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APPLICABILITY OF METAHEURISTICS FOR ENERGY MINIMIZING VEHICLE ROUTING PROBLEM (EMVRP)

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Abstract:

Energy Minimizing Vehicle Routing Problem (EMVRP) has become extremely important as well as complex in recent years due to the high logistic needs arising throughout the world. Strategic transport practices have become essential to serve the dynamic demanding customers located in various locations. Due to the Np-hard nature of the EMVRPs, these cannot be optimally solved within a feasible time due to large and complex nature of problems. The modern researchers have used heuristics to solve these problems in a reasonably feasible time. Metaheuristics such as Genetic Algorithm (GA) and Tabu Search (TS) are widely used in solving VRPs, where sequence of solutions are represented for each vehicle for each customer to ultimately minimize the total distance traveled by the fleet. The authors critically reviewed the literature of EMVRP and analyzed comparatively each of the metaheuristics utilized in the literature to solve variants of EMVRP. Furthermore, the scrutiny identifies the knowledge gaps in the current published literature and proposes future research directions in the EMVRP as well as methodological advancements in the broad metaheuristics domains.

Key words:

Energy Minimizing Vehicle Routing Problem, Metaheuristics, Strategic Transport Practices

INTRODUCTION

In the field of combinatorial optimization, the Vehicle Routing Problem (VRP) is considered to be one of the most challenging and most widely researched problems. It has been formulated more than 40 years ago, the problem involves assigning the optimal set of routes for fleets of vehicles while minimizing the distance travelled serving a given set of

geographically dispersed customers with various demands. The interest in VRP is motivated by its practical relevance as well as its considerable difficulty in solving optimally with reasonable timeframe.

Energy minimizing vehicle routing problem is a form of VRP with the new load-based cost objective has been developed to minimize the energy consumption of a fleet while adhering to the aforementioned constraints stipulated by the classical VRPs.

EMVRP was first formulated by Kara et al. [4] by proposing a new cost function for vehicle routing problems as a multiple of length of the arc traveled and the total load of the vehicle on this arc. Objective function is as equation 1.

$$\text{Min} \sum_{i=0}^n \sum_{j=0}^n d_{ij} y_{ij} \tag{1}$$

Where: d_{ij} - the distance from node i to node j ,

Y_{ij} - weight of a vehicle if it goes from i to j , and zero otherwise,

Typically, EMVRRs cannot be optimally solved in feasible time due to the NP-hard nature of the problem. The researchers have used diverse set of heuristics where, it employs independent discovery, and relies heavily on common sense, creativity, and learning from experience. Metaheuristic is a class of heuristics which are specially used for combinatorial optimization.

