ISSN: 0976-3104
SPECIAL ISSUE: Computer Science

ARTICLE

REVENANT OF THE ECOSYSTEM: AN ENVIRONMENTAL BASED GREEN COMPUTING MODELS FOR VEHICULAR ROUTING PROBLEMS USING GENETIC ALGORITHM OPTIMIZATION APPROACH

M. Shanmugam[1*], J. Amudhavel[2]

[1] *Department of CSE, VFSTRU, Guntur, AP, INDIA*

[2] *Department of Computer Science and Engineering, KL University, Andhra Pradesh, INDIA*

ABSTRACT

Background: *Transportation plays a crucial role in our day to day life, without transportation facility it's really impossible to lead modern day routine life. The scope of transportation, supply chain management, logistics management plays a vital role within the delivery of products and services. The objective of this problem is to minimize the transportation cost and achieve efficient routing.* ***Methods:*** *We proposed an environmental oriented hybrid optimal routing algorithm for the road transportation system, we are looking this problem as a multi objective multi criteria because the goal is to minimize the distance and also the pollution.* ***Results:*** *The hybrid optimal based routing is achieved depending on the average convergence of distance and the pollution from the initial population.* ***Conclusions:*** *The experimental results evident that the new proposed technique performance well with the environmental factors. In addition to that, it is also outlined that further research work can be carried out to promote the proposed system with Vehicular Ad-hoc Network to provide betterment of Intelligent Transportation System.*

INTRODUCTION

KEY WORDS
Genetic Algorithm, Routing, TSP, Transportation, *Optimization.*

Received: 23 June 2017
Accepted: 1 Aug 2017
Published: 17 Sept 2017

Vehicle Routing Problem is one of the most studied and well know problem. The complexity of this problem is providing efficient route for the fleet of vehicles. The formal factors affecting the routing strategy are time and distance bounds of the system. VRP is derived from the well know and stage Travelling Salesman Problem (TSP) [1]. There many optimization methods available to solve the NP hard problems, but some of the most complex asymmetric TSP [2] solved with the improved Genetic Algorithms (GA) optimization technique. GA employees three main process to formulate the optimal solution selection that is selection, cross over and mutation. Selection is one of the important modules and plays a vital role in optimal solution selection, in which the individuals are directly interconnected to their fitness value. If the fitness value is higher, then the chance of choosing the individual is higher. Next is cross over where the most typical solution is used. It takes place between the individual. The position of gene is chosen, where swapping operation may be carried out for possible set of solution. The point at which it is broken depends on the unusual selection of cross over point. This process represents the combinational operation of the individuals. The combination of both selection and cross over will generate the less quality solution. The last process of implementation is mutation. After the computation of selection and cross over, we may obtain a solution with same or different characteristics, done by the means of swapping operation (cross over) or by normally obtained one. [3] In this process, the possible setting of an individual has to be changed. Using this mutation alone, an unusual walk to search space has been generated. Generally mutation in GA will fine tune the optimal result. Our paper is organized as follows: Section 2 gives the fine-tuned literature survey and background information. In Section 3, we have discussed about the proposed system and algorithm, description for different scheme. In section 4 we will discuss about the experimentation methodologies and Section 5 describes about the experimental analysis of different scheme with different initialization techniques and their results. Finally Section 6 concludes the paper.

RELATED WORKS

***Corresponding Author**
Email: shaninfo247@gmail.com
Tel.: +91-900-391-2326

Helsgaun, K et al [4] discussed Lin–Kernighan heuristic for symmetric TSP. [5,6] Introduced neighborhood based seeding technique to initialize the base population into GA for finding better route or individual. To improve the efficiency [7] introduced the new mutation operator to refine the TSP route. Heterogeneous Fleet Vehicle Routing Problem (HFVRP) is one of the common routing methods in VRP, which is based on different type of vehicle, capacities and the cost. The idea is to find the best route and to reduce the total distance. To solve this problem, [8] proposed a hybrid algorithm which consists of two methods, one is Local Search (LS) based heuristic and the second one is Set Partitioning (SP) formulation. While processing, the LS is used by the Mixer Integer Programming (MIP) solver to solve the SP model. This algorithm is only applicable for small scale, in that the efficiency is also less. By the influence of this problem same author proposed [9] Vehicle Routing Problems with homogeneous fleet, a parallel method that dynamically controls the dimension of the SP model. In [9] the LS based metaheuristic approach generates the routes with respect to a sequence of SP models with columns and analyzed that, this method is working properly for the large scale.

IIOAB JOURNAL
ISSN: 0976-3104

To solve the Multi-Objective Vehicle Routing Problems (MO-VRP) [10] proposed a fast approximation heuristics and the heuristic depends on the savings approach. The solutions are enhanced by the local search against the pare to-front in iterative process. Based on the savings heuristic the initial solutions are generated and the solution is approximated by pare to - front and then enhanced by the local search. This method has been tested on the beach mark it improves the initial approximation. [11] Proposed new microarray gene ordering strategy for solving combinatorial TSP optimization problem. [12,13,14] Introduced a hybrid particle swarm optimization algorithm for suggesting the best route for the fleet of vehicles, [15] discussed the adaptive neighborhood search method in VRP with time windows, [16] did the study with extended Variable Neighborhood Search problem (VNS) with Particle Swarm Optimization (PSO) and found that in context to time bound GA provide better results when compared to PSO.

The quality of the individual in the current generation is sent to the next generation, influenced by the Lamark's method. This method has been used to maintain the best solution throughout the process and many proposals are used to solve the application local search operator [17,18,19]. In [20] an enhanced the genetic operators (crossover and mutation) using the feasible solution and proposed an Improved Genetic Algorithm (IGA). To improve the effectiveness [7] [21], established three optimization strategies: immigration, local optimization and global optimization. Random population method is used, while generating the initial population, the chance of finding the optimal solution is very less and also the computation cost will be more.

In our survey we discussed, how the VRP is solved in using different methods, with different parameters and constrains like time windows constraints, multi-objective services, multi criteria vehicle routing [22,23,24]. We proposed a socially inspired transportation problem, which is based on the pollution in the path, we are routing the vehicle. The experiments are done using the slandered TSP bench mark instances [25] and then analyzed the performance with different Genetic Algorithm (GA) initialization techniques [26].

