Defence Science Journal, Vol. 72, No. 3, May 2022, pp. 382-391, DOI : 10.14429/dsj.72.17727

A PSO-Optimized Model for Identifying Spatio-Temporal Hotspots of Terrorist Incidents in India

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ABSTRACT

Terrorism is a global issue that prevails throughout the world on all scales. As the distribution of terrorist activities does not follow a random pattern in space and time, its spatiotemporal analysis has drawn considerable attention in recent years. Further, timely identification of Spatio-temporal terrorist activity hotspots is vital to prioritize the security efforts put by a country's security enforcement agencies. The state-of-the-art methods for Spatio-temporal hotspot detection are based on scan statistics, which enumerates many Spatio-temporal cylinders, making it a computationally expensive approach. Therefore, this paper presents a time-efficient Particle Swarm Optimizer (PSO) based algorithm to detect the most significant Spatio-temporal hotspots. We formulated an optimization model for the problem and applied three variants of PSO viz. conventional PSO, HCL-PSO, and Ensemble PSO. Finally, these schemes have been used to detect spatio-temporal hotspots of different terrorist attacks in India. The results obtained by PSO-based methods have been compared with SaTScan over two parameters: the time required to detect the hotspot and its quality. All the PSO-based schemes significantly outperformed SaTScan in the timely identification of the hotspots. In addition, the quality of hotspots detected by HCL-PSO is at par with SaTScan, whereas the quality of hotspots detected by the other two approaches is slightly lesser than SaTScan. However, the quality of hotspots detected by the other two variants of PSO is slightly lesser than SaTScan. The results are statistically validated using Friedman's statistical test.

Keywords: Spatio-temporal hotspots; Terrorist activities; Particle Swarm optimization; Defense

1. INTRODUCTION

Terrorism is a global concern, and recently a remarkable surge in the number of terrorist activities has been witnessed worldwide. Indian sub-continent is no exception. As reported in the Global Terrorism Database (GTD), India's number of terrorist attacks has increased from 1 in 1972 to 966 in 2017[1]. Also, the number of terrorism-related fatalities (including civilians and security personnel) in India was 465, 940, and 621 in 2017, 2018, and 2019 respectively[1].

Understanding the geographical aspects (like spatial and temporal patterns) of terrorist incidents is vital to counter them[2]. Timely identification of spatial and temporal patterns (like hotspots) of terrorist incidents is indispensable to reduce the loss of life and property. As defined in [3], the spatial hotspot is a region where the number of incidents inside the region is considerably higher than those outside it. Identifying the terrorist hotspots may play a vital role in countering terrorist activities. In case of scarce resources identifying the most significant hotspots of terrorist incidents offers an effective way to prioritize the security efforts. As discussed in[4], early detection of emerging hotspots might help the defense forces and governments prioritize "where and when should they allocate their resources and efforts in their fight against terrorism."

In monitoring (or countering) the terrorist activities, security forces are more concerned in those hotspots (Spatio-temporal) which are active till date (the end of the study period), often called emerging hotspots. Unlike spatial hotspots, incorporating time as a third dimension (i.e., Spatio-temporal hotspots) helps in the identification of active, emerging, diminishing, or persistent hotspots [5]. An example of the Spatio-temporal hotspots is shown in Figure 1, where hotspot A (blue hotspot) is active/alive till the end of the study period. Hence, it is an emerging hotspot.

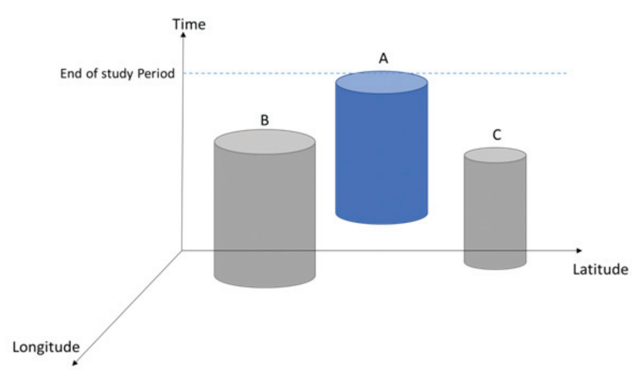


Figure 1. Example of emerging hotspot, i.e., the hotspot which is active till the end of the study period (blue cylinder).