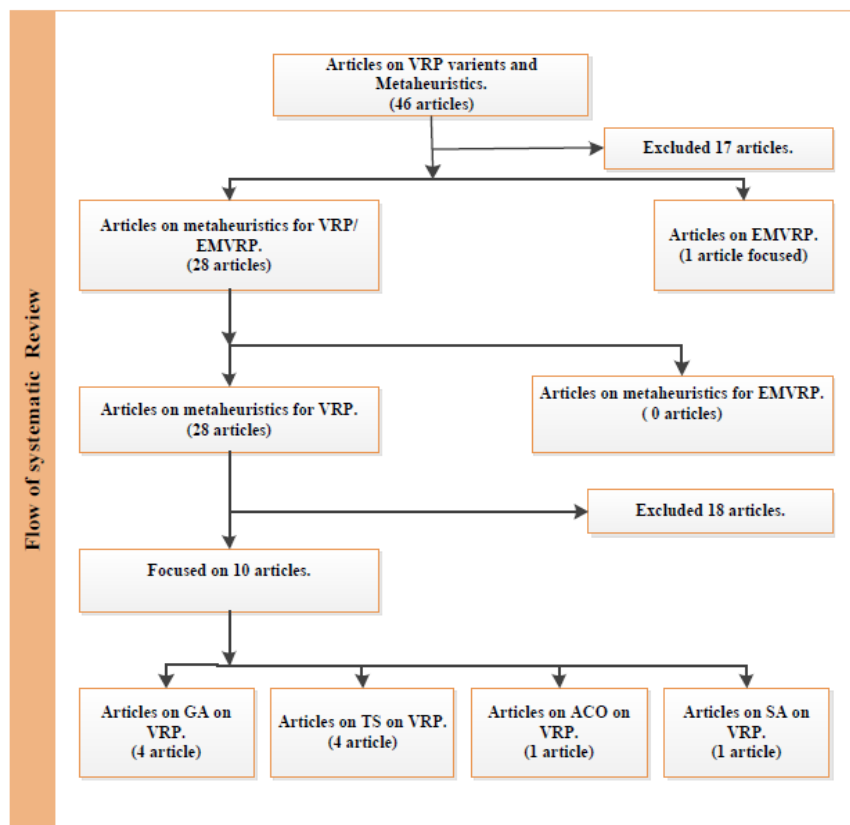


Fig.1 Flow of systematic review

The authors have analyzed the use of different modeling techniques varying from exact solutions to metaheuristic to solve EMVRP and identified knowledge gaps in the research domain. A flow diagram depicts process undertaken in the systematic review of literature and is shown in Figure 1.

1 METHODOLOGY OF THE RESEARCH STUDY

The research is conducted mainly under the energy minimizing logistics broad domain area where the authors have critically reviewed the EMVRP and related literature in terms of metaheuristics as a solutions method.

1.1 Systematic Review of Literature

1.1.1 Energy Minimizing Vehicle Routing Problem (EMVRP)

The objective of EMVRP is to reduce the energy consumption of vehicles traveling from node to node and where energy has been justified to be the product of length travelled into the load of the vehicle. Concretely EMVRP aims at minimizing the sum of the product of load and distance for each arc.

Most of the variables that affect the cost of the vehicle traveling between two nodes such as load of the vehicle, fuel consumption per mile, fuel price, and time spent or distance travelled up to a given node, depreciation of the tires and the vehicles, maintenance, driver wages etc. can be approximated by the distance.

However, some variables that cannot be represented by distance between the nodes or involve travelling cost may not be taken as a constant. Examples of such variables are vehicle load, fuel consumption per km, fuel cost or time spent up to a given node. Most of these types of variables can be represented as a function of the flow, as function of the load of the vehicle on the corresponding arc. Thus for some cases we need to include load of the vehicle as additional indicator of the cost Kara et al. [4]. The milestones in the literature under the broad domain of minimizing energy in logistic process are summarized in table 1.

Tab. 1 Milestones in the domain of minimizing energy

Author/(s)	Problem Domain	Objective	Solving Method
Figliozzi [5]	Emissions Minimization Vehicle Routing Problem	Multi-objective function that includes minimizing the costs of vehicles, distance travelled, route durations, and emissions	Exact mathematical methods
Chebbi and Chaouachi [6]	Evolutionary Approach for Minimizing Consumed Energy in a Personal Rapid Transit Transportation System with a Multi-Depot Network Topology	Minimize total energy consumption in a multiple depot network topology while considering the battery capacity of vehicles	Metaheuristics
Ghahremani et al. [7]	Vehicle Routing Problem for Minimizing Consumption of Energy in Three Dimensional Space	Minimizing cost of total consumed energy by considering finite set of points in three dimensional Euclidean space	Metaheuristics
Mirzaei et el. [10]	Energy-Efficient Location-Routing Problem With Time Windows with Dynamic Demand	Minimizing the distance traveled regardless of the amount of energy consumed	Exact mathematical methods
Lam and Victor [12]	Energy Loss Minimization for Vehicular Energy Network Routing	Minimizing the total energy in routing energy for a particular source destination pair along possible energy paths	Exact mathematical methods
Thalei [8]	Heuristics for Energy Efficient Vehicle Routing Problem	Modify vehicle routing problem heuristics and make sensitive to issue of energy consumption	Heuristic

Kara et al. [4]	Energy Minimizing Vehicle Routing Problem	Introduced a new cost function for EMVRP, Present polynomial size integer programming formulations for EMVRP for collection and delivery cases.	Exact mathematical methods
Liyanage and Rupasinghe [20]	An Analytical Model Formulation To Enhance the Green Logistics (GL) Operations: From the Perspective Of Vehicle Routing Problem (VRP)	Integrating environmentally sound choices into supply-chain management	Exact mathematical methods

The Emission Minimization Vehicle Routing Problem, was proposed by Figliozzi [5] and Chebbi & Chaouachi [6] proposed a new MDADCVRP related to PRT as a promising solution to enhance urban transportation tools efficiency and efficacy. The Vehicle routing problem for minimizing consumption of energy in a three dimensional space proposed by Ghahremani et al. [7] was able to minimize energy between points that are not Euclidian but in three dimensional space. Mirzaei et al. [10] had worked on Energy-Efficient Location-Routing Problem with time windows with dynamic demands was able to formulate EELRP with a soft or hard time windows and with EELRP with a time-dependent demand. The study by Thalei [8] on Heuristics for Energy Efficient Vehicle Routing Problem introduced two heuristic, Energy efficient Clarke and Wright algorithm to address the capacitated VRP. Liyanage & Rupasinghe [20], have introduced a conceptual analytical model where the canonical capacitated vehicle routing problem is extended to add the measures of Carbon Dioxide (CO₂) emissions by tackling the conflicting objectives of CO₂ emission reduction and cost minimization. Analyses of solution methods in the domain of VRP are depicted in Table 2.

