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Cellular Automata-based Improved Ant Colony-based Optimization Algorithm for mitigating DDoS attacks in VANETs

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ABSTRACT

In Vehicular Ad hoc NETworks (VANETs), reliable data dessimination between vehicular nodes necessitate maximum degree of colloboration as they play a significant role for ensuring the core objective of communication. But the malicious action of vehicular nodes may distrupt the established degree of co-operation as they lead to poor performance inspite of high resource utilization. The malicous activity of vehicular nodes like DDoS attack must be detected and resolved in a potential way by identifying optimal nodes and optimal paths using cellular automata that modifies the search ability in a global way for increasing the speed of convergence. To prevent the search from falling into local optimum point and to enhance the convergence speed, global searching potential, an enhanced version of ant colony optimization (ACO) algorithm called Cellular Automata-based Improved Ant Colony-based Optimization Algorithm (CA-IACOA) is propounded. In CA-IACOA, the update rules and dynamic adaptive adjustment technique in pheromones of the traditional ACO is enhanced to a significant level based three threshold level of tolerance.This enhancement in the adopted pheromoneis mainly for attaining better quality solution through reliable and dynamic increment of pheromone that considers the past history related to the visited paths of the ant agents. Further significant tradeoff that exists between solving quality and solving efficiency is resolved using updated dynamic evaporation factor strategy that aids in rapid convergence. Furthermore, trusted boundary symmetric mutation strategy is incorporated in CA-IACOA for improving mutation and to strengthen mutation efficiency. The simulation experiments of CA-IACOA infers that they are potential in handling DDoS attacks as they obtain quality solutions in identifying optimal nodes and optimal paths for reliable routing.

Keywords-Improved Ant Colony Optimization, Cellular Automata, symmetric mutation strategy, global minimum, adaptive adjusttment technique,Dynamic Evaporation Factor Strategy.

1. Introduction

In VANET, the reliability of vehicular nodes quantifies their co-operation that ensures thedegree the participation with which they forward packets for the sake of their neighbours due to the devoid of a centralized control point for communication[1]. But the extent of collaboration rendered by the vehicular nodes for forwarding packets significant decreases in the presence of malicious activity like DDoS attacks as they intentionally or unintentionally use the resources and degrade the performance of the network for the reason to remainactive in the network without a genuine cause[2-4].The presence of DDoS attacks potentially reduces the rate of packet delivery and throughput inspite of incurring a greater level of delay, control overhead and total overhead. From the past decade, a significant number of mitigation algorithms were proposed for handling DDOs attacks through the integration of meta-heuristic stochastic optimization algorithms that includes Particle swarm optimization(CA-PSO), Ant Colony Optimization(CA-ACO),Genetic algorithm and Artificial Bee Colony Algorithms(ABCA). These meta-heuristic stochastic optimization algorithms are mainly proposed for improving the global search ability for identifying and assessing quality solutions at an optimal rate [5-7]. Further meta-heuristic stochastic optimization algorithms are utilized for the following reasons[8-10] viz., i)It is suitable for resolving any issues that could be derived in a finite dimensional space for identifying an optimal solution,ii) They are experimentally proved and confirmed to be highly suitable for approximation of solution than the heuristic stochastic optimization algorithms in most real time complex environments, iii) They possess a maximum search potential that makes it highly suitable for its applicability in VANET and iv) They are proved to exhibit an higher level of precison when enhanced and integrated for maximizing the exploration extent.

In this paper, Cellular Automata-based Improved Ant Colony-based Optimization Algorithm (CA-IACOA) is proposed for eliminating the concept of stagnation that exists in the traditional Ant Colony-based OptimizationAlgorithm(CA-ACO). CA-IACOA used for mitigation assures an effective and efficient global search space for identifying and replacing the DDoS compromised node with optimally elected vehicular node. The traditional CA-ACO algorithm for DDoS mitigation is improved in the following dimensions viz., i) the movements of ants are modified based on dynamic movement probability rule, ii) the pheromone updating rules are improved based on pheromone intensity constant, iii) a pheromone adaptive adjustment strategy is incorporated for modifying the non-uniform distribution of pheromone to unform distribution of pheromone and iv) Dynamic evaporation factor strategy is used for increasing the search potential that in turn enhances the rate of convergence to a considerable level.

The proposed algorithm can be applied in all VANET applications like Traffic Management, Cooperative Collision Warning (CCW)System, Gaming, Internet services and etc,. The experiment was conducted for Traffic management to prevent driver from getting caught into traffic congestion by providing uninterrupted services at all times.

The remaining sections of the paper are organized as follows. Some of the potentialresearch works pertaining to Ant Colony-based Optimization Algorithm for mitigation are analyzed with their suitability and applicability in section 2. Section 3 highlights on the four modified steps of the proposed CA-IACOAwith their need, roles and significance. Section 4 depicts the performance investigation of CA-IACOA carried out with CA-ACOA, CA-GA and CA-PSO through five constructive experiments. Finally, the contributions of CA-IACOA with the plan of future enhancement are depicted in section 5.

Related Work

In this section, Some of the significant research papers existing in the literature that are closely related to ant colony optimization algorithms are detailed with their significance and improvement focus.

Initially, Leng et al.[11] introduced an enhanced ant colony optimization (ACO) algorithm that possess the ability to manage three different constrains like resource utilization constraint, overhead cost of data transmission and time. The enhance ACO algorithm is designed based on dynamic pheromone updating which in turn facilitates flexible and dynamic seraching process. The dynamism in cell scheduling process is achieved by means of weighted directional diagram. Yang and Lai[12] introduced a novel ant colony algorithm which deals with p//T that is referred as (p//T-ACO). Both theoretical and experimental analysis of p//T-ACO show that the proposed novel ant colony optimization algorithm is more effective and efficient in terms of creating solutions for large scale real time problems. Mao and Zhao [13] recommended an adaptive optimization strategy for inter-cluster and intra-cluster routing process in the network. In this optimization is performed based on the energy utilization. The proposed adaptive optimization method in this paper is referred as max-min ant colony optimization. Here the energy based optimization process is performed by means minimum and maximum values. The proposed optimized routing process handles hot spot problems in wireless sensor networks.

Similarly, Ugur and Aydin [14] recommended that there is need of additional data structure which is referred as best tours graph feeding the pheromone trail information for ACO algorithms. This enhancement in the ant colony optimization algorithm is evaluated using travelling sales person problem by means of TSPLIB(Travelling Salesman Problem benchmark LIBrary). The proposed enhancement in ACO on experimentation and result evaluations show that the performance is improved to the considerable percentage when compared to all other enhancements. Xu et al.[15] presented an extension in ant colony optimization algorithm by means of chaotic map. The proposed enhancement is evaluated using VRP problem. The experimental results show that the enhancements of ACO presented in this paper is highly efficient and effective in terms of precision rate for obtaining the global optimal solutions. Xue et al. introduced PIACO algorithm which is an enhancement of ant colony optimization algorithm. The PIACO algorithm is proposed for solving scheduling problems in cloud PDT. Li et al. [16] presented solution for project group management based on the enhancements made on the ant colony optimization algorithms. The enhancements of the ant colony optimization algorithm are performed by means of meta-information. This aids in dynamic scheduling of process in the project management.

Walid et al.[17] recommended a novel approach of hybridization of swarm optimization (PSO) and ant colony optimization (ACO) algorithms which is referred as PSO-ACO. This PSO-ACO is evaluated on solving travelling sales person problem. The evaluation result proves that the proposed hybridization process outperforms the individual performances of optimization algorithms. The theoretical and experimental analysis shows the effectiveness of the proposed improvised ant colony optimization algorithm in terms of load balancing in vehicular network.Escario et al.[18] introduced an extended version of ant colony optimization algorithm. In this extended version, two specific features are included i) the categorization of tasks between two kinds of ants and the control measure for optimizing the number of ants utilized for searching process. Li and Jin innovated an ant colony optimization which is referred as GACO. The proposed GACO is designed based on Compute Unified Device Architecture (CUDA) enabled GPU.Zhang et al. [19] presented an enhancement in ant colony optimization process which is referred as PMACO algorithms. This algorithm improves the number of pheromone in the critical paths which in turn enhances the exploitation of the optimal solution. Experimental result proves that the PMACO algorithms are more efficient than all other enhancements in ant colony optimization algorithm.

In VANET environment Optimization techniques are applied to find the optimal routing path [26], optimal combination of parameters as in [25]. The Cellular Automata is also applied for mobility of the vehicles. Furthermore, VANET supports many techniques like scheduling [10], authentication [27] and etc., which takes more time when compared to optimization techniques. The Meta-heuristics Stochastic Optimization algorithm integrated with Cellular Automata results in reduced time in finding the optimal vehicle.

3. The proposed CA-IACOA mechanism

CA-IACOA is an Improved cellular automaton based Ant Colony Optimization algorithm that is specifically enhanced for handling the drawback of stagnation that is considered as the major critical issue during mitigation process when CA-ACO is employed for handling DDoS attacks in vehicular ad hoc networks. The steps of CA-IACOAis similar to the traditional procedure of CA-ACO, but four steps such as dynamic movement probability rule-based ant agent movement, Pheromone intensity constant based rule updation, dynamic evaporation factor startegy and bounday symmetric muttaion scheme are enhanced to a signifcant level for effective searching in a global potential.The improved steps of the traditional Ant Colony Optimization algorithm with their importance and role are discussed below.

