LSCP	Aboolian et al. (2021)
Probabilistic models	SMCLM	
	SLSCP	
Robust models	RMCLM	Alinaghian et al. (2017)
	RLSCP	
Dynamic models	DMCLM	Tanaka et al. (2011)
	DLSCP	Alizadeh and Tatsushi (2020)

2.1.1. Deterministic Models

Deterministic models assume that all parameters, such as demand, travel time, and service capacity, are known with certainty. These models are relatively simple and computationally efficient, making them a popular choice in the literature. Some additional deterministic models include:

Maximum Covering Location Model (MCLM)[6-9]: This model aims to maximize the total demand covered within a pre-specified service distance or time by placing a fixed number of facilities. The model assumes that each demand point can be served by any facility within the service distance or time.

Location Set Covering Problem (LSCP)[10-14]: This model seeks to minimize the number of facilities required to cover all demand points at least once, without considering service distance or time constraints. It assumes that each facility can serve an unlimited number of demand points.

2.1.2. Probabilistic Models

Probabilistic models incorporate uncertainty in the demand, travel time, and/or facility service capacities by considering probability distributions or stochastic parameters. These models can provide more realistic solutions, as they account for the inherent uncertainty in real-world situations. Additional probabilistic models include:

Stochastic Maximum Covering Location Model (SMCLM): This model extends the MCLM by considering the probability of demand point coverage, which depends on the stochastic nature

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of demand or travel time. The objective is to maximize the expected total demand covered within the service distance or time.

Stochastic Location Set Covering Problem (SLSCP): This model generalizes the LSCP by introducing uncertainty in demand or travel time. The goal is to minimize the number of facilities required to cover all demand points with a pre-specified probability.

2.1.3. Robust Models

Robust models are designed to provide solutions that perform well under various scenarios or in the presence of uncertainty. These models can be particularly useful in emergency situations, where the exact nature of the uncertainty may be unknown or difficult to predict. Additional robust facility location models are:

Robust Maximum Covering Location Model (RMCLM)[15]: This model seeks to maximize the total demand covered within the service distance or time in the worst-case scenario, ensuring system resilience to unforeseen events.

Robust Location Set Covering Problem (RLSCP): This model aims to minimize the number of facilities required to cover all demand points at least once in the worst-case scenario, guaranteeing a robust solution that maintains service coverage even under adverse conditions.

2.1.4. Dynamic Models

Dynamic models consider the temporal dimension, accounting for changes in demand, travel time, or facility capacities over time. These models can provide more accurate and adaptive solutions for emergency facility location, as they can better represent the dynamic nature of real-world situations. Additional dynamic models include:

Dynamic Maximum Covering Location Model (DMCLM)[16]: This model extends the MCLM by considering temporal variations in demand, travel time, or facility capacities, aiming to maximize the total demand covered within the service distance or time over time.

Dynamic Location Set Covering Problem (DLSCP)[17-20]: This model accounts for time-varying demand, travel time, or facility capacities in the LSCP, with the goal of minimizing the number of facilities required to cover all demand points at least once over time.

These extended discussions provide a comprehensive overview of various emergency facility location models, which are essential in the planning and management of emergency response systems. By understanding the differences among deterministic, probabilistic, robust, and dynamic models, researchers and practitioners can select the most appropriate model for their specific problem and context. Each of these models serves a different purpose and provides unique insights into the optimal location of emergency facilities.

Deterministic models offer a foundation for understanding the basic principles of emergency facility location, and they can be useful for situations where uncertainty is minimal. However, in real-world emergency situations, there are often significant uncertainties in demand, travel times, and capacities. As a result, probabilistic and robust models have gained popularity, as they can better handle uncertainty and provide more reliable solutions.

Probabilistic models are valuable for addressing stochastic variations in the problem parameters, which can lead to more realistic and adaptable solutions. Robust models, on the other hand, focus on worst-case scenarios, ensuring that the system is resilient even when facing unforeseen events or extreme conditions.

Dynamic models are particularly relevant in emergency facility location problems, as they take into account the time-varying nature of demand, travel times, and capacities. By incorporating temporal information, these models can provide more accurate solutions that adapt to changing conditions and needs.