Tab. 2 Solution methods applied in literature in the broad domains of VRP

<i>Solution Type</i>	Exact Methods	Constructive Methods	2-Phase Algorithm	Heuristic	Metaheuristics
<i>Branch and bound</i>	•				
<i>Branch and cut</i>	•				
<i>Clark and Wright</i>		•			
<i>Matching based</i>		•			
<i>Thompson and Psaraftis</i>		•			
<i>Van Breedam</i>		•			
<i>Kinderwater and Savelsbergh</i>		•			
<i>Fisher and Jaikumar</i>			•		
<i>The Petal Algorithm</i>			•		
<i>The Sweep Algorithm</i>			•		
<i>Taillard</i>			•		
<i>Route-First, Cluster-Second Algorithms</i>			•		
<i>Tabu Search</i>					•
<i>Simulated Annealing</i>					•
<i>Genetic Algorithms</i>					•
<i>Ant Colony Algorithms</i>					•
<i>Basic Local Search</i>					•
<i>Variable Neighborhood Search</i>					•
<i>Sweep Algorithm</i>				•	
<i>Petal algorithm</i>				•	

The vehicle routing problem has been very extensively studied in the optimization literature which has been started with the seminal papers. The literature of VRP is classified into exact methods, heuristics approaches, meta-heuristics, and hybrid methods. Exact algorithms can only tackle problems of a relatively small scale. Approximate algorithms are able to find very near-optimal solutions for large-scale problems within a very satisfactory computation time, and thus are commonly used in practice. The research by Volna & Kotyrba [10] declared variety of approximate algorithms, including classical heuristics and metaheuristics since the 1980s, are proposed in the literature to efficiently solve different variants of VRP. Most of the models developed for the VRP in the literature considered deterministic parameters, such as deterministic travel times, demands, and service times. Compared with the classical heuristics, metaheuristics carry out a more thorough search of the solution space, allowing inferior and sometimes infeasible moves, in addition to re-combining solutions to create new ones. As a result, metaheuristics are capable of consistently producing high-quality solutions, in spite of greater computation time than early heuristics

1.1.2 Metaheuristics

Metaheuristics have been gaining more and more popularity over the past two decades. The term metaheuristic was first introduced by Glover [2] and is used to define higher level procedures, in contrast to problem specific heuristics, which attempt to explore the search space in an effective and efficient manner through combining different concepts and learning strategies. The main goal of metaheuristic algorithms is to escape from local optima by applying strategies that guide the search process. This is done by either accepting worsening moves in the search process, or by generating new initial solutions for the search, based on a more sophisticated set of rules, not just random generation as stated by Blum & Roli [9].

Metaheuristic algorithms are approximate, and are often applied to large-size problem instances, where exact solution methods are unpractical, as they deliver satisfactory solutions within reasonable computational time. Thus, even though metaheuristics do not guarantee finding the global optimum in a given problem, by exploring a broad range of good solutions they locate a quality solution at an acceptable cost.

An attractive feature of metaheuristic algorithms is their applicability in many areas, as they are not problem specific. Such algorithms span from complex learning schemes, to basic local search procedures that implement a set of rules for moving from one solution to another and evaluate them based on a given criterion, Blum & Roli [9]. There is a wide variety of metaheuristics, which are mostly explored in an empirical fashion throughout the literature. Examples include ant colony optimization, genetic algorithms (GA), guided local search, greedy randomized adaptive search (GRASP), variable neighborhood search, simulated annealing (SA), tabu search and iterated local search.

When analyze the EMVRP formulation and through literature on solving VRP, it can be identified that some features of metaheuristics are in favor for solving EMVRP. Metaheuristic methods applied in the domain of VRP and their inheriting features which are in favor of solving EMVRP in the literature can be classified as in table 3.

Tab. 3 Analysis of metaheuristics which consist of features that are favorable for solving EMVRP.