3.3.1 Improved Movement Rules of Ants

Naturally, Ants are potential in searching and analyzing the quality of the food sources through optimal shortest paths that are identified by their intelligence in an iterative manner. Inspired by the intelligence of ants, Improved Ant colony Optimization (IACO)Algorithm which is an enhanced version of Ant colony Optimization (ACO)propounded by Marco Dorigo is used in CA-IACOA for searching the optimal vehicular nodes that could aid in selecting the shortest path and alternative vehicular nodes for resolving issues that arise due to the influence of DDoS attacks during data dissemination. Since the principle of stagnation is the primitive limitation of ACO optimization process, CA-IACOA uses dynamic movement probability rule for integrating the benefits of random and deterministic selection for overcoming the limitation of ACO and for improving the global selection strategy. This improvement in CA-IACOA is facilitated by formulating and updating dynamic movement probability rule in which the paths that are maximum and minimum visited by the ant agents are used as the modification of pheromone as ACO is an evolutionary changing process. Thus the transistion rules for each search with probability ‘ P_{ij}^{k} ‘ is computed based on number of ant agents’m’ , present itertaion’ I_p ‘, maximum heuristic function ‘ $\eta_{\max}$ ‘ and total number of initially used for performing global search ‘ $Q_c(i,j)$ ‘ through (1) as

$$P_{ij}^{k} = \frac{R_{ij}(t)^{\alpha} * \eta_{ij}(t)^{\beta} * x_{ij}(t)}{\sum_{k \in per(k)} R_{ik}(t)^{\alpha} * \eta_{ik}(t)^{\beta} * x(t)} \qquad (1)$$

Where $$x_{ij(t)} = \frac{m * I_p}{m * I_p + \delta * Q_c(i,j) * (\eta(i,j)/\eta_{\max})} \qquad (2)$$

and $\eta_{ij}(t)$ is the packet forwarding potential of a vehicle, based on the reliability factor. It is calculated from the past PDR of the vehicle.

$$\eta_{ij}(t) = \frac{\mathcal{F}_{\mathcal{P}}}{\mathcal{T}_{\mathcal{P}}} \times 100 \qquad (3)$$

where $\mathcal{F}_{\mathcal{P}}$ is number of packets forwarded and $\mathcal{T}_{\mathcal{P}}$ is the total packets received by vehicle_{ij} at time t-1.

If the number of ant agents in CA-IACOA are contiouly increased then the value of ‘ x_{ij} ‘ is periodically decreased.In this context, the iteration of search approcages to a suboptimal solution even when the value of pheromone is gradually improved. When the optimal nodes and the paths are identified, the exploration may lead to premature convergence due to the use of excessive amount of pheromone.But, CA-IACOA tackles it by depressing the level of pheromone based on the degree of exploration required. The cellular automata model space used in CA-IACOA is facilitated with four points such as source vehicle point, destination vehicle point, intermediate router node points and free space that follows Moore model. The distance between the source vehicle point and destination vehicle point is considered as ‘L’ and the intermediate router nodes can move around a width of L/2.Thus the space

$$S = \{(x,y) / x \in \{0,\ldots,X_{\max}\}, y \in \{0,\ldots.,Y_{\max}\} \qquad (4)$$

The position of each vehicle pertains to a point (x, y), when S (x, y) =1, the collision of vehicles is possible and if S (x, y) =0 represents the collision free space of the cellular automata.

The cellular automata model employed in CA-IACOA consists of cells and cellular spaces for discretizing time and space in the search space. Cellular Automata Moore Neighborhood model is applied in the proposed algorithm to select the neighboring vehicles since they focus on more neighbors when compared to other available models like Von Neumann model, Morgolous model. Further, from literature, it is proved that Moore neighborhood is highly suitable for VANETs environment.The time and space are discretized for analyzing and describing the dynamic behaviour of vehicular nodes in the 2D space as shown in figure 1 and figure 2. Each and every cell employed in the lattice grid space exhibits finite number of discrete states and the behavioural states are updated based on the newly innovated local space rule. This complex dynamically changing complex behavioural state process identification is modeled into a discrete interactive process. The Cellular Automata Moore model used in CA-IACOA is represented using a 4-tuple $C_A = (L_d, S_c, N_c, R_c)$

Where, C_A : Moore model based cellular automata.

L_d : Cellular space with 'd' positive dimension used in the Moore model (d=2 in CA-IACOA)

S_c: Possible state space of cellular automata (0, 1)

N_c : Neighbours of each individual cellular cell defined based on Moore model represented through S=$\{n_1, n_{2,}, \ldots\ldots, n_r, \ldots. n_n\}$.where 'S' and 'r' denotes the spatial vector that incorporates 'n' feasible cellular states and direction of the artificial bee colony respectively. In CA-IACOA, $r \in [1,8]$ and $s_r \in [0,1]$ which infers that the transition will decide to choose any direction, else if $s_r = 1$, the artificial bee colony optimization is not possible.

R_c : Rule for cellular transition or cellular state transformation function

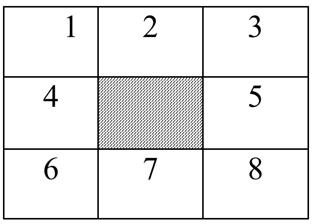


Figure 1: Moore Model for CA-IACOA

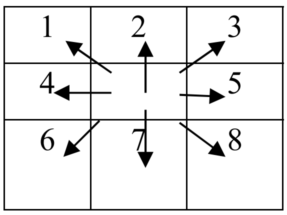


Figure 2: Direction of transfer in CA-IACOA

3.3.2 Enhanced Pheromone updating rules of CA-IACOA

The pheromone rules for CA-IACOA is enhanced by updating the residual pheromone after each iterative search as the heuristic factor of search should not be integrated with the estimated residual pheromone data elucidated. Hence the pheromone rules for CA-IACOA is improved based on

$$R_{ij}(t+1) = \rho R_{ij}(t) + \Delta R_{ij} + \Delta R_{ij}{}^{c} \qquad (5)$$

$$\Delta R_{ij}{}^{c} = \sum_{k=1}^{m} \Delta R_{ij}{}^{k} \qquad (6)$$

$$\Delta R_{ij}^{k} = \frac{Q}{L_k} \text{(the path (i,j) traversed by each ant agent in specicic iterations)} \qquad (7)$$

$$\Delta R_{ij}{}^{c} = \frac{\delta Q}{L_c} \text{ (the path (i,j) is the identified optimal solution)} \qquad (8)$$

Where, ‘ Q ’-Pheromone intensity constant

‘ $R_{ij}(t)$ ‘-Pheromone value at time ‘t’

‘ $R_{ij}(t+1)$ ‘-Pheromone value at time ‘t+1’

‘ ρ ’-Evaporation factor rate.

3.3.3 Pheromone Adaptive Adjustment Strategy for CA-IACOA

In the traditional ACO algorithm, fixed level of pheromone is used for updating the pheromone-based search strategy. This kind of strategy ignores several characteristics of distribution that pertains to the identified solution of each iteration and hence it is susceptible to process of stagnation and slow convergence that highly results ACO to fall into a local optima in the premature stage of searching that prevents the algorithm from identifying the optimal vehicular nodes for handling DDoS attacks. Therefore a Pheromone Adaptive Adjustment Strategy for CA-IACOA is incorporated to modify the non-uniform distribution to be converted to a relative uniform pheromone distribution that resolves the tradeoff that exists between the deviation in search expansion and the exploration of optimal soultion for attaining the local optimum solution.in this Pheromone Adaptive Adjustment Strategy of CA-IACOA, the influential function referred as pheromone intensity constant ‘ ρ ’ is replaced by a real dynamic ranging variable function ‘ $V(t)$ ‘ based on adjusting pheromone represneted through (6) as

$$\Delta R_{ij(t)}^{(k)} = \frac{V(t)}{L_k} \qquad (9)$$

The afforementioned real dynamic ranging variable function '$V(t)$'is defined in CA-IACOA is potrayed from (6)-(8) as follows

$$V(t) = V_1, t \leq Th_1 \qquad (10)$$

$$V(t) = V_1, t \leq Th_2 \qquad (11)$$

$$V(t) = V_1, t \leq Th_3 \qquad (12)$$

Where, V_1, V_2 and V_3 refers to three levels of tolerance pertaining to dynamic pheromone intensity. Th_1, Th_2, Th_3 represents the number of vehicular nodes in a particular cell.

The replacement of real dynamic ranging variable function is mainly to sustain the balance that exists between exploitation and exploration key of dynamic searching of ant agents that aids to maintain the evocation function to a constant level under the influence of pheromone evaporation. It also checks that the optimal quality solution is constant over a period of time under searching and it also seem to prevent the search to suddenly fall into an critical point of convergence.Then the Pheromone Adaptive Adjustment Strategy plays a vital role in decreasing the level of information used for searching the critical point convergence and once the point is found, the number of optimal paths are discriminated from worst paths based on the positive feedback scheme used by the classical ACO. But in CA-IACOA, considerable amount of negative feedback pheromone is used in the search for minimizing the deviation in pheromone of each and every optimal path solutions identified. This Pheromone Adaptive Adjustment Strategy step also aids in expanding the possibility of global search.

3.3.4 CA-IACOA Dynamic Evaporation Factor Strategy

In CA-IACOA**,** the evaporation factor'ρ 'of the pheromone cannot be a constant as it directly represents the convergence speed and global searching ability of the algorithm. Generally, the Evaporation Factor of ACO in the least unexplored region and paths converges to 0.This property of evaporation factor convergence greatly minimizes the global searching potential of the implemented algorithm. In reverse, if pheromone used is high than it also affects the global searching potential of ACO. The idea of initilazing the pheromone's value remains a critical issue that need to be dynamically resolved as it is the core mechansim of controlling and synchronizing the rate of release and evaporation.Thus Dynamic Evaporation Factor Strategy in CA-IACOA is necessary for setting the value of pheromone for improving the global exploring skill of the deployed algorithm. The utilized Dynamic Evaporation Factor Strategy in CA-IACOA is capable of improving the global search potential and further induces the rate of convergence to a significant level.This strategy uses the idea of incorporating maximum value to the dynamic evaporation factor at the intial state for improving the rate of searching potential. Even when the evaporation factor is intially high, they gradually decay and starts to converge into a optimal solution. To study the decay rate of evaporation factor, three decay models such as scale decay model, line decay model and curve decay model can be used. In CA-IACOA, Dynamic Evaporation Factor is estimated based on curve decay model through (13) as

$$\rho(t) = \frac{T(R_{\max} - R_{\min})t}{T-1} + \frac{T(R_{\min} - R_{\max})}{T-1} \tag{13}$$

where ‘ ρ ‘, ‘ T ‘, ‘ t ‘, ‘ $R_{\max}$ ‘, ‘ $R_{\min}$ ‘ refers to the evaporation rate of pheromone, maximum number of iterations used for identifying optimal nodes and optimal paths, minimum number of iterations used for identifying optimal nodes and optimal paths, upper and lower threshold of pheromone value respectively.The upper and lower threshold value of pheromone is set based on the traffic in the selected path. The pheromone values are scaled in the range 1 to 10. The upper threshold value is 8 and lower threshold value is 4 for balancing the exploration and exploitation level. In CA-IACOA, curve delay model is mainly used for investigating about the decay rate of evaporation factor as it is the predominant model that can discriminate the deviation that exists between the evaporation and release rate of pheromone in a significant way.

