Clustering-based Augmented Tabu Search for Energy Minimizing Vehicle Routing Problem (EMVRP)

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Abstract

Application of metaheuristics for Energy Minimizing Vehicle Routing Problem (EMVRP) has become extremely important because of practical relevance. The EMVRP aims at serving dynamic demanding customers distributed throughout the world while consuming minimum possible energy, which represent as a product of load and distance. The NP-hard problem nature urges the researchers to utilize metaheuristics to solve them in non-polynomial time. Although there exists several metaheuristics, as of to date the EMVRP is only formulated and solved using the Genetic Algorithm (GA). According to the authors' knowledge there is only one instance reported in literature of metaheuristic based on GA on EMVRP. There are no studies reported on the development of TS based metaheuristic for the EMVRP and use of machine learning to guide the local search in formulating EMVRP. In this study, at first the authors formulate EMVRP using Tabu Search (TS) and evaluate its performance with test cases from the CVRPLib repository for the vehicle routing problems (VRPs). As the second stage, the authors improve the local search in the data set embedding machine learning (ML) techniques in the developed TS algorithm and critically evaluate the applicability using the same test cases. The study introduces a new TS based formulation for EMVRP for the literature as well as derives the fact of augmenting ML brings super performance in metaheuristics in solving EMVRP. Furthermore, the study lays foundation in filling the knowledge gaps in the current literature and proposes future research directions in machine learning augmented metaheuristics to enhance solving the EMVRPs.

Keywords *- Vehicle Routing, Machine Learning, Tabu Search*

1. Introduction

Energy Minimizing Vehicle Routing Problem (EMVRP) comes under combinatorial optimization and importance is gained importance during the past years due to its relevance with the developing industrial world. It is one of the most known np-hard problem which finds optimal route to satisfy dynamic demanding customers distributed throughout the world from a given distribution center while minimizing the total energy [4]. NP-hard problems such as EMVRP is solved using techniques of heuristics because they cannot be solved in a realistic computational time by using exact mathematical models due to its increased variables and complexity [6]. The term-met heuristic was first introduced in [10]. Metaheuristic is a class of heuristic which is more realistic in reaching global optimum due to its nature of accepting temporary deterioration of solutions, which allows them to explore more thoroughly the solution space and thus to get a better solution [5].

EMVRP is mathematically formulated in [1] with the objective of minimizing energy consumption while serving distributed set of customers and the study highlights the computational times of CPLEX for even moderate sized problems are not feasible.

According to [1] the real cost of a vehicle traveling between two nodes depends on many variables, the load of the vehicle, fuel consumption per mile (kilometer), fuel price, time spent or distance traveled up to a given node, depreciation of the tires and the vehicle, maintenance, driver wages, time spent in visiting all customers and total distance traveled etc. As most of the above-mentioned variables are distance or time based and can be approximated by the distance alone. The variables which are not a constant within the route can be vehicle load, fuel consumption per mile (kilometer), fuel price or time spent up to a given node. In a recent study, these variables are presented as a function of the load of vehicles on the corresponding arc being energy of a given route to be equal to the product of distance travelled and the load of the vehicle [1].

The research presented by [7] introduce variety of approximate algorithms, including classical heuristics and metaheuristics to efficiently solve different variants of VRP. The research of [12] is one such special VRP context where it objects to minimize the number of vehicles while minimizing the total route duration. The study of [13] is a heuristic based solution to make constructive routes to pick up and deliver goods based on time windows. Application of metaheuristic for the variant of EMVRP is first ever published by [3] where GA is used as the type of metaheuristic to formulate EMVRP. Literature is novel to EMVRP formulation with other types of metaheuristic. An analysis of metaheuristic application for EMVRP for the research history is done in the study of [9]. It brings out the fact that metaheuristic application on EMVRP other than GA is novel to the literature and no ever publication done in that regard. The authors attempt at bring TS for EMVRP to the literature which will eye open further research domains. Use of information on the past progress of the search in maximizing local search comes under the metaheuristic of Tabu Search (TS), [8]. 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 [11] findings, TS can use both explicit and attributive memory.