● = EMVRP favored features of metaheuristics
○ = Other features of metaheuristics

Metaheuristic Features Metaheuristic Types	Nature Inspired	Non-nature Inspired	Population-based	Dynamic Objective Function	One Neighborhood Structure	Various Neighborhood Structure	Use Adaptive Memory	Memory less
Genetic Algorithm	●		●	●	○			○
Ant Colony optimization	●		●	●	○			○
<i>Basic Local Search</i>		●		●	○			○
<i>Simulated Annealing</i>		●		●	○			○
<i>Tabu Search</i>		●		●	○		●	
<i>Variable Neighborhood Search</i>		●		●		○		○

According to Table 3, special feature we identifies in TS when compared with other metaheuristics is adaptive memory, which creates a more flexible search behavior and guided nature which is a type of artificial intelligence. It remembers travelled paths when hill climbing and make strategic decisions on the way to peak or decent. Preventing of cycling of repetitive solutions in TS has made TS the fastest metaheuristic in solving VRP which uses least computational time. The research of Gamal et al. [12] declares the fact that TS is the fastest metaheuristic in solving VRP when compared with other metaheuristics (TS gives fastest solutions for combinatorial problems and proved to be the fastest metaheuristic among the other trajectory-based metaheuristic as well as supersede population-based metaheuristics like GA in computational time, but as for the solution quality GA superseded TS).

Tabu list is identified as the main feature in TS which prevents cycling of repetitive solutions in solving VRPs in a realistic time period. The purpose of the Tabu list is to record a number of most recent moves and prohibits a repetition or cycling. The memory can be recency or frequency based. In case of recency-based memory, also known as short-term memory, the Tabu list of size N records the last N moves or configurations the algorithm has encountered and sets them as ‘Tabu’. Frequency based memory, also known as long term memory, complements the recency-based memory by providing the additional information of how many times the Tabu moves or Tabu solutions have been attempted. Frequency-based memory naturally provides better incentive as to the choice of next move. Despite that some of the moves are taboos, they can still materialize if they meet certain aspiration criteria. One obvious criterion to use is if the moves results in a global-best (GB), it should be adopted even if it has been made very recently or frequently, Tan et al. [13].

Though the literature is enriched with thorough analysis of metaheuristics in the domain of VRP, there is no any comparative analysis carried out on the metaheuristics in the domain of EMVRP as for the best of authors' knowledge. The EMVRP formulation using metaheuristic is a novel idea of research and as for the authors knowledge there is only one study of using metaheuristics(GA) for solving EMVRP by Cooray and Rupasinghe [21] as this will be the first instance of using metaheuristics,TS in solving EMVRP. Categorized bibliography done by Gendreau et al. [25] declared that the most used metaheuristics applied for VRP are Tabu Search, Genetic Algorithm, Simulated Annealing and Ant Colony Optimization which are described in the later part of the research. The summary of bibliography of Gendreau et al. [25] is depicted in figure2. According to figure 2, it is identified that the most used metaheuristic for VRP is TS which consist of 64 research papers, contribution is up to 37% to VRP context. Secondly used type is GA which consist of 43 papers, contribution is up to 24% to the VRP literature. The special feature is these two metaheuristics comprises of two main metaheuristics types of path-based and population-based. The researches for analyses of different metaheuristics in combinatorial optimization is done by Blum & Roli, 2003 [9], and analysis of different metaheuristics for combinatorial optimization of quadratic assignment problem is done by Gamal et al. [12]. Comparison of metaheuristics in the context of EMVRP is a novel idea in literature and no ever publication is done in that regard.

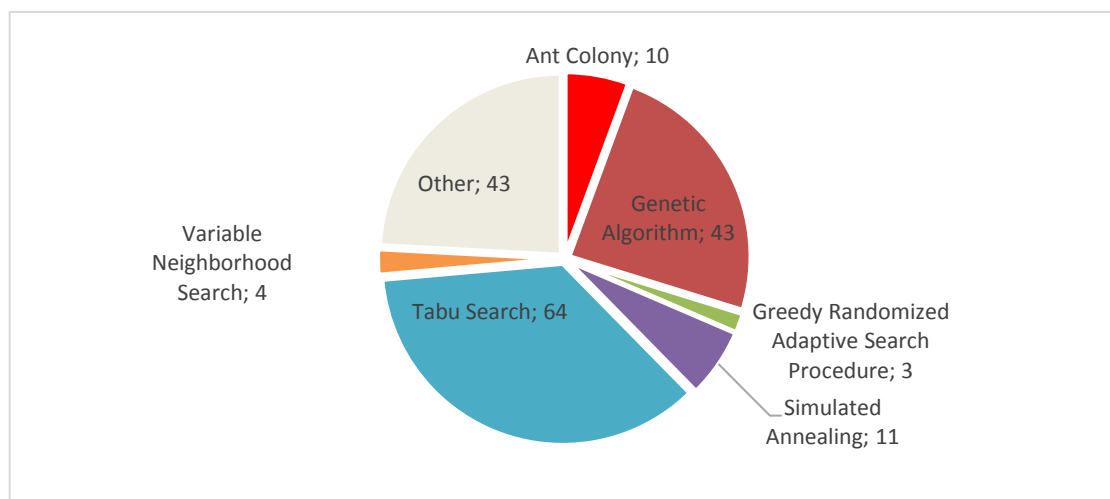


Fig. 2 Summary of bibliography of Gendreau et al. [25]

