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An Optimized Solution to Multi-Constraint Vehicle Routing Problem

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***Abstract*-A Vehicle Routing Problem (VRP) is a Non-Polynomial Hard Category (NP-hard) problem in which the best set of routes for a convoy of vehicles is traversed to deliver goods or services to a known set of customers. In VRP, some constraints are added to improve performance. Some variations of VRP are Capacitated Vehicle Routing Problem (CVRP), Vehicle Routing Problem with Stochastic Demands (VRPSD), Vehicle Routing Problem with Time Window (VRPTW), Dynamic Vehicle Routing Problem (DVRP), and Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD) where vehicle and routes have multiple constraints. Swarm intelligence is a well-used approach to solve VRPs. Moreover, different hybrid combinations of global and local optimization techniques are also used to optimize the said problem. In this research, an attempt is made to solve CVRP with VRPSD by using two different hybridized population-based approaches, that is, the Cuckoo Search Algorithm (CSA) and Particle Swarm Optimization (PSO). The experiments showed the accuracy of the improved CVRP that is superior to one obtained by using other classical versions and better than the results achieved by comparable algorithms. Besides, this improved algorithm can also improve search efficiency.**

***Index Terms*-Cuckoo Search (CS), customer, Particle Swarm Optimization (PSO), Vehicle Routing Problem (VRP)**

I. Introduction

A set of customers with known locations across the route and known requirements to be supplied from a single depot, to design an optimal route for these vehicles to minimize cost and distance is known as Vehicle Routing Problem (VRP) [1]. The purpose of a VRP is to find out the ideal vehicle route from a set of customers' underside constraints. Over the passage of years, designing VRP has emerged as a new, exclusive, and enthralling topic for researchers in the IT market.

The benefits of VRPs are undeniable. They have been

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propitious in reducing the cost and distance of the selected route; however, there are certain difficulties associated with them as well. Opting for an optimized route and controlling fuel consumption while traveling across numerous/various routes is one of the major dilemmas faced by the world today [2]. In the Classical Vehicle Routing Problem (CVRP), a travel cost matrix is given, several identical capacitated vehicles are available, and customers have demands that would be enclosed when the vehicle came to the customer [3]. However, the current VRPs are unable to provide the best solution to ambiguous demands put forth by the customers. A VRP is an NP-hard problem [4]. In other words, there is a necessity for an upgraded and efficient way to solve the complicated routing issues.

This research deals with a novel variation of VRPs where customer demands are uncertain and are supposed to follow the given distinct probability distributions. It surveys the current literature on VRPs to identify the research gap. To overcome the shortcomings in the existing work, an algorithm is proposed that is inspired by the existing techniques of Particle Swarm Optimization (PSO) and Cuckoo Search Algorithm (CSA). The proposed algorithm provides an efficient model to deal with the constraints of VRPs, such as 'time window' and 'Pickup and Delivery' that heighten the processing time and distance. The proposed technique is also evaluated and compared with the existing techniques.

A. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a technique used to explore the search space of a given problem to find the settings or parameters required to maximize a particular objective [5]. It is a population-based swarm contact design. The basic steps of PSO are given below.

```
Algorithm 1: Working of PSO

Input: A Set of Reviews (Di)
Output: All Preprocessed Words (W^all)
For each particle, Initialize
Do
until maximum iterations or minimum error criteria
If the fitness value is better than pBest
Set pBest = current fitness value
If pBest is better than gBest

Set

pBest = current fitness value

If pBest is better than gBest

Set gBest = pBest

For each particle
Calculate particle velocity use gBest and velocity to update particle Data
End
```

B. Cuckoo Search Algorithm (CSA)

There are some intelligent and advanced algorithms developed for solving complex NP-hard problems [6]. Cuckoo Search Algorithm (CSA) is one of them and it is based on three idealized and important rules given below.

- Each cuckoo lays one egg at a time and dumps its egg in a randomly chosen nest.
- The best nest with high-quality eggs will carry over to the next generation.
- The number of available host nests is fixed and the egg laid by a cuckoo is discovered by the host bird with a probability pa ε [0, 1].