In summary, selecting the appropriate emergency facility location model is a crucial step in ensuring an effective emergency response system. By understanding the strengths and

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limitations of each model, decision-makers can choose the most suitable approach for their specific problem and ensure that emergency facilities are optimally located to maximize coverage, minimize response times, and improve overall system performance. Moreover, by combining these models with the optimization algorithms discussed in section 2.2, researchers and practitioners can develop advanced methodologies for addressing the complex and dynamic nature of emergency facility location.

2.2. Optimization Algorithms

In this section, we provide an extended discussion of the four primary categories of optimization algorithms used for solving emergency facility location models: exact algorithms, metaheuristic algorithms, hybrid algorithms, and machine learning-based algorithms. These algorithms are essential in finding optimal or near-optimal solutions for the models discussed in sections 2.1.

Table 2 Taxonomy of optimization algorithms

Primary categories	Optimization algorithms	References
Exact algorithms	Branch and bound	Hamadi and Naffeti (2023)
	Branch and cut	Zhang et al. (2022)
	Dynamic programming	Mauricio et al. (2023)
Metaheuristic algorithms	Genetic algorithms	Chromik and Arnrich (2021)
	Simulated annealing	Nahavandi et al. (2022)
	Particle swarm optimization	Zhu et al. (2020)
	Ant colony optimization	Mavrovouniotis et al. (2020)
Hybrid algorithms	Genetic algorithm with local search	Wang et al. (2022)
	Simulated annealing with constraint programming	Kizilay (2022)
	Particle swarm optimization with dynamic programming	Bilal et al. (2020)
Machine learning-based algorithms	Reinforcement learning	Li et al. (2021)
	Neural networks	RamachandranPillai and Arock (2020)
	Supervised learning for solution construction	Elola et al. (2016)
	Unsupervised learning for clustering	Han et al. (2023)

2.2.1. Exact Algorithms

Exact algorithms guarantee optimal solutions for facility location problems by exploring the entire solution space. These algorithms are generally computationally expensive, and their applicability may be limited to small- and medium-sized problems. Some widely-used exact algorithms include:

Branch and Bound[21-25]: This algorithm systematically divides the solution space into smaller subproblems and computes bounds on the optimal solution. Subproblems with bounds that cannot lead to better solutions are discarded, reducing the search space.

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Branch and Cut[26,27]: This algorithm extends the branch and bound method by incorporating cutting planes, which are linear inequalities that remove non-optimal solutions from the search space, thus accelerating the convergence to the optimal solution.

Dynamic Programming[28,29]: This algorithm solves a problem by dividing it into smaller overlapping subproblems and combining their solutions in a systematic manner. The algorithm is particularly suitable for problems with optimal substructure and overlapping subproblems.

2.2.2. Metaheuristic Algorithms

Metaheuristic algorithms are approximate optimization methods that search for near-optimal solutions within a reasonable computational time. These algorithms can be applied to large-scale and complex problems and are often inspired by natural phenomena. Some popular metaheuristic algorithms include:

Genetic Algorithms[30-40]: These algorithms are inspired by the process of natural selection and evolution. They use a population of candidate solutions that evolve over time through mutation, crossover, and selection operations.

Simulated Annealing[41-46]: This algorithm is inspired by the annealing process in metallurgy. It uses a stochastic search that accepts worse solutions with a decreasing probability as the search progresses, allowing the algorithm to escape local optima.

Particle Swarm Optimization[47-50]: This algorithm is inspired by the social behavior of bird flocks or fish schools. It uses a population of particles that move through the search space and adapt their positions based on their own best experiences and the best experiences of their neighbors.

Ant Colony Optimization[51-53]: This algorithm is inspired by the foraging behavior of ants. It uses a population of artificial ants that build solutions incrementally by following pheromone trails, which represent the quality of the solutions.

2.2.3. Hybrid Algorithms

Hybrid algorithms combine elements from exact algorithms, metaheuristic algorithms, or other optimization methods to exploit the advantages of each method and improve overall performance. These algorithms can provide high-quality solutions with reduced computational time. Examples of hybrid algorithms include:

Genetic Algorithm with Local Search[54,55]: This hybrid algorithm incorporates local search methods, such as hill climbing or tabu search, within a genetic algorithm to improve the quality of the solutions generated by the genetic operators.

