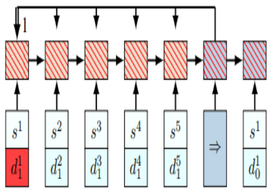
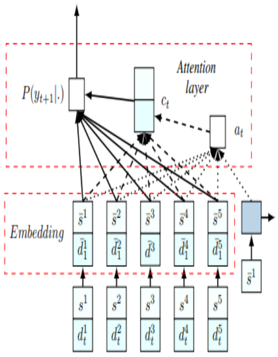
Department of Computer Science and Engineering Bangladesh University of Business and Technology (BUBT)

CSE 478: Literature Review Records

Student's Id and Name	**Name:** Shaneen Ara and **ID:** 19201103138
Capstone Project Title	Vehicle Routing Problem Solving Using Reinforcement Learning
Supervisor Name & Designation	**Name:** Md. Shahiduzzaman & **Designation:** Assistant Professor, Department of CSE, BUBT
Course Teacher's Name & Designation	**Name:** Khan Md. Hasib & **Designation:** Assistant Professor, Department of CSE, BUBT

Aspects	**Paper # 1 (Title)**
Title / Question	**Reinforcement Learning for Solving the Vehicle Routing Problem** Mohammadreza Nazari
Objectives / Goal	The goal of this study is to create a complete framework for applying reinforcement learning to solve the Vehicle Routing Problem (VRP). The objective is to develop a single model that can identify nearly optimal solutions for issue cases taken from a particular distribution. Without the requirement for retraining for each new problem instance, the solution should be generated instantly. In terms of solution quality and computation speed, the suggested framework ought to beat conventional heuristics and current software tools like Google's OR-Tools.

Methodology/Theory	Reinforcement learning is used in the proposed framework, where a single model is trained to find close to ideal answers to the VRP. The model is a parameterized stochastic policy, and the parameters are optimized using a policy gradient technique. In real time, the trained model generates the solution as a series of subsequent actions while paying attention to reward cues and abiding by feasibility restrictions. The framework is built to deal with capacitated VRP issues and split delivery issues.  Figure 1: Limitation of the Pointer Network. After a change in dynamic elements (d_1^1 in this example), the whole Pointer Network must be updated to compute the probabilities in the next decision point.  Figure 2: Our proposed model. The embedding layer maps the inputs to a high-dimensional vector space. On the right, an RNN decoder stores the information of the decoded sequence. Then, the RNN hidden state and embedded input produce a probability distribution over the next input using the attention mechanism.
Software Tools	Python is the main programming language, and the PyTorch deep learning package is utilized to build the framework. For data manipulation and optimization methods, the researchers also use a variety of optimization libraries, including NumPy, SciPy, and Pandas.
Test / Experiment	To test the proposed framework, the researchers compare its performance with classical heuristics and existing software tools such as Google's OR-Tools.The researchers put the suggested framework to the test by evaluating how well it performs in comparison to conventional heuristics and current software programs like Google's OR-Tools. Performance is evaluated in terms of calculation time and solution quality. Additionally, the researchers investigate how split deliveries affect the caliber of solutions. The suggested framework is evaluated using medium-sized capacitated VRP instances. Using a cross-validation methodology, the performance is assessed on examples that were not used for training. The outcomes are contrasted with the most recent techniques used in the industry.

Simulation/Test Data	They generated 1000 instances for each problem size and compared the solutions obtained from their framework with those obtained from the Clarke-Wright savings heuristic (CW), the Sweep heuristic (SW), and Google's optimization tools (OR-Tools).
Result / Conclusion	By training a single model to find near-optimal solutions, their approach outperformed classical heuristics and Google's OR-Tools on medium-sized instances of capacitated VRP in terms of solution quality. The trained model produced solutions in real-time without the need for re-training on new problem instances. The framework also demonstrated the ability to handle problems with split delivery and showed potential for application to other variants of the VRP and combinatorial optimization problems in general.
Obstacles/Challenges	The article does not explicitly mention any methodological obstacles or challenges faced during the development and implementation of the framework. However, it is important to note that applying reinforcement learning to optimization problems, such as the VRP, can have challenges related to training stability, exploration-exploitation trade-offs, convergence, and scalability. The authors likely had to address these challenges and design appropriate algorithms and techniques to ensure the effectiveness and efficiency of their RL-based framework.
Terminology	Vehicle Routing Problem (VRP): A combinatorial optimization problem involving finding optimal routes for a fleet of vehicles to visit a set of customers, with the objective of minimizing distance or maximizing customer service while considering constraints. Clarke-Wright savings heuristic (CW): A heuristic algorithm for the VRP that constructs routes by merging pairs of customers with the largest savings in distance. Sweep heuristic (SW): A heuristic algorithm for the VRP that groups customers based on their polar angles with respect to a depot and constructs routes by sweeping through the angles. Google's optimization tools (OR-Tools): A set of open-source optimization tools provided by Google, including solvers for various combinatorial optimization problems.
Review Judgment	The experiments conducted in this study provide a comprehensive comparison of different algorithms and solvers for the VRP. The authors' framework, particularly the RL-BS method with a beam width of 10, demonstrated competitive performance, outperforming the classical heuristics (CW and SW) and achieving similar results to OR-Tools. The results suggest that the proposed approach is promising and robust, especially for larger problem instances.

Aspects	**Paper # 2(Title)**

Title / Question	**An Optimization Model and Solution Algorithms for the Vehicle Routing Problem with a "Factory-in-a-Box"** Junayed Pasha1 , Maxim A. Dulebenets1 , (Member, IEEE), Masoud Kavoosi2 , Olumide F. Abioye3 , Hui Wang4 , and Weihong Guo5
Objectives / Goal	The objective of the study is to develop an optimization model and solution algorithms for the "factory-in-a-box" supply chain, specifically addressing the second sub-problem related to vehicle routing. The goal is to optimize the transportation of sub-assembly modules between suppliers, manufacturers, and customers, aiming to minimize the total cost of the supply chain.