In literature, one of the most popular methods to detect alive or emerging hotspots is based on space-time scan

Received : 13 November 2021, Revised : 18 January 2022
Accepted : 01 February 2022, Online published : 01 July 2022

statistics, proposed by Kulldorff [6] and is popularly known as SaTScan. Spatio Temporal SaTScan (ST-SaTScan) uses a cylindrical window with a circular base representing the space (region) and height representing the time. This cylindrical window moves in spatial and temporal domains to enumerate candidate cylindrical hotspots. Spatially, many cylinder bases with different geographical centers and radius are generated. Each activity point is considered as center and distance to every other activity point as radii [6]. Temporally, consideration of different starting dates for each cylinder base results in different cylinder heights. Hence, many candidate cylindrical hotspots with varying bases and heights are generated. A statistical measure called Log-Likelihood Ratio [7], which indicates a hotspot's strength, is then calculated for each cylinder. The significance of a hotspot is confirmed by relying on randomization tests to determine whether the observed pattern is significant or has occurred by chance. As ST-SaTScan is a brute force algorithm, the hotspots detected by ST-SaTScan are considered actual hotspots (i.e., 100% accurate) in the given search space. However, the generation of too many cylinders, followed by a randomization test, makes ST-SaTScan a high computational cost method [3]. Therefore, in applications where timely identification of hotspots matters like terrorist activities, evacuation planning, natural disasters, etc., the usage of ST-SaTScan is inefficient.

Even though terrorist activities are major security threats at national/international levels, limited contributions have been reported in the literature to detect the emerging terrorism hotspots. In one study, Siebeneck et al. used autocorrelation, cluster detection, and hotspot identification to understand the terrorism patterns in space and time [8]. Also, Braithwaite and Li presented an autocorrelation method to detect transnational terrorism hotspots [4]. Autocorrelation is a local spatial statistics method. The authors identified a few countries (terrorism hotspots) which may encounter more attacks in the future. However, their analysis's spatial and temporal data were not tightly coupled. In another study, Guo et al. [9] applied a prospective statistical scanning algorithm (ST-SaTScan) to identify terrorist incident hotspots. Few other studies have used ST-SaTScan as well to detect terrorist hotspots [10,11]. To find an efficient solution to hotspot detection problem, some studies have used Nature-Inspired Algorithms like Genetic Algorithms and Particle Swarm Optimizer [12,13]. However, these studies do not address terrorist hotspots and are more focused on optimizing the shape of hotspots.

Considering the inefficiency of ST-SaTScan and limitations of other approaches, in this paper, we present a time-efficient Particle Swarm Optimizer (PSO) based algorithm to detect the most significant emerging terrorist hotspots. We formulate an optimization model for the problem and apply three variants of PSO viz. constriction coefficient PSO, HCL-PSO, and Ensemble PSO to the proposed model. These approaches have been compared with ST-SaTScan for different types of terrorist attacks in India from 2016 to 2021. The comparison is made in terms of the time taken to detect the hotspots and their quality (in terms of Log-Likelihood Ratio).

The rest of the paper is organized as follows: Section 2 presents the proposed optimization model and PSO-based schemes for detecting emerging hotspots. In Section 3, first, we detail the terrorist activity dataset used in this paper. Also, a comparative analysis of ST-SaTScan with proposed PSO-based schemes is presented. Finally, conclusions and future scope of the work are discussed in Section 4.

2. PROPOSED WORK

This section briefly describes PSO and its variants, the proposed optimization model, and the PSO-based schemes to detect emerging terrorist hotspots.

2.1 Particle Swarm Optimizer

In the PSO algorithm [14], every particle owns a position X_i (representing a possible solution) and a velocity, V_i, which are d dimensional vectors where d is the dimension of the search space. The quality (or fitness) of each particle is evaluated with a fitness function $f()$. The algorithm begins with the initialization of the position X_i and the velocity V_i. In subsequent steps, each particle iteratively moves to better positions in the search space by updating its velocity Eqn (1) and position Eqn. (2)[15]. Each particle's movement is guided by its own local best position (called $pbest_i$) as well as the best position obtained by the entire group of particles (called $gbest$).

$$v_i(t+1) = \omega \times v_i(t) + \alpha \times rand_1 \times (pbest_i - x_i(t)) + \beta \times rand_2 \times (gbest - x_i(t)) \tag{1}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

Where, ω represents the inertia weight of the particle, $rand_1$ and $rand_2$ are random numbers in the range [0,1], α and β represent the swarm's cognitive and social components, respectively.

The iterative process continues until some convergence criteria, which can be a maximum number of iterations or the same fitness obtained for a fixed number of iterations. Often, PSO stagnates in local optima due to its sensitivity to cognitive and social parameters[15-16]. This issue has been handled differently by various authors. In[16], the authors introduced a constriction coefficient for the careful setting of PSO parameters which helped in the increased ability of PSO to reach global optima. In another contribution, the authors introduced a Heterogeneous Comprehensive Learning PSO (HCL-PSO)[17], dividing particles into two groups (subpopulations), each focusing on exploration and exploitation. In 2017, Lynn *et al.*[18] proposed an Ensemble approach by hybridizing five variants of PSO. The variants are self-adaptive, and the best-performing algorithm is identified for each generation and is used next. Inspired by the No Free Lunch (NFL) theorem[19], we applied the discussed three variants of PSO viz. Constriction Coefficient based PSO (CC-PSO), HCL-PSO, and Ensemble PSO to detect the most significant emerging hotspots.