Simulated Annealing with Constraint Programming[56]: This hybrid algorithm combines the stochastic search capabilities of simulated annealing with the constraint propagation techniques of constraint programming, allowing for more efficient exploration of the search space.

Particle Swarm Optimization with Dynamic Programming[57]: This hybrid algorithm integrates the global search capabilities of particle swarm optimization with the efficient solution construction techniques of dynamic programming, aiming to balance exploration and exploitation in the search process.

2.2.4. Machine Learning-based Algorithms

Machine learning-based algorithms use data-driven approaches to optimize facility location problems. These algorithms can learn from historical data, adapt to changes in the problem parameters, and provide real-time solutions. Examples of machine learning-based algorithms include:

Reinforcement Learning[58,59]: This algorithm learns an optimal decision-making policy by interacting with the environment and receiving feedback in the form of rewards or penalties. It can be applied to facility location problems by modeling the decision-making process as a

Markov Decision Process (MDP) and iteratively updating the policy based on the observed outcomes.

Neural Networks[60,61]: These algorithms consist of interconnected layers of artificial neurons that can learn complex relationships between input and output data. They can be used to predict travel times, demands, or other problem parameters, and can be incorporated into optimization algorithms to improve their performance.

Supervised Learning for Solution Construction[62]: In this approach, machine learning algorithms, such as Support Vector Machines (SVMs) or Decision Trees, are used to learn patterns in historical solutions of facility location problems. These patterns can then be used to guide the construction of new solutions or to improve the performance of other optimization algorithms.

Unsupervised Learning for Clustering[63,64]: In this approach, unsupervised learning algorithms, such as K-means or Hierarchical Clustering, are used to group demand points or facilities based on their spatial or temporal characteristics. These clusters can then be used as input for other optimization algorithms.

In conclusion, the choice of optimization algorithms for solving emergency facility location problems depends on various factors, such as problem size, complexity, and the desired solution quality. Combining different optimization algorithms or incorporating machine learning techniques can lead to more efficient and effective solutions that cater to the dynamic and uncertain nature of emergency situations.

3. Recommendations for Future Research Directions and Applications

In this section, we provide an extended discussion of recommendations for future research directions and applications in the field of highway emergency facility locating.

Table 4 Recommendations for future research directions and applications

Future research directions and applications	Recommendations
Application of advanced optimization techniques	Exploring the use of machine learning-based optimization algorithms
	Investigating the potential of quantum computing
	Developing hybrid optimization algorithms
Emerging technologies and data availability	Developing dynamic and adaptive optimization models
	Designing algorithms and decision support systems
	Evaluating the benefits of incorporating real-time data and dynamic decision-making
Development of robust and resilient models	Formulating stochastic and robust optimization models
	Investigating the trade-offs between solution robustness
	Designing adaptive algorithms
Implementation in intelligent transportation systems	Developing ITS frameworks
	Investigating the interactions between emergency response planning and other ITS components
	Designing adaptive algorithms

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3.1. Application of Advanced Optimization Techniques

Applying advanced optimization techniques to emergency facility location problems can lead to more efficient and effective solutions. Future research directions include:

Exploring the use of machine learning-based optimization algorithms, such as reinforcement learning and deep learning, to improve solution quality and computational efficiency.

Investigating the potential of quantum computing for solving large-scale and complex emergency facility location problems.

Developing hybrid optimization algorithms that combine the strengths of exact, heuristic, and metaheuristic methods to enhance solution quality and computational efficiency.

3.2. Incorporation of Real-time Data and Dynamic Decision Making

Incorporating real-time data into optimization models and enabling dynamic decision-making can improve emergency response performance in rapidly changing situations. Future research can focus on:

Developing dynamic and adaptive optimization models that leverage real-time data from traffic sensors, social media, and crowdsourcing platforms to update facility location decisions.

Designing algorithms and decision support systems that can process large volumes of real-time data, provide timely updates to emergency response plans, and support dynamic decision-making.

Evaluating the benefits of incorporating real-time data and dynamic decision-making in emergency response scenarios, including improved response times, coverage, and adaptability to changing conditions.