Methodology/Theory

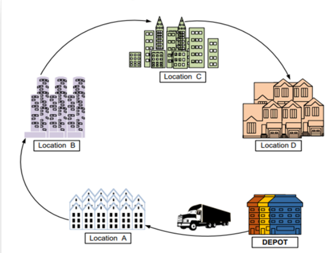


FIGURE 1. An example of a "factory-in-a-box" route.

The provided text describes the main steps of an Evolutionary Algorithm (EA) developed to solve the Vehicle Routing Problem with a "Factory-in-a-Box" (VRPFIB) mathematical model. The EA is a popular solution methodology for vehicle routing problems and has shown promising performance in previous studies.

Here is a summary of the main steps described in the text:

Chromosome Representation: The VRPFIB problem is represented using 4-dimensional integer chromosomes. Each chromosome represents a solution and contains genes that represent vehicle identifiers, supplier identifiers, manufacturer identifiers, and customer identifiers.

Customers	3	8	10	1	4	2	5	6	7	9
Manufacturers	10	2	8	3	1	5	2	9	7	6
Suppliers	4	10	2	1	5	2	6	7	8	1
Vehicles	1	1	1	2	2	3	3	3	3	3

FIGURE 4. The chromosome representation.

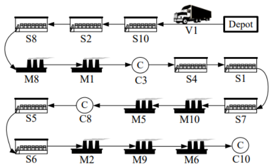


FIGURE 6. The route of vehicle "1".

Initial Population Generation: An initial population of chromosomes is generated to start the algorithmic search. The population is created randomly, with rows for customers and vehicles generated randomly, and rows for suppliers and manufacturers generated based on customer requirements.

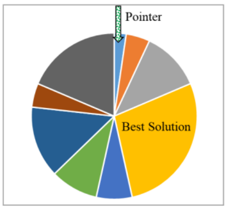


FIGURE 7. Roulette wheel selection.

Parent Selection: Promising chromosomes are selected as parents based on a roulette wheel selection strategy. Each chromosome's selection probability is proportional to its objective value.

Crossover Operator: A crossover operator called order crossover is applied to the parent chromosomes to produce child chromosomes. The order crossover ensures that each customer is served only once and prevents repetitive alleles in the chromosome.

Mutation Operator: The child chromosomes undergo a mutation operation called swap mutation. The swap mutation randomly selects two genes and exchanges their alleles to introduce small genetic changes in the chromosomes.

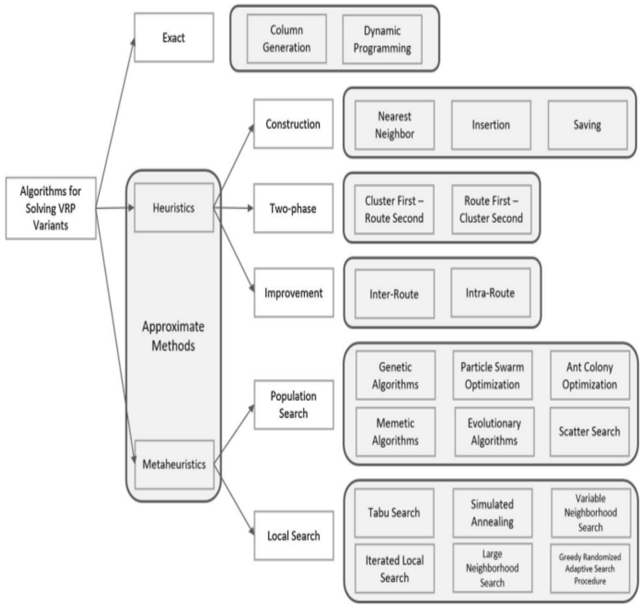
C	7	8	10	1	4	2	3	6	5	9
M	2	10	8	3	1	1	8	5	6	7
S	2	6	2	1	5	5	1	10	7	1
V	2	2	1	2	2	2	3	3	1	1

C	7	8	3	1	4	2	10	6	5	9

Software Tools	The article does not explicitly mention the specific program or software used for design, coding, and simulation.
Test / Experiment	To test and characterize the design/prototype of the "factory-in-a-box" concept, you can consider the following steps: Functional Testing: Evaluate whether the design meets the intended functionality and objectives. This involves testing each module and subsystem to ensure they operate as expected. For example, check if the raw material assignment, sub-assembly decomposition, task assignment, and transportation processes are functioning correctly. Performance Testing: Assess the performance of the design/prototype by measuring key metrics such as production capacity, production time, transportation time, and resource utilization. Compare the achieved performance with the predetermined targets or industry standards. Scalability Testing: Determine how well the design/prototype scales with increasing demands and problem sizes. Test the system with various scenarios and evaluate its ability to handle larger volumes of raw materials, suppliers, manufacturers, tasks, and transportation routes. Assess whether the solution algorithms and optimization model can effectively handle large-scale problem instances. Reliability and Robustness Testing: Assess the reliability of the design/prototype by subjecting it to different operational conditions and stress testing. Simulate various scenarios such as supplier delays, manufacturing disruptions, and transportation route changes. Evaluate how well the system adapts to unexpected situations and recovers from failures. Comparative Analysis: Compare the performance of the solution algorithms, such as the Evolutionary Algorithm, Variable Neighborhood Search, Tabu Search, and Simulated Annealing. Assess their efficiency, accuracy, and convergence properties. Analyze their strengths and weaknesses in solving the "factory-in-a-box" supply chain optimization problem. Cost Analysis: Evaluate the cost-effectiveness of the design/prototype. Compare the total cost of the "factory-in-a-box" supply chain achieved through the optimization model and solution algorithms with alternative approaches or traditional supply chain methods. Assess the savings and efficiency improvements achieved by implementing the proposed concept. User Feedback and Evaluation: Obtain feedback from potential users, stakeholders, and experts in the field. Conduct surveys or interviews to gather opinions on the usability, effectiveness, and practicality of the "factory-in-a-box" concept. Identify areas for improvement and address any concerns raised.
Simulation/Test Data	The specific parameters determined for the simulation or test data are not mentioned in the article.