2.2 Proposed Optimization Model for Emerging Hotspot Detection

For a given set of terrorist attack locations A (latitude, longitude, time of event) and a search space R, it is desired to find such cylinders in R that have the highest log-likelihood ratio (LLR). The obtained cylinder with the highest LLR is the most significant hotspot in our model. Therefore, our proposed model aims to maximize the LLR. The decision variables of our optimization model are $(x_c, y_c), r$ *and* T (presented in Table I).

Table 1. Decision Variables in the optimization model for detecting emerging hotspots

Decision Variable	Description
(x_c, y_c)	Center of the base of cylinder (a latitude-longitude pair representing a location in search space)
r	The radius of the cylinder
T	Height of cylinder from the end of the study period (representing time window $(T-t+1)^{th}$ *to* T^{th} day/month/year). This allows only emerging hotspots.

These variables represent a candidate emerging cylindrical hotspot Z in our model. Subsequently, we formulate the proposed optimization model.

Maximize $LLR\left(Z\left(x_c, y_c, r, t\right)\right)$

where,

$$LLR(Z) = \log\left(\left(\frac{c_a(Z)}{c_e(Z)}\right)^{c_a(Z)} \times \left(\frac{A-c_a(Z)}{A-c_e(Z)}\right)^{A-c_a(Z)} \times I\left(c_a(Z), c_e(Z)\right)\right), c_e(Z) = \frac{A \times vol(Z) \times t}{vol(R) \times T} \quad (3)$$

Subject to

$$\left(x_c, y_c\right) \in A \quad (4)$$

$$\min\_rad \le r \le \max\_rad \quad (5)$$

$$2 \le t \le T/2 \quad (6)$$

The objective function presented in Eqn. (3) represents the Log-Likelihood Ratio[20] of the candidate cylinder Z. It is defined using the center, radius, and height which are decision variables for the model. In Eqn. (3), A is the total number of terrorist activity count in the set, $c_a(Z)$ is the actual number of terrorist activities within cylinder Z and $c_e(Z)$ is the expected number of terrorist activities within Z. Futher, $vol(Z)$ is the volume of cylinder Z, $vol(R)$ is the total volume of search space R, T is the number of days/months under consideration for analysis and $I(c_a(Z), c_e(Z))$ is a binary function having value as 1 if, $c_a(Z) > c_e(Z)$ otherwise, it is 0. The constraints in the proposed model are presented in Eqn (4-6). Constraint (4) is used to keep the center (x_c, y_c) of the cylinder as an activity point in set A. Constraint (5) represents the bounding condition for the radius of the cylinder. The lower bound and upper bound on height representing the temporal dimension is presented in (6). These bounds are kept the same for all the compared schemes for fair analysis.

2.3 Proposed PSO-based Schemes for Emerging Terrorist Hotspot Detection

This section presents an overall scheme for emerging hotspot detection by applying PSO to the proposed optimization model. The presented scheme is now onwards referred to as EHD-PSO (Emerging hotspot detection using PSO). Figure 2 illustrates the major steps of the proposed scheme as a block diagram. It indicates that EHD-PSO has three main steps: (1) Generating the distribution of Log-Likelihood ratio under null hypothesis H_0, (2) Finding the cylindrical hotspot with maximum likelihood ratio in the search space R, and (3) Statistical significance using hypothesis test.

A prerequisite of Step 1 is defining a hypothesis test to check candidate cylinders for statistical significance. The following question needs to be addressed for each cylinder: "Is there any difference in the concentration of activities inside vs outside the cylinder?". The hypothesis test is constructed with two outcomes, null hypothesis (H_0) and alternate hypothesis (H_1). The null hypothesis states that "The number of terrorist activities follows complete spatial randomness in the study area R". In contrast, the alternate hypothesis states that "the frequency of occurrence of terrorist activities is higher within the cylinder as compared to outside". Once the hypothesis is defined, it is then used in Step 1 to find the distribution of LLR value under the null hypothesis H_0. This distribution indicates what to expect when there are no hotspots in the study area R. Randomization test is carried out to obtain this distribution as follows: Monte Carlo Simulations (MCS) are used to perform the randomization test and get the distribution of LLR under H_0. In total, 'm' random datasets in the study area R are generated using complete spatial randomness. All possible cylinders are enumerated for each of the 'm' random datasets. The maximum LLR value is stored in a list maxLLRs in descending order to obtain the required distribution.

In the second step, the proposed scheme uses PSO to find the cylindrical hotspot with maximum likelihood ratio in the search space R using terrorist activity set A. The decision variables, fitness function, and constraints used by PSO are presented in Section 2.4. Initially, each of the K particles is randomly placed in the search space where each particle has four dimensions representing the center (x_c, y_c), radius (r), and height (t) of the cylindrical window. To ensure the detection of emerging hotspots only, the height (t) of the cylindrical window is considered from the end date of the study period. The fitness value (LLR) of each particle is calculated using Eqn (3) to identify the global best ($gbest$) and personal best ($pbest_i$) position of each particle.