PROPOSED SYSTEM

In this work, the standard VRP is considered in a different perspective to propose a new environment concerned transportation problem in which the optimal path should be of least distance and also minimum air-pollution along the route. A pollution matrix of TSP, similar to distance matrix, is formulated to specify the pollution between each pair of cities. A pollution limit between the cities is the maximum allowed pollution value between any two cities in any feasible solution for the problem. During the formulation of solution, at each stage, inclusion of a new city is allowed only if the pollution value between the previous and the new city is less than that of maximum allowed pollution limit between the cities else, it would try to select the alternate city. The intelligent routing strategy for VRP in Hybrid Optimal routing can be represented as follows:

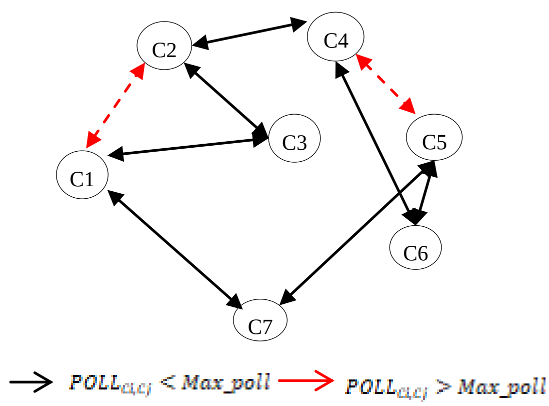


Fig.1: Sample intelligent routing strategy for VRP.

Let, the complete undirected graph $G = \{City_n, A\}$ and $DM(City_i, City_j)$ is the distance between the cities $City_i$ and $City_j$ such that $City_i \neq City_j$ and $DM(City_i, City_j) = DM(City_j, City_i)$.The pollution matrix for the TSP problem of size 'n'can be represented as $POLL\,(n \times n)$and $POLL\,(City_i, City_j)$ is the pollution between the $City_i$ and the $City_j$. In this proposal, the starting city remains same because the vehicle should start from a single predetermined source. The working principle of the proposed intelligent routing strategy with an example is illustrated below:

Algorithm

Hybrid Optimal based routing Algorithm (Pop, TP, Tc, G, n)

Step 1: Initialize $Gen \leftarrow 1, i \leftarrow 1, Size \leftarrow 1, TTC \leftarrow 0, TTP \leftarrow 0$

Step 2: Set optimal Distance, optimal Pollution and Maximum pollution $Opt\_Dist, Opt\_Poll \text{ and } Max\_Poll$

Step 3: Store the Population into a temporary variable, $CPop_{n\times n} \leftarrow Pop_{n\times n}$,

Step 4: Repeat through Step 13 **Until** $Gen \leq G$, Step 3 else go to Step 14

Step 5: Repeat through step 5.3 **Until** $l <= Popsize$, else goto Step 6

Step 5.1: $TCC \leftarrow (1-(TC_l - Opt\_Dist)/Opt\_Dist) * 100$ //calculating the cost convergence of the individual

Step5.2: $TPC \leftarrow (1-(TP_l - Opt\_Poll)/Opt\_Poll) * 100$//calculating the pollution convergence of the individual

Step5.3: $TradeOff\_Con_l \leftarrow TCC + TPC / 2$// calculating the average of pollution and distance convergence the individual

Step 6: Select the best individual which is having maximum tradeoff Convergence and pass the best Individual to the next generation

Step 6.1: Repeat through Step 6.3 **Until** $i < ER$, else goto Step 7

Step 6.2: $position \leftarrow max(TradeOff\_Con)$// Position of the Individual with Maximum tradeoff convergence value will be acquired.

Step 6.3 $Pop_i \leftarrow CPop_{position}$// the individual in the position in temporary population is moved to the population

Step 7: Repeat through Step 8.6 **Until** $Size \leq PopSize$, else goto Step 9 $where\ ER < Size \leq PopSize$

Step 8: Choose the random parents Individuals, $P\_Indiv1 \text{ and } P\_Indiv2$

Step 8.1:Select the initial City $Init\_City, \text{ and } Length \leftarrow 1$, Size$\leftarrow$1

Step 8.2: $Indiv[Length] \leftarrow Init\_City$ // the first city in the parent individual is selected as initial city

Step 8.3: Repeat through Step 8.5 **Until** $Length \leq n$, else goto Step 5

$Cur\_City \leftarrow Indiv[Length]$ //the current city in the offspring individual assigned as current city

Find the Position $Pos1 \text{ and } Pos2$ of the Current City in the Parent Individuals

$Pos1 \leftarrow find(P\_indiv1\,(Cur\_City)),\ Pos2 \leftarrow find(P\_indiv2\,(Cur\_City))$

In the [Fig. 1], the red dashed line shows the path between any cities, which current air-pollution is higher than the pollution limit of the problem and the black line shows the path with pollution within the limit. Assume that $C1$ is the starting city and the neighboring cities are organized in ascending order of their distance such that $(d(C1,C2) \leq d(C1,C3) \leq \cdots \leq d(C1,C7))$. The objective of the intelligent routing strategy for VRP in hybrid optimal routing is to choose the adjacent city devising lowest normalized value and the pollution between the cities are within the pollution limit has selected as next city. Starting from the city $C1$, the adjacent city is $C2$ with least normalized value but the pollution between the cities $C1$ and $C2$ exceeds the pollution limit. i.e. $POLL_{C1,C2} < Max\_poll$.

IIOAB JOURNAL ISSN: 0976-3104

IF$Pos1 = 1,\ LLoc1 \leftarrow n$
Else IF$Pos1 = n,\ \ RLoc1 \leftarrow 1$
IF$Pos2 = 1\ ,LLoc2 \leftarrow n$
Else IF$Pos2 = n\ ,RLoc2 \leftarrow 1$
Evaluate the Tradeoff$Treadeoff_z$ from Previous City to Current City and Current City to Next City from the Parent Individuals using Normalization
$d_1 \leftarrow DM(P\_Indiv1(LLoc1), P\_Indiv1(Pos1))$
$d_2 \leftarrow DM(P\_Indiv1(Pos1), P\_Indiv1(RLoc1))$
$d_3 \leftarrow DM(P\_Indiv1(LLoc2), P\_Indiv1(Pos2))$
$d_4 \leftarrow DM(P\_Indiv1(Pos2), P\_Indiv1(RLoc2))$
$p_1 \leftarrow POLL(P\_Indiv1(Pos1 - 1), P\_Indiv1(Pos1))$
$p_2 \leftarrow POLL(P\_Indiv1(Pos1), P\_Indiv1(Pos1 + 1))$
$p_3 \leftarrow POLL(P\_Indiv2(Pos2 - 1), P\_Indiv2(Pos2))$
$p_4 \leftarrow POLL(P\_Indiv2(Pos2), P\_Indiv2(Pos2 + 1))$
$TC = \sum_{t=1}^{size(d)} {d_t}^2\ , TP = \sum_{t=1}^{size(p)} {p_t}^2$ //sum of pollution and distance for the locations
$d'_t = \sum_{t=1}^{size(d)} d_t\ /TC\ , p'_t = \sum_{t=1}^{size(p)} p_t/TP$// normalizing the pollution and distance
$\forall[1, \leq z \leq Size(Loc)], \Omega_z\ \leftarrow TR * p'_z + (1 - TR) * d'_z$
Step 8.4: Repeat through Step 8.6 Until$k < 4\ ,\ else\ goto\ Step\ 9\ \ where\ 0 < k \leq 4$
$Next\_City \leftarrow min(Tradeoff)$ //the location of the city with minimum cost will be acquired
Step 8.5: IF$Next_City\ \notin\ Indiv\ and\ \ POLL_{Cur_City\ ,Next_City} < Max_Poll$, else goto Step 8.4
$Length \leftarrow\ \ Length + 1$,Update$Indiv[Length] \leftarrow next_City$
Step 8.6: $k \leftarrow k + 1$// increment the individual in the population
Step 9: Generate Random values $GeneC1, GeneC2$, $\quad where\ 1 \leq GeneC1, GeneC2 \leq n$
$Swap\ \ Indiv(GeneC1) \leftarrow Indiv(GeneC2)\ ,\ SwapIndiv(GeneC2) \leftarrow Indiv(GeneC1)$
Step 10:$Pop_{size} \leftarrow Indiv\ ,\ Size \leftarrow Size + 1$ // move to the next individual
Step 11: Evaluate the cost of each Individual in the Population