Result / Conclusion	The study presents a mixed-integer linear programming model for the ”factory-in-a-box” supply chain and employs CPLEX to solve the model optimally. Additionally, four metaheuristic algorithms (Evolutionary Algorithm, Variable Neighborhood Search, Tabu Search, and Simulated Annealing) are used to solve the model for large-scale problem instances. The numerical experiments demonstrate that the Evolutionary Algorithm outperforms the other metaheuristic algorithms in terms of optimizing the supply chain. Some managerial insights are also outlined based on the experiments conducted.
Obstacles/Challenges	The article does not mention specific methodological obstacles or challenges faced during the research.
Terminology	The common basic words frequently used in this research field include: Factory-in-a-box Metaheuristics Supply chains Urgent demand Vehicle routing problem
Review Outcome	They presented a mixed-integer linear programming model to minimize the total cost of the ”factory-in-a-box” supply chain. They used CPLEX to solve the model to global optimality and employed four metaheuristic algorithms (Evolutionary Algorithm, Variable Neighborhood Search, Tabu Search, and Simulated Annealing) for large-scale problem instances. The numerical experiments showed that the Evolutionary Algorithm outperformed the other metaheuristic algorithms. The article also provided some managerial insights based on the numerical experiments.

Aspects	**Paper # 3 (Title)**
Title / Question	Reinforcement Learning for Solving the Vehicle Routing Problem
Objectives / Goal	The objective of this paper is to classify the various variants of the Vehicle Routing Problem (VRP) related to freight transportation that logistics and distribution companies commonly encounter in their daily operations. The authors aim to identify the trends in VRP variants and the algorithms used to solve them over the last decade. The paper also aims to analyze the correlation between the VRP variants and the applied algorithms.

Methodology/Theory	The authors applied a research methodology that involved conducting a comprehensive literature review. Initially, they collected a large number of papers and then sorted them to focus on the subject of freight transportation. They analyzed the selected papers to identify the different VRP variants and the algorithms used to solve them. The methodology likely involved categorizing the papers based on problem characteristics, solution approaches, and optimization techniques.  **Fig. 1** Classification of algorithms for the VRP. Adopted from Labadie et al. (2016) and Lin et al. (2014)
Software Tools	The article does not specify the specific program or software tools used for design, coding, and simulation
Test / Experiment	Decision for New Research Methodology: To prepare a separate and new methodology for your own research project, you can utilize the knowledge obtained from this article by: Understanding the importance of scheduling and routing in supply chain operations. Recognizing the significance of the vehicle routing problem (VRP) in operational research and logistics. Considering the impact of multiple factors on the distribution of goods in VRP. Exploring the creation of different variants of VRP based on transformed factors and constraints. Investigating the use of algorithms and information systems for optimizing real-life distribution cases. Gaining insights into the classification of VRP variants and the correlation with applied algorithms through literature review. Recognizing the challenges in classifying VRP variants and managing a large volume of literature. With this understanding, you can design your own research methodology that addresses specific objectives and research questions in your project, considering the challenges and terminology relevant to your field of study.

Simulation/Test Data	The article does not mention any specific simulation or test data used in the research. As it primarily focuses on a literature review and classification of VRP variants and algorithms, the study did not involve practical simulations or experiments to determine parameters.
Result / Conclusion	The research methodology resulted in a collection of 334 papers related to VRP variants. From this set, 263 papers specifically focused on freight transportation. The authors analyzed these papers to identify trends in VRP variants and the applied algorithms. The paper presents both quantitative and qualitative results of the literature review, highlighting the significant impact of certain scientific publications on the research community. The conclusion likely summarizes the key findings, discusses the observed trends, and potentially suggests areas for future research or improvement in freight transportation optimization algorithms.
Obstacles/Challenges	some potential challenges in classifying VRP variants and analyzing the applied algorithms could include: Defining clear criteria for classifying VRP variants: VRP has numerous variants, and determining the criteria for categorizing them can be complex. Ensuring consistent and comprehensive classification across the selected papers may have been challenging. Handling the vast amount of literature: With 334 papers initially collected and further narrowing down to 263 papers, managing and processing such a large volume of literature can be time-consuming and demanding.

Terminology	Freight transportation: The process of transporting goods or cargo from one location to another, typically involving the movement of goods by trucks, ships, trains, or planes. Logistics: The management and coordination of the flow of goods, information, and resources between the point of origin and the point of consumption to meet customer requirements. Distribution: The process of physically delivering goods from a centralized location or warehouse to the end customers or retail outlets. Scheduling: The allocation of resources, such as vehicles and time, to different tasks or activities in an optimal manner to achieve efficient operations. Routing: The determination of the most efficient path or sequence of locations to be visited by vehicles to complete a set of deliveries or tasks. Supply chain operations: The activities involved in the planning, procurement, production, storage, and transportation of goods from suppliers to customers, including all the processes that occur within the supply chain. Optimization: The process of finding the best solution or arrangement that maximizes or minimizes a specific objective or set of objectives, such as minimizing costs or maximizing customer satisfaction. Algorithms: Step-by-step procedures or methods used to solve computational problems or perform specific tasks, often involving mathematical or logical operations. Constraints: Limitations or conditions that must be satisfied in a problem or optimization model, such as capacity constraints on vehicles, time windows for deliveries, or other operational restrictions. Variants: Different variations or versions of a problem, often resulting from incorporating additional constraints or modifying the problem's objectives. Customer satisfaction: The degree to which customers' expectations are met or exceeded, often measured by factors such as on-time deliveries, product quality, and responsiveness to customer needs. Costs: The expenses or expenditures incurred in the process of transportation, including fuel costs, labor costs, maintenance costs, and other related expenses. Information systems: Computer-based systems and technologies used to collect, process, store, and analyze data and information related to logistics and supply chain operations, enabling efficient management and decision-making.
Review Judgment	The objectives of the reviewed articles were to classify VRP variants related to freight transportation and identify the trends in applied algorithms over the last decade. The results of the literature review involved the collection and analysis of 263 papers, highlighting the correlation between VRP variants and the algorithms used. The reviewed articles likely aimed to provide insights into the current state of research in freight transportation optimization and identify areas of focus for future studies.