While calculating LLR for a cylindrical zone, all those activities whose coordinates lie within the circular spatial base of the cylinder are considered inside the zone Z. The sum of activity count of cases from $(T-t+1)^{th}$ to T^{th} month inside Z is used as $c_a(Z)$. Particles then update their velocities and positions based on $pbest_i$ and $gbest$ using Eqn(1-2). All the particles keep wandering in the search space to reach the optimum value of LLR until a convergence criterion is met. The EHD-PSO scheme converges if the best solution in the swarm does not improve continuously for a fixed number of iterations or a maximum number of iterations $iter$ has been reached. The global best value $gbest$ after convergence represents the cylindrical hotspot CH with maximum LLR value.

The third step of the proposed scheme checks the statistical significance of hotspot CH using a hypothesis test. The $p-value$ of CH is required to check CH for statistical significance. The relative position of $LLR(Z)$ in maxLLRs list is determined first to calculate the $p-value$ of the cylindrical zone CH. The $p-value$ is then calculated by taking the ratio between pos_i and $m+1$ where m is the number of Monte Carlo Simulations. If the $p-value$ of CH is less than α_p, then we print CH as the most significant emerging hotspot.

The time complexity of the proposed PSO-based scheme for hotspot detection is $O(m \times iter \times K \times |A|)$. Whereas the total time complexity of ST-SaTScan is $O(m \times |A|^3 \times iter)$. It is evident that the proposed scheme is more efficient than the conventional ST-SaTScan method for emerging hotspot detection.

3. EXPERIMENTS AND RESULTS

In this section, we present the experimental details and results obtained for ST-SaTScan and EHD-PSO schemes on the terrorist activities datasets of India. We first describe the terrorist activity datasets used in our experiments, followed by the performance analysis of ST-SaTScan and three EHD-PSO schemes viz. EHD-CCPSO, EHD-HCLPSO, and EHD-EPSO. The experiments are conducted on an Intel CORE i7 processor with 8 GB RAM using MATLAB R2018a.

3.1 Dataset

In our experiments, we have used the terrorist activities that occurred in India. This dataset is obtained from The Armed Conflict Location & Event Data Project (ACLED)[21], which is openly available for research and analysis. For our experiments, we extracted previous 5-year data (2016-2021) of different types of terrorist activities in India. The extracted data includes the date of the event, event type, actor, latitude, and longitude, etc. We segregated the data into 4 case studies based on the type of terrorist event. These events include grenade explosions (GE), remote explosion or landmine (RE), violence against civilians (VAC), and attacks in North-East states of India (NEA). These datasets include 358, 732, 251, and 442 activity points.

3.2 Comparative Analysis

Performance of the various hotspot detection schemes presented in the paper have been analyzed over the following parameters: LLR, Relative error (computed using Eqn. (7)), and the required execution time (excluding the time for Monte Carlo simulations).

$$RE = \frac{|MaxLLR_{SaTScan} - MaxLLR_{EHD-PSO}|}{MaxLLR_{SaTScan}} \times 100\% \quad (7)$$

As discussed earlier, the analysis has been done independently for the following four events i.e., GE, RE, VAC, and NEA. All the PSO-based parameters (listed in Table II) are kept the same for impartial comparison among the presented

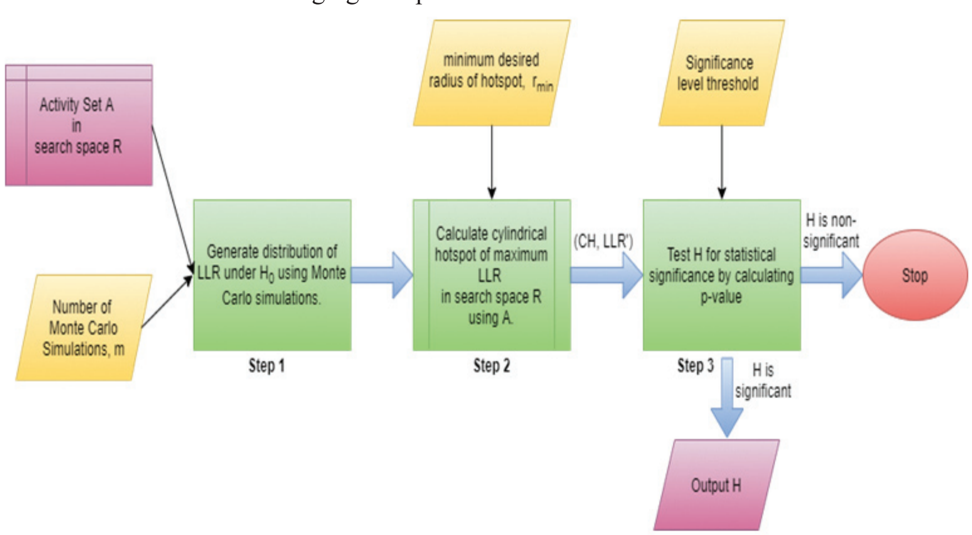


Figure 2. Block Diagram of the proposed scheme EHD-PSO, where A is the Activity set, R is the search space, r_{min} is the minimum desired radius of the hotspot.