$$\forall[1, \leq i\ \leq PopSize], TC_i\ \leftarrow \sum_{j=1}^{n} DM\,(Indiv_i(j)\ , Indiv_i(j+1)\ )\ ,\quad j + 1\ \equiv 1$$

Step 12: Evaluate the Pollution of each Individual in the Population

$$\forall[1, \leq i\ \leq PopSize], TP_i\ \leftarrow \sum_{j=1}^{n} POLL\,(Indiv_i(j)\ , Indiv_i(j+1)\ )\ ,\quad j + 1\ \equiv 1$$

Step 13: $Gen \leftarrow Gen + 1$//Current generation is completed, increment the Gen for next generation
Step 14: Return Pop

So, the process of inclusion of the city $C2$ adjacent to the city $C1$ in the route is aborted and the condition is verified with the next least normalized value city of $C1$ which is $C3$. The same procedure is repeated until the complete route is generated with n number of cities and the possible route would be $(C1, C3, C2, C4, C6, C5, C7, C1)$. It not guaranteed that the individuals in the population yields optimal solution to the problem for both air pollution and distance, based on the genetic operations the individuals in the populations are improved.

The objective of intelligent routing strategy for VRP in Hybrid Optimal routing is to minimize the air pollution and the distance of the individuals in the population, for that different tradeoff method should be provided.

IIOAB JOURNAL
ISSN: 0976-3104

Algorithm explanation

The algorithm for Hybrid Optimal routing has the following arguments; Pop is the initial population generated using random or heuristic technique, TC is the total cost of each individual in the initial population using equation (1), G is the generation limit for termination of GA and n is the size of the problem instance. Elitism Rate (ER) is the number of high quality / elitist individuals are transferred from the current generation to the next without any modification. This elitism transfer technique avoids the replacement of best fit individuals with poor individuals in the successive generations and also improves the performance of crossover operation, if the parent is selected from the elitist individuals. The total cost and total pollution of each individual in the population is determined and represented as TC_j and TP_j. The total cost convergence rate TCC and the total pollution convergence rate TPC of the individuals in the population is derived through equations (2) and (3). The average of both pollution and distance convergence has been computed (i.e.) $TradeOff\_Con_i$ of the each individual in the population. The ER numbers of individuals having best fitness (i.e.) maximum tradeoff convergence value are hand-picked based on the position and send to consecutive generation.

$$TC_j = \begin{vmatrix} TC_1 \\ TC_2 \\ TC_3 \\ \cdots \\ TC_{PopSize} \end{vmatrix} = \begin{vmatrix} DM(\mathrm{Indiv}_1) \\ DM(\mathrm{Indiv}_2) \\ DM(\mathrm{Indiv}_3) \\ \cdots \\ DM(\mathrm{Indiv}_{PopSize}) \end{vmatrix} = \begin{vmatrix} \mathrm{Indiv}_1 \\ \mathrm{Indiv}_2 \\ \mathrm{Indiv}_3 \\ \cdots \\ \mathrm{Indiv}_{PopSize} \end{vmatrix} = \begin{vmatrix} City_1 & City_i & City_i & \cdots & City_{n-1} & City_1 \\ City_1 & City_i & City_i & \cdots & City_{n-1} & City_1 \\ City_1 & City_i & City_i & \cdots & City_{n-1} & City_1 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ City_1 & City_i & City_i & \cdots & City_{n-1} & City_1 \end{vmatrix}$$
$$= CPOP_{PopSize \times n} \quad (1)$$

$$TCC \leftarrow (1 - (TC_i - Opt\_Dist)/Opt\_Dist) * 100 \qquad (2)$$
$$TPC \leftarrow (1 - (TP_i - Opt\_Poll)/Opt\_Poll) * 100 \qquad (3)$$

First, two parent solutions P_Indiv1 and P_Indiv2 are chosen randomly from the current population and the first city of the parents is copied as the first city of the off-springs, thus the $Length = 1$. The construction of a complete offspring $Indiv$ of length $'n'$ using the greedy crossover is explained in the subsequent discussion:
The position of the current city Cur_City of the partially built offspring $Indiv$ in the two selected parents is identified using the following conditions,

$$Pos1 \leftarrow find(P_{indiv1}(Cur\_City)) \qquad (4)$$
$$Pos2 \leftarrow find(P_{indiv2}(Cur\_City)) \qquad (5)$$

The position of current city in the parents is used to identify the location of left $LLoc$ and right $RLoc$ adjacent cities of Cur_city in the concerned parent solutions and the corresponding location value can be acquired by following the following heuristic:

IF $Pos1 = 1$
    $LLoc1 \leftarrow n, RLoc1 \leftarrow Pos1 + 1$
Else IF $Pos1 = n$
    $LLoc1 \leftarrow Pos1 - 1, RLoc1 \leftarrow 1$
Else
    $LLoc1 \leftarrow Pos1 - 1, RLoc1 \leftarrow Pos1 + 1$
IF $Pos2 = 1$
    $LLoc2 \leftarrow n, RLoc2 \leftarrow Pos2 + 1$
Else IF $Pos2 = n$
    $LLoc2 \leftarrow Pos2 - 1, RLoc2 \leftarrow 1$
Else
    $LLoc2 \leftarrow Pos2 - 1,\ RLoc2 \leftarrow Pos2 + 1$