Review Outcome	Understanding the importance of scheduling deliveries and routing vehicles in supply chain operations. Recognizing the factors that affect the distribution of goods, including demands from transportation companies, customers, and the external environment. Exploring the creation and study of different variants of the Vehicle Routing Problem (VRP). Investigating the application of algorithms for optimizing real-life distribution cases in logistics and supply chain operations. Gaining insights from the literature review methodology used in the article to classify VRP variants and identify trends in applied algorithms. Considering the common terminology and keywords used in the field of VRP and logistics distribution. Based on this understanding, you can develop your own research methodology that aligns with your specific objectives and research questions, leveraging the knowledge gained from the article to guide your approach and analysis.

Aspects	**Paper # 4 (Title)**
Title / Question	**A GVNS Algorithm for Solving the Multi-Depot Vehicle Routing Problem** Sinaide Nunes Bezerra a,1 S´ergio Ricardo de Souza a,2 Marcone Jamilson Freitas Souza
Objectives / Goal	The objective of the research paper is to present an algorithm based on the General Variable Neighborhood Search (GVNS) metaheuristic for solving the Multi-Depot Vehicle Routing Problem (MDVRP). The goal is to design a set of vehicle routes that serve all customers while respecting the maximum number of vehicles per depot, vehicle capacity constraints, and minimizing the total cost of transportation
Methodology/Theory	The proposed algorithm utilizes the General Variable Neighborhood Search (GVNS) metaheuristic, which is a local search method that explores different neighborhoods to improve the solution. It also incorporates the Randomized Variable Neighborhood Descent (RVND) as the local search method within the GVNS framework. The algorithm aims to iteratively improve the solution by exploring different neighborhoods and making local modifications.
Software Tools	The research paper does not explicitly mention the specific software tools used for the design, coding, and simulation of the algorithm. However, typical programming languages and optimization libraries (e.g., C++, Python, MATLAB) may be used for the implementation.

Test / Experiment	The algorithm is tested on classical instances of the Multi-Depot Vehicle Routing Problem to evaluate its performance. The specific instances used and the performance measures are not mentioned in the provided information.
	
	Algorithm 1 : GVNS
	Let s an initial solution;
	$k \leftarrow 1$; ▷ Initial $N_k(s)$.
	$s' \leftarrow s$;
	while $iter < IterMax$ or $t < maxTime$ **do** ▷ Stopping criterion
	    $s' \leftarrow Perturbation(s, k, level)$; ▷ Generate s' with neighborhood N_k
	    $s'' \leftarrow RVND(s')$; ▷ Best Improvement Strategy
	    if $f(s'') < f(s)$ **then**
	        $s \leftarrow s''$;
	        $k \leftarrow 1$;
	        $iter \leftarrow 0$;
	    else
	        $iter \leftarrow iter + 1$;
	        $k \leftarrow k + 1$; ▷ Change of neighborhood
	    end if
	end while
	return s;
	
	Algorithm 2 : RVND(s)
	Let L_r the list of r neighborhoods for local searches;
	$L_r \leftarrow$ randomize (L_r); ▷ Put the list of neighborhoods in a random order
	$k \leftarrow 1$; ▷ Initial $N_k(s)$.
	while $k \leq r$ **do**
	    $p \leftarrow L_r(k)$;
	    Find the best neighbor $s' \in N^{(p)}(s)$;
	    if $f(s') < f(s)$ **then**
	        $s \leftarrow s'$;
	        $k \leftarrow 1$;
	    else
	        $k \leftarrow k + 1$; ▷ Neighborhood exchange
	    end if
	end while
	return s;
	
	Algorithm 3 : Perturbation(s, k, $level$)
	$p \leftarrow$ rand($level$); ▷ Generate a number between 1 and *level*
	for $(i = 1; i \leq p; i++)$ **do**
	    switch k **do**
	        case 1: Shift(1,0)(s);
	        case 2: Swap(2,2)(s);
	        case 3: Swap(2,1)(s);
	end for
	return s;

Simulation/Test Data	The research paper does not provide details about the specific parameters or data used for testing and characterizing the algorithm. The test instances typically consist of information about the customers, depots, vehicle capacities, and transportation costs.
Result / Conclusion	The obtained results are presented and discussed in the research paper. However, the specific results and conclusions are not mentioned in the provided information.
Obstacles/Challenges	The research paper does not mention any methodological obstacles or challenges faced during the study.
Terminology	Multi-Depot Vehicle Routing Problem (MDVRP): A variant of the Vehicle Routing Problem where multiple depots are considered. General Variable Neighborhood Search (GVNS): A metaheuristic approach that explores different neighborhoods to find an improved solution. Combinatorial Optimization: The field of optimization that deals with discrete or combinatorial problems, such as routing problems.

Review Outcome	Based on the obtained knowledge from the research paper, it can be used as a reference to understand and implement a GVNS-based algorithm for solving the Multi-Depot Vehicle Routing Problem (MDVRP). However, further research and experimentation would be necessary to adapt and enhance the algorithm for specific problem instances and requirements in your own research project.

Aspects	**Paper # 5 (Title)**
Title / Question	**A Firefly Algorithm for the Environmental Prize-Collecting Vehicle Routing Problem** Dimitra Trachanatzi, Manousos Rigakis, Magdalene Marinaki, Yannis Marinakis
Objectives / Goal	The objective of the research is to introduce and solve a new variant of the Vehicle Routing Problem (VRP) called the Environmental Prize-Collecting Vehicle Routing Problem (E-PCVRP). The goal is to maximize the aggregated prize values collected from visited nodes while minimizing the fixed and variable costs of the routes. The variable cost is determined by considering the CO2 emissions of the vehicles as a load-distance function.
Methodology/Theory	The proposed solution approach is based on the Firefly Algorithm (FA), which is originally designed for continuous optimization problems. To address the discrepancy between the discrete nature of the E-PCVRP and the continuous optimization nature of the FA, the Firefly Algorithm based on Coordinates (FAC) is introduced. The FAC incorporates the "Coordinates Related" (CR) encoding/decoding process, which uses auxiliary vectors containing Cartesian coordinates of each node to allow the FA's original movement equation to be applied directly.
Software Tools	The research paper does not explicitly mention the specific software tools used for the design, coding, and simulation. However, it is likely that programming languages and optimization libraries were used for the implementation of the algorithm.