1.1.3 Genetic Algorithm on EMVRP

GA is inspired by Darwin's theory of evolution which states that the survival of an organism is affected by rule "the strongest species that survives". Darwin also stated that the survival of an organism can be maintained through the process of reproduction, crossover and mutation, Hermawanto [11]. GA is applied to solve VRP which is defined as most known Np-hard problem in the research of BjarnadÚttir [22].

1.1.4 Tabu Search on EMVRP

Information on the past progress of the search can be used to record the information in memory structures. Metaheuristics that use this strategy are commonly grouped under the umbrella term TS algorithms Glover [2], sometimes also called adaptive memory programming algorithms. Various types of memory structures are commonly used to remember specific properties of the trajectory through the search space that the algorithm has undertaken. A tabu list records the last encountered solutions or some attributes of them and forbids these solutions from being visited again as long as they are on the list. Alternatively,

the tabu list may also record the last moves that have been made for the purpose of preventing them from being reversed. Whereas a tabu list can be viewed as a type of short-term memory, that records information on recently visited solutions, frequency memory is used as a type of long-term memory. This memory structure records how often certain attributes have been encountered in solutions on the search trajectory, which allows the search to avoid visiting solutions that display the most often encountered attributes or to visit solutions with attributes seldom encountered. The decision on how to use the frequency memory can be based on the quality of the solutions in which the attributes were found.

1.1.5 Adaptive memory in tabu search

A distinctive feature of TS compared to memory-less metaheuristics is the use of adaptive memory to explore the search space in a responsive manner. According to Georgieva and Sin [1] findings TS can use both explicit and attributive memory. Explicit memory keeps complete solutions. Most often these are the elite solutions found throughout the search. Attributive memory is used to guide the search, and record attributes of the solution that change when moving from one solution to the next.

Formulation of EMVRP using TS is a novel area of research and no ever publication of literature under that according to authors’ knowledge. Analysis of The TS algorithms that solve various types of VRP categories are represented in Table 4.

Tab. 4 *TS algorithm types for solving VRP*

Algorithm	Authors	Type of solving procedure	Key Features
<i>Osman Algorithm</i>	Sigauke & Talukder [18]	Two strategies of Best Admissible(BA) and First Best Admissible (FBA)use to select neighbors	Used key Tabu tenures and no intensification
<i>The Gendreau, Hertz and Laporte Taburoute algorithm</i>	Cordeau & Gilbert [19]	Moving a vertex from its current route r to another route s containing one of its closest neighbors by local re-optimization to obtain neighbors.	Routes are periodically updated using the US post-optimization heuristic, used intensification
<i>Taillard's algorithm</i>	Cordeau & Gilbert [19]	Decomposition scheme that lends itself to the use of parallel computing, in non-planar problems, regions are defined through the computation of shortest spanning arborescence rooted at the depot	Do not allow infeasibilities, many iterations in one running time
<i>The Rochat and Taillard Adaptive Memory Procedure</i>	Cordeau & Gilbert [19]	When applied periodically during the search process, it provides a diversification process by allowing new high quality solutions to emerge, when applied as a post-optimizer, it is best seen as an intensification procedure	Probabilistic diversification and intensification.
<i>The Xu and Kelly algorithm</i>	Cordeau & Gilbert [19]	Define neighbors by oscillating between ejection chains and vertex swaps between two routes.	A pool of best known solutions is maintained, ejection chains are determined by minimizing the flow on a network.
<i>Rego's Flower algorithm</i>	Cordeau & Gilbert [19]	Applies an ejection process to move from a VRP solution made up of several blossoms (or routes) to another solution by suitably deleting and introducing edges creating intermediate structures consisting of one path, called stem.	Long-term diversification with tabu tenures.