  The rest of the paper is organized as follows. Section 2 surveys the existing literature in detail, Section 3 presents and discusses the proposed technique, and the evaluation of the proposed approach is carried out in Section 4.

II. Literature Survey

Various issues concerning a VRP, such as the determination of the exact location as well as an optimized solution, are under the cogitation of the scientists. In this regard, multiple approaches adopted after thorough groundwork and probing by using various types of resources, including those from existing results and existing resources, have rendered useful results during the process.

Multiple problems related to routing have been focused from the determination of the exact location to the determination of the optimized solution. The problems have been resolved by making use of multiple resources i.e. The existing literature has been adding value in the existing times from existing results, from existing values, etc. in the domain.

In the study [5], the proposed technique is a hybrid chaotic Particle Swarm Optimization (PSO). The main aim of this technique is to solve the Capacitated Vehicle Routing Problem (CVRP). This task was accomplished by applying three main components. Firstly, a mutual mapping method was used to encrypt and decrypt between integers and decimal numbers solution [6]. Secondly, to attain chaotic initialization and to recommence ergodicity and compassion in the early conditions of the chaos theory ate utilized. Thirdly and finally, local search strategies, such as the neighborhood change approach and move scheme were used to get local search optimality between performing various experiments. Seemingly, the proposed technique is efficient and effective as compared to the previous research. It may produce very good results for small and medium-sized problems. However, for large scale problems, it needs more effort and time to give a pool of good results.

The authors [7] used an exact L-shaped algorithm to solve Vehicle Routing Problems with Stochastic Demands (VRPSD). They tackled/dealt with a failure situation in which a vehicle does not have enough resources to fulfill the required demand, which is acquired after the vehicle has reached the customer. When the failure happened, the vehicle returned to the depot and after procuring the required resources, it resumed its route from where it failed. In the end, it added to the cost of scheduled routes as well as the predictable recourse cost. This study also discussed three lower-bounding functions based on the generation of partial routes to identify violated cuts. A lot of experiments is taken place with 270 benchmarks instances.

The authors [8] worked on Vehicle Routing Problems with Simultaneous Pickup and Delivery (VRPSPD) using a heuristic approach. They used five neighborhood structures (crossover, swap, shift, exchange, and reverse) to update the position. For the presentation of a solution to the problem, the authors used combination encoding that is a huge tour with no trip delimiters.

A Robust Manifold Ant Colony System (RMACS) was proposed in [9] to generate a group of solutions based on several ant colonies . Further improbability was figured out by linear formulation in the field of vigorous optimization. In comparison with other solution pools, pools generated by RMACS are better and have a greater ability to improve the solution pools for Refrigerated Capacitated Vehicle Routing Problem (RCVRP).

The authors [10] worked on Capacitated Vehicle Routing Problems (CVRP) with inexact travel costs using the ant colony system. To handle uncertainty, they used a robust optimization methodology. Their approach was successful in generating sets of solutions with different conservatism levels. The algorithm was applied frequently and the results were obtained with different conservatism configurations. The proposed approach also dealt with uncertainty in the objective function.

VRP aims at discovering an optimum solution from a restrained set of results and is also considered to be an integer programming problem [11]. It was introduced by George Dantzig and John Ramser in 1959. The proposed approach was applied to petrol transportation. The basic purpose was to transport goods situated at a central point called depot to geo, which were the locations from where the figure calmly dispersed clients who placed orders for the particular goods. Achieving an optimum result of VRP is an NP-hard problem in combinatorial optimization, so there exists a circumscribed scope of issues that can be entangled/resolved perfectly.