<table>
<tr>
<td>Test / Experiment</td>
<td>The algorithm is tested and evaluated through computational experiments and statistical analysis.
The specific details of the experiments, including the test instances, performance measures, and comparison with other bio-inspired algorithms
and a mathematical solver, are not mentioned in the provided information.

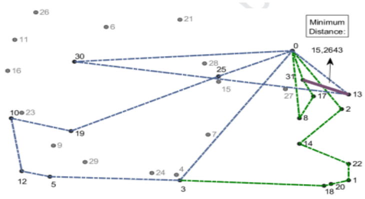


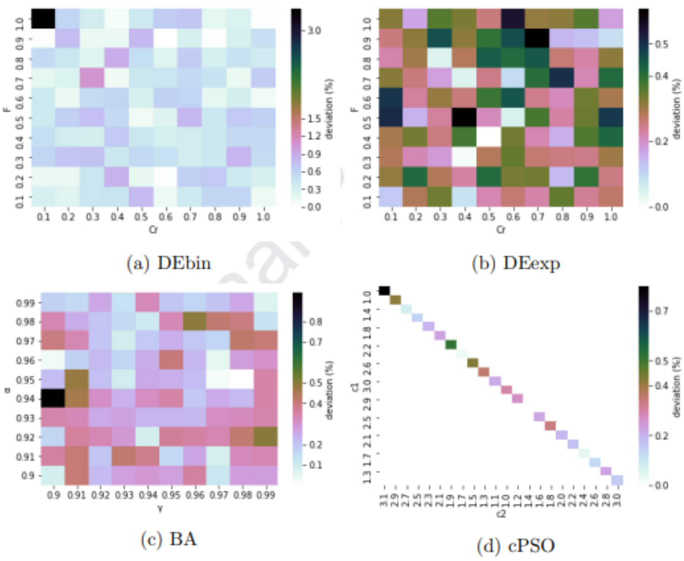
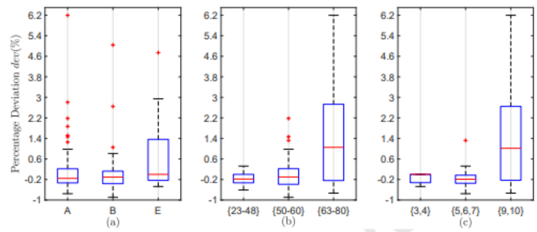
Figure 1: Solution distance calculation example.

Algorithm 2 Firefly Algorithm based on Coordinates
Define: size population W, number of iterations L
Initialize the firefly population via $Initial - Swarm$ (Algorithm 3)
Define the light absorption coefficient γ
for each x_i in the population do
Compute the objective function value f_i
Initialize light intensity $I_i \leftarrow 1/f_i$
end for
repeat
for each x_i do
for each x_j do
if $I_j > I_i$ then
Calculate distance of x_i and x_j
Move firefly x_i towards x_j, using the node coordinates, (Equation 28)
Construct the updated x_i: x_i' based on the new coordinates
Make the x_i' feasible via $Enforce - Feasibility$
Improve x_i' via $Augment - Route$
Improve x_i' via $Remove - node$ (Algorithm 4)
Improve x_i' via $Exchange - node$ (Algorithm 5)
end if
Vary the attractiveness (Equation 27)
Evaluate new solutions and update light intensity
end for
end for
Rank the fireflies and find the current best
Update the randomization parameter (Equation 29)
until L iterations are reached
Rank the fireflies and return the best one

Algorithm 3 $Initial - Swarm$
repeat
Create M initial routes: [1 node 1]
Combine the initial routes to vector
while Total capacity $< Q_{low}$ do
Create stack: sorted non-included nodes
for Each node k in stuck do
Calculate the efficient position of node k
Correlate position to route m
if including node k in route m does not violate the capacity constraint
Q then
Include k and update the solution
end if
end for
end while
Calculate the solutions' value in the objective function
until Population W is constructed

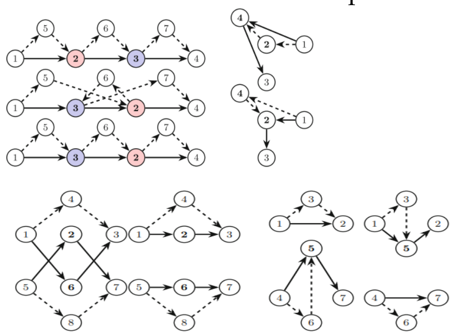
Algorithm 4 $Remove - node$
repeat
Find route m with the highest value of total distance traveled
Find the node k with the smaller prize in route m
if Reducing the capacity of route m by the prize of node k does not violate the constraints then
Calculate new distance traveled, connecting the nodes immediate before and after k
Calculate the objective function of the new formation
if New objective function value is smaller than the initial one then
Update the solution accordingly
end if
end if
until Max iterations reached

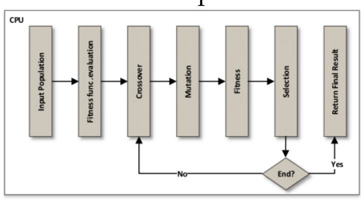
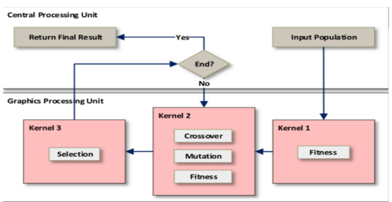
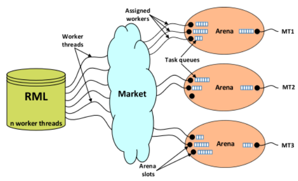
Algorithm 5 $Exchange - node$
repeat
Randomly select routes: m_1 and m_2
Randomly select position in m_1, node: i
Compute distance vector of route m_2
Select position with the greatest distance value, node j
Compute total demand of both routes after the exchange
if New total demand values do not exceed the capacity limit then
Calculate new distance traveled, exchanging the position of nodes i, j
Calculate the objective function of the new formation
if New objective function value is smaller than the initial one then
Update the solution accordingly
end if
end if
until Max iterations reached</td>
</tr>
</table>