3.3.5 Boundary Symmetric Mutation Scheme of CA-IACOA

Statistical theory infers that most of the distribution will tend to be normal or will meet normal distribution based on the increasing number of vehicular nodes used in the cellular automata model. The co-ordinates of each vehicular node are initially sorted based on the co-ordinates of vehicular nodes in the cellular automata model. When the number of number of nodes in the cellular co-ordinate is small, the global search is carried based upon the idea of Centrotaxis as most of the selected optimal nodes for handling DDoS will the concentrated in the center and the optimal nodes for routing are also elected with respect to the same phenomenon. In this CA-IACOA approach, initially the ant agents are made to explore the possibilities starting from the boundary towards the center of the employed Moore-based cellular automata. After each and every incremental time, the search is performed from the center towards the boundary. Thus ant agents in CA-IACOA are made to obey the trajectory model of boundary-center-boundary during the exploration of identifying the optimal nodes and optimal paths for mitigating DDoS attacks. The trajectory model is used to overcome the perplexing paths that might arise during the exploration in the center area and further a number of overlapping paths with critical limitations may arise in the boundary paths. Furthermore effective mutation strategy is integrated with CA-IACOA for estimating the quantification of mutation degree along the boundary paths. This boundary symmetric mutation strategy has a phenomenal improvement by not only enhancing the mutation efficiency but also helps to achieve better quality exploration results.

In CA-IACOA paper, the idea of probabilistic quartile is used to mutate nearly one-third from the initial and end of the paths explored. Thus mutation in the boundary happens only in the interior part of the limits and does not happen exterior to the exploration area. Hence, Cellular Automata-based Improved Ant Colony-based Optimization Algorithm combines improved dynamic transition rules of ant agents, enhanced update rules of pheromone, pheromone's adjustment strategy of pheromone and dynamic evaporation factor strategy with boundary symmetric mutation for speeding the rate of search.

The steps of CA-IACOA used in improving the search quality for identifying optimal nodes for handling DDoS attacks and finding optimal quality path solutions are given in Alorithm 3.1 and flow diadram is as shown in Figure 3.

Algorithm 3.1-Steps inCA-IACOA

Step 1: Set the parameters, T_{max} = number of intermediate nodes

Step 2: Find the fitness function of each vehicular nodes

Step 3: Deploy the vehicles and ants in Moore model and update their position

Step 4: When the cache list is not empty, select the vehicular nodes by the selection probability

$$P_{ij}^{k} = \frac{R_{ij}(t)^{\alpha} * \eta_{ij}(t)^{\beta} * x_{ij}(t)}{\sum_{k \in per(k)} R_{ik}(t)^{\alpha} * \eta_{ik}(t)^{\beta} * x(t)}$$

Step 5: After the ant agents have been identified the optimal paths and optimal node, the path length is calculated and updated in the cache list.

Step 6: The current optimal node and path are saved and the global optimal path are updated in each iteration.

Step 7: Update the pheromone according to the updating rules of pheromone.

$$R_{ij}(t+1) = \rho R_{ij}(t) + \Delta R_{ij} + \Delta R_{ij^c}$$

Step 8: Set the iteration control by periodic increments of 1 based on pheromone adaptive adjustment, Dynamic evaporation factor and Boundary symmetric mutation scheme.

Step 9: The iteration control is processed until $t<T_{max}$. go to step (4)

Step 10: Otherwise, CA-IACOA is terminated and the identified optimal node and path are used for mitigation DDoS attack.

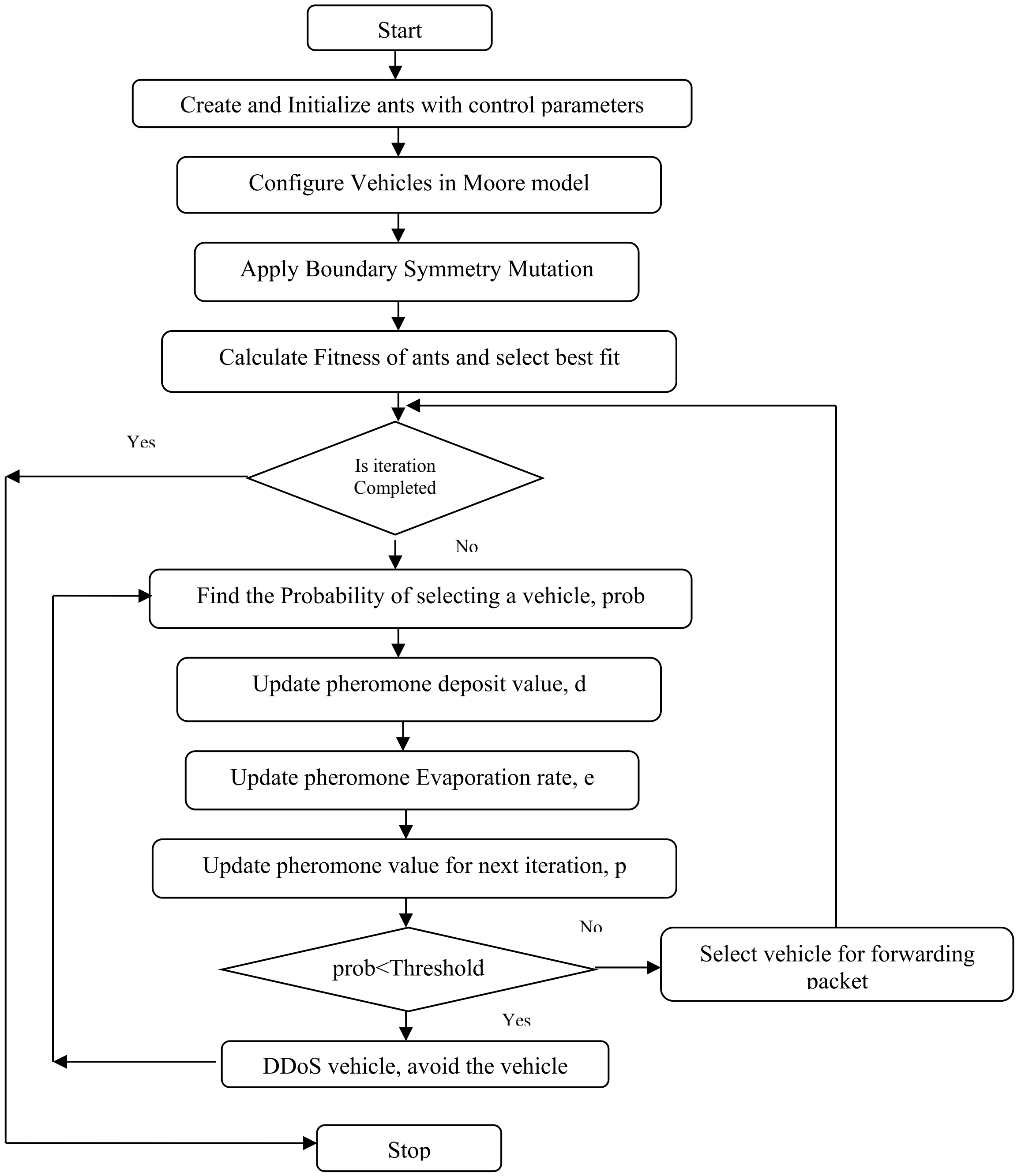


Figure 3: Flow Diagram of CA-IACOA mechanism.

4. Experimental Results and Discussions

The performance investigation of CA-IACOA with CA-ACOA, CA-GA and CA-PSO is evaluated based on ns-2 simulator and SUMO traffic simulator is used for generating vehicular mobility traces. Initially, evaluation parameters such as prediction variance (meters) and prediction variance (seconds), average prediction variance are used for investigating the performance of CA-IACOA.

Prediction variance is the residual error in predicting the position of the optimal neighbor for packet forwarding. The value is calculated by using the following formula

$$\text{Prediction Variance} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x-\bar{x})^2 + (y-\bar{y})^2}$$

where N is the optimization factor based on the selected prediction interval.

The delay in predicting the optimal neighbor vehicle is measured in terms of prediction variance in seconds. The proposed CA-IACOA algorithm aim is to reduce the variance in the predicted position of the neighbor vehicles and delay in prediction.

In this performance analysis, the experiments are carried out either by varying the number of nodes or by varying the prediction interval. The comparative analysis of CA-IACOA is based on five experiments discussed below.

In the first three experiments, the performance of CA-IACOA with CA-ACOA, CA-GA and CA-PSO is analyzed through evaluation factor such as variance (meters) and prediction variance (seconds), average prediction variance obtained by varying the prediction interval and vehicular nodes. In experiment 4 and 5, the importance CA-IACOA over CA-ACOA, CA-GA and CA-PSO is estimated based on four benchmark multimodal functions like Quartic, Schwefel-2.26, Exponential and SumSquare with search dimension D=5 and D=10 respectively.

The simulation setup used for comparative performance analysis of CA-IACOA with CA-ACOA, CA-GA and CA-PSO are detailed in Table 1.

Table 1: Simulation setup for evaluating CA-IACOA

Parameters	Value
Number of vehicular nodes	100,200,300
Range of transmission	600m

Threshold speed	40-60 m/sec
Acceleration of vehicular node	1.2 m/s^2
Retardation of vehicular node	6.5 m/s^2
Simulation time	600s
Prediction interval	10-140 s
MAC protocol	IEEE 802.11p
Refresh interval time	50s

Experiment 1-Performance analysis of CA-IACOA based on prediction variance (meters) by varying prediction interval

In experiment 1, the performance investigation of CA-IACOA over existing cellular automata based DDoS mitigation approaches like CA-ACOA, CA-GA and CA-PSO are investigated.

