HYBRID APPROACH FOR ORDER-BASED OPTIMIZATION USING EVOLUTIONARY ALGORITHMS: CASE OF CAPACITATED VEHICLE ROUTING PROBLEM

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ABSTRACT

Evolutionary Algorithms (EA) have proved their efficiency in solving combinatorial optimization problems. However, in the literature, the proposed solutions focused on the use of a single crossover and/or mutation operators. Hence, our work studies the possibilities of classifying and combining these variation operators resulting in a better performance. We propose a Hybrid Genetic Algorithm combining different strategies and operators in pursuance of a better population diversity and elitism preservation. The HGA is applied to the Capacitated Vehicle Routing Problem (CVRP) and it could be easily extended to any problem that could be formulated as an order-based optimization problem.

PROBLEM FORMULATION

The vehicle routing problem (VRP) is an important problem class in the field of operations research and transport logistics optimization. Its original formulation has been defined over 60 years ago by [1] and consists of a fleet of identical vehicles serving a set of customers with a certain demand from a single depot and having a certain capacity. This formulation is referred to as the capacitated vehicle routing problem (CVRP).
The CVRP can be stated as follows:

$$min \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{K} d_{ij} X^{k}_{i,j}$$

where $$X^{k}_{i,j} = \begin{cases} 1 & if\ the\ vehicle\ V_k\ travels\ from\ node\ i\ to\ node\ j \\ 0 & otherwise \end{cases}$$

Determining the optimal solution to CVRP is NP-Hard since it has to verify a set of constraints:

- Each customer has to be visited only once.
- The total demand of the customers being served by a vehicle does not exceed the vehicle capacity.
- All routes start and finish at the depot.
- There are a maximum of K routes for serving the customers.

Solution Encoding as Order-Based Representation

To encode CVRP solution, we used a vector representation encapsulating the significant informations for each individual.

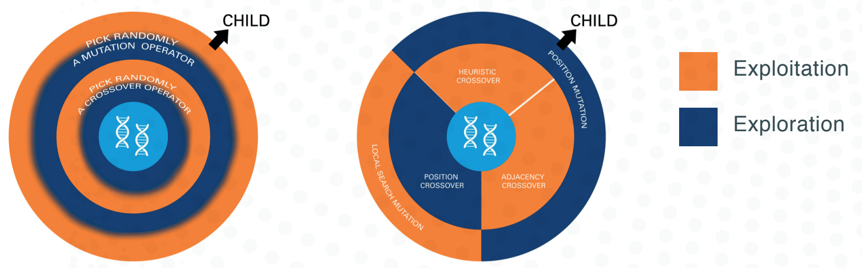
ALGORITHM: THE HYBRID STEADY STATE GENETIC ALGORITHM (HSSGA)

1: Initialize population with N feasible solutions
2: Evaluate initial population
3: **While** Non Stop Condition **do:**
4: Select two parents(Pi ,Pj) from the population using tournament selection
5: C ← Reproduction(Pi ,Pj) // Random or Balanced Hybridization
6: Select randomly an individual W from the population's second half according to either fitness or violation rate
7: Replace W with C in the population
8: **end**

HYBRIDIZATION STRATEGIES

One of the main problems encountered when using the same operators class for both crossover and mutation is Premature Convergence. It occured when the population converges too early, exposing that the genetic operators are not able to generate offsprings outperforming their parents. To prevent this phenomenon, combining these operators regarding their nature (exploitative or explorative) can lead to better performance. We designed the two hybridization strategies below :

- Random Hybridization: It consists of selecting randomly a crossover and mutation operators and use them respectively to generate an offspring.
- Balanced Hybridization: It aims to balance the GA exploration and exploitation abilities by mixing heuristic operators with position operators.



Random Hybridization Balanced Hybridization

STEADY STATE

The steady state genetic algorithm is a simpler version of the generational and consists of selecting two parents, crossing and mutating them, to finally obtain an offspring inserted to the population. Compared to generational replacement, where a larger portion of the population is replaced, It was shown in [2] that genetic drift is accelerated when using steady state replacement instead of generational replacement.

COMPUTATIONAL RESULTS

We compared our results to the current best results available online (accessed on August 5th 2019). We record the best found solution as well as the worst in each of 30 independent, randomly initialized GA runs using different hybridization strategies.
The results are listed in Table.1