Augmenting metaheuristic using ML for EMVRP is a new research domain. The study of [2] proposes a comparative analysis of different clustering techniques where grouping of similar objectives to clusters. Augmenting metaheuristic with ML is first reported by [3] using k-means clustering for the EMVRP domain. This was carried out tuning the main parameters, which are mutation rate, population size, and number of generations for the better performance of the parameters in concern to improve overall performance of the metaheuristics. Except for [3] literature is silent on the application of ML augmented metaheuristics to solve EMVRP or related variants.

Table 1. Main Stages of Research

Stage	Description
Phase 01	Formulating the EMVRP problem using TS (Generic TS)
Phase 02	Augmenting machine learning concepts to the Generic TS to enhance the performance (ML-TS)
Phase 03	Comparison of energy obtained with Generic TS with ML-TS to identify any performance improvement using test cases extracted from the CVRP Library

2. Methodology

A. *Phases of Research*:

The research flow is designed mainly focusing on 3 stages. First, a new TS metaheuristics is developed and the results for elite energy, which is the lowest achievable energy is obtained. Then, the developed metaheuristic is augmented with ML by guiding local search and elite energies are obtained. Lastly, the comparative study focusing on two methods is done and identify new knowledge gaps to the literature. Main stages of research can be represented as in Table 1.

B. *Data Collection*:

The test data is obtained from a vehicle routing problem library CVRPLib publically available in the internet under the link of http://vrp.atd-lab.inf.puc-rio.br/index.php/en/ and this repository is a prominently used library in many research studies found in the literature. The repository consist data collections of various no of customers class, each class with data sets with specific customer demands, vehicle capacity, and exact geographical location of the customers. The authors has selected an average no of customer class (about 32-80 customers) for testing in result generation.

C. *Development Environment*:

The experiments were carried out on a personal computer with the following configurations of Core i5, with 8GB RAM, and 2.30GHz-2.40GHz CPU speed. Left and right-justify your columns. Use tables and figures to adjust column length. Use automatic hyphenation and check spelling. All figures, tables, and equations must be included *in-line* with the text. Do not use links to external files.

3. Results

A. *Phase 01- Formulating EMVRP problem using TS*

Generic TS algorithm for the formulation of EMVRP is represent in Figure1.

//Assumptions

Energy is assumed as the product of load and the distance travelled

Weight of the vehicle is 0

There is only a central depot

Every vehicle starts and ends in the depot

Vehicle Capacity is C

//Input

Read list of cities to be served with demands {city1,city2,…,city} from CVRP Lib file Read vehicle capacity from text file

Number of iteration (i)

Number of solutions (n)

Size of tabu list (10)

//Initialization

Take starting point as depot

Create a tour with a random order of cities

Estimated rounds=total energy/capacity

Initial energy = energy consumption of the solution

Loop start {

//Tabu Search

Do this for defined no of times to create a solution pool

Get the best tour from the solution pool

Save as the elite

Energy=energy of the fittest tour in solution pool

//Maintain tabu list

Remember lastly visited cities by the vehicle

Check the next move

If the move is tabu, cut them out in the search

Else if if possible untabu move, go for untabu move

Update the tabu list

Else if no any untabu move

Apply Freeing strategy

//Stopping criteria

Check the number of solutions obtained

While number of solutions is equal to i

Add one more iteration

} End loop start

Figure. 1. Generic TS algorithm for EMVRP

B. *Design of Experiment for parameter setting of TS*

Design of experiment (DOE) is carried out to select ideal parameter values in obtaining minimized energy with practical relevance.

1) *Setting number of iterations*

To execute the series of experiments with the CVRP test cases, different number of iteration levels were identified through the Design of Experiments (DOE). The results are presented in Table II.

2) *Identifying the energy obtained for each iteration*

For each test case, the energy is obtained and identify the best matching iteration level for the study. See Table 2.