The location of adjacent cities in the parent solutions are used to find the city with the least distance from the Cur_City is determined,

$$d_1 \leftarrow DM(P\_Indiv1(LLoc1), P\_Indiv1(Pos1)) \qquad (6)$$
$$d_2 \leftarrow DM(P\_Indiv1(Pos1), P\_Indiv1(RLoc1)) \qquad (7)$$
$$d_3 \leftarrow DM(P\_Indiv1(LLoc2), P\_Indiv1(Pos2)) \qquad (8)$$
$$d_4 \leftarrow DM(P\_Indiv1(Pos2), P\_Indiv1(RLoc2)) \qquad (9)$$

The location of adjacent cities in the parent solutions are used to find the city with the least air pollution from the Cur_City is determined,

$$p_1 \leftarrow POLL(P\_Indiv1(LLoc1), P\_Indiv1(Pos1)) \quad (10)$$
$$p_2 \leftarrow POLL(P\_Indiv1(Pos1), P\_Indiv1(RLoc1)) \quad (11)$$
$$p_3 \leftarrow POLL(P\_Indiv1(LLoc2), P\_Indiv1(Pos2)) \quad (12)$$
$$p_4 \leftarrow POLL(P\_Indiv1(Pos2), P\_Indiv1(RLoc2)) \quad (13)$$

Normalizing the calculated adjacent cities distance and pollution values using equation (14) and (15).Ω_z Represents the tradeoff values for distance and pollution of each adjacent city that is estimated using equation (16).

$$\forall[1, \le t \le 4], D_t' = \frac{D_t}{\sum_{x=1}^{4} D_x} \quad (14)$$
$$\forall[1, \le t \le 4], P_t' = \frac{P_t}{\sum_{x=1}^{4} P_x} \quad (15)$$
$$\forall[1, \le z \le 4], \Omega_z \leftarrow D_z' + P_z' \quad (16)$$

The least tradeoff value among the four $\Omega_1, \Omega_2, \Omega_3 \, and \, \Omega_4$ is selected and the city at the corresponding location of the concerned parent is chosen as the next city $Next\_City$. The chosen city $Next\_City$ is verified for two conditions,

Condition 1: The chosen city should not present in the partially built offspring i.e. $Next\_City \notin Indiv$.

Condition 2: The pollution value between the current city Cur_City and the chosen next city $Next\_City$ should be within the maximum pollution limit $POLL_{Cur\_City, Next\_City} < Max\_Poll$.

If the chosen city satisfies both the conditions, it is added as the next city in the offspring$Indiv$ and the length of the offspring is incremented, $Length \leftarrow Length + 1$ otherwise the city with next least distance is chosen and verified. If all the possible cities are checked, next city is added randomly. The same steps are repeated until the length of the offspring $Indiv1$ is n which indicates that the offspring is a feasible solution/route of n cities. The similar procedures are followed to construct the second offspring $Indiv2$. The swap mutation is applied at the resultant offspring's by exchanging the randomly chosen cities equation (17) and (18), within the offspring as,

$$GeneC1 \leftarrow RAND\,(1,n,) \quad (17)$$
$$GeneC2 \leftarrow RAND\,(1,n) \quad (18)$$
$$Indiv(GeneC1) \leftarrow Indiv(GeneC2) \quad (19)$$
$$Indiv(GeneC2) \leftarrow Indiv(GeneC1) \quad (20)$$

This stage confirms that the construction of offspring is completed and it is included in the next population and the size of the population is incremented $Size \leftarrow Size + 1$. The generation of next population Pop of individuals is said to be completed if the $Size = PopSize$ and the population generation is repeated for G number of times, then the execution stops. The final population is assessed for the best solution in terms of distance and pollution using equation (21) and (22) respectively.

$$\forall[1, \le i \le PopSize], TC_i \leftarrow \sum_{j=1}^{n} DM(Indiv_i(j), Indiv_i(j+1)), \quad j+1 \equiv 1 \quad (21)$$
$$\forall[1, \le i \le PopSize], TP_i \leftarrow \sum_{j=1}^{n} POLL(Indiv_i(j), Indiv_i(j+1)), \quad j+1 \equiv 1 \quad (22)$$

METHODS

As discussed in section 3, The Hybrid Optimal based Routing in TSP is based on the tradeoff between the distance and air pollution exploring this problem as a multi objective. The intension is to find the optimal route based on "the total distance of the route" and "the total air pollution of the route". In each of the performance criteria associated with this scenario, the cost refers to the total distance of the solution obtained.

IIOAB JOURNAL ISSN: 0976-3104

Hybrid optimal routing in VRP

In this scenario of experiments, the intelligent routing in VRP has been performed by optimizing the total distance of the route and the total air pollution of the route. Experimental results for this scenario were analyzed with Random, Nearest Neighbor and ODV based EV population seeding techniques are shown in the [Table 1]. From the [Table 1] following observations can be made:

Observation 1: For all the problem instances, the ODV-EV population seeding technique yields higher convergence rate for the best individual within the population w.r.t air pollution and distance. In best convergence rate or the maximum convergence rate for distance obtained in ODV-EV technique is 98.830% for eil51 and for the air pollution the Maximum of 100% obtained in ODV-EV technique for eil51. The minimum convergence rate for distance and air pollution are 40.407% and 57.213% obtained in random technique for the instance KroA100.

Observation 2: It is observed from the result that the worst convergence rate or the worst individuals in the population of ODV-EV technique showed better performance. The maximum and minimum convergence rate obtained in NN and Random technique are 57.139% and -42.884 for distance. The worst individuals acquired for Air pollution with the maximum rate of 76.864 and the minimum rate of -53.138.

Observation 3: Performance analyses in distance based on the error rate reveal that the ODV-EV technique performs outstandingly and has maximum of 19.234% for the instance Swiss42 where as NN and random techniques have maximum of 40.412% and 59.593% respectively for the instance KroA100. The minimum and maximum worst error rate in terms of air pollution obtain from that worst individuals are 23.136 % in ODV-EV for the instance KroA100 and 153.138% in NN technique for the instance uysses22.

Observation 4: The average convergence is working better in ODV –EV technique, Average Convergence for Hybrid Optimal routing (Pollution) is less in small cities, and it increases gradually when we are moving towards the large instances. The average convergence of NN technique is less than the random technique. As it is the evident from [Table 1], both the minimum and maximum average convergences for pollution is obtained in ODV-EV technique ranges from -18.298 to 84.636 in uysses22 and eil51 respectively.

Observation 5: The Convergence diversity of distance as well as pollution values of all the instances is better in ODV-EV technique. The minimum and maximum values of convergence rate w.r.t distance are acquired in random technique are 38.684 and 91.535. The convergence diversity w.r.t pollution in ODV-EV technique is obtained the minimum value is 18.545 and the maximum value is 150.29.

Observation 6: It is observed from the [Table 1] that, the computational time varies for each problem instances. Based on the Problem Instance, ODV-EV and NN techniques showed a gradual increase. The performance of random technique is irregular and it showed unexpected changes in the computation time for the instance eil76. The ODV-EV technique performs well and has less computational time for the entire instance except eil76.