					Random Hybridization				Balancing Hybridization			
Instance	C	Q	V	BKS	*Best*	*Worst*	*Average*	*% Deviation*	*Best*	*Worst*	*Average*	*% Deviation*
A-n32-k5.vrp	32	100	5	784	**784**	856	806	0	**784**	866	803	0
A-n33-k5.vrp	33	100	5	661	**661**	714	689	0	**661**	718	694	0
A-n33-k6.vrp	33	100	6	742	**742**	800	757	0	743	808	761	0.13
A-n34-k5.vrp	34	100	5	778	**778**	833	797	0	**778**	839	800	0
A-n36-k5.vrp	36	100	5	799	805	865	831	0.75	814	889	840	1.88
A-n37-k5.vrp	37	100	5	669	670	742	706	0.15	670	739	703	0.15
A-n37-k6.vrp	37	100	6	949	953	1206	1009	0.42	953	1311	1036	0.42
A-n38-k5.vrp	38	100	5	730	731	839	763	0.14	733	811	759	0.41
A-n39-k5.vrp	39	100	5	822	834	936	863	1.46	825	947	864	0.36
A-n39-k6.vrp	39	100	6	831	839	908	866	0.96	839	925	875	0.96
A-n44-k7.vrp	44	100	7	937	947	1040	984	1.07	957	1020	981	2.13
A-n45-k7.vrp	45	100	7	1146	1166	1238	1203	1.75	1176	1235	1206	2.62
A-n46-k7.vrp	46	100	7	914	953	1046	986	4.27	923	1034	978	0.98
A-n48-k7.vrp	48	100	7	1073	1115	1216	1164	3.91	1107	1190	1150	3.17
A-n53-k7.vrp	53	100	7	1010	1031	1316	1100	2.08	1038	2100	1189	2.77
A-n54-k7.vrp	54	100	7	1167	1193	2224	1362	2.23	1222	2582	1548	4.71
A-n55-k9.vrp	55	100	9	1073	1075	2287	1168	0.19	1104	2554	1507	2.89
A-n60-k9.vrp	60	100	9	1354	1414	3132	1596	4.43	1405	2522	1619	3.77
A-n62-k8.vrp	62	100	8	1290	1338	1601	1395	3.72	1349	2839	1456	4.57
A-n63-k9.vrp	63	100	9	1634	1685	3469	2441	3.12	1717	3594	2960	5.08
A-n64-k9.vrp	64	100	9	1402	1472	3288	1903	4.99	1459	2923	2136	4.07
A-n65-k9.vrp	65	100	9	1177	1289	3474	2698	9.52	1219	3434	2754	3.57
A-n69-k9.vrp	69	100	9	1168	1186	3325	1491	1.54	1219	3284	1549	4.37
A-n80-k10.vrp	80	100	10	1764	1827	3961	2266	3.57	1831	4092	2529	3.8

Table.1 : Results of running HSSGA on CVRP: A-set instances

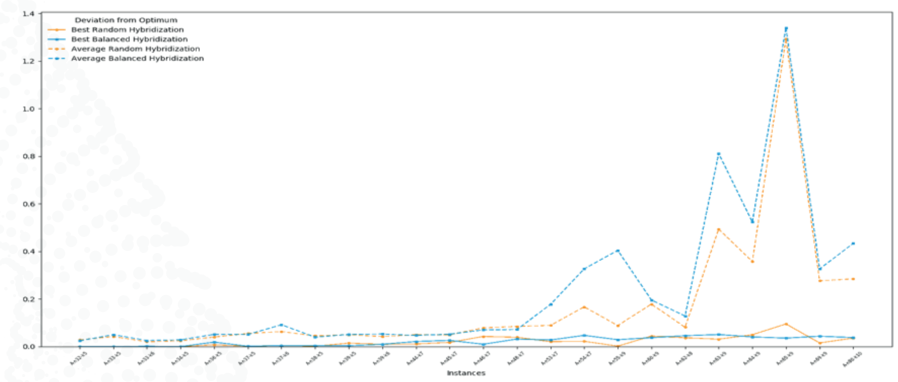
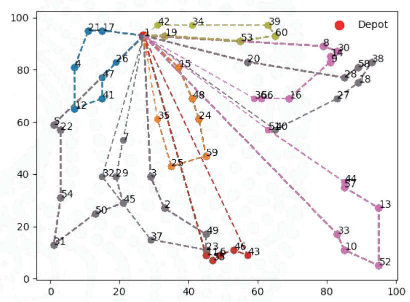
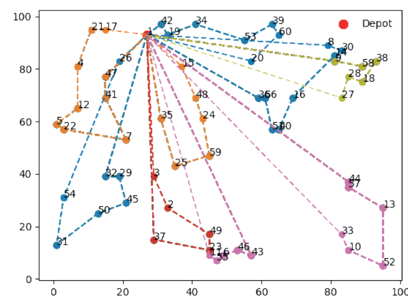


Figure.2 : Random vs Balanced hybridization



Optimal solution routes
1354



Optimal solution routes
1408

Conclusion

The conducted work expose that evolutionary algorithms can lead to remarkable results for solving the CVRP problem. Nevertheless, different strategies involving the nature of crossover/mutation operators, the selection methods, and replacement strategies affect the population evolution and fitness. Taking the described factors into consideration, two strategies were designed and were able to act optimally on some instances while delivering good solutions on others. Thus, It can be concluded that problem-specific tuning would be necessary for instances more than 60 customers.

References

[1] G. B. Dantzig and J. H. Ramser, "The truck dispatching problem", Management Science, vol. 6, no. 1, pp. 80–91, 1959.
[2] A. Rogers and A. Prugel-Bennett, "Modelling the dynamics of a steady state genetic algorithm," Foundations of Genetic Algorithms 5 , pp. 57– 68, September 1999.