Table 2. Energy Obtained For Different Iteration Levels

CVRPLib file	Energy(J) obtained for various iterations considered in the DOE			
	10	100	1000	100000
A-n32-k5.vrp	82467	69588	65275	52065
A-n33-k5.vrp	73065	71548	68312	51201
A-n33-k6.vrp	63340	70347	62139	53890
A-n34-k5.vrp	71789	69281	68391	54139
A-n36-k5.vrp	73629	71341	66288	53189
A-n37-k5.vrp	80186	75904	67190	54399
A-n37-k6.vrp	82950	78491	71291	55193
A-n38-k5.vrp	85006	82132	73190	51298
A-n39-k5.vrp	81298	82467	73575	58104
A-n39-k6.vrp	93020	79978	75198	56104
A-n44-k5.vrp	96424	79296	81211	75120
A-n45-k6.vrp	114476	85195	86241	87368
A-n45-k7.vrp	100666	93184	99761	83190
A-n46-k7.vrp	102963	96929	92078	83094
A-n48-k7.vrp	112557	99159	88241	84201
A-n53-k7.vrp	130355	111328	86131	81445
A-n54-k7.vrp	128316	116288	101901	88412
A-n55-k9.vrp	130226	123899	120458	86945
A-n60-k9.vrp	126910	124902	133073	101405
A-n61-k9.vrp	120946	132199	128394	105399
A-n62-k8.vrp	159454	141271	129385	112901
A-n63-k9.vrp	158459	143199	132787	121678
A-n63-k10.vrp	150705	148134	144283	121328
A-n64-k9.vrp	140798	142908	138779	126803
A-n65-k9.vrp	164953	150344	153373	119045
n65-k9.vrp	168469	148299	142254	119480
A-n69-k9.vrp	177771	151236	142352	128357
A-n80-k10.vrp	197167	148913	143178	126983

C. *Phase 02– Combining machine learning to enhance the performance of formulated EMVRP with TS and Acronyms*

ML-TS algorithm for the formulation of EMVRP is represent in Figure 2. The special feature in ML-TS algorithm than the Generic algorithm is it make internal search more intelligent by making clusters of customers who are in nearby locations and with under optimized level of constrain of demand which satisfying the vehicle capacity.

//Input
Read list of cities to be served with demands {city1,city2,…,city}
from CVRP Lib file
Vehicle Capacity is C
Number of iteration (i)
Number of solutions (n)
Size of tabu list (10)
Number of clusters is X

//Setting no of clusters
Check the demand of each cities
Total demand=sum of demand of all cities
X =(Total demand / C) + 1

//Create city lists
Set starting city as depot
While all the cities are counted
And if next city=! depot
Add each city to the city list

//Create cluster cities
Select x random cities as centers of clusters
While citylist is empty
Add cities to each cluster IDs of x

//Redefine the centers to obtain lowest possible distance
Get the cluster cities
Calculate the centres of each clusters
Until cluster centers are get fixed
Redefine the new cluster centres by calculating the best middle
Again list the cities to new cluster IDs of X
Obtain the clusters with lowest possible distance to move on

//Get current energy
Current enegy=enrgy to visit the city list while satisfying the demands of cities
While currentEnergy < Elite Energy
Set Elite Energy=Current Energy
Set Elite tour=tour of city list

//Tabu Search
Do this for defined no of times to create a solution pool
Get the best tour from the solution pool
Save as the elite
Energy=energy of the fittest tour in solution pool

//Maintain tabu list
Remember lastly visited cities by the vehicle
Check the next move
If the move is tabu, cut them out in the search
Else if possible untabu move, go for untabu move
Update the tabu list
Else if no any untabu move
Apply Freeing strategy

//Stopping criteria
Check the number of solutions obtained
While number of solutions is equal to i
Add one more iteration
} End loop start

Figure. 2. ML-TS algorithm for EMVRP

D. Phase 03 – Comparative study of Generic TS Vs ML-TS

The Generic TS and ML-TS was compared against each other in order to identify any significant improvement and is presented in Table 3.