1.1.6 Ant Colony Optimization on EMVRP

Ant Colony optimization is a member of the ant colony algorithms family, in swarm intelligence methods, and it constitutes some metaheuristic optimizations. Initially proposed by Marco Dorigo in 1992 in his PhD thesis, the first algorithm was aiming to search for an optimal path in a graph, based on the behavior of ants seeking a path between their colony and a source of food. The original idea has since diversified to solve a wider class of numerical problems, and as a result, several problems have emerged, drawing on various aspects of the behavior of ants. From a broader perspective, ACO performs a model-based search and share some similarities with Estimation of Distribution Algorithms.

Population-based nature of ACO adds as a favorable feature in order to find an optimal solution by exploring the optimal solution through a pool of solutions. ACO is shown to be consistently more effective for a larger number of trials and to provide more reliable solutions. Further, as a master-slave parallelism is possible for the nature of ACO algorithm, its implementation is suggested to reduce the overall execution time allowing the opportunity to solve real-time signal control systems.

1.1.7 Local Search Algorithms on EMVRP

Most local search heuristics for TSP can be described in a way as Lin's λ -Opt algorithm. The algorithm removes λ edges from the tour and the remaining segments are reconnected in every other possible way. If a profitable reconnection is found, i.e. the first or the best, it is implemented. The process is repeated until no further improvements can be made and thus a locally optimal tour has been obtained. The most famous LSA are the simple 2-Opt and 3-Opt algorithms ($\lambda=2$ and $\lambda=3$). The 2-Opt algorithm, which was first introduced by Croes in 1958 removes two edges from a tour and reconnects the resulting two sub tours in the other possible way. Local search is known to perform less on benchmarks with a central depot because it targets the longest edges first, even though these are often part of an optimal solution. This should make the comparison between our meta-heuristics more reliable.

1.1.8 Simulated Annealing on EMVRP

Among VRP solutions using SA, the method proposed by Osman [14] is popular. In its main procedure, one node or two nodes are exchanged between existing two vehicle routes. The move of one node or two nodes from one vehicle route to another is also allowed.

SA solve VRP by randomly choosing current solution in each iteration a solution from the neighborhood. If the new solution is better than the current one, the current solution is replaced by the new one. If not, it is replaced by the new one with a certain probability which is a function of the number of iterations which passed since the beginning of the optimization and of the difference in objective function values between the two considered solutions. Probability of accepting a solution which is worse than the current one decreases as the algorithm proceeds. In the first stages of optimization simulated annealing behaves more like a random search procedure, then it's biased toward accepting only better solutions increases and in the final stages of optimization it operates according to the greedy search principle.

According to research of Gendreau et al. [25], TS is identified as most effective metaheuristic in solving VRPs and solutions based on SA, GA and ACO are not even competitive with TS. It also declares that though SA is not competitive, there is a possibility of GA and ACO to be competitive with TS in future because currently GA and ACO are not fully exploited in giving solutions for VRP yet.

No comparative analysis of metaheuristics with the domain of EMVRP is published in the literature as for the authors' best of the knowledge.

Cooray and Rupasinghe [3] presented an analysis of different methodologies in solving GVRP which is a type of VRP. According to the research of metaheuristic application on GVRP is depicted in table 5.

Tab. 5 Analysis of metaheuristics in solving GVRP

Author' Name	Research Study	GVRP Category	Critical Review of the Solving Method
Xiao et al. [23]	Development of a fuel consumption optimization model for the capacitated VRP	Green VRP	Developed a string-model based simulated annealing algorithm with a hybrid exchange rule.
Yiyo [24]	Using simulated annealing to minimize fuel consumption for the time-dependent VRP	Green VRP	Developed a simulated annealing algorithm to solve the formulated TDVRP.
Schneider et al. [15]	The electric vehicle-routing problem with time windows and recharging stations	Green VRP	Hybridization of Variable Neighborhood Search and Tabu Search.
Küçükoğlu et al. [16]	A Memory Structure Adapted Simulated Annealing algorithm	Green VRP	Developed a Memory Structure Adapted Simulated Annealing (MSA-SA) algorithm to solve Green VRP with time windows.
Iman et al. [17]	An Adaptive Large Neighborhood search heuristic	PRP	Used Adaptive Large Neighborhood Search (ALNS) algorithm and at the second stage used a Speed Optimization Algorithm (SOA) on the resulting VRPTW solution to find the optimal speed on every arc.
Bektas et al. [26]	The bi-objective Pollution-Routing Problem	PRP	Used Adaptive Large Neighborhood search algorithm and a speed optimization proceed.