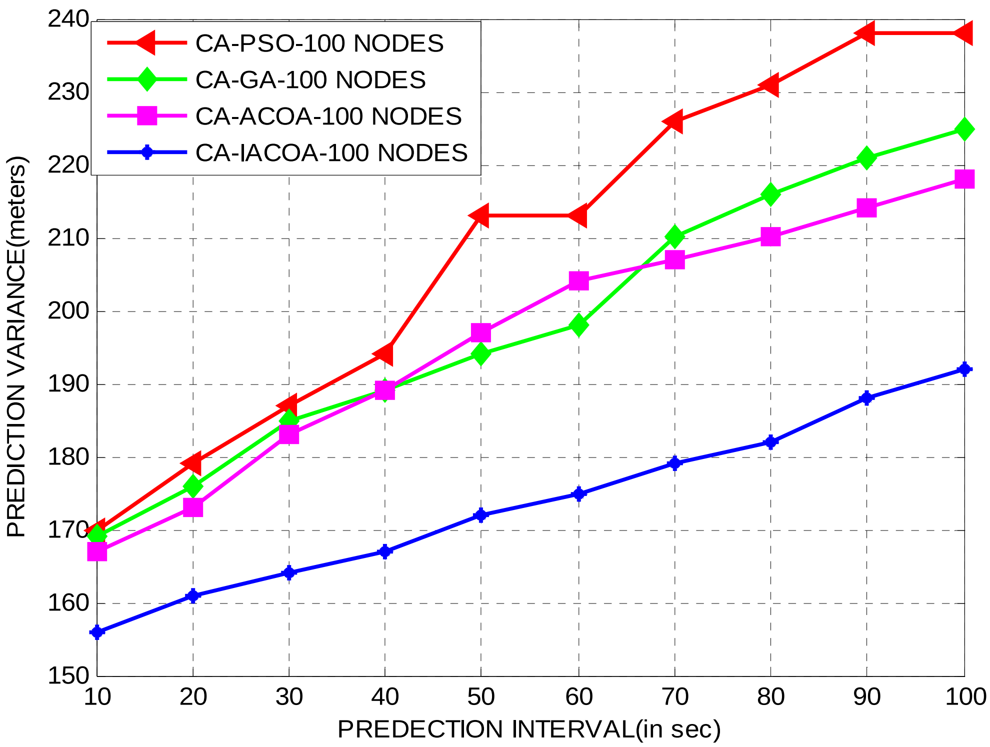


Figure 4 -Experiment 1-Performance of CA-IACOA-Prediction variance (meters)-100 nodes

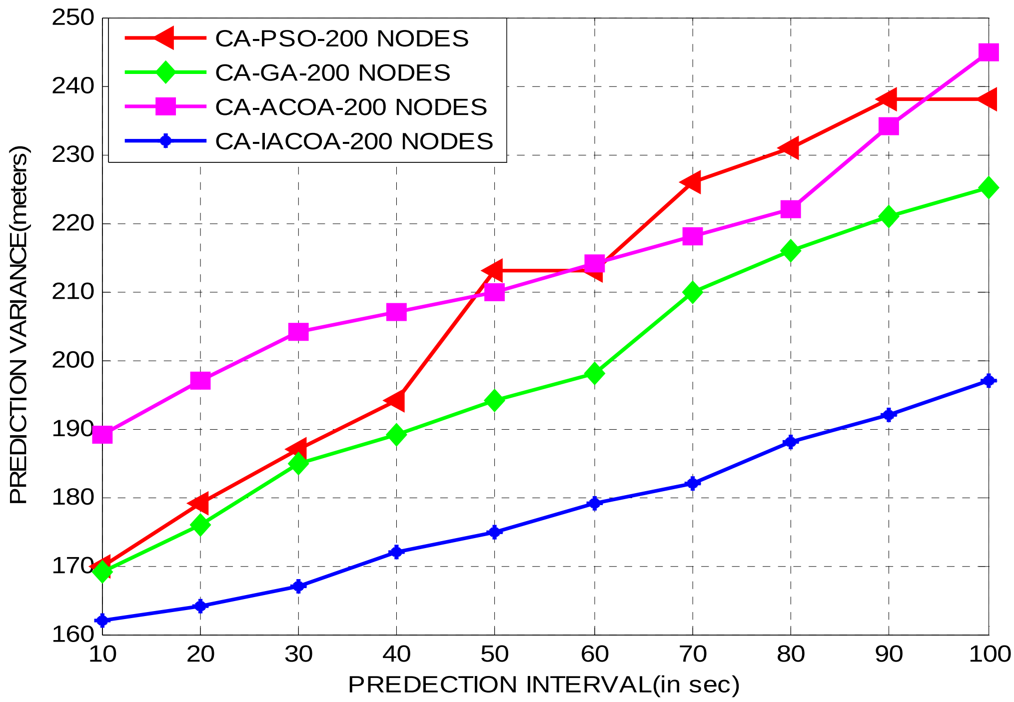


Figure 5 -Experiment 1-Performance of CA-IACOA -Prediction variance (meters)-200 nodes

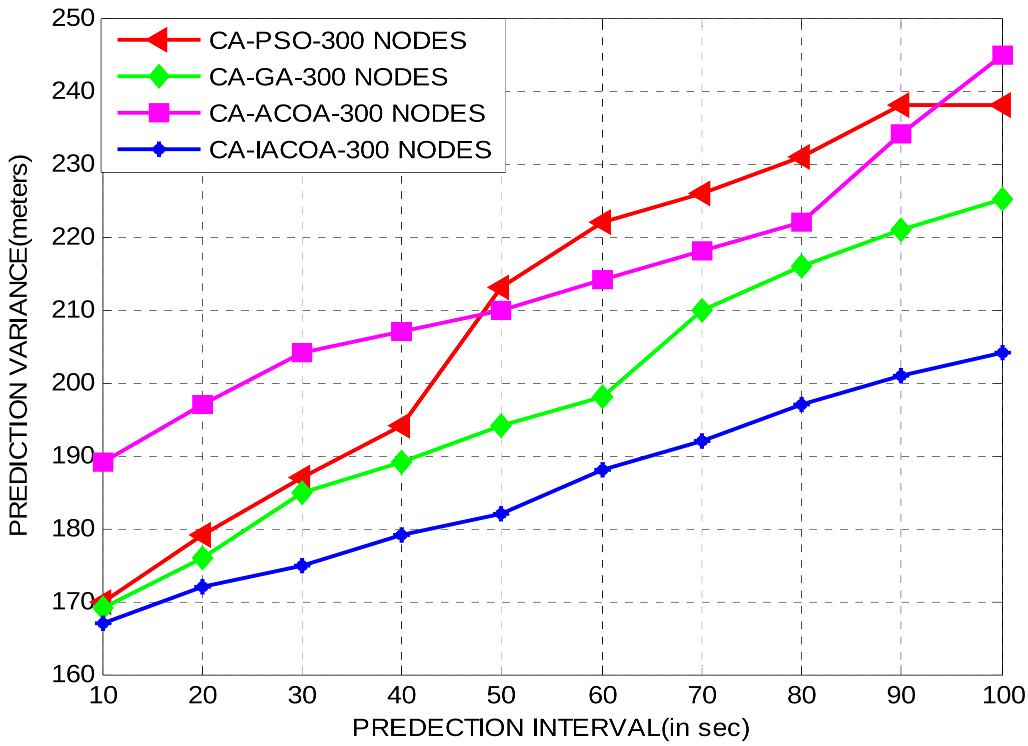


Figure 6 - Experiment 1-Performance of CA-IACOA-Prediction variance (meters)-300 nodes

Figure 4 portrays the performance of CA-IACOA in terms of prediction variance (meters) obtained by varying the prediction interval (seconds) with respect to 100 vehicular nodes. Results make it clear that the prediction variance for CA-IACOA, CA-ACOA, CA-GA and CA-PSO increases phenomenally when prediction interval is varied from 10 to 100 seconds. But, CA-IACOA is able to dynamically decrease the variation especially when the prediction interval increases. CA-IACOA is found to exhibit a decrease in prediction variance to a maximum level of 16% than the compared baseline approaches.

Figure 5 portrays the performance of CA-IACOA in terms of prediction variance (meters) obtained by varying the prediction interval (seconds) with respect to 200 vehicular nodes. Results make it clear that the prediction variance for CA-IACOA, CA-ACOA, CA-GA and CA-PSO also increases phenomenally when prediction interval is varied from 10 to 100 seconds under the influence of 200 nodes. But, CA-IACOA is able to dynamically decrease the variation even when the numbers of nodes are increased by 200 especially when the prediction interval increases. CA-IACOA is found to exhibit a decrease in prediction variance to a maximum level of 19% than the compared baseline approaches.

Figure 6 portrays the performance of CA-IACOA in terms of prediction variance (meters) obtained by varying the prediction interval (seconds) with respect to 300 vehicular nodes. Results make it clear that the prediction variance for CA-IACOA, CA-ACOA, CA-GA and CA-PSO also increases phenomenally when prediction interval is varied from 10 to 100 seconds under the influence of 300 vehicular nodes. But, CA-IACOA is able to dynamically decrease the variation even when the numbers of nodes are increased by 200 especially when the prediction interval increases. CA-IACOA is found to exhibit a decrease in prediction variance to a maximum level of 23% than the compared baseline approaches.

Experiment 2- Performance analysis of CA-IACOA based on prediction variance by varying number of nodes

In experiment 2, the performance analysis of CA-IACOA, CA-ACOA, CA-GA and CA-PSO is carried out in terms of prediction variance per second by varying the number of vehicular nodes from 100 to 300 based on varying prediction interval.