RESULTS

In this section we have discussed each and every performance factors of the proposed system and also from the result we have identified ODV-EV seeding technique performs better than other seeding techniques. The rest of the section is evident the performance of the proposed system.

Best Convergence rate w.r.t distance: The best convergences of distance in ODV-EV technique of are performing well when compared to the best convergence of distance in other techniques. The NN technique is performing better than the random technique in many instances as showed in the [Fig.2]. The performance of random technique for each instance is uneven, gradually decreased, then increased and then decreased.

Best Convergence rate w.r.t pollution: From the Graph it is analyzed that, the best convergence of pollution in NN and Random techniques have showed lower performance, when compare to the best convergences of pollution in ODV-EV technique. Most of the time the performance of random technique is superior to the NN technique in many instances is showed in the [Fig.8]. Moving towards the higher instances the convergence - rate is gradually decrease in ODV-EV and NN technique, in case of random technique sudden decrease in best convergence rate.

Best Error rate w.r.t distance: the best convergence rate is high in ODV-EV; obviously the best error rate is less in ODV-EV technique. Because, the pollution in the path between current city and the next minimum distance city is high. It will move to the next minimum distance city. So the convergence rate is high and the error rate is less. The random technique has higher error rate than the NN technique in many instances is showed in the [Fig.3], shows that the performance of NN technique is better than the random technique.

IIOAB JOURNAL
ISSN: 0976-3104

Best Error rate w.r.t pollution: The [Fig.9] showed that the Best convergence rate is higher for every instance, which clearly states that the best error rate of ODV-EV is lower than other techniques. This openly implies the quality of the individuals in the population of the desire technique. Based on comparison and analysis of NN and Random technique, random has satisfactory performance projected in [Fig. 9].

Convergence diversity w.r.t distance: The convergence diversity is an aspect that illuminates the distribution of good and bad quality individuals among the population. It plays a vital role to increase the chance of evolving optimal solutions and to avoid premature convergence. [Fig.7] shows the convergence diversity of the optimal distance based routing scenario using different population seeding techniques for the problem instances. From the [Fig.7], it is understood that the ODV-EV technique has lesser convergence diversity w.r.t. other population seeding techniques which shows that the quality of individuals is improved as a population rather than the single individual. For most of the instances, random and NN techniques have nearly equal convergence diversity.

Convergence diversity w.r.t. Air Pollution: The convergence diversity of the air pollution based optimal routing scenario using different population seeding techniques for the problem instances in shown in the [Fig.13]. From the [Fig.13], it is observed that the convergence diversity of the instances decreases with increase in the problem size despite the population technique applied.

Average convergence w.r.t distance: The Average convergence of a population is used to measure the quality of the population generated by finding the average of fitness of individuals in the population as shows in [Fig.6] the average convergence rate for hybrid optimal routing (distance) using different population seeding techniques for the problem instances. From the [Fig.6], it can be observed that every population seeding technique yields better average convergence rate for some of the large size problem instances than the small size instances. For most of the instances, the ODV-EV technique outperforms other population initialization techniques and random performs worst for the larger size instances. For the instance bays29, performance of random, NN and ODV-EV techniques are very poor; this is possibly because of the peculiarity of the instance with small size and large distance based fitness value.

Average convergence w.r.t pollution: [Fig.12] shows the average convergence rate for air pollution based optimal routing using different population seeding techniques for the problem instances. From the [Fig.12], it can be understood that average convergence rate increases with increase in the size of the problem instances regardless of the population technique used. In the case of average convergence rate, all the population seeding techniques perform nearly equal though ODV-EV technique yields marginally better result than other techniques.

Average error rate w.r.t distance: The average error rate is working better in ODV –EV technique, compare to other techniques. Average error rate of NN technique is less than the random technique is showed in [Fig.14]. The performance of random technique is unpredictable; it shows huge variation for each problem instance, this evidently indicates that the quality of the individuals in the population is less.
Average error rate w.r.t pollution: the Average error rate w.r.t pollution, the ODV-EV technique shows high values in smaller instances and performance is increases as increase in problem instance. The [Fig.15] exposed, that the average convergence of NN technique showed a reasonable output for all the instances. The analysis shows that performance of NN technique in terms of average convergence is better than other techniques.
[
Worst Convergence rate w.r.t distance: [Fig.4] shows the worst convergence rate for Worst Convergence Rate for Hybrid Optimal routing (Distance) using different population seeding techniques for the problem instances. From the [Fig.4], it can be observed that ODV-EV technique yields better results than the NN and random technique. For the instance eil51, the random technique outperforms than the other techniques.

Worst Convergence rate w.r.t Pollution: The worst convergence rate of distance and pollution in ODV- EV technique is good, than the other two techniques. [Fig. 10] shows the worst convergence rate for optimal pollution based routing using different population seeding techniques for the problem instances. From the [Fig.10], it is observed that every population seeding technique yields better, worst convergence rate for some of the large size problem instances than the small size instances.