Simulation/Test Data	The research paper does not provide information about the specific parameters or data used for testing and characterizing the algorithm. The test instances for the E-PCVRP would typically include details about the nodes, prizes, costs, and CO2 emissions associated with the problem.
Result / Conclusion	 (a) DEbin (b) DEexp (c) BA (d) cPSO Figure 3: Parametric study of the comparison algorithms.  Figure 4: Box-and-whisker diagrams of the percentage deviation of the solutions obtained by FAC, from the corresponding solutions of the Gurobi Optimizer. The depicted values correspond only to the instances solved by the Gurobi Optimizer, categorized by (a) the respective instance groups, (b) the number of the included nodes, N, and (c) the number of utilized vehicles, M.
Obstacles/Challenges	The research paper does not mention any specific methodological obstacles or challenges faced during the study.
Terminology	Vehicle Routing Problem (VRP): A combinatorial optimization problem that involves designing optimal routes for a fleet of vehicles to serve a set of customers or nodes. Environmental Prize-Collecting Vehicle Routing Problem (E-PCVRP): A variant of the VRP where the objective is to maximize the aggregated prize values collected from visited nodes while minimizing costs and considering environmental factors. Firefly Algorithm (FA): A bio-inspired optimization algorithm inspired by the flashing behavior of fireflies that is typically used for continuous optimization problems. Coordinates Related (CR): A novel encoding/decoding process introduced to adapt the FA for discrete problems by utilizing auxiliary vectors with Cartesian coordinates of each node

Review Outcome	Based on the obtained knowledge from the research paper, it can be used as a reference to understand and implement the Firefly Algorithm based on Coordinates (FAC) for solving the Environmental Prize-Collecting Vehicle Routing Problem (E-PCVRP). However, further research and experimentation would be necessary to adapt and enhance the algorithm for specific problem instances and requirements in your own research project.

<table>
<tr><th>Aspects</th><th>Paper # 6 (Title)</th></tr>
<tr><td>Title / Question</td><td>Algorithms for Solving the Vehicle Routing Problem with Drones
Daniel Schermer, Mahdi Moeini(B) , and Oliver Wendt</td></tr>
<tr><td>Objectives / Goal</td><td>The objective of the research paper is to address the Vehicle Routing Problem with Drones (VRPD) and develop heuristic algorithms to solve it.
The goal is to evaluate the performance of the heuristics through numerical experiments on large-scale instances and demonstrate the potential benefits of using drones in last-mile logistics and delivery.</td></tr>
<tr><td>Methodology/Theory</td><td>The specific methodology and theory used to solve the VRPD are not mentioned in the provided information.
However, since the paper focuses on heuristic algorithms, it can be inferred that the approach is based on developing solution methods that provide near-optimal or good-quality solutions through efficient and effective techniques.
Algorithm 1. Two-Phase Heuristic (TPH)<pre>
procedure OPTIMIZE(m, α, β, Instance)
    solution ← routeFirstClusterSecond(Instance,m);
    while !stoppingCriterion do
        if phaseOne then
            solution.twoOpt();
            solution.stringMix();
        else
            solution.insertDrones();
            solution.deliveryExchange();
        end if
    end while
    return solution;
end procedure
</pre>Algorithm 2. Single-Phase Heuristic (SPH)<pre>
procedure OPTIMIZE(m, α, β, Instance)
    solution ← routeFirstClusterSecond(Instance,m);
    solution.insertDrones();
    while !stoppingCriterion do
        solution.twoOpt();
        solution.stringMix();
        solution.insertDrones();
        solution.deliveryExchange();
    end while
    return solution;
end procedure
</pre></td></tr>
<tr><td>Software Tools</td><td>The research paper does not explicitly mention the specific software tools used for design, coding, and simulation. However, typical programming languages and optimization libraries may be used for the implementation of the heuristic algorithms and conducting numerical experiments.</td></tr>
</table>

Test / Experiment	The performance of the developed heuristic algorithms is evaluated through numerical experiments conducted on large-scale instances. The specific details regarding the test instances, experimental setup, and performance measures are not mentioned in the provided information  **Fig. 2.** A visual example of the implemented multi-route improvement operators: string exchange (left) and string relocation (right). In the case of string exchange, the vertices labeled 2 and 6 are exchanged between two tours. In the case of string relocation, the vertex labeled 5 is moved from one tour to another tour.
Simulation/Test Data	The research paper does not provide information about the specific parameters or data used for testing and characterizing the heuristic algorithms. The test instances for the VRPD would typically include details about the delivery locations, vehicle capacities, drone capabilities, delivery times, and other relevant factors.
Result / Conclusion	The final results and conclusions of the research paper are not mentioned in the provided information.
Obstacles/Challenges	The research paper does not mention any specific methodological obstacles or challenges faced during the study.
Terminology	Vehicle Routing Problem (VRP): A combinatorial optimization problem that involves designing optimal routes for a fleet of vehicles to serve a set of customers or nodes. Vehicle Routing Problem with Drones (VRPD): A variant of the VRP where drones are integrated with vehicles to improve delivery times and efficiency, typically in last-mile logistics scenarios. Last-Mile Logistics: The final stage of the delivery process where goods are transported from a central hub or facility to the end customer's location. Heuristic: A problem-solving approach or algorithm that provides approximate solutions or good-quality solutions in a timely manner, often sacrificing optimality for efficiency.
Review Outcome	Based on the obtained knowledge from the research paper, it can be used as a reference to understand the challenges and potential benefits of integrating drones in the Vehicle Routing Problem with Drones (VRPD). It also provides insights into the development and evaluation of heuristic algorithms for solving this problem. However, further research and experimentation would be necessary to adapt and enhance the algorithms for specific problem instances and requirements in your own research project.