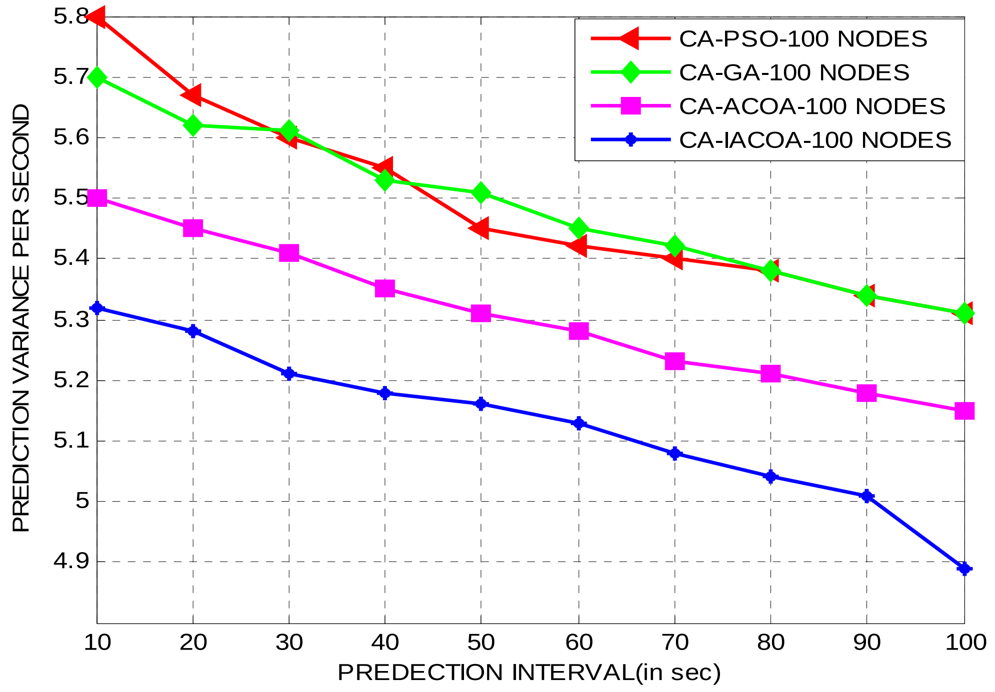
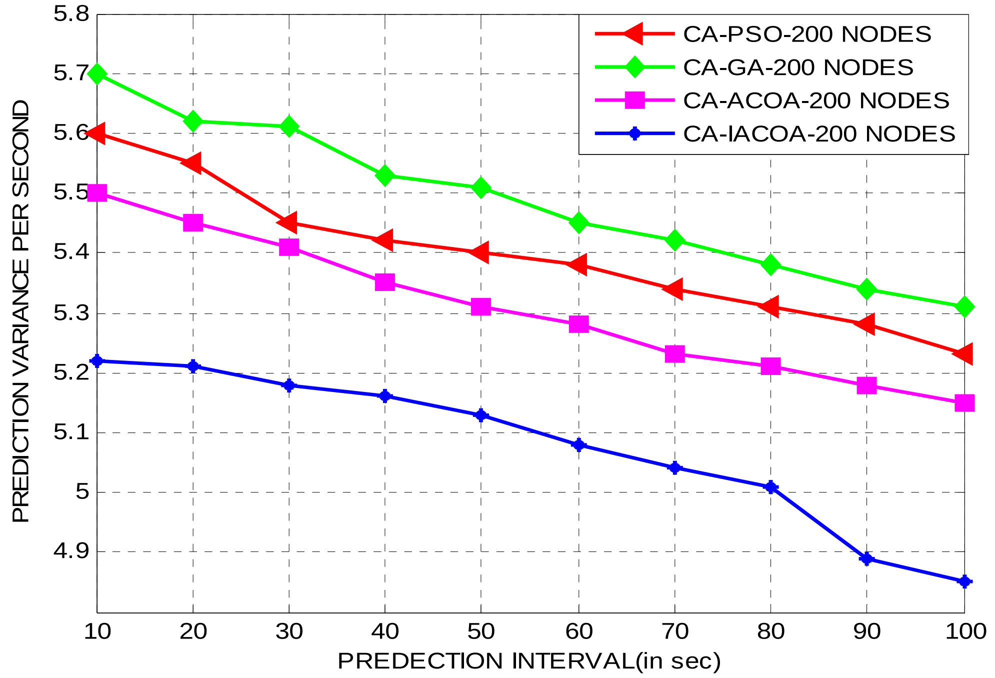


Figure 7- Experiment 2-Performance of CA-IACOA-Prediction variance per second-100 nodes



F igure 8 - Experiment 2-Performance of CA-IACOA-Prediction variance per second-200 nodes

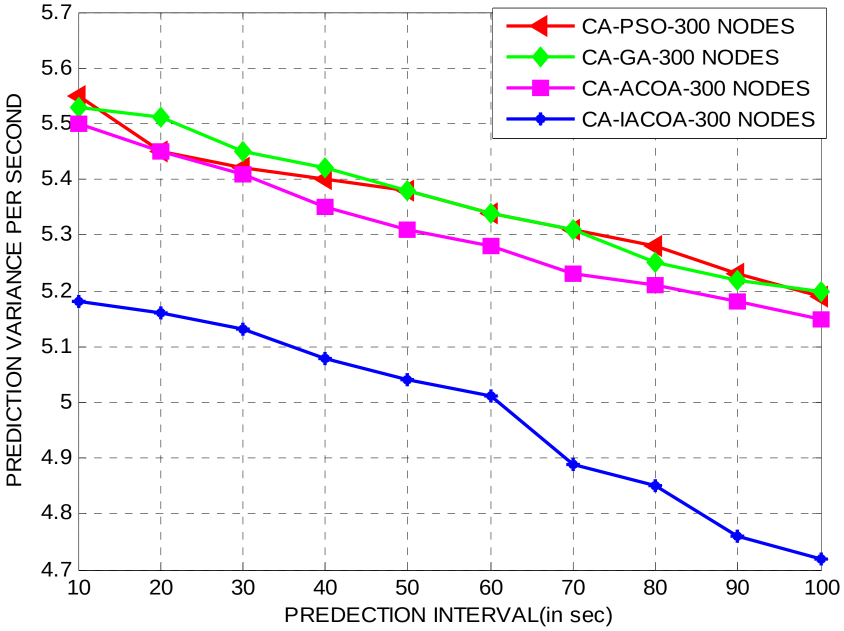


Figure 9 - Experiment 2-Performance of CA-IACOA-Prediction variance per second-300 nodes

Figure 7 describes the performance of CA-IACOA, CA-ACOA, CA-GA and CA-PSO based on prediction variance in seconds evaluated by varying the prediction interval. It is found that the prediction variance per second for CA-IACOA, CA-ACOA, CA-GA and CA-PSO is considerably decreasing when the prediction interval is increased. But CA-IACOA is able to increase the dimension of searching and prevents it from being trapped into local minimum. Hence CA-IACOA decreases the prediction variance in seconds than CA-ACOA, CA-GA and CA-PSO to a considerable level of 21%, 23% and 26% under the influence of 100 nodes.

Figure 8 describes the performance of CA-IACOA, CA-ACOA, CA-GA and CA-PSO based on prediction variance in seconds evaluated by varying the prediction interval with 200 nodes. It is found that the prediction variance per second for CA-IACOA, CA-ACOA, CA-GA and CA-PSO is considerably decreasing not only with respect to prediction interval but also based on number of nodes. CA-IACOA decreases the prediction variance in seconds than CA-ACOA, CA-GA and CA-PSO to a considerable level of 15%, 17% and 20% respectively.

Figure 9 describes the performance of CA-IACOA, CA-ACOA, CA-GA and CA-PSO based on prediction variance in seconds evaluated by varying the prediction interval with 300 nodes. It is found that the prediction variance per second for CA-IACOA, CA-ACOA, CA-GA and CA-PSO is highly decreasing when the number of nodes is increased to 300. But CA-IACOA decreases the prediction variance in seconds than CA-ACOA, CA-GA and CA-PSO to a considerable level of 11%, 14% and 18% respectively.

Experiment 3- Performance analysis of CA-IACOA based on prediction variance by varying number of nodes

In experiment 3, the performance of CA-IACOA, CA-ACOA, CA-GA and CA-PSO is investigated in terms of prediction variance (meters) by varying the number of vehicular nodes from 100 to 300 with fixed accuracy interval of 80s, 90s and 100s respectively.

Figure 10 portrays the relationship that infers the optimal average prediction accuracy facilitated by CA-IACOA, CA-ACOA, CA-GA and CA-PSO when vehicular nodes are significantly varied. This investigation is initially with an accuracy level of 80sec as it is considered as the minimum optimal value for accuracy prediction in CA-IACOA, CA-ACOA, CA-GA and CA-PSO mechanism. The average prediction variance of CA-IACOA shows a meager variation of approximately 56-60m with varying number of vehicular nodes, whereas CA-ACOA, CA-ACOA, CA-GA exhibits a deviation of 69-74m, 80-84m and 91-97m respectively

Similarly, Figure 11 also portrays the relationship that infers the optimal average prediction accuracy facilitated by CA-IACOA, CA-ACOA, CA-GA and CA-PSO when vehicular nodes are significantly varied with an accuracy level of 90sec as it is considered as the minimum optimal value for accuracy prediction. The average prediction variance of CA-IACOA shows a meager variation of approximately 52-55m with varying number of vehicular nodes, whereas CA-ACOA, CA-ACOA, CA-GA exhibits a deviation of 59-64m, 67-73m and 77-80m respectively.