IIOAB JOURNAL
ISSN: 0976-3104

Instance	Seeding Technique	Model	Optimal Solution	Computation Time	Quality of the Solution			Convergence Rate (%)		Error Rate (%)		Convergence Diversity	Average Convergence
					Best	Worst	Average	Best	Worst	Best	Worst		
		Pollution	2.5596		2.849	6.120	5.092	88.686	-39.100	11.314	139.100	127.786	1.044
	EV	distance	74.1087	11.230	82.465	124.907	109.448	88.725	31.454	11.275	68.546	57.270	52.315
		Pollution	2.5596		2.915	6.418	5.070	86.134	-50.737	13.866	150.737	136.871	1.923
	NN	distance	74.1087	11.370	84.086	130.483	113.127	86.537	23.930	13.463	76.070	62.606	47.350
		Pollution	2.5596		2.887	6.378	4.918	87.211	-49.187	12.789	149.187	136.399	7.863
uysses16	Random	distance	74.1087	11.270	83.914	135.927	110.031	86.768	16.585	13.232	83.415	70.184	51.528
		Pollution	3.194		3.462	8.002	6.972	91.603	-50.537	8.397	150.537	142.140	-18.298
	EV	distance	75.6615	16.700	80.566	129.462	129.719	93.518	28.893	6.482	71.107	64.624	28.553
		Pollution	3.194		3.285	8.085	6.529	97.152	-53.138	2.848	153.138	150.290	-4.429
	NN	distance	75.6615	17.190	93.653	155.851	131.725	76.221	-5.984	23.779	105.984	82.205	25.902
		Pollution	3.194		2.976	7.872	6.136	83.762	-46.474	16.238	146.474	130.236	7.878
uysses22	Random	distance	75.6615	16.850	95.554	148.302	132.271	73.708	3.993	26.292	96.007	69.715	25.181
		Pollution	5.1614		5.609	9.234	9.429	91.330	21.095	8.670	78.905	70.235	17.317
	EV	distance	2020	21.860	2186.000	3842.800	4024.220	91.782	9.762	8.218	90.238	82.020	0.781
		Pollution	5.1614		6.511	10.454	8.932	73.861	-2.544	26.139	102.544	76.406	26.955
	NN	distance	2020	23.830	2800.000	4622.600	3990.376	61.386	-28.842	38.614	128.842	90.228	2.457
		Pollution	5.1614		6.186	10.773	9.331	80.153	-8.724	19.847	108.724	88.877	19.209
bays29	Random	distance	2020	23.510	2946.600	4795.600	4149.330	54.129	-37.406	45.871	137.406	91.535	-5.412
		Pollution	6.2613		7.466	8.762	9.561	80.766	60.061	19.234	39.939	20.705	47.297
	EV	distance	1273	23.550	1330.600	1918.800	1642.133	95.475	49.269	4.525	50.731	46.206	71.003
		Pollution	6.2613		8.301	9.925	9.219	67.416	41.489	32.584	58.511	25.928	52.766
	NN	distance	1273	22.730	1474.400	2134.400	1807.974	84.179	32.333	15.821	67.667	51.846	57.975
		Pollution	6.2613		8.120	9.785	9.028	70.314	43.727	29.686	56.273	26.587	55.808
swiss42	Random	distance	1273	23.040	1486.400	2050.400	1777.124	83.236	38.932	16.764	61.068	44.305	60.399
		Pollution	7.6588		7.659	10.669	8.835	100.000	60.697	0.000	39.303	39.303	84.636
	EV	distance	426	28.290	430.983	683.409	516.770	98.830	39.575	1.170	60.425	59.255	78.693
		Pollution	7.6588		8.257	11.268	10.016	92.183	52.872	7.817	47.128	39.311	69.227
	NN	distance	426	28.850	471.989	725.836	606.292	89.205	29.616	10.795	70.384	59.589	57.678
		Pollution	7.6588		7.974	10.073	9.285	95.879	68.484	4.121	31.516	27.395	78.768
EIL51	Random	distance	426	29.550	443.793	608.587	543.201	95.823	57.139	4.177	42.861	38.684	72.488
		Pollution	11.3454		11.554	15.132	13.993	98.163	66.620	1.837	33.380	31.543	76.667
	EV	distance	538	48.020	551.174	850.545	761.941	97.551	41.906	2.449	58.094	55.645	58.375
		Pollution	11.3454		13.157	16.341	15.162	84.036	55.971	15.964	44.029	28.064	66.356
	NN	distance	538	46.190	632.503	901.407	798.463	82.434	32.452	17.566	67.548	49.982	51.587
		Pollution	11.3454		13.199	16.510	15.207	83.658	54.477	16.342	45.523	29.181	65.959
eil76	Random	distance	538	30.470	638.987	950.171	805.874	81.229	23.388	18.771	76.612	57.841	50.209
		Pollution	14.5057		15.172	17.862	17.096	95.408	76.864	4.592	23.136	18.545	82.143
	EV	distance	21285	55.690	21918.398	33873.150	30479.214	97.024	40.859	2.976	59.141	56.165	56.804
		Pollution	14.5057		19.222	22.244	21.007	67.490	46.652	32.510	53.348	20.838	55.184
	NN	distance	21285	60.120	29886.677	46054.165	40052.584	59.588	-16.369	40.412	116.369	75.957	11.827
		Pollution	14.5057		20.712	23.666	22.315	57.213	36.849	42.787	63.151	20.364	46.162
kroA100	Random	distance	21285	64.220	33969.432	51697.878	43604.118	40.407	-42.884	59.593	142.884	83.291	-4.858

Table 1: Result analysis of Hybrid optimal based routing

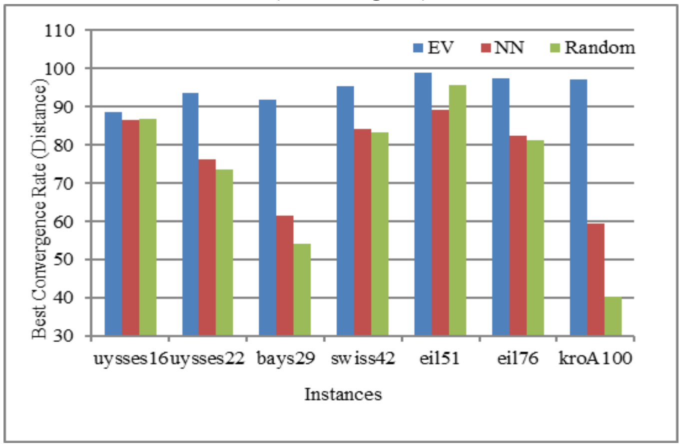
Worst Error rate w.r.t distance: [Fig.5] indicate that the ODV-EV technique performing better than the NN and random technique and it got lower values for all the instances. Although the performance of ODV-EV technique showed good result in worst error rate, the random technique showed a least value for the instance eil51. For most of the instances the worst error rate of NN technique is lesser than the random technique, infers the NN performance is better than the random technique.

Worst Error rate w.r.t Pollution: As shown in the figure [Fig.11], it is clearly perceptible that the worst convergence rate of pollution in ODV- EV technique is virtuous, apart from the other two techniques. It has been observed that, the performance of worst convergence rate in terms of pollution in NN and random technique are inversely proportional to the performance of worst convergence rate in terms of distance. In pollution, the performance of random technique is superior to the NN technique.

Computational Time: [Fig.16] significantly proves that the computation time increases based on the problem instances, each technique has its own computation time for every problem instances. In terms of computation time, it is obvious that the random technique showed good result in classical TSP or any other problem. In this

IIOAB JOURNAL
ISSN: 0976-3104

case, each technique should validate the pollution between the corresponding cities before adding the next city. Hence, the computation time of each technique for different instances has slight changes. Furthermore, analyzed from the [Fig.16] the random technique has showed an abnormal change for the instance eil51, except that the ODV-EV technique shows good performance.