Aspects	Paper # 7 (Title)
Title / Question	**An efficient parallel genetic algorithm solution for vehicle routing problem in cloud implementation of the intelligent transportation systems** Mahdi Abbasi1* , Milad Rafiee1 , Mohammad R. Khosravi2,3, Alireza Jolfaei4 , Varun G. Menon5 and Javad Mokhtari Koushyar1
Objectives / Goal	The objective of the research paper is to address the Vehicle Routing Problem with Drones (VRPD) and develop heuristic algorithms to solve it. The goal is to evaluate the performance of the heuristics through numerical experiments on large-scale instances and demonstrate the potential benefits of using drones in last-mile logistics and delivery.
Methodology/Theory	The specific methodology and theory used to solve the VRPD are not mentioned in the provided information. However, since the paper focuses on heuristic algorithms, it can be inferred that the approach is based on developing solution methods that provide near-optimal or good-quality solutions through efficient and effective techniques.
Software Tools	The research paper does not explicitly mention the specific software tools used for design, coding, and simulation. However, typical programming languages and optimization libraries may be used for the implementation of the heuristic algorithms and conducting numerical experiments.
Test / Experiment	The performance of the developed heuristic algorithms is evaluated through numerical experiments conducted on large-scale instances. The specific details regarding the test instances, experimental setup, and performance measures are not mentioned in the provided information.   
Simulation/Test Data	The research paper does not provide information about the specific parameters or data used for testing and characterizing the heuristic algorithms. The test instances for the VRPD would typically include details about the delivery locations, vehicle capacities, drone capabilities, delivery times, and other relevant factors.

Result / Conclusion	The final results and conclusions of the research paper are not mentioned in the provided information.
Obstacles/Challenges	The research paper does not mention any specific methodological obstacles or challenges faced during the study.
Terminology	Vehicle Routing Problem (VRP): A combinatorial optimization problem that involves designing optimal routes for a fleet of vehicles to serve a set of customers or nodes. Vehicle Routing Problem with Drones (VRPD): A variant of the VRP where drones are integrated with vehicles to improve delivery times and efficiency, typically in last-mile logistics scenarios. Last-Mile Logistics: The final stage of the delivery process where goods are transported from a central hub or facility to the end customer's location. Heuristic: A problem-solving approach or algorithm that provides approximate solutions or good-quality solutions in a timely manner, often sacrificing optimality for efficiency.
Review Outcome	Based on the obtained knowledge from the research paper, it can be used as a reference to understand the challenges and potential benefits of integrating drones in the Vehicle Routing Problem with Drones (VRPD). It also provides insights into the development and evaluation of heuristic algorithms for solving this problem. However, further research and experimentation would be necessary to adapt and enhance the algorithms for specific problem instances and requirements in your own research project.

Aspects	**Paper # 8 (Title)**
Title / Question	**Waiting strategy for the vehicle routing problem with simultaneous pickup and delivery using genetic algorithm** Hyungbin Park a , Dongmin Son a , Bonwoo Koo b , Bongju Jeong
Objectives / Goal	The objective of the research study is to address the real-world vehicle routing problems that arise in the context of online shopping and dynamic orders. The goal is to propose a waiting strategy for the vehicle routing problem with simultaneous pickup and delivery, considering real-time demands. The study aims to validate the significance and application of the waiting strategy through experiments and demonstrate its value in accommodating the increasing demand for delivery and return of products.

Methodology/Theory	The specific methodology and theory used for the waiting strategy and the genetic algorithm are not mentioned in the provided information. However, the study implements an index called the rerouting indicator as a decision-making threshold to determine the rerouting point for real-time demands. A genetic algorithm is proposed as a solution approach for solving the complex vehicle routing problems, and its accuracy and performance are validated through computational results.
Software Tools	The research paper does not explicitly mention the specific software tools used for design, coding, and simulation. However, it is likely that programming languages, optimization libraries, and simulation environments were utilized for implementing the waiting strategy, the genetic algorithm, and conducting computational experiments
Test / Experiment	The waiting strategy and the genetic algorithm are tested and evaluated through experiments. The specific details regarding the experimental setup, test instances, performance measures, and comparison with other methods are not mentioned in the provided information.
Simulation/Test Data	The research paper does not provide information about the specific parameters or data used for testing and characterizing the waiting strategy and the genetic algorithm. The test instances for the vehicle routing problem would typically include details about the delivery locations, demands, time windows, vehicle capacities, and other relevant factors.
Result / Conclusion	The final results and conclusions of the research paper are not mentioned in the provided information.
Obstacles/Challenges	The research paper does not mention any specific methodological obstacles or challenges faced during the study.
Terminology	Vehicle Routing Problem (VRP): A combinatorial optimization problem that involves designing optimal routes for a fleet of vehicles to serve a set of customers or nodes. Genetic Algorithm: An optimization algorithm inspired by the principles of natural selection and genetics, used to solve optimization problems by simulating the process of evolution. Waiting Strategy: A strategy that incorporates waiting time into the vehicle routing problem, allowing for real-time demands and decision-making thresholds.

Review Outcome	Based on the obtained knowledge from the research paper, it can be used as a reference to understand and implement a waiting strategy for the vehicle routing problem with simultaneous pickup and delivery in the context of online shopping and dynamic orders. The proposed genetic algorithm and the evaluation methodology can also provide insights into solving complex vehicle routing problems. However, further research and experimentation would be necessary to adapt and enhance the proposed methods for specific problem instances, evaluate their performance in comparison to other approaches, and incorporate additional factors or constraints in your own research project.

Aspects	**Paper # 9(Title)**
Title / Question	**A memory-based iterated local search algorithm for the multi-depot open vehicle routing problem** José Brandãoa
Objectives / Goal	The objective of the research study is to address the multi-depot open vehicle routing problem, which involves multiple depots and vehicles that do not return to the depot after deliveries. The goal is to develop an iterated local search algorithm that utilizes historical search information to define perturbation procedures and improve the exploration of the solution space. The aim is to find competitive solutions for the problem and potentially outperform existing algorithms.
Methodology/Theory	The proposed methodology involves an iterated local search algorithm that incorporates historical search information to guide the perturbation procedures. The algorithm uses the memory of previous searches to determine moves performed during the local search and increase the chances of finding better regions of the solution space. The algorithm also includes neighborhood constraints, a simple heuristic for improving each route based on the structure of the Hamiltonian path, and the use of elite solutions for intensifying the search around good local optima.
Software Tools	The research paper does not mention the specific software tools used for design, coding, and simulation. However, it is likely that programming languages and optimization libraries were employed for implementing the iterated local search algorithm and conducting computational experiments.