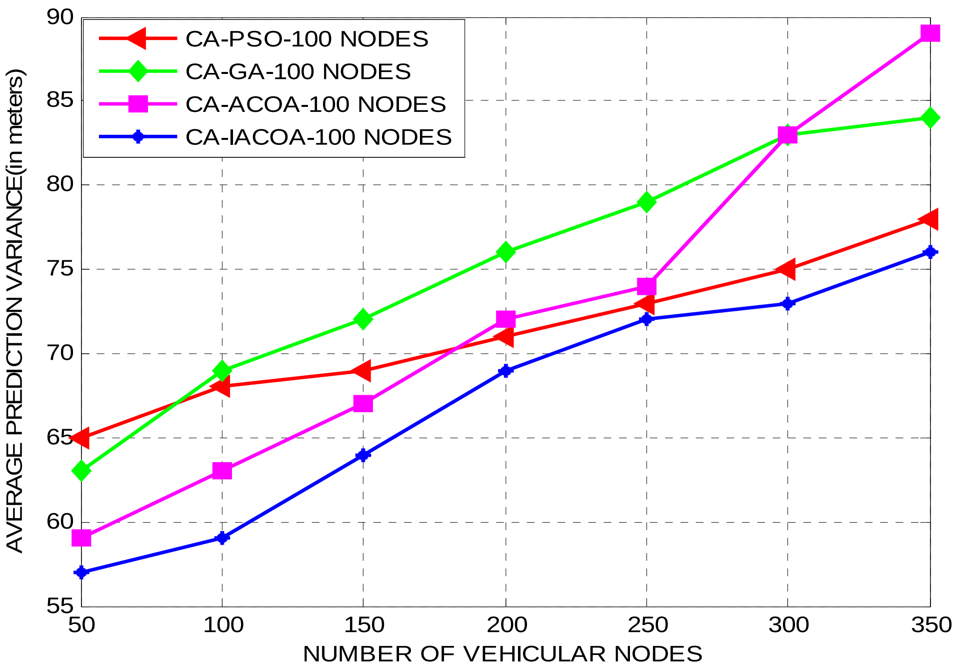


Figure 10 - Experiment 3-Performance of CA-IACOA-Average Prediction variance-60 seconds

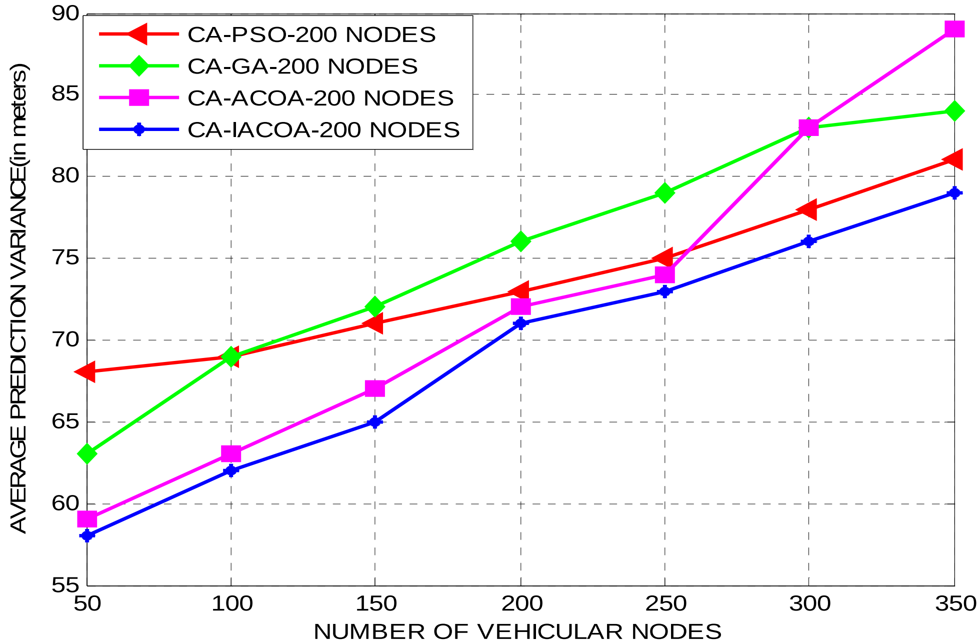


Figure 11 - Experiment 3-Performance of CA-IACOA-Average Prediction variance-70seconds

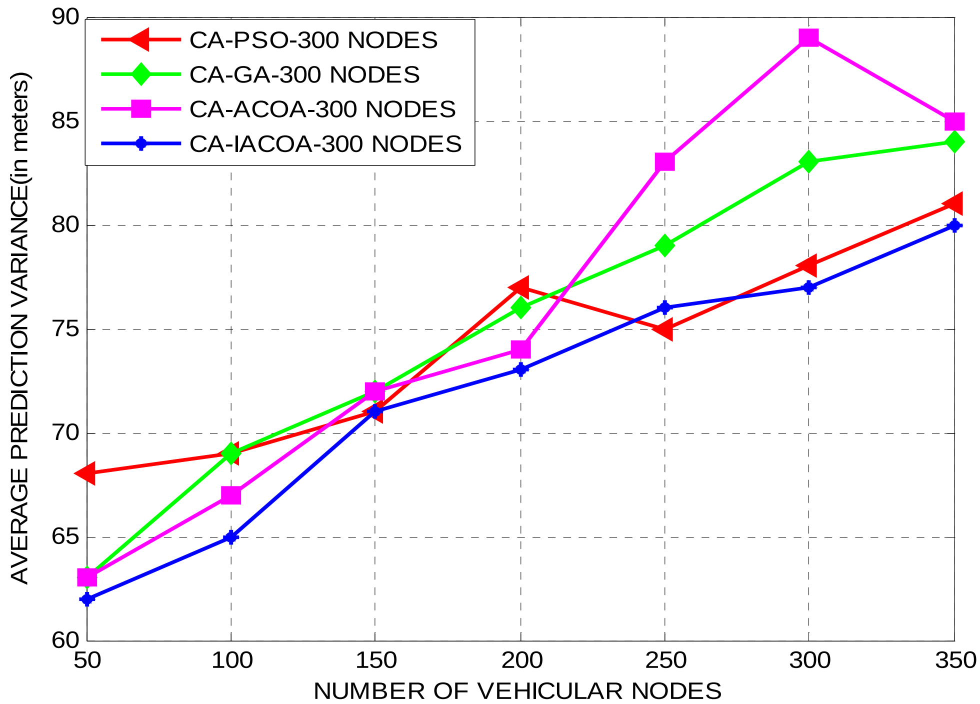


Figure 12 - Experiment 3-Performance of CA-IACOA--Average Prediction variance-80 seconds

In addition, Figure 12 also portrays the relationship that infers the optimal average prediction accuracy facilitated by CA-IACOA, CA-ACOA, CA-GA and CA-PSO when vehicular nodes are significantly varied under an accuracy level of 100sec. The average prediction variance of CA-

IACOA shows a meager variation of approximately 50-53m with varying number of vehicular nodes, whereas CA-ACOA, CA-ACOA, CA-GA exhibits a deviation of 57-64m, 68-73m and 78-89m respectively.

Experiment 4-Performance analysis of CA-IACOA with search dimension (D=5)

In experiment 4, the comparative performance of CA-IACOA over CA-ACOA, CA-GA and CA-PSO is investigated with respect to four benchmark functions such as Quartic, Schwefel-2.26, Exponential and SumSquare with search dimension D=5 by varying the number of search iterations that pertains to the average rate of function values.

From Figures 13, 14 and 15 and 16, it is found that CA-IACOA initially provides a unique level of performance with Quartic, Schwefel-2.26, Exponential and SumSquare benchmark multimodal functions. CA-IACOA confirms a systematic growth than CA-ACOA due to permissible global search facility made possible by it. In addition, CA-IACOA provides better convergence degree than CA-ACOA, CA-GA and CA-PSO and it attains the global point after 275 iterations using Schwefel-2.26. From the graph it is shown that the existing algorithms start its convergence only after 100th iteration where the proposed algorithm converges from 50th iteration.