Table 3. Energy Obtained With Generic Ts and Ml-Ts Ts

CVRPLib file	Elite energy with Generic TS (Kj)	Time taken to obtained energy(Sec)	Elite energy with ML-TS(Kj)	Time taken to obtained energy (Sec)
A-n32-k5.vrp	52065	3.2	28560	303
A-n33-k5.vrp	51201	3 3	29789	306
A-n33-k6.vrp	53890	3.3	29045	308
A-n34-k5.vrp	54139	3.3	31284	308
A-n36-k5.vrp	53189	3.6	32149	306
A-n37-k5.vrp	54399	3.6	32798	306
A-n37-k6.vrp	55193	3.5	33892	308
A-n38-k5.vrp	51298	3.5	36782	12
A-n39-k5.vrp	58104	3.6	35123	314
A-n39-k6.vrp	56104	3.6	33290	329
A-n44-k5.vrp	75120	3.6	34295	341
A-n45-k6.vrp	87368	3.6	34890	328
A-n45-k7.vrp	83190	3.7	37821	327
A-n46-k7.vrp	83094	3.7	41294	329
A-n48-k7.vrp	84201	3.7	43193	341
A-n53-k7.vrp	81445	3.7	42159	338
A-n54-k7.vrp	88412	3.7	45248	345
A-n55-k9.vrp	86945	3.9	46193	342
A-n60-k9.vrp	101405	3.9	46890	339
A-n61-k9.vrp	105399	4.1	48923	346
A-n62-k8.vrp	112901	4.0	52134	348
A-n63-k9.vrp	121678	4.1	54389	351
A-n63-k10.vrp	121328	4.2	51239	357
A-n64-k9.vrp	126803	4.2	52489	359
A-n65-k9.vrp	119045	4.2	54256	362
A-n65-k9.vrp	119480	4.2	63295	363
A-n69-k9.vrp	128357	4.3	66390	363
A-n80-k10.vrp	126983	4.5 s	69578	368

4. Discussion

A. Comparison of Generic TS Vs ML-TS

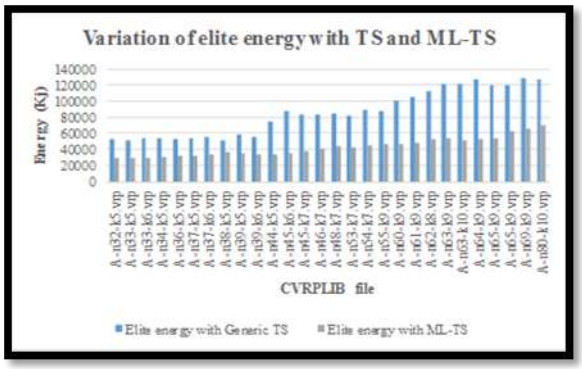

Figure 3. Variation of elite energy with TS and ML-TS

With the results obtained it is identified an

improvement in elite energies obtained with two algorithms and also a increment in computational time as depicted in Figure 3 and Figure 4.

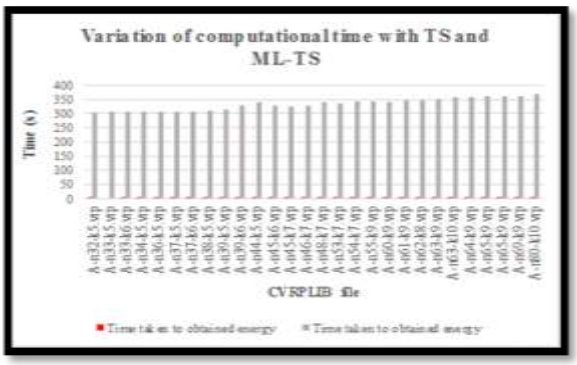

Figure 4. Variation of computational time with TS and ML-TS

Figure 5 represents the tradeoff between the computational time increment and elite energy improvement with TS and ML-TS.