Test / Experiment	The performance of the iterated local search algorithm is tested using a large set of benchmark problems for the multi-depot open vehicle routing problem. The algorithm is compared with other algorithms to evaluate its competitiveness. However, the specific details regarding the experimental setup, performance measures, and comparison methods are not mentioned in the provided information.
Simulation/Test Data	The research paper does not provide information about the specific parameters or data used for testing and characterizing the iterated local search algorithm. The benchmark problems for the multi-depot open vehicle routing problem would typically include details about depots, customers, distances, demands, vehicle capacities, and other relevant factors
Result / Conclusion	The final results of the research study indicate that the proposed iterated local search algorithm, referred to as MBILSA, is very competitive. It found solutions that matched or improved the best-known solutions for the multi-depot open vehicle routing problem in a short computing time. The algorithm yielded new best solutions, improved the total traveling distance, and demonstrated competitive performance compared to other algorithms.
Obstacles/Challenges	The research paper does not mention any specific methodological obstacles or challenges faced during the study..
Terminology	Multi-Depot Open Vehicle Routing Problem (MDOVRP): A variant of the vehicle routing problem where there are multiple depots, and vehicles do not return to the depot after delivering goods. Iterated Local Search Algorithm: An optimization algorithm that iteratively explores the solution space by using a combination of local search and perturbation procedures.
Review Outcome	Based on the obtained knowledge from the research paper, it can be used as a reference to understand and implement an iterated local search algorithm for solving the multi-depot open vehicle routing problem. The proposed methodology, including the use of historical search information, neighborhood constraints, and heuristic improvements, can be considered in the development of a new methodology for your own research project. However, further research and experimentation would be necessary to adapt and enhance the proposed algorithm, evaluate its performance on different problem instances, and compare it with other state-of-the-art algorithms in the field.

Aspects	**Paper # 10 (Title)**

Title / Question	**An improved ant colony optimization algorithm for the multi-depot** **green vehicle routing problem with multiple objectives** Yongbo Li a, b , Hamed Soleimani c, * , Mostafa Zohal
Objectives / Goal	The objective of the research study is to address the multi-depot green vehicle routing problem (MDGVRP) by maximizing revenue and minimizing costs, time, and emissions. The goal is to develop an improved ant colony optimization (IACO) algorithm that efficiently solves the MDGVRP and provides high-quality solutions compared to conventional ant colony optimization (ACO). The study aims to achieve multiple objectives simultaneously in the vehicle routing problem, considering environmental impacts and other factors beyond cost reduction.
Methodology/Theory	The proposed methodology involves developing a multi-objective linear mathematical model to solve the MDGVRP with conflicting objectives. The conventional ACO algorithm is improved by introducing a new technique for updating the development of pheromone. The IACO algorithm uses this innovative approach to update the pheromone and provides better solutions. The model and algorithm are validated through small-scale and large-scale networks resembling real-world distribution problems.
Software Tools	The research paper does not specify the specific software tools used for design, coding, and simulation. However, it is likely that programming languages and optimization libraries were utilized for implementing the improved ant colony optimization algorithm and conducting computational experiments.
Test / Experiment	The performance of the IACO algorithm is tested and compared with optimal solutions produced by LINGO and another developed ACO algorithm. Six small-scale and ten large-scale networks are used to test the algorithm's performance in conditions similar to real-world distribution problems. However, specific details about the experimental setup, performance measures, and comparison methods are not provided.
Simulation/Test Data	The research paper does not provide information about the specific parameters or data used for testing and characterizing the IACO algorithm. The test networks would typically include information such as depots, customers, distances, demands, costs, time windows, emissions, and other relevant factors.

Result / Conclusion	The results of the study demonstrate the satisfying performance of the IACO algorithm for solving the MDGVRP with multiple objectives. The algorithm provides higher solution quality compared to the conventional ACO and outperforms another developed ACO algorithm. It produces close-to-optimal solutions at a significantly low cost and offers potential for improving solution quality and time through innovative modifications.
Obstacles/Challenges	The research paper mentions limitations such as the proposed model being applicable to a single product. Future research is recommended to consider models that can handle multi-product cases. Additionally, the nondeterministic behavior of parameters like demand and price in real-world problems suggests the need for considering stochastic, fuzzy, interval, or chaos approaches in future works.
Terminology	Multi-Depot Green Vehicle Routing Problem (MDGVRP): A variant of the vehicle routing problem that involves multiple depots and incorporates environmental objectives, such as minimizing emissions, in addition to traditional objectives like cost and time optimization. Improved Ant Colony Optimization (IACO): An optimization algorithm inspired by the foraging behavior of ants, enhanced with innovative approaches for updating pheromone and improving solution quality.
Review Judgment	The research paper aims to address the multi-depot green vehicle routing problem by introducing an improved ant colony optimization algorithm. It focuses on optimizing multiple objectives, including revenue, costs, time, and emissions. The IACO algorithm is evaluated through computational experiments and compared with other algorithms, demonstrating its competitiveness in terms of solution quality and performance.
Review Outcome	Based on the obtained knowledge from the research paper, it can be used as a reference to understand and implement an improved ant colony optimization algorithm for solving the multi-depot green vehicle routing problem with multiple objectives. The proposed methodology and the innovative approach for updating pheromone can be considered in the development of a new methodology for your own research project. However, it is important to consider the mentioned limitations and challenges, such as extending the model to handle multi-product cases and exploring stochastic or other approaches for uncertain parameters in real-world problems. Further research and experimentation would be required to adapt and enhance the proposed algorithm and evaluate its performance in different problem instances and scenarios.