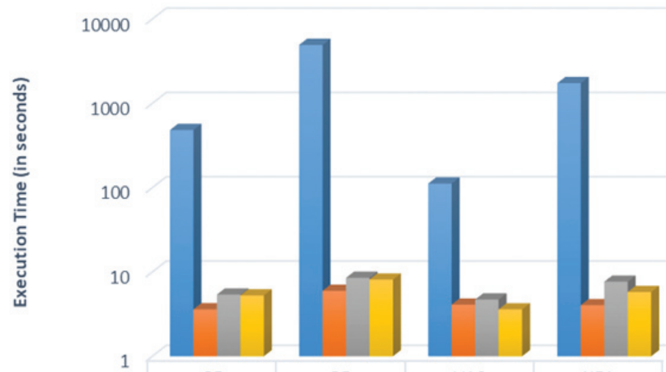
schemes. Table 2 presents the values of these parameters widely used in the literature [16,22] and hence used in our experiments. Each experiment is conducted for 10 independent runs, and the maximum LLR value (bestLLR), the average of LLR values (avgLLR), their standard deviation, and average relative error (avgRE) are reported in Table III. Table III presents the obtained bestLLR, avgLLR, stdev, and avgRE of the emerging hotspots detected by ST-SaTScan, EHD-CCPSO, EHD-HCLPSO, and EHD-EPSO schemes over the following datasets: GE, RE, VAC, and NEA.

Table 2. Parameter setting in EHD schemes

Parameter	Value
Population Size	50
α (cognitive component)	2.05
β (social component)	2.05
Ω (inertia weight)	Linearly decreased from 0.9 to 0.2
Maximum number of iterations	500
Number of iterations for convergence	100
m (Number of Monte Carlo Simulations)	99
α_p (p-value threshold)	0.01

As observed from Table 3, out of the three PSO-based schemes, performance (in terms of the bestLLR) of EHD-HCLPSO and EHD-EPSO seems to be more promising than EHD-CCPSO. The maximum relative error for EHD-HCLPSO and EHD-EPSO is 0.202% and 4.552%, respectively. In contrast, the maximum relative error for EHD-CCPSO is 43.9%. The results indicate that EHD-CCPSO gets trapped in local optima and hence is a non-promising approach.

The execution time taken by all the schemes on different datasets is presented in Fig. 3. It is observed that the time taken by EHD-CCPSO, EHD-HCLPSO, and EHD-EPSO is significantly less than the execution time of the ST-SaTScan approach. Among the three PSO-based schemes, EHD-CCPSO takes minimum time which may be attributed to its pre convergence on local optima, which is also evident from its high average relative error (43.9%). The extremely high difference in execution time of PSO based schemes and ST-SaTScan is attributed to their O(m × iter × K × |A|) and O (m × $|A|^3$ × iter) time complexities, respectively.



	GE	RE	VAC	NEA
ST-SatScan	482.695	4930.831	111.874	1737.822
EHD-CCPSO	3.604	5.969	4.093	4.034
EHD-HCLPSO	5.397	8.522	4.708	7.665
EHD-EPSO	5.271	8.119	3.595	5.782

Figure 3. Execution time taken by ST-SaTScan, EHD-CCPSO, EHD-HCLPSO, and EHD-EPSO for detecting emerging hotspots on four datasets, viz., GE, RE, VAC, and NEA.

Table 3. bestLLR, avgLLR, Standard Deviation (stdev), and average relative error (avg RE) obtained in 10 independent runs of ST-SaTScan, EHD-CCPSO, EHD-HCLPSO, and EHD-EPSO on four case studies viz. GE, RE, VAC, and NEA.

Dataset and number of points		ST-SaTScan	EHD-CCPSO	EHD-HCLPSO	EHD-EPSO
GE	bestLLR	1367.247	1347.763	1367.247	1366.775
(358)	avgLLR		1186.829	1367.247	1361.542
	stdev		125.656	0	4.171
	avg RE		13.196	0	0.417
RE	bestLLR	740.847	505.855	740.847	740.847
(732)	avgLLR		415.594	740.847	740.847
	stdev		99.799	0	0
	avg RE		43.903	0	0
VAC	bestLLR	111.233	95.204	111.233	107.105
(251)	avgLLR		77.649	111.009	106.17
	stdev		24.236	0.309	1.08
	avg RE		30.193	0.202	4.552
NEA	bestLLR	213.478	138.766	213.478	213.478
(442)	avgLLR		135.316	213.436	203.989
	stdev		2.654	0.028	23.522
	avg RE		36.614	0.02	4.445

(a)

(b)