The proposed LBF outperforms with lower bound activity on large solution space and for small solution space, a strong bond was required. The authors [12] solved two variants of VRP in their research, namely Multi-Depot VRP and Stochastic VRP. They solved, for the first time, a combination of MDVRP through stochastic time of travel by using Genetic Algorithms (GAs), a metaheuristic technique in evolutionary computation. In the first population, a hybrid population seeding method was planned to produce possible solutions. A random primary population generation depot clustering technique, nearest neighbor clustering. To obtain initial solutions, Clarke-wright saving algorithms were used and for scheduling further routes, Nearest Neighborhood Search was used. The results were compared with those offered by mixed populace seeding method. Afterwards, the results were matched with GA random initialization technique. It was found that the proposed results were better in terms of the time and distance traveled.

Different approaches for various solutions related to VRP have been implemented. VRP algorithm is an elaborate and extensive algorithm. It takes its inspiration from the general behavior of living organisms and generates adequate solutions following them [12-15]. The existing literature on VRP not only strives to analyze all the possible hindrances in achieving optimized solutions but also generates sufficient solutions in response to those hindrances.

III. Proposed Conceptual Model

The proposed model is described in two different sections namely Capacitated Vehicle Routing Problem with Stochastic Demands (CVRPSD) and Cuckoo Search Particle Swarm Optimization (CSPSO) algorithm. Scrutinizing the problems reveals that issues arise if constraints, such as Vehicle Capacity (VC) and Customer Stochastic Demand (CSD) are applied in VRP. Thus, an approach is introduced to recuperate the feasibility of the proposed model.

A. Capacitated Vehicle Routing Problem with Stochastic Demands

CVRP can be introduced as follows: Let $= (\mathrm{N}, \mathrm{E})$ be an undirected figure, where $\mathrm{N} = \{1,2, \ldots \ldots \mathrm{n}\}$ is the group of nodes and E is the group of ends. The number of vehicles used is unknown and remains a decision variable. Each route must begin and end at the same depot. Furthermore, its total load must not exceed vehicle capacity and the total load of the routes assigned to a depot must fit the capacity of that depot. The total cost of a route includes the sum of the costs of the traversed edges. The objective is to find the routes that should be created to diminish the entire cost.

Mathematically,

$$\text{mini} = \sum_{v_i=0}^{N} (TravelingCost) \qquad (a)$$

where v denotes vehicle and N denotes the total number of vehicles.

Another important issue that was improved in this research is the Vehicle Routing Problem with Stochastic Demands (VRPSDs) in which the customers have a finite demand T and there is a fixed capacity of vehicles. The vehicles are used to fulfill the demands of customers. There exist many ways to deal with this issue; however, in this research, a preventive restocking [11] approach was used.

Customer demands are revealed when a vehicle reaches a customer. There exist two possibilities after a vehicle has reached. Firstly, the vehicle has the resources to fulfill the demand and continue its tour. Secondly, the vehicle does not have enough resources to fulfill customer demands and returns to the depot for replenishment. After getting its maximum load, the vehicle once again starts its tour. The distance for vehicle travel for replenishment is an extra cost that increases the total cost of VRP. To get rid of this extra cost, ‘preventive restocking’ was used [11]. This type of mechanism allows the use of a threshold value. The detailed mathematical description of the prescribed model is as follows:

1) Model Variables

- No. of Customers (N)
- No. of Vehicles (K)
- Cost from customer $i$to

$j(C_{ij})$

- Service time required S_i where $S_0 = 0$
- Maximum load that a vehicle can lift (Q)
- Maximum distance a vehicle can travel (T)
- Demand of ith customer d_i , $d_0 = 0$
- Edge moved from customer i to j by vehicle k$\left(X_{ij}^k\right)$, $\left|X_{ij}^k\right| = \begin{cases} 1 & , ifitojtrevelledbyk \\ 0, & otherwise \end{cases}$
- Group of customers served by a Vehicle (R), $|R| iscordinalityofR$
- Penalty Coefficient (P)

2) Objective Function

$$f(x) = \text{minimize} \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K}\left(C_{ij}.X_{ij}^k\right), \quad (1)$$

Equation 1 is the objective function for CVRPSD. Where, C_{ij} represents the combined cost which is multiplied by the total edges X_{ij}^k that all the vehicles have covered t[o facilitate all customers.