2 CONCLUSIONS

Out of the solution methods discussed, the heuristics approaches are identified as the most practical solution approaches in the context of EMVRP due to np-hard nature of the problem domain. Even though the exact methods and constructive methods give optimal solutions they have a tendency to take much longer computational time. While heuristics are problem-dependent techniques and usually adapted to the problem at hand; however, can become too greedy, they usually get trapped in a local optimum and thus fail, in general, to obtain the global-optimum solution. Metaheuristics which is a class of heuristic, in spite being a problem-independent solving technique; can be modified to be adaptive and less greedy. Where, the techniques may even accept temporary deterioration of solutions, which allows them to explore more thoroughly the solution space and thus to get a better solution.

In the analysis, a critical review of metaheuristics in the context of VRP and EMVRP has been presented. The TS has been identified as most used metaheuristic technique in the literature (37% of metaheuristic technique used in the domain of VRP is TS).

One of the main components of TS as opposed to the other metaheuristics is; it's use of adaptive memory, which creates a more flexible search behavior and guided nature which is a type of artificial intelligence. Intelligence needs adaptive memory and responsive exploration, remembers travelled paths when hill climbing (adaptive memory) and make strategic decisions (responsive exploration) on the way to peak or decent. A bad strategic decision may give more information than a good random one to come up with quality

solutions which is another benefit of responsive exploration. Prevention of cycling of solutions in TS, has made TS the fastest metaheuristic of solving VRP which uses least computational time. Due to these features TS has been identified as the next decade metaheuristic which guarantees satisfactory solutions for large instance practical problems. The performance of tabu search was also satisfactory and importantly – guaranteed stable “run to run” optimization results.

Researchers have identified that TS is most effective metaheuristic in solving VRP while GA, SA, and ACO are not even competitive when compared with it. But studies have identified that GA and ACO still have the possibility to compete with TS as GA, and ACO not fully exploited in solving VRP and there is still possibility to fully utilize these techniques to supersede TS. However, it is proven that TS is the fastest metaheuristic to generate solutions where, GA is more suited to create better number of quality solutions, due to being population-based technique.

According to the inherent characteristics of metaheuristics in favor of solving EMVRP, the following can be selected as the best fitting modelling and is depicted in table 6.

Tab. 6 *Summary of best fit metaheuristic to select to solve EMVRP with type of solution required*

EMVRP Feature	Best Fitting Metaheuristic
Best Solution Quality	GA
Fastest solutions	TS
Metaheuristic that use artificial intelligence	TS
Most used path-based metaheuristic for VRP	TS
Most used population-based metaheuristic for VRP	GA

Although the literature is nourished with solving VRP using metaheuristics, the research is novel of solving EMVRP using metaheuristics. For the authors knowledge there is no such study reported on the applicability of metaheuristics in context of EMVRP. The formulation of EMVRP using metaheuristic is another lucrative research domain for future researchers. As minimizing energy has been identified as one of the main factors in logistics in the developing world; a comparative EMVRP analysis is demanded in the supply chain management. Contributions to EMVRP using artificial intelligence, optimization, and higher computational power are necessary and will open immense avenues for future researchers.