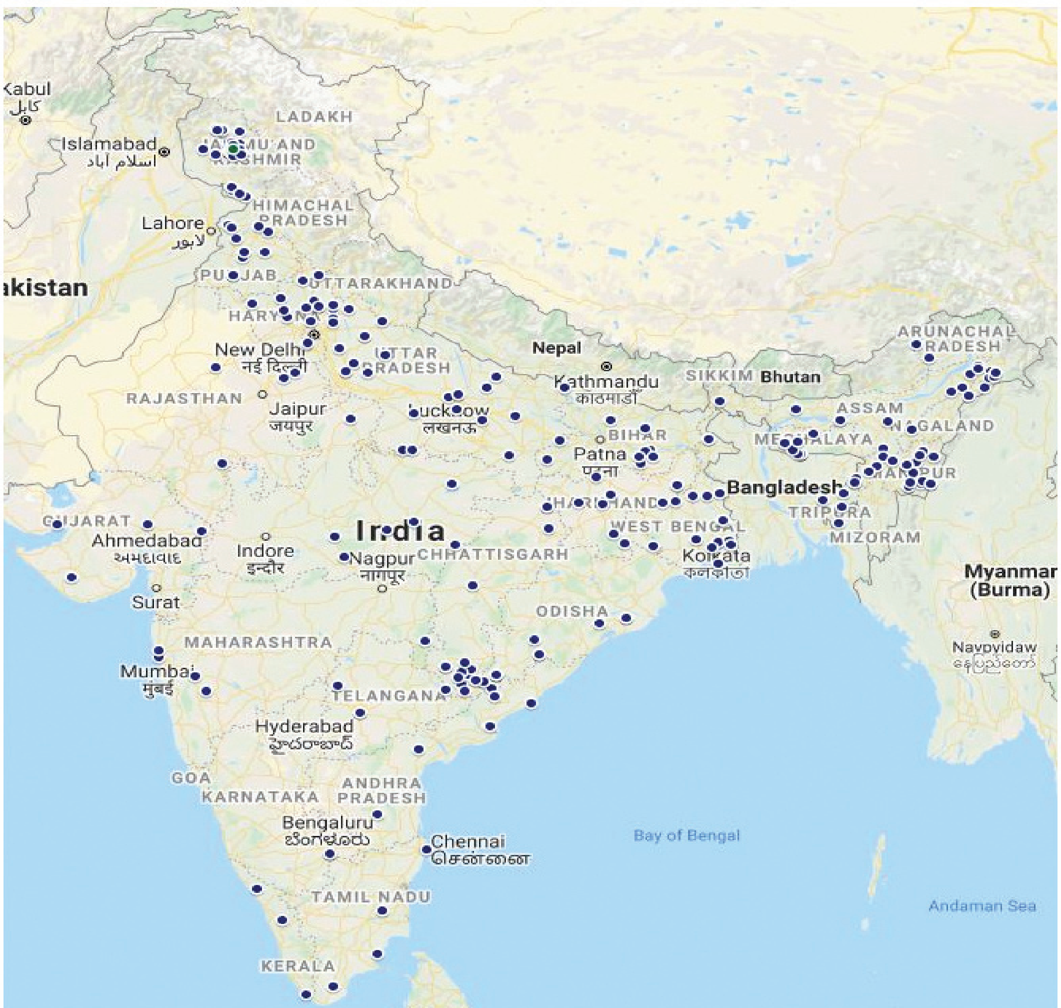
(c)

Figure 4. (a) Terrorist activity dataset GE (Grenade Explosions) and GE hotspots identified by: (b) ST-SaTScan (c) EHD-CCPSO (d) EHD-HCLPSO and (e) EHD-EPSO.

(d)

(e)

Figure 4. (a) Terrorist activity dataset GE (Grenade Explosions) and GE hotspots identified by: (b) ST-SaTScan, (c) EHD-CCPSO, (d) EHD-HCLPSO, and (e) EHD-EPSO.



(a)

Figure 5. (a) Terrorist activity dataset VAC (Violence against Civilians) and VAC hotspots identified by: (b) ST-SaTScan (c) EHD-CCPSO (d) EHD-HCLPSO and (e) EHD-EPSO.