3) Constraints

$$\sum_{k=1}^{K}\sum_{i=0}^{N} X_{ij}^k = 1 \quad , \quad j = 1,2,3 \dots, N, \quad (2)$$

$$\sum_{k=1}^{K}\sum_{j=0}^{N} X_{ij}^k = 1 , \quad i = 1,2,3 \dots, N. \quad (3)$$

Equations 2 and 3 confirm that every client can be attended by one vehicle only. One customer is facilitated by only one vehicle and vehicle k travels through an edge only once.

$$\sum_{i=0}^{N} X_{iu}^k - \sum_{j=0}^{N} X_{uj}^k = 0, k = 1,2 \dots, K \quad , u = 1,2 \dots, N. \quad (4)$$

Equation 4 maintains continuity at every customer for each vehicle. Equation 3.4 ensures that a tour is not broken in between customers and is completed. In this regard, X_{0u}^k is the starting point, while X_{iu}^k can be any central edge, and X_{uj}^k is the final edge that completes a tour.

$$\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ij}^k.di \le Q \quad , k = 1,2 \dots, K. \quad (5)$$

Equation 5 guarantees that the entire customer demand cannot surpass a vehicle's capacity. In this regard, X_{ij}^k is the product of all edges multiplied by each edge's cost di.

$$\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ij}^k(C_{ij} + Si \ ) \le T \quad , k = 1,2, \dots, K, \quad (6)$$

Equation 6 establishes that the total distance traveled by a vehicle cannot exceed the maximum distance limit of a vehicle. In this regard, X_{ij}^{k} comprises the edges in between customers that is multiplied with C_{ij} and Si service time by each customer.

$$\sum_{j=1}^{N} X_{ji}^{k} = \sum_{j=1}^{N} X_{ij}^{k} \leq 1, \quad i = 0, k = 1,2, \dots, K, \tag{7}$$

Equation 7 ensures that each vehicle's starting and ending point is the depot and it can be used at most once. Where, i=0 shows the central depot.

$$\sum_{i,j \in R}^{N} X_{ij}^{k} \leq |R| - 1, R \dot{\subseteq} |1, \dots\dots, N|, 2 \leq |R| \leq N - 1; k = 1, \dots, K, \tag{8}$$

Elimination inside a tour is settled by equation (8) which covers sub-tour elimination. All the tours which are broken during its tour are eliminated from total tours by minimizing X_{ij}^{k} by $|R|$.

$$X_{ij}^{k} \in \{0,1\}, \quad i, j = 0,1, \dots . N; \quad k = 1,2, \dots, K \tag{9}$$

Equation 9 is the integrality constraint. X_{ij}^{k} has the integrality value. Which has a binary value of 0 or 1.

Two penalty functions discussed in equations (5) and (6) are added to an objective function to increase the value of infeasible solutions. One penalty is for additional vehicle capacity and the other is for access/assessing vehicle's route length. So, the extended objective function becomes

$$f(x) = minimize \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K}(C_{ij}X_{ij}^{k}) + p\sum_{k=1}^{K}\left[max\left\{0, \sum_{i=0}^{N}\sum_{j=0}^{N} X_{ij}^{k}d_i - Q\right\} + max\left\{0, \sum_{i=0}^{N}\sum_{j=0}^{N} X_{ij}^{k}(C_{ij} + S_i) - T\right\}\right] \tag{10}$$

B. CSPSO Algorithm

In this section, subtle elements of the proposed crossover calculation are investigated. As specified earlier in this section, the proposed algorithm namely CSPSO is a hybrid of two nature-inspired methodologies, that is, Cuckoo Search Algorithm (CSA) and Particle Swarm Optimization (PSO) technique.