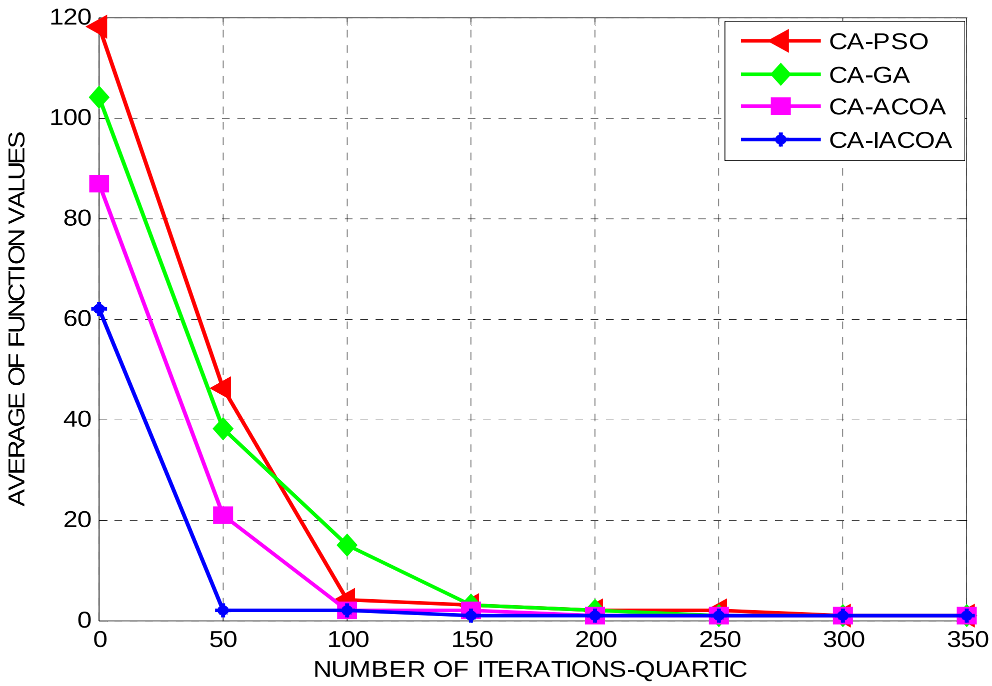


Figure 13 - Experiment 4-Performance of CA-IACOA-Quartic

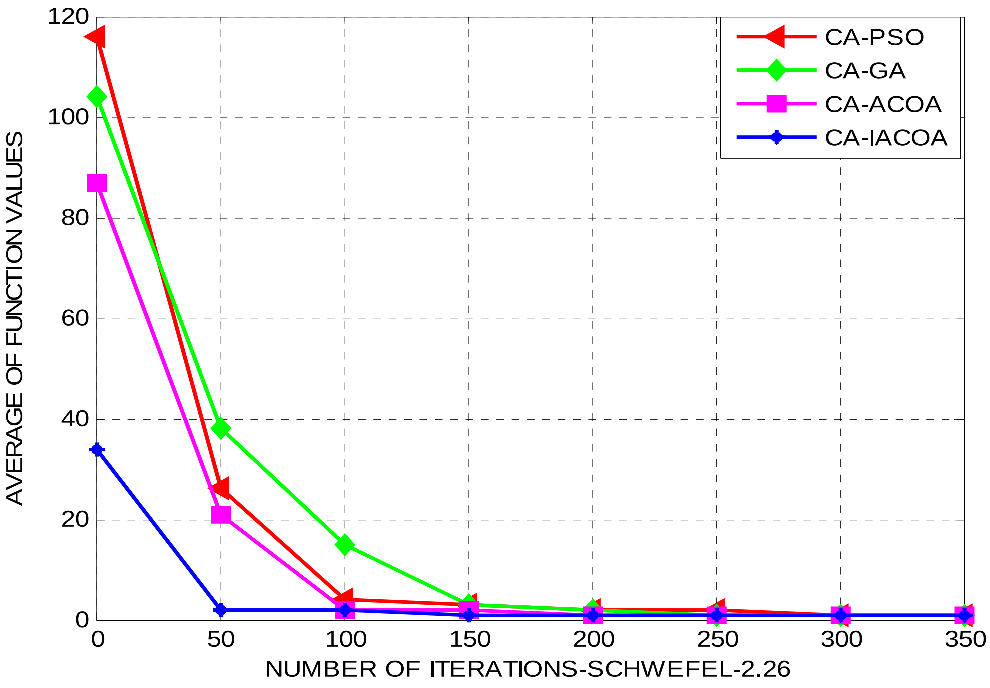


Figure 14 - Experiment 4-Performance of CA-IACOA-Schwefel-2.26

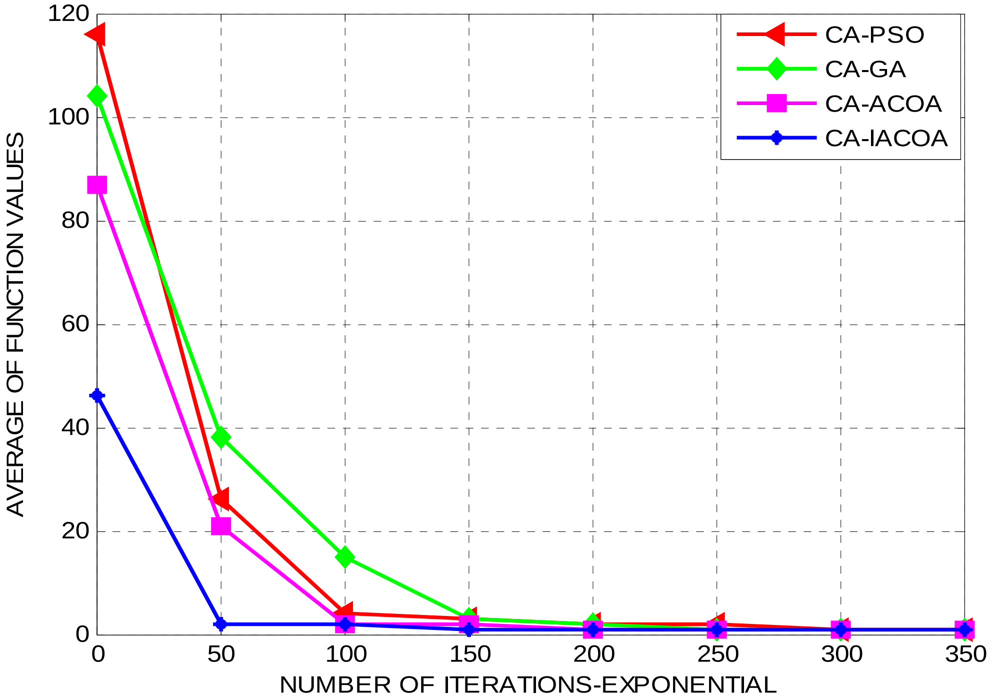


Figure 15 - Experiment 4-Performance of CA-IACOA-Exponential

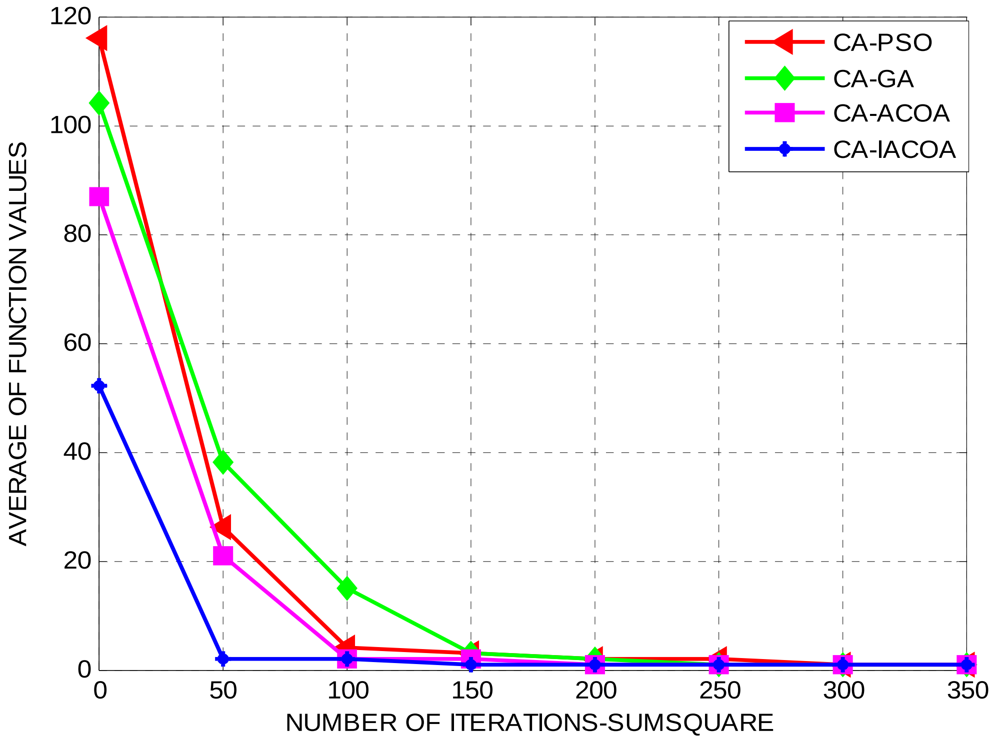


Figure 16 - Experiment 4-Performance of CA-IACOA-Sumsquare

Similarly, CA-IACOA attains the mean global optimum for Quartic, Exponential and Sumsquare after 285,290 and 298 iterations respectively. Hence CA-IACOA is potent in its performance during the investigation with Schwefel-2.26 function as it reaches the optimal point of convergence at a rapid rate of 21% than the compared Quartic, Exponential and Sumsquare functions.

Experiment 5-Performance analysis of CA-IACOA with search dimension (D=10)

In experiment 5, the comparative performance of CA-IACOA over CA-ACOA, CA-GA and CA-PSO is investigated with respect to four benchmark functions such as Quartic, Schwefel-2.26, Exponential and SumSquare with search dimension D=10by varying the number of search iterations which pertains to the average rate of function values.

From Figures 17, 18,19 and 20, it is found that CA-IACOA initially provides a unique level of performance with Quartic, Schwefel-2.26, Exponential and Sumsquare benchmark multimodal functions. CA-IACOA provides better convergence degree than CA-ACOA, CA-GA and CA-PSO, and it attains global optimal point after 285 iterations using Schwefel-2.26. From the graph it is shown that the existing algorithms start its convergence only after 100th iteration where the proposed algorithm converges from 50th iteration.