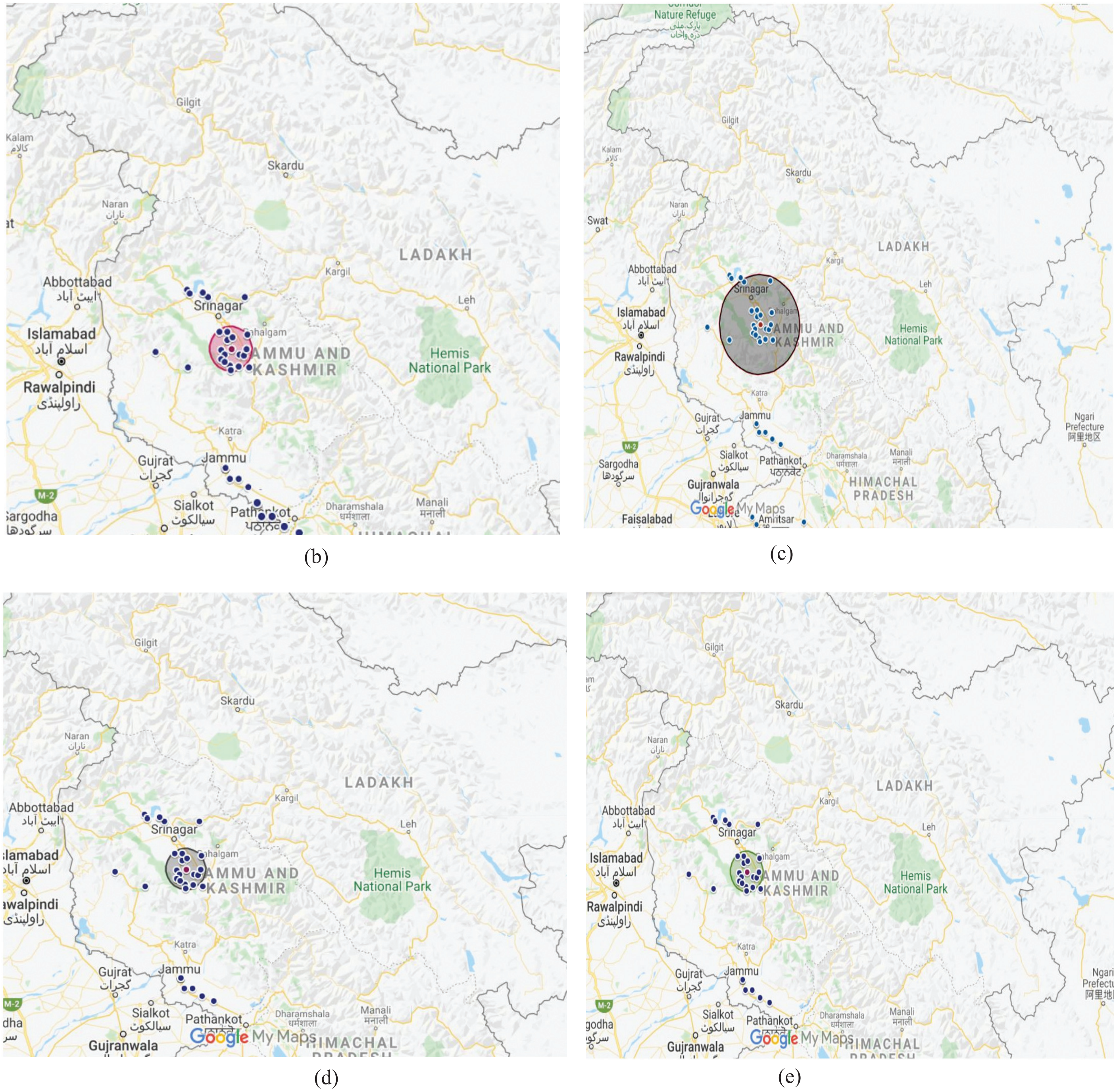


Figure 5. (a) Terrorist activity dataset VAC (Violence against Civilians) and VAC hotspots identified by: (b) ST-SaTScan (c) EHD-CCPSO (d) EHD-HCLPSO and (e) EHD-EPSO.

Finally, the hotspots identified by different schemes on two (GE and VAC) of the four case studies are shown in Figure 4 (GE) and Figure 5 (VAC). The detected hotspots have been presented on maps created using the Google MyMaps application. In both Figure 4(a) and Figure 5(a), the various terrorist activity points have been presented on the map of India, whereas (b) to (e) in Figure 4 and Figure 5 represents hotspots detected by ST-SaTScan, EHD-CCPSO, EHD-HCLPSO, and EHD-EPSO respectively. These hotspots have been presented in the zoomed map of India.

For the terrorist activity type GE, all the four schemes have detected the center of the emerging hotspot around Srinagar in Jammu and Kashmir and cover the localities like Pulwama, Barsoo, Pinglena, Tral, etc. The hotspot radius detected by ST-SaTScan, EHD-HCLPSO, and EHD-EPSO is 46.9 km. The timespan of the emerging hotspot is from 2016 to the end of the study period. However, the radius of the hotspot detected by EHD-CCPSO is slightly less, i.e., 43 km, and the timespan of the emerging hotspot is from 2017 to the end of the study period.

For the terrorist activity type VAC, all the four schemes have detected the center of the emerging hotspot around Hawal in Jammu and Kashmir and cover the localities like Shopian, Ramnagri, Bara Pora, etc. The period of the emerging hotspot is from 2016 to the end of the study period. The hotspot radius detected by ST-SaTScan, EHD-HCLPSO, and EHD-EPSO is around 22.24 km. However, the radius of the hotspot detected by EHD-CCPSO is a little more, i.e., 59.5 km, and the timespan of the emerging hotspot is from 2018 to 2021.