CSPSO is inspired by the nature of the cuckoo bird in two ways. Firstly, cuckoo bird neither raises its eggs nor assemble its eggs in its own nest; rather, it lay its eggs in other birds' nests. Secondly, cuckoo birds explore their path and determine their optimal route based on the availability of food. They advise each other of their position and help each other to move to a superior spot. The properties of the proposed algorithm are similar to the cuckoo bird's behavior. Thirdly, Cuckoo Search (CS) allows the enhanced exploration of the search space in comparison with other evolutionary computing algorithms. The proposed calculation function includes the capability of association for/with cuckoo search.

On the contrary, PSO is one of the modish evolutionary optimization techniques introduced by Kennedy and Eberhart in 1995. PSO algorithm is an adaptive method that can be used to elucidate optimization problems. Searching uses a population of particles. Each particle corresponds to an individual in an evolutionary algorithm. A flock or swarm of particles is randomly generated initially, with each particle's position personifying a possible solution point in the problem space.

Since the PSO and CS algorithms are both inspired by the survival and migration of birds, it is natural to utilize the superiority of the CS algorithm to improve the searching ability of the traditional PSO algorithm.

IV. Results and Discussion

In this section, exploratory setup and usage of the proposed method are examined. The outcome acquired by applying the proposed method was contrasted and diverse from the existing systems. The proposed algorithm was applied to the actual data set. The results of CSPSO were compared with those of the already existing techniques. The outcome demonstrated that CSPSO strives for/yields better results in some cases than PSO. It was observed that the execution of our system was entirely up to the state of the art/Moreover, the execution of the current system was state-of-the-art.

A. Dataset

The dataset used in the current research contains 11 test problems and is open-access. The aggregate number of clients fluctuates from/in the range of 13-70 and the aggregate number of vehicles reaches 3-8. In the dataset, fluctuated clients are spread at various coordinates. The direction framework utilized is a 2-Dimensional framework. Clients are arbitrarily scattered or semi-clustered. The number of vehicles used is identified in each circumstance and the capacity of the vehicles is set to be constant at 100. Whereas, the varied customers have contrasting demands and these demands are undisclosed until the vehicle has reached them. Additionally, there is only one goods depot and its location is (1,-1), which is usually situated at the center of the customer's existing location. To test their CVRP-based algorithms. The sample of the dataset can also be seen in Figure 2.

B. System Requirement

The code for simulation was implemented on Intel ® Core TM i3 4005U CPU @1.70 GHz using MATLAB R2014a. The parameter setting for Cuckoo Search Particle Swarm Optimization (CSPSO) is shown in Table I. For obtaining the ideal values of CVRPSD parameters through CSPSO, 1000 iterations were executed with multiple scenarios, as shown in Table II. An intense result comparison with the existing approaches is also given in Table III. The convergence behavior for the ideal values of appropriateness function for 1000 runs is shown in the figure series 1, 2, and so on. It is clear that a hybrid of CS with PSO tackles/addresses the fitness function very easily and the convergence of the solution is also efficient. Convergence is fast because cuckoo nests try to diverge the fitness but the social behavior of PSO carries them back near conjunction. To substantiate the current results, it was necessary to compare them with some sort of standard. So, to authenticate the current work, it was equated with the best-known results which have been previously deduced.