3.3. Development of Robust and Resilient Models

Developing robust and resilient optimization models that can handle uncertainty and provide reliable solutions is essential for effective emergency response planning. Future research directions include:

Formulating stochastic and robust optimization models that account for various sources of uncertainty, such as demand, travel times, and resource availability.

Investigating the trade-offs between solution robustness, solution quality, and computational efficiency in emergency facility location problems.

Designing adaptive algorithms that can update solutions in real-time based on new information and assess the performance of these methods under different levels of uncertainty and risk.

3.4. Implementation in Intelligent Transportation Systems

Integrating emergency facility location models and algorithms into intelligent transportation systems (ITS) can enhance emergency response performance and overall transportation system resilience. Future research can focus on:

Developing ITS frameworks that incorporate optimization models and algorithms for emergency facility location, leveraging emerging technologies such as connected and autonomous vehicles, drones, and the Internet of Things (IoT).

Investigating the interactions between emergency response planning and other ITS components, such as traffic management, information dissemination, and incident management.

Conducting real-world case studies and pilot projects to evaluate the benefits of implementing optimization models and algorithms in ITS, including improved emergency response performance, system resilience, and cost-effectiveness.

By addressing these future research directions and applications, the field of highway emergency facility locating can continue to advance, leading to more efficient, effective, and resilient emergency response systems.

4. Conclusion

In this review paper, we have provided an extensive overview of the state-of-the-art models, algorithms, and methods in the field of highway emergency facility locating. We have discussed the various types of emergency facility location models, as well as the optimization algorithms used to solve them. We have also provided recommendations for future research directions and applications, such as the development of integrated models, application of advanced optimization techniques, incorporation of real-time data and dynamic decision making, development of robust and resilient models, and implementation in intelligent transportation systems.

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References

[1]Yao Junfeng, Yan Longhao, Xu Zhuohang, et al. Collaborative Decision-Making Method of Emergency Response for Highway Incidents[J]. Sustainability, 2023, 15(3):2099-2099.
[2]Takedomi Shogo, Ishigaki Tsukasa, Hanatsuka Yasushi, et al. Facility location optimization with pMP modeling incorporating waiting time prediction function for emergency road services[J]. Computers & Industrial Engineering, 2022, 164.
[3]Liu Yang, Yuan Yun, Shen Jieyi, et al. Emergency response facility location in transportation networks: A literature review[J]. Journal of Traffic and Transportation Engineering (English Edition), 2021, 8(2):153-169.
[4]Julia Monzón, Federico Liberatore, Begoña Vitoriano, et al. A Mathematical Pre-Disaster Model with Uncertainty and Multiple Criteria for Facility Location and Network Fortification[J]. Mathematics, 2020, 8(4):529-529.
[5]Yu Wuyang, Liu Jijun, . Optimization Model Based on Reachability Guarantee for Emergency Facility Location and Link Reinforcement[J]. Journal of Advanced Transportation, 2020, 2020:1-12.
[6]Ansari Mehdi, Borrero Juan S., Lozano Leonardo, et al. Robust Minimum-Cost Flow Problems Under Multiple Ripple Effect Disruptions[J]. INFORMS Journal on Computing, 2022, 35(1).
[7]Narjes Sabeghi, Hamed Reza Tareghian, . Using the generalized maximum covering location model to control a project's progress[J]. Computational Management Science, 2020, 17(1):1-21.
[8]ÖZKAN Barış, METE Süleyman, ÇELİK Erkan, et al. Gis-based Maximum Covering Location Model in Times of Disasters: The Case of Tunceli[J]. Beykoz Akademi Dergisi, 2019, :100-111.
[9]Shihui Tian, Guowei Hua, T. C. E. Cheng, et al. Optimal Deployment of Charging Piles for Electric Vehicles Under the Indirect Network Effects[J]. Asia-Pacific Journal of Operational Research, 2019, 36(1):17.
[10]Xu Yanqing, Zhang Yue, Fu Cong, et al. Optimizing the Spatial Location of Street Lights in Belle Isle, Michigan[J]. ISPRS International Journal of Geo-Information, 2022, 11(2):115-115.
[11]Syahputra Rizki Agam, Andriansyah, Sentia Prima Denny, et al. Determining Optimal New Waste Disposal Facilities Location by Using Set Covering Problem Algorithm. 2022, 210.
[12]Aboolian Robert, Berman Oded, Karimi Majid, et al. Probabilistic Set Covering Location Problem in Congested Networks[J]. Transportation Science, 2021, 56(2).
[13]Hashim Nur Idayu Mah, Sarifah Radiah Shariff S, Deni Sayang Mohd, et al. Allocation of Relief Centre for Flood Victims Using Location Set Covering Problem (LSCP)[J]. Journal of Physics: Conference Series, 2021, 2084(1).