References

- [1] Georgieva, A., and Sin, C., 2015, "Solving Green Vehicle Routing Problem Using Tabu Search," Aarhus University.
- [2] Glover, F., 1989, "A user's guide to tabu search, Graduate School of Business," University of Colorado, Boulder, CO, USA.
- [3] Cooray, P.L.N.U., and Rupasinghe, T. D., 2016, "An Analysis of Methodologies for Solving Green Vehicle Routing Problem: A Systematic Review of Literature," Proceedings of the conference on Research for Transport and Logistics Industry, ISSN 2513-2512., Colombo, Sri Lanka, 2016.
- [4] Kara, I., Kara, Y.B., and M. Kadri, Y., 2007, "Energy minimizing vehicle routing problem. Combinatorial optimization and applications," Springer Berlin Heidelberg, 62-71.
- [5] Figliozzi, M., 2009, "Emissions Minimization Vehicle Routing Problem," Department of Civil and Environmental Engineering, Portland State University, Portland.
- [6] Chebbi, O., and Chaouachi, C., 2016, "Evolutionary Approach for Minimizing Consumed Energy in a Personal Rapid Transit Transportation System with a Multi-Depot Network Topology, GECCO'15 Companion," Madrid, Spain, ISBN 978-1-4503-3488-4/15/07.
- [7] Ghahremani, H., Didehvar, F., and Razavi, A., 2016, "Vehicle routing problem for minimizing consumption of energy in three dimensional space, 1,2,3," Department of Mathematics and Computer Science, Amirkabir University of Technology, 424 Hafez Ave., Tehran, 1591634311, Iran.
- [8] Thalei, M., 2009, "Heuristic for Energy Efficient Vehicle Routing Problem, Department of manufacturing engineering," Faculty of graduate school of Wichita state university.
- [9] Blum, C., Roli, A., 2003, "Metaheuristics in Combinatorial Optimization: Overview and Conceptual Comparison," Journal of ACM Computer Surveys (CSUR) Volume 35 Issue 3, September 2003 pages 268-308.
- [10] Volna, E., and Kotyrba, M., 2015, "Unconventional Heuristics for Vehicle Routing Problems," Journal of Numerical Analysis, Industrial and Applied mathematics (JNAIAM), European Society of Computational Methods, Journal of Numerical Analysis, in Sciences and Engineering (ESCMSE).
- [11] Hermawanto, D., 1997, "Genetic Algorithm for Solving Simple Mathematical Equality Problem," Indonesian Institute of Sciences (LIPI), INDONESIA.
- [12] Gamal, A., Abeer, M.M., and Sayed, M., 2014, "A Comparative Study of Meta-heuristic Algorithms for Solving Quadratic Assignment Problem," International Journal of Advanced Computer Science and Applications, Vol. 5, No. 1.
- [13] Tan, K. C., Lee, L. H., Zhu, Q. L., and Ou, K., 2000, "Heuristic methods for vehicle routing problem with time windows," ELSEVIER, Artificial Intelligence in Engineering, Singapore.
- [14] Osman, I. H., 1993, "Metastrategy simulated annealing and tabu search algorithms for the vehicle routing problem," Annals of Operations Research, 1993, Volume 41, Number 4, Page 421
- [15] Schneider, Michael., Andreas S., and Dominik G, "The electric vehicle-routing problem with time windows and recharging stations," Transportation Science 48.4 (2014): 500-520.
- [16] Küçüköğlü., and İlker., 2015, "A memory structure adapted simulated annealing algorithm for a green vehicle routing problem," Environmental Science & Pollution Research 22.5(2015):3279-3297.

- [17]Iman, D., Teodor, G.C., Michel, G., and Walter, R., 2016, “An adaptive large-neighborhood search heuristic for a multi-period vehicle routing problem,” *Transportation Research Part E: Logistics and Transportation Review*, Volume 95, November 2016, Pages 95-123.
- [18]Sigauke, C., Talukder, H. M., 2003, “A Modified Osman’s Simulated annealing and Tabu Search Algorithm for the Vehicle Routing Problem,” *ASOR BULLETIN*, Volume 22.
- [19]Cordeau, J. F., Gilbrt, L., 2005, “Tabu Search Heuristic for the Vehicle Routing Problem,” *Metaheuristic Optimization Via Memory and Evolution*. Kluwer Academic Publishers, Boston, London.
- [20]Liyanage, R.P., and Rupasinghe, T.D., 2016, “An Analytical Model Formulation to Enhance the Green Logistics (GL) Operations: From the Perspective of Vehicle Routing Problem (VRP),” *American Journal of Engineering Research (AJER)*, 5(8), pp. 294–299.
- [21]Cooray, P.L.N.U., and Rupasinghe, T.D., 2017, “Machine Learning Augmented Energy Minimizing Vehicle Routing Problem (EMVRP),” *International Journal of Industrial Engineering*, Volume 2017 (2017), Article ID 3019523, 13 pages <https://www.hindawi.com/journals/jie/aip/3019523>.
- [22]BjarnadÚttir, A. S., 2004, “Solving the Vehicle Routing Problem with Genetic Algorithms, Informatics and Mathematical Modelling,” IMM Technical University of Denmark, DTU.
- [23]Xiao., Yiyong., and Abdullah K., 2012, “Development of a fuel consumption optimization model for the capacitated vehicle routing problem, ” *Computers & Operations Research* 39.7 (2012): 1419-1431.
- [24]Yiyo, K., 2010, “Using simulated annealing to minimize fuel consumption for the time-depe ndent vehicle routing problem, ” *Journal of Computers and Industrial Engineering*, Volume 59 Issue 1, August, 2010, Pages 157-165.
- [25]Gendreau, M., Potvin, J. Y., Bräumlaysy, O., Hasle, G., and Løkketangen, A., 2008, “Metaheuristics for the vehicle routing problem and its extensions,” *A categorized bibliography* (pp. 143-169). Springer US.
- [26]Bektaş., Tolga., and Gilbert L., 2011, “The pollution-routing problem,” *Transportation Research Part B: Methodological* 45.8 (2011): 1232-1250.