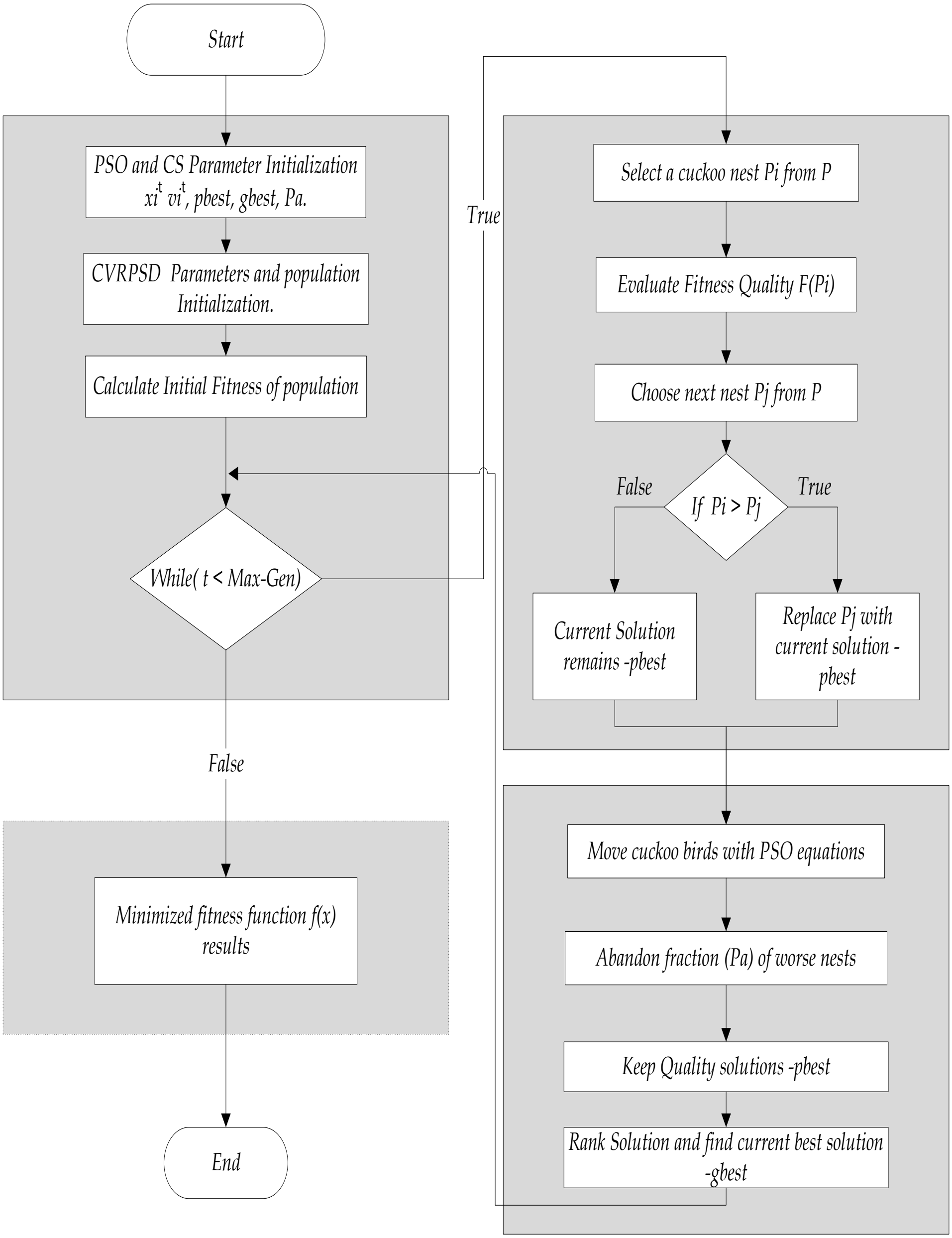
Table I
Parameter Initialization of CSPSO

Parameters	CSPSO Value
No. of Nests	100
Tol-Fun	$1e^{-6}$
Tol-Con	$1e^{-6}$
Alien Eggs Discovery rate	0.75
Lower Bound	5 * ones (1 , 15)
Upper Bound	5 * ones (1 , 15)

When the proposed technique was compared with PSO, it was determined that the dataset contains a vehicle capacity of 100 items, demands, and target locations. In this experimentation, the results are much better than PSO because of the enhanced working of the CS technique. The data is presented in figures as well as in tabular form, which is considered as the best illustration of results. The detailed results are shown Figure 1.