[14]Dragana Šarac, Miloš Kopić, Katarina Mostarac, et al. Application of Set Covering Location Problem for Organizing the Public Postal Network[J]. Promet (Zagreb), 2016, 28(4):403-413.
[15]Mahdi Alinaghian, S.Reza Madani, Hossain Moradi, et al. A New Robust Mathematical Model for the Multi-product Capacitated Single Allocation Hub Location Problem with Maximum Covering Radius[J]. International Journal of Supply and Operations Management, 2017, 4(3):248-262.
[16]Tanaka K I . Maximum flow-covering location and service start time problem and its application to Tokyo metropolitan railway network[J]. Journal of the Operations Research Society of Japan, 2011, 4(4).
[17]Alizadeh Roghayyeh, Nishi Tatsushi, . Hybrid Set Covering and Dynamic Modular Covering Location Problem: Application to an Emergency Humanitarian Logistics Problem[J]. Applied Sciences, 2020, 10(20):7110-7110.
[18]Amir Ebrahimi-zade, Hasan Hosseini-Nasab, Yahya zare-mehrjerdi, et al. Multi-period hub set covering problems with flexible radius: A modified genetic solution[J]. Applied Mathematical Modelling, 2016, 40(4):2968-2982.
[19]Anita Schöbel, . Locating Stops Along Bus or Railway Lines - A Bicriteria Problem.[J]. Annals OR, 2005, 136(1):211-227.
[20]Gunawardane Gamini. Dynamic versions of set covering type public facility location problems[J]. European Journal of Operational Research, 1982, 10(2):190-195.
[21]Jex Martin, Mikyška Jiří, . An improved branch and bound algorithm for phase stability testing of multicomponent mixtures[J]. Fluid Phase Equilibria, 2023, 566
[22]Ammar Hamadi, Naffeti Bechir. A branch and bound algorithm for Holder bi-objective optimization. Implementation to multidimensional optimization[J]. Mathematics and Computers in Simulation, 2023, 204:181-201.
[23]Liu Hui, Yue JiaWei, Liu WenKai, et al. Multi-baseline phase unwrapping with robust branch and bound pure integer programming algorithm[J]. Optics and Lasers in Engineering, 2023, 161.
[24]Zhang Bo, Gao Yuelin, . An Output-Space Based Branch-and-Bound Algorithm for Sum-of-Linear-Ratios Problem[J]. Asia-Pacific Journal of Operational Research, 2023, 40(02).
[25]Forget Nicolas, Gadegaard Sune Lauth, Nielsen Lars Relund, et al. Warm-starting lower bound set computations for branch-and-bound algorithms for multi objective integer linear programs[J]. European Journal of Operational Research, 2022, 302(3):909-924.
[26]Behnamian J., . Multi-agent capacitated scheduling for profit-maximizing using a decomposition-based branch and cut algorithm[J]. International Journal of Management Science and Engineering Management, 2021, 16(2):73-82.
[27]Zhang Xiangyi, Chen Lu, Gendreau Michel, et al. A branch-and-cut algorithm for the vehicle routing problem with two-dimensional loading constraints[J]. European Journal of Operational Research, 2022, 302(1):259-269.
[28]Chen Shuang, Hu Minghui, Guo Shanqi, et al. Fast dynamic-programming algorithm for solving global optimization problems of hybrid electric vehicles[J]. Energy, 2023, 273
[29]Annear Luis Mauricio, Akhavan-Tabatabaei Raha, Schmid Verena, et al. Dynamic assignment of a multi-skilled workforce in job shops: An approximate dynamic programming approach[J]. European Journal of Operational Research, 2023, 306(3):1109-1125.
[30]Chromik Jonas, Arnrich Bert, . Optimal Deployment in Emergency Medicine with Genetic Algorithm Exemplified by Lifeguard Assignments.[J]. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference, 2021, 2021:1806-1809.
[31]Feiyue Wang, Zhongwei Pei, Longjun Dong, et al. Emergency Resource Allocation for Multi-Period Post-Disaster Using Multi-Objective Cellular Genetic Algorithm[J]. IEEE Access, 2020, 8:82255-82265.
[32]Leiwen Chen, Yingming Wang, Geng Guo, et al. An Improved Genetic Algorithm for Emergency Decision Making under Resource Constraints Based on Prospect Theory[J]. Algorithms, 2019, 12(2):43.
[33]Manuel Fogue, Julio A. Sanguesa, Francisco J. Martinez, et al. Improving Roadside Unit Deployment in Vehicular Networks by Exploiting Genetic Algorithms[J]. Applied Sciences, 2018, 8(1)