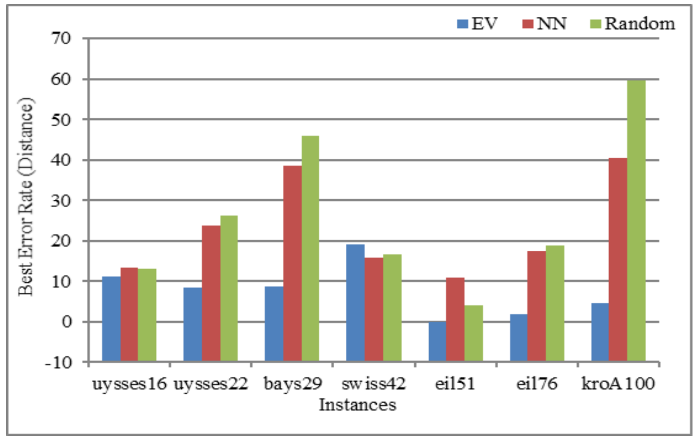
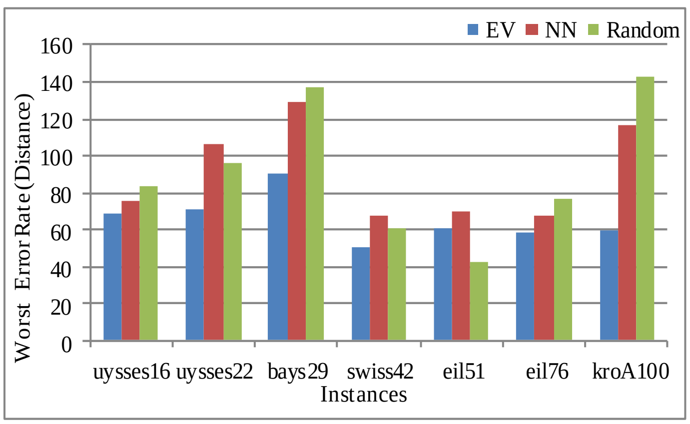


Fig.2: Best convergence rate for hybrid optimal routing (Distance).

Fig.3: Best error rate for hybrid optimal routing (Distance).

……………………………………………………………………………………

……………………………………………………………………………………



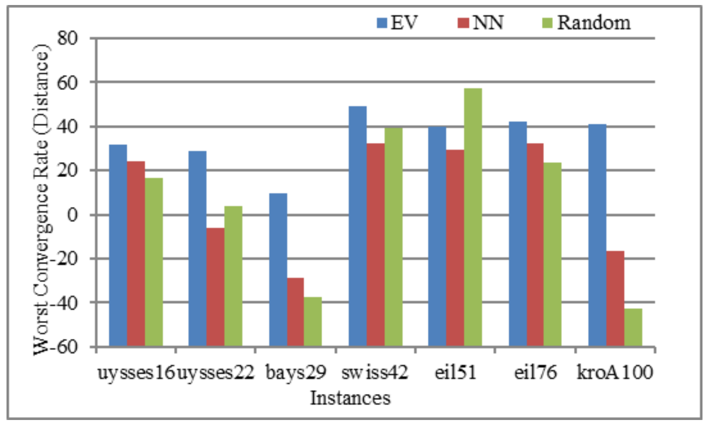
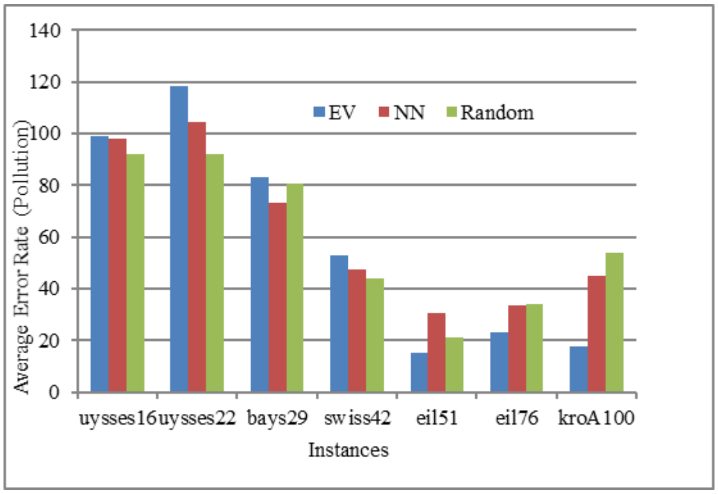


Fig. 4: Worst Convergence Rate for Hybrid Optimal routing (Distance).

Fig. 5: Worst error rate for hybrid optimal routing (Distance).

………

ISSN: 0976-3104



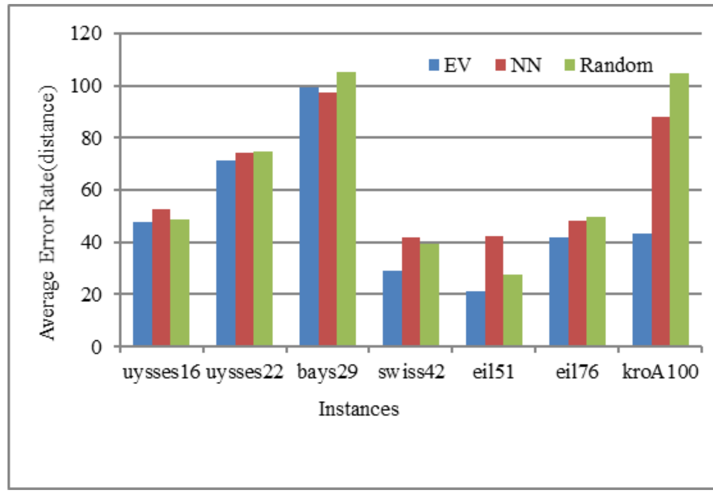


Fig. 14: Average error rate for hybrid optimal routing (Distance). **Fig. 15:** Average error rate for hybrid optimal routing (Pollution).

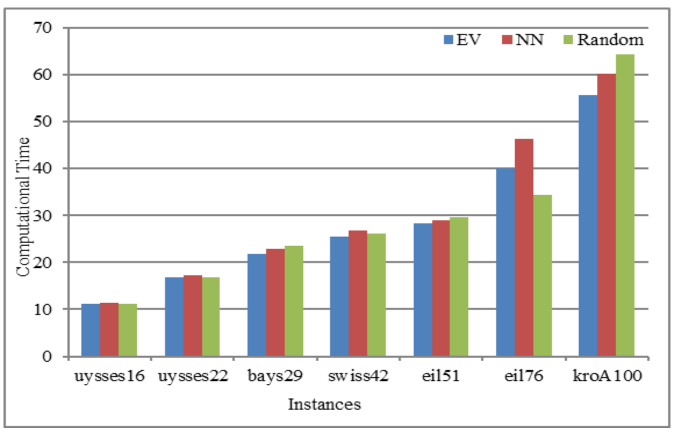


Fig.16: Computational Time for Hybrid Optimal routing.