The results of the current study were also compared with Advance PSO proposed by [13]. The comparison showed that CSPSO competes with advance PSO in some scenarios. The detailed results are shown in Figure 2

C. Proposed CSPSO Algorithm Flow Diagram



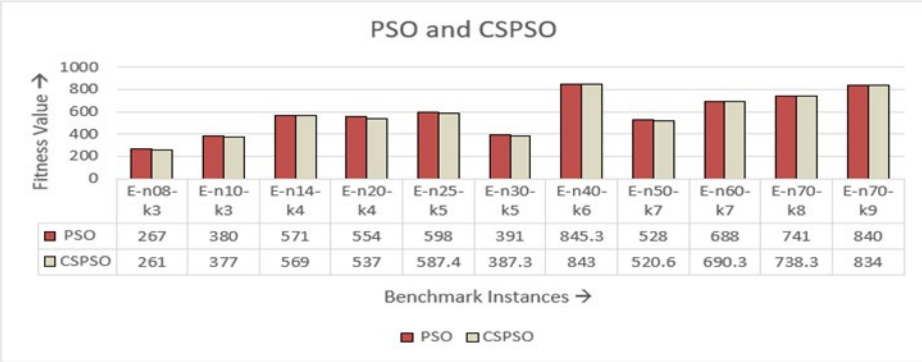


Fig. 1. Comparison between PSO and CSPSO

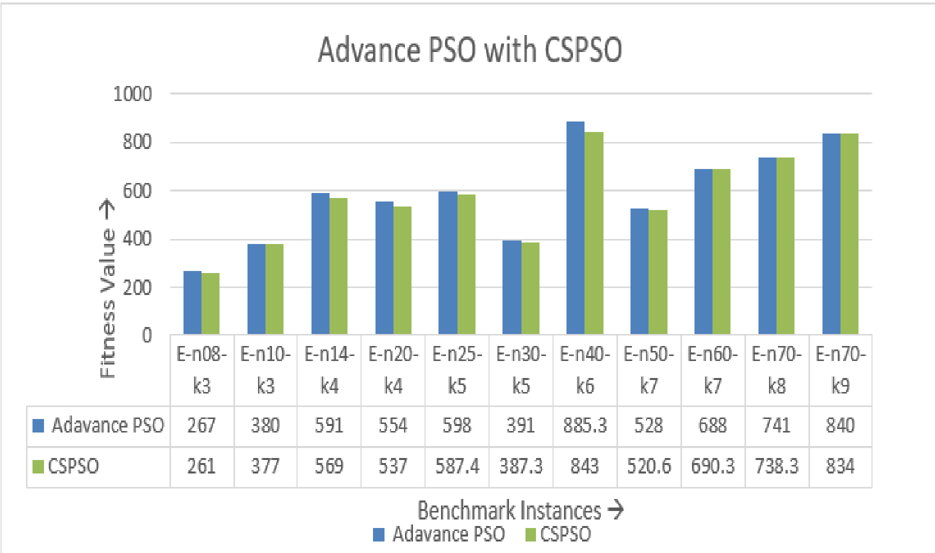


Fig. 2. Comparison between Advance PSO and CSPSO

The third experiment was performed with Simulated Annealing (SA) which is a heuristic approach. It works by heating the metal and then slowly cooling it down. So, in each temperature state, the optimality of the function is checked. Comparison was done between CSPSO and SA and detailed results are shown in Figure 3.