ISSN: 2664-9640

[34]Meryam Benabdouallah, Othmane El Yaakoubi, Chakib Bojji, et al. Genetic algorithm hybridised by a guided local search to solve the emergency coverage problem[J]. Int. J. of Mathematical Modelling and Numerical Optimisation, 2017, 8(1):23-41.
[35]Jesimar da Silva Arantes, Márcio da Silva Arantes, Claudio Fabiano Motta Toledo, et al. Heuristic and Genetic Algorithm Approaches for UAV Path Planning under Critical Situation[J]. International Journal on Artificial Intelligence Tools, 2017, 26(1):30.
[36]Roghayyeh Alizadeh, Tatsushi Nishi, . A Genetic Algorithm for Multi-Period Location Problem with Modular Emergency Facilities and Backup Services[J]. Transactions of the Institute of Systems, Control and Information Engineers, 2020, 32(10):370-377.
[37]Altarabsheh Ahmad, Altarabsheh Ibrahim, Ventresca Mario, et al. A hybrid genetic algorithm to maintain road networks using reliability theory[J]. Structure and Infrastructure Engineering, 2023, 19(6):810-823.
[38]Guo Yiming, Cao Junhai, Chen Chunliang, et al. Research on Task Scheduling of Emergency Repair Team in Wartime Based on Improved Genetic Algorithm. 2022, :897-906.
[39]David Werth, Robert Buckley, . The Application of a Genetic Algorithm to the Optimization of a Mesoscale Model for Emergency Response[J]. Journal of Applied Meteorology and Climatology, 2022, 61(4):329-343.
[40]Zhao Dan, Zhao Yunsheng, Li Zhenhua, et al. Multi-objective Emergency Facility Location Problem Based on Genetic Algorithm. :97-103.
[41]Changxi Ma, Yinzhen Li, Ruichun He, et al. xResearch on location problem of emergency service facilities based on genetic-simulated annealing algorithm[J]. International journal of wireless and mobile computing: IJWMC, 2012, 5(2):206-211.
[42]Bijan Nahavandi, Mahdi Homayounfar, Amir Daneshvar, et al. Hierarchical structure modelling in uncertain emergency location-routing problem using combined genetic algorithm and simulated annealing[J]. International Journal of Computer Applications in Technology, 2022, 68(2):150-163.
[43]Yi Huaihai, Yang Xingang, . A metaheuristic algorithm based on simulated annealing for optimal sizing and techno-economic analysis of PV systems with multi-type of battery energy storage[J]. Sustainable Energy Technologies and Assessments, 2022, 53
[44]Faisal Alkhateeb, Bilal H. Abed-alguni, . A Hybrid Cuckoo Search and Simulated Annealing Algorithm[J]. Journal of Intelligent Systems, 2019, 28(4):683-698.
[45]Michal Podolski, Mariusz Rejment, . Scheduling the Production of Precast Concrete Elements Using the Simulated Annealing Metaheuristic Algorithm[J]. IOP Conference Series: Materials Science and Engineering, 2019, 471(11):112083 (8pp).
[46]Assif Assad, Kusum Deep, . A Hybrid Harmony search and Simulated Annealing algorithm for continuous optimization[J]. Information Sciences, 2018, 450:246-266.
[47]Zacharakis Ilias, Giagopoulos Dimitrios, . Model-Based Damage Localization Using the Particle Swarm Optimization Algorithm and Dynamic Time Wrapping for Pattern Recreation[J]. Sensors, 2023, 23(2):591-591.
[48]Biabani Fatemeh, Shojaee Saeed, Hamzehei-Javaran Saleh, et al. A new insight into metaheuristic optimization method using a hybrid of PSO, GSA, and GWO[J]. Structures, 2022, 44:1168-1189.
[49]Zhu Shun-Peng, Keshtegar Behrooz, Ben Seghier Mohamed El Amine, et al. Hybrid and enhanced PSO: Novel first order reliability method-based hybrid intelligent approaches[J]. Computer Methods in Applied Mechanics and Engineering, 2022, 393
[50]Chen Yingxue, Gou Linfeng, . A Boosted Particle Swarm Method for Energy Efficiency Optimization of PRO Systems[J]. Energies, 2021, 14(22):7688-7688.
[51]Michalis Mavrovouniotis, Shengxiang Yang, Mien Van, et al. Ant Colony Optimization Algorithms for Dynamic Optimization: A Case Study of the Dynamic Travelling Salesperson Problem [Research Frontier][J]. IEEE Computational Intelligence Magazine, 2020, 15(1):52-63.
[52]Raya Lilysuriazna Binti, . A metaheuristic ant colony optimization algorithm for symmetric and asymmetric traveling salesman problems. 2018,
[53]Anandkumar Prakasam, Nickolas Savarimuthu, . Metaheuristic algorithms and probabilistic behaviour: a comprehensive analysis of Ant Colony Optimization and its variants[J]. Artificial Intelligence Review, 2016, 45(1):97-130.