CONCLUSION

In summary, we proposed and investigated hybrid optimal based routing with different GA initialization techniques like Random, NN and ODV-EV techniques respectively for finding the best optimal (pollution free as well as minimum distance) route for transportation system. We have analyzed our algorithm with standard TSP bench marks and we created the corresponding air pollution matrix, for the instances ulysses16, ulysses22, bays29, att48, eil56, eil76 and kroA100. In the result analysis, we have analyzed our algorithm with different validation criteria's like Best convergence rate, worst convergence rate, average convergence rate, Best error rate, worst error rate and convergence diversity. The algorithm performed well in the ODV-EV technique for all the TSP instances. Next The NN technique is performing better in many instances than the random technique. The ODV-EV technique for optimal distance based routing yielding the best distance convergence of 95.560 % in the instance eil51 and for the optimal pollution based routing yields the best pollution convergence 98.29% in the instance eil76. The hybrid optimal based routing algorithms best convergence rate of distance and pollution are 98.830 % and 100 % in the instance eil51. Since we are calculating the distance from the display coordinates, we are not getting 100%

IIOAB JOURNAL
ISSN: 0976-3104

best convergence rate. From results we analyzed that the ODV-EV technique is performing well. To improve the smartness of ITS we are focusing on enacting this proposed green computing VRP model with VANET for providing next generation ITS.

CONFLICT OF INTEREST

We, Dr. M. Shanmugam* and Dr. J. Amudhavel authors of the manuscript titled "REVENANT OF THE ECOSYSTEM: AN ENVIRONMENTAL BASED GREEN COMPUTING MODELS FOR VEHICULAR ROUTING PROBLEMS USING GENETIC ALGORITHM OPTIMIZATION APPROACH" declaring that there is no conflict of interest regarding the publication of this paper in Institute of Integrative Omics and Applied Biotechnology-IIOAB.

ACKNOWLEDGEMENTS

This work is not part of any organization or institution.

FINANCIAL DISCLOSURE

This work doesn't get any financial assistance.

REFERENCES

[1] Shanmugam M, Saleem Basha MS, Dhavachelvan P, Baskaran R. [2013] Performance Assessment over Heuristic Population Seeding Techniques of Genetic Algorithm: Benchmark Analyses on Traveling Salesman Problems, International Journal of Applied Engineering Research, Research India Publications, 10(8):1171-1183.

[2] Ling-NingXing, Ying-Wu Chen, Ke-Wei Yang, FengHou, Xue-Shi Shen, Huai-Ping Cai. [2008] A hybrid approach combining an improved genetic algorithm and optimization strategies for the asymmetric traveling salesman problem, Engineering Applications of Artificial Intelligence 21:1370–1380.

[3] Albayrak M, Allahverdi N.[2011] Development a new mutation operator to solve the traveling salesman problem by aid of genetic algorithms, Expert Systems with Applications 38:1313–1320.

[4] Helsgaun K.[2000] An effective implementation of the Lin–Kernighan traveling salesman heuristic, European Journal of Operational Research 126(1):106–130.

[5] Marinakis Y, Migdalas A, Pardalos PM.[2005] Expanding neighborhood GRASP for the traveling salesman problem. Computational Optimization and Applications 32: 231–257.

[6] Milthers NPM. [2009] Solving VRP using Voronoi Diagrams and Adaptive Large Neighborhood Search. Master's thesis, University of Copenhagen, Denmark.

[7] Vose MD.[1998] The simple genetic algorithm: foundations and theory." Cambridge, MA: MIT Press, Book

[8] Subramanian A, Penna PHV, Uchoa E, Ochi LS.[2012] A hybrid algorithm for the heterogeneous fleet vehicle routing problem. European Journal of Operational Research 221 :285–295.

[9] Anand Subramanian., Eduardo Uchoa .[2010] Luiz Satoru Ochi., A hybrid algorithm for a class of vehicle routing problems, Computers & Operations Research 40:2519–2531.

[10] Martin Josef Geiger. Fast Approximation Heuristics for Multi-Objective Vehicle Routing Problems. In: Di Chio C et al. (Eds.): Evo Applications, Part II, LNCS 6025

[11] Shubhra SR, Sanghamitra B, Sankar KP.[2007] Genetic operators for combinatorial optimization in TSP and microarray gene ordering, Journal of Applied Intelligence 26: 183-195.

[12] Yannis Marinakis, Magdalene Marinakib, Georgios Dounias.[2010] A hybrid particle swarm optimization algorithm for the vehicle routing problem, Engineering Applications of Artificial Intelligence 23 :463–472.

[13] Yannis Marinakis, Georgia-Roumbini Iordanidou., Magdalene Marinaki. [2013]Particle Swarm Optimization for the Vehicle Routing Problem with Stochastic Demands, Applied Soft Computing 13: 1693–1704.

[14] Kennedy J, Eberhart R.[1995] Particle swarm optimization. Proceedings of 1995 IEEE International Conference on Neural Networks 4: 1942–1948.

[15] Ropke S, Pisinger D.[2006] An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. Transportation Science 40 (4):455–472.

[16] Mostepha R, Khouadjia, Briseida Sarasola, Enrique Alba, Laetitia Jourdan El, GhazaliTalbi A.[2012] comparative study between dynamic adapted PSO and VNS for the vehicle routing problem with dynamic requests, Applied Soft Computing 12:1426–1439.

[17] Gorges-Schleuter M.[1997] Asparagos96 and the traveling salesman problem, Proceedings of IEEE International Conference on Evolutionary Computation, Indianapolis, 171–174.

[18] Merz P, Freisleben B.[1997] Genetic local search for the TSP: new results. In: Proceedings of the IEEE International Conference on Evolutionary Computation. IEEE Press, Indianapolis, 159–164.

[19] Ross BJ.[1999] A Lamarckian evolution strategy for genetic algorithms, Practical Handbook of Genetic Algorithms: Complex Coding Systems, 3: 1–16.

[20] Norstad I.[2011] Agerholt, Laporte, G, Tramp ship routing and scheduling with speed optimization. Transportation Research Part C: Emerging Technologies & Science 5: 853–865.

[21] Winter G, Périaux J, Galaán M, Cuesta P.[1995] Genetic algorithms in engineering and computer science, New York: Wiley

[22] Jozefowiez N, Semet F, Talbi EG.[2008] Multi-objective vehicle routing problems. European Journal of Operational Research 189(2):293–309.

[23] Park YB, Koelling CP.[1989] An interactive computerized algorithm for multi-criteria vehicle routing problems. Computers & Industrial Engineering 16(4):477–490.

[24] Solomon MM.[1987] Algorithms for the vehicle routing and scheduling problems with time windows constraints. Operations Research 35(2):254–265.

[25] Marinakis Y, Migdalas A, Pardalos PM.[2005] A hybrid genetic—GRASP algorithm using Lagrangian relaxation for the traveling salesman problem. Journal of Combinatorial Optimization 10: 311–326.

[26] Victer Paul, Ramalingam P, Baskaran A, et al. [2013] Performance Analyses on Population Seeding Techniques for Genetic Algorithms, International Journal of Engineering and Technology 5 (3):2993-3000.