3.3 DISCUSSIONS

This section presents the analysis and discussions of the comparative results obtained in subsection 3.2. As discussed in previous sections, the time complexities of ST-SaTScan and EHD-PSO are O (m × |A|3) and O (m × iter × K × |A|), respectively. Unlike ST-SaTScan, PSO-based schemes do not require enumeration of all the cylinders in the search space. Instead, particles in PSO use social and cognitive intelligence to reach the approximate optimum cylinder depicting a hotspot. Thus, reducing the time complexity by two orders of magnitude. This considerable difference in the execution time of ST-SaTScan and PSO-based schemes is also evident in the experimental results shown in Fig. 3. However, it is observed that this reduction in running time is not at the cost of the accuracy of hotspot detection, which is evident from the relative errors reported by PSO-based schemes as presented in Table 3.

Further, among the three PSO-based schemes, it is observed that the time taken EHD-CCPSO is minimum, followed by EHD-EPSO and EHD-HCLPSO, respectively. The less time taken by EHD-CCPSO may be attributed to its pre convergence on local optima, which is also evident from its high average relative error (43.9%). The average relative error of 0.202%,4.552%, and 43.9% obtained by EHD-HCLPSO, EHD-EPSO, and EHD-CCPSO, respectively, indicate the superiority of HCL-PSO for hotspot detection. The superiority of EHD-HCLPSO can be attributed to the fact that HCLPSO maintains a balance between exploration and exploitation by dividing particles into two groups (subpopulations), each focusing on one aspect and bypassing the local optima to reach the global optima.

A non-parametric statistical test called Friedman Test is used to validate the observations statistically. The null hypothesis assumes that all the three schemes are equivalent in their average relative error. In contrast, the alternatives hypothesis states that the three schemes differ in average relative error. Table 4 reports the ranks assigned to each scheme for each of the four datasets, and thus Friedman's statistic is computed 23. The obtained p-value of 0.0028 suggests that the three approaches differ significantly, and the null hypothesis is rejected. The significant difference is the squared rum of ranks of the three schemes also supports the rejection of null hypothesis.

The superiority of EHD-HCLPSO can be pictorially validated by representation ranks using a radar chart, as shown in Figure 6.

Finally, as observed from the presented case studies, among the PSO-based schemes, the performance of EHD-HCLPSO is relatively better. Also, EHD-HCLPSO takes significantly lesser execution time than ST-SaTScan and seems a more promising approach among the four presented schemes.

Table 4. Comparison of EHD-CCPSO, EHD-HCLPSO, and EHD-EPSO in terms of ranks

Dataset	EHD-CCPSO	EHD-HCLPSO	EHD-EPSO
GE	3	1	2
RE	3	1.5	1.5
VAC	3	1	2
NEA	3	1	2
Average Ranks	3	1.125	1.875
Squared sum of ranks	144	20.25	56.25

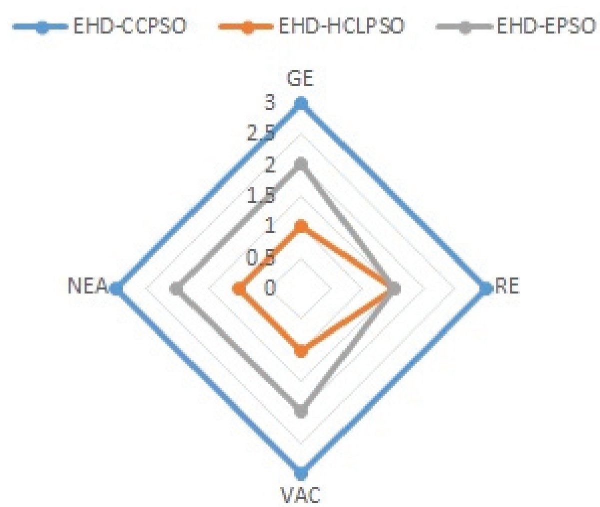


Figure 6. Radar plot for the ranks of EHD-CCPSO, EHD-HCLPSO and EHD-EPSO

4. CONCLUSIONS

In this paper, we modeled the emerging hotspot detection problem as an optimization problem. We applied three variants of PSO viz. CCPSO, HCL-PSO, and EPSO to identify the emerging terrorist hotspots in India. The experiments for emerging hotspot detection have been performed over four types of terrorist activities data viz. GE, RE, VAC, and NEA from the year 2016 to 2021 obtained from The Armed Conflict Location & Event Data Project. The performances of EHD-HCLPSO and EHD-EPSO are at par with SaTScan in terms of the quality of detected hotspots. Among these two PSO based schemes, EHD-HCLPSO is comparatively better than EHD-EPSO in terms of average relative error. In contrast, they are significantly better than ST-SaTScan in terms of required computational time. The observed performances indicate the suitability of EHD-HCLPSO for rapid and effective surveillance of terrorist activities and hence their remedial planning by appropriate government agencies.

Besides the strengths and applicability of this study, the addition of some relevant information in the context of terrorist activities, *viz*. time of the event, count of affected people, etc., may help strengthen the conclusions in future studies.

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