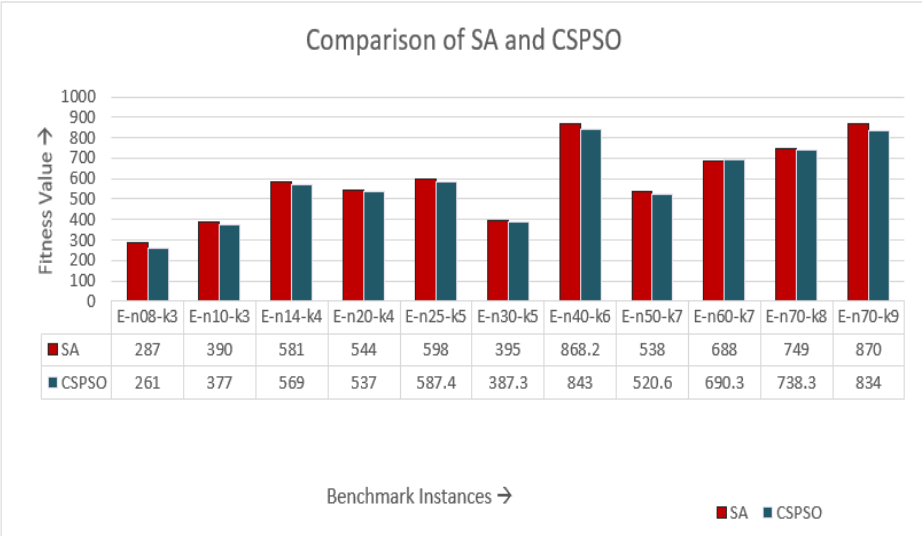


Fig. 3. Comparison between SA and CSPSO

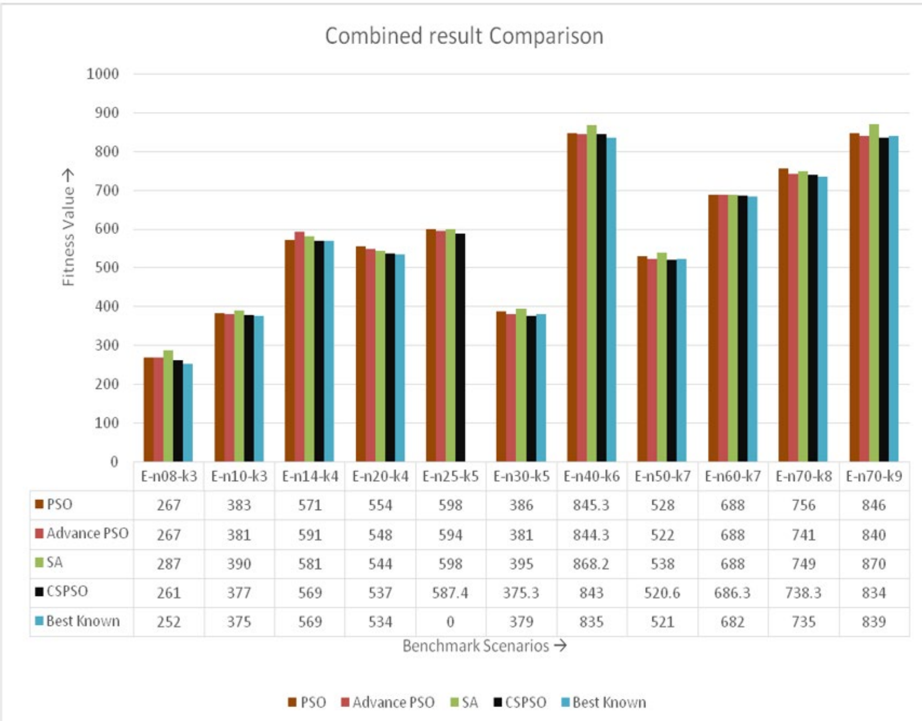


Fig. 4. Combined result comparison with the best known values

In the end, the proposed approach (CSPSO) was compared with simple PSO and Advance PSO. Their comprehensive results are depicted in Figure 4.

V. Conclusion and Future Work

In this research work, an attempt was made to integrate two nature-inspired algorithms. In the suggested algorithm, swarm intelligence was integrated with CSA to increase the performance from local optima to the global optima. From experimental results, it was observed that the approach produces better results in terms of efficiency. CSPSO was assessed on/keeping in view some standard functions and the outcomes demonstrated that the hybrid algorithm proposed in this study outperforms the classical CS A by 20% and PSO-2007 by 25%. Due to the enhancement in mathematical modeling, more accurate and optimized results were achieved. A possible enhancement in this work would be to contain/compare the hybrid approach of the CS algorithm with different nature-inspired algorithms, such as Simulating Annealing (SA), Firefly Algorithm (FFA), Artificial Bee Colony (ABC), and Genetic Algorithm (GA) with different constraints of VRP including 'time window' and 'pickup and delivery'.

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