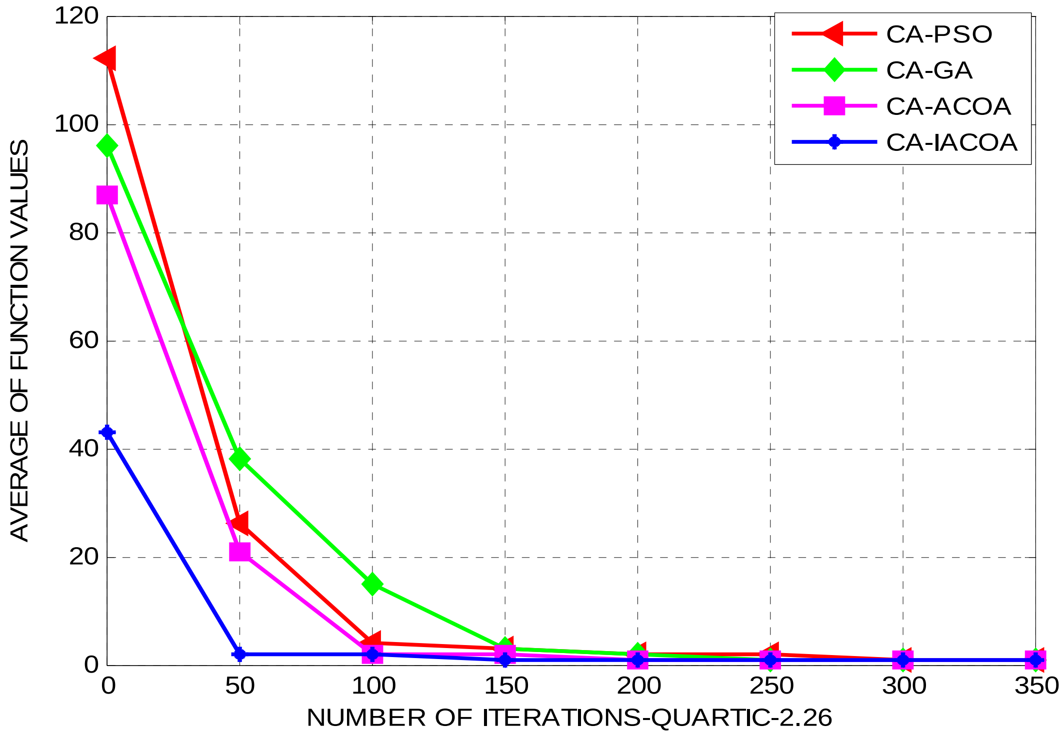


Figure 17 - Experiment 5-Performance of CA-IACOA-Quartic

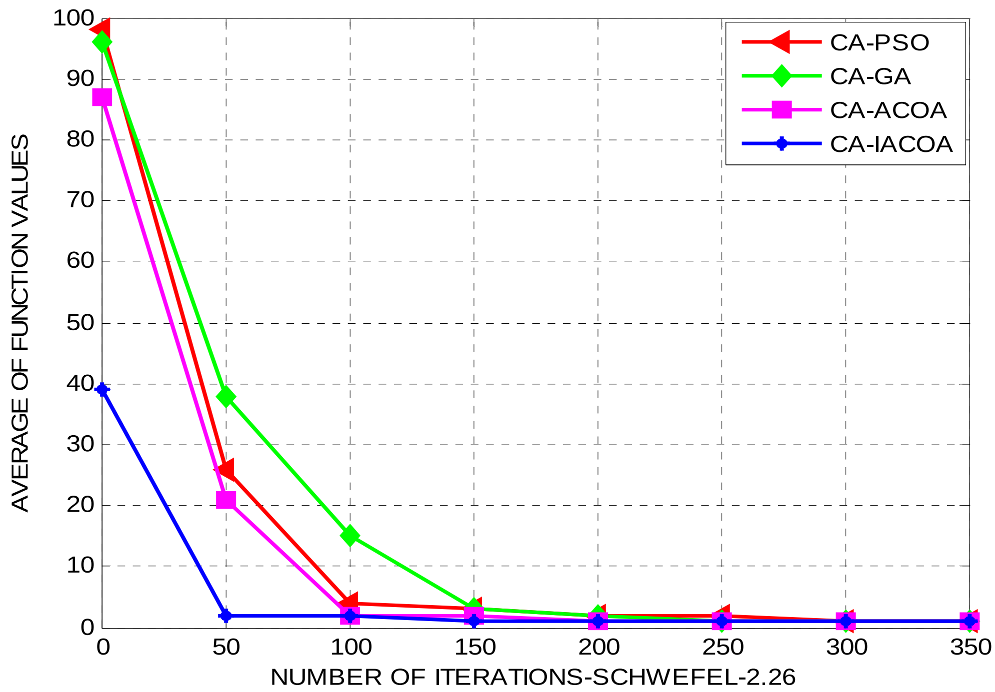


Figure 18 - Experiment 5-Performance of CA-IACOA-Schwefel-2.26

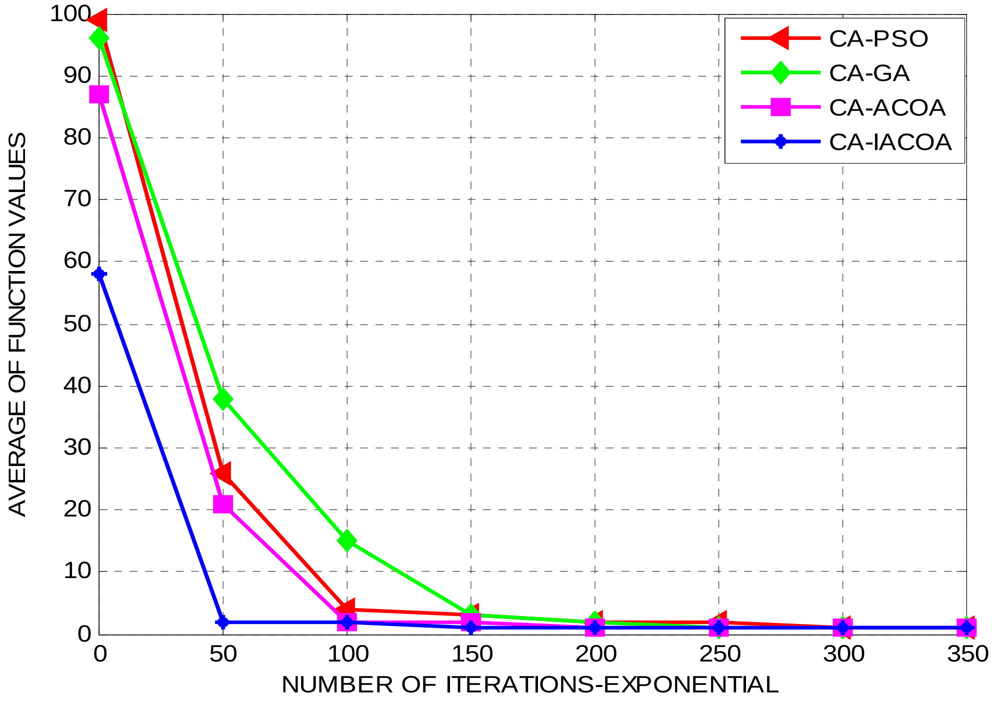


Figure 19 - Experiment 5-Performance of CA-IACOA-Exponential

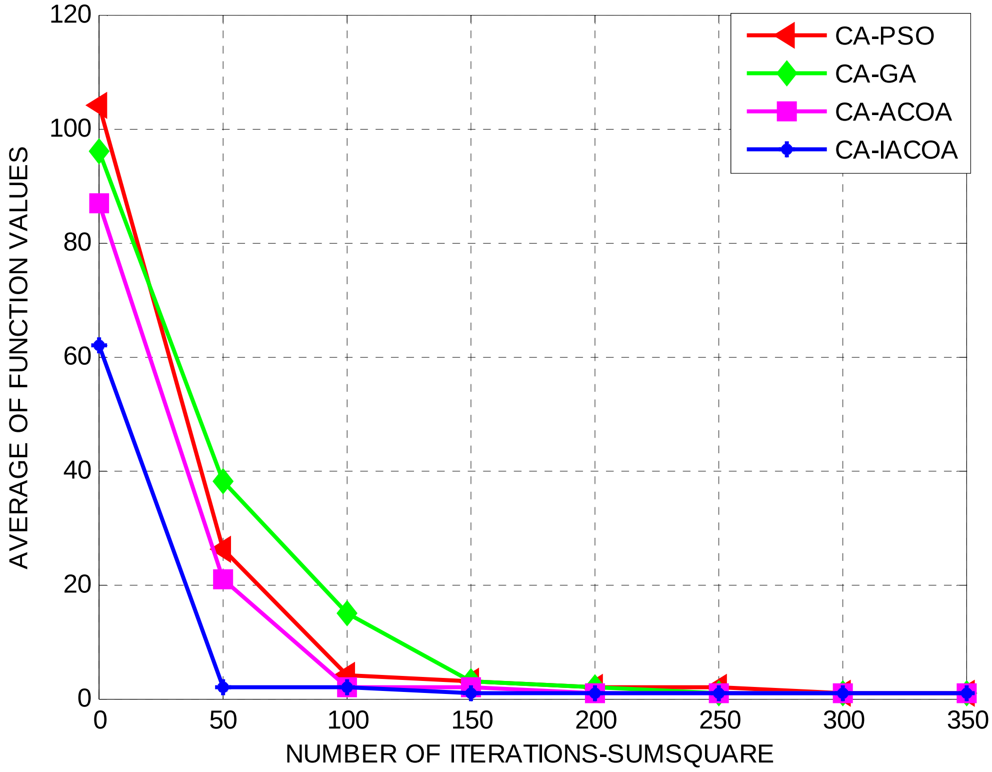


Figure 20 - Experiment 5-Performance of CA-IACOA-Sumsquare

Similarly, CA-IACOA attains the mean global optimum for Quartic, Exponential and Sumsquare after 295, 298 and 305 iterations respectively. Hence CA-IACOA is potent in its performance during the investigation with Schwefel-2.26 function as it reaches the optimal point of convergence at a rapid rate of 17% than the compared Quartic, Exponential and Sumsquare functions even when the search dimensions are increased.

Packet Delivery Ratio

The Packet Delivery Ratio(PDR) of the proposed algorithm is measured by varying the number of vehicular nodes from 100 to 300 under the influence of varying prediction interval. It is noticed that the PDR of CA-IACOA increases proportionally with the increase in the prediction interval as the amount of traffic introduced into the network increases. However, the PDR of CA-IACOA is comparatively higher and ranges from 92-75% for 100 nodes, 84-67% for 200 nodes and 74-54% for 300 nodes as prediction interval increases.

Conclusion

CA-IACOA is propounded and analyzed for isolating the concept of stagnation which is the major drawback for CA-ACOA mitigation algorithm for facilitating a global searching environment based on Pheromone adaptive adjustment strategy, dynamic evaporation factor strategy and Boundary symmetric mutation scheme through dynamic update rule for reliable packet dissemination between vehicular nodes.CA-IACOA incorporates the advantages of Pheromone adaptive adjustment strategy by replacing the pheromone intensity constant which is a real dynamic changing variable function.CA-IACOA achieves this dynamic adaptation through negative feedback concept for identifying optimal solution. It confirms a trusted and accurate global search dimension for enhancing the degree and probable extent of attacker's mitigation. It is also proved that the accuracy in mitigation facilitated by CA-IACOA considerably increases as the pheromone intensity constant is increased systematically. The performance analysis of CA-IACOA with CA-IACOA, CA-ACOA, CA-GA and CA-PSO confirms that it is potential in minimizing the prediction variance and delay to a maximum level of 17% and 21% under the influence of increasing numbers of vehicular nodes. It is concluded that CA-IACOA is optimal in its searching performance with respect to multi-modal function Schwefel-2.26 as it facilitates the global optimal point of convergence at an average rate of 19% than the compared Quartic, Exponential and Sumsquare multimodal functions. In the near future, it is planned to devise a mitigation algorithm based on Artificial Bee Colony algorithm using Exponential and Erlang operator distribution for improving the detection and mitigation rate.

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Cellular Automata-based Improved Ant Colony-based Optimization Algorithm for mitigating DDoS attacks in Vehicular Ad- hoc Networks

- Mitigates DDoS attacks in Vehicular Adhoc Networks for forwarding the data packets efficiently by maintaining the degree of cooperation among the neighbor vehicles.
- The Cellular Automata neighborhood model is applied to give strategy for selecting of the correct neighbor to route packets.
- The exploration and exploitation of the Ant Colony Optimization algorithm is enhanced by adopting the dynamism in pheromone updating rule, pheromone evaporation rate and movement of ant agents.
- The improved Ant Colony Optimization is integrated with Cellular Automata to select the optimal node with the better convergence rate.
- The CA-IACOA enhances the availability of the reliable neighbor at all time for making the VANET services available to all legitimate vehicles in reasonable time.