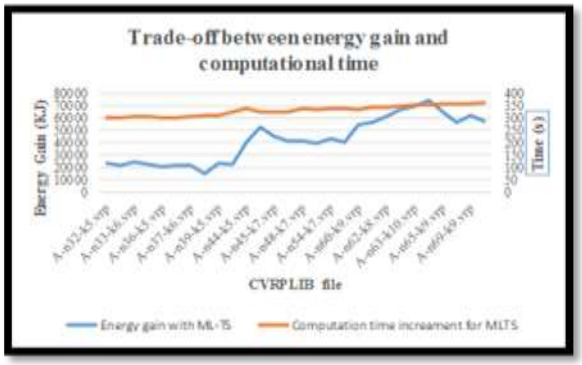

Figure 5. Tradeoff between computational time increment and elite energy improvement with TS and ML-TS

In order to identify that using ML has created a significant impact on the elite energy obtained, data obtained are tested using Freedman's non-parametric test. Here the two hypothesis are built and confidence level is selected as 95% and are summarized in table IV.

Table 4. Factors Considered In Comparison

Null hypothesis H_0	Means of elite energy from Generic TS-EMVRP and ML-TS-EMVRP are the same
Alternative hypothesis H_1	Means of elite energy from Generic TS-EMVRP and ML-TS-EMVRP are not the same.
Significance	0.05
Confidence level	95%
Reject criteria	Reject null hypothesis if p-value <= 0.05

Test statistics has been calculated and the results are depicted in Table V. Through the test statistics obtained p value is 0.000 which is less than the significance level, P value obtained = 0.000 < 0.05. According to the statistic, null hypothesis is rejected, $H_{o,}$ "Means of elite energy from Generic TS-EMVRP and ML-TS-EMVRP are the same" is rejected accepting the alternative hypothesis. Therefore, it concludes that "Means of elite energy from Generic TS-EMVRP and ML-TS-EMVRP are not the same."

Table 5. Test Statistic Result

	N	Mean	on	um	um	Percentiles		
						25th	50th	75th
Generic TS	28	85454.86	28335.234	51201	128357	54597.50	83695.50	117509.00
ML-TS	28	43121.00	11571.090	28560	69578	33440.50	41726.50	51910.25

Post hoc analysis is necessary in order to analyze which algorithm generate means of lowest elite energy. Post hoc analysis is necessary in order to analysis which algorithm generate means of lowest elite energy and the results of box plot is represented in Figure 6.

Post of analysis clearly shows that there is a significant variance in means of elite energies obtained with Generic TS algorithm and ML-TS algorithm. ML-TS shows greater reduction in mean in elite energies and is best suit for EMVRP.

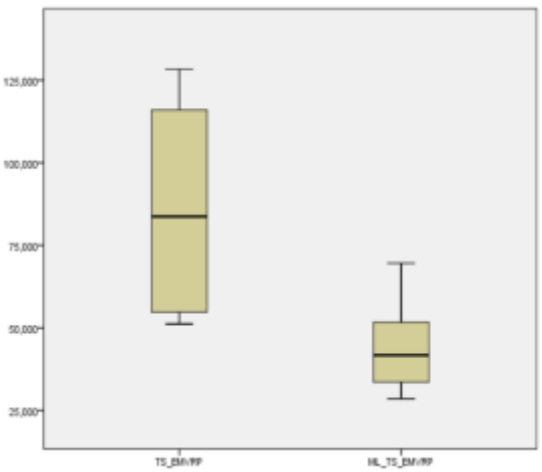

Figure 6. Box plot for mean comparison

5. Conclusion

Application of metaheuristic is a new research domain especially for the problem of EMVRP. According to the authors' knowledge there is only one significant study done on development of metaheuristic based on GA on EMVRP and tuning of parameters of the problem to arrive at practically satisfactory solutions for non-

polynomial problems. There are no studies reported on the development of TS based metaheuristic for the EMVRP and use of machine learning to guide the local search in formulating EMVRP.

This study yields a new TS- based algorithm for EMVRP and the solutions is further augmented with K-means clustering based machine learning algorithm which results in higher solution quality. The results clearly show that augmenting ML has significantly impact on the performance of metaheuristic on formulating EMVRP. The study proves the fact that augmentation with ML results in a significant increment in solution quality while the time taken to arrive at solution also increased. The study will open future research directions on using of metaheuristics in the domain of EMVRP and use of ML to enhance performance of the metaheuristics, which will eye open new research domain.

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