[54]Wang Hao, Wang Yujue, Lv Xianwei, et al. Genetic Algorithm with Local Search for the Multi-Target Scheduling in Flexible Manufacturing System[J]. Journal of Circuits, Systems and Computers, 2022, 31(16)

[55]Zhou Guangyao, Tian WenHong, Buyya Rajkumar, et al. Growable Genetic Algorithm with Heuristic-based Local Search for multi-dimensional resources scheduling of cloud computing[J]. Applied Soft Computing Journal, 2023, 136

[56]Kizilay Damla, . A novel constraint programming and simulated annealing for disassembly line balancing problem with AND/OR precedence and sequence dependent setup times[J]. Computers and Operations Research, 2022, 146

[57]Bilal, Deepti Rani, Millie Pant, et al. Dynamic programming integrated particle swarm optimization algorithm for reservoir operation[J]. International Journal of System Assurance Engineering and Management, 2020, 11(2):1-15.

[58]Li Jingwen, Ma Yining, Gao Ruize, et al. Deep Reinforcement Learning for Solving the Heterogeneous Capacitated Vehicle Routing Problem.[J]. IEEE transactions on cybernetics, 2021,

[59]Maria Amélia Lopes Silva, Sérgio Ricardo de Souza, Marcone Jamilson Freitas Souza, et al. A reinforcement learning-based multi-agent framework applied for solving routing and scheduling problems[J]. Expert Systems With Applications, 2019, 131:148-171.

[60]Hamid Mousavi, Soroush Avakh Darestani, Parham Azimi, et al. An artificial neural network based mathematical model for a stochastic health care facility location problem[J]. Health Care Management Science, 2021, 24(3):1-16.

[61]Resmi RamachandranPillai, Michael Arock, . An Adaptive Spiking Neural P System for Solving Vehicle Routing Problems[J]. Arabian Journal for Science and Engineering, 2020, 45(3):2513-2529.

[62]Andoni Elola, Javier Del Ser, Miren Nekane Bilbao, et al. Hybridizing Cartesian Genetic Programming and Harmony Search for adaptive feature construction in supervised learning problems[J]. Applied Soft Computing, 2016, 52:760-770.

[63]Giuseppe Campobello, Giuseppe Patané, Marco Russo, et al. An efficient algorithm for parallel distributed unsupervised learning[J]. Neurocomputing, 2007, 71(13):2914-2928.

[64]Han Chulwoo, He Zhaodong, Toh Alenson Jun Wei, et al. Pairs trading via unsupervised learning[J]. European Journal of Operational Research, 2023, 307(2):929-947.