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INTEGRATING PRIVACY PRESERVING IN INTERNET OF THINGS TO ENSURE DATA SECURITY USING VERTICAL PARTITIONING APPROACH

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Abstract
Guaranteeing security and data privacy are key issues in the Internet of Things (IoT). For the management of numerous security services, privacy plays a significant role. Devices which capable of being utilized anywhere any place, any device anything, any context anytime, anybody anytime, any business any service, in any network any path is the definition of IoT. Routing for IoT needs to be energy efficient. For multimodal problems, traditional evolutionary algorithms commonly result in population convergence towards a search space's restricted area, hence, disregarding the local optima's remainder. The Ant Colony Optimization (ACO) algorithm has garnered much interest and has been researched extensively since it is one of the most efficient techniques for the resolution of optimization problems. This is a population-based heuristic evolution algorithm that is influenced by the results of research of actual ants' natural collective behaviour. Multimodal optimization's Evolutionary algorithms can generally identify many optima within a single run and also retain their diversity of population throughout a run. Hence, for multimodal functions, these algorithms have the capability of global optimization. In this work, a hybrid ACO-Evolutionary Multimodal is proposed for energy-efficient routing**.** The data collected are stored in a vertically partitioned dataset to maintain the privacy of the data.

Keywords: Internet of Things (IoT), Privacy, Multimodal problems, Ant Colony Optimization (ACO) algorithm, Evolutionary Algorithms, Global Optimization, Hybrid ACO-Evolutionary Multimodal, and Vertical Partitioning approach.

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INTRODUCTION

The most recent evolution of the internet is the Internet of Things (IoT) which constitutes (i) the incorporation of millions of wearable devices, smartphones, displays, cameras, internet-connected sensors, and other smart devices which can communicate via the internet (collectively, these objects are termed as IoT things), and (ii) utilization of the IoT things' functionalities and data for the provision of socially beneficial novel smart products and services. Gartner's latest forecast has given the projection that by 2020, there will be a $1.7 trillion market consisting of 28.1 billion connected things [1] for IoT and its associated ecosystem. A paradigm shift of an entirely connected world where there is interconnection of daily objects which have the ability of collective provision of smart services and also direct communication with each other is fuelled by the IoT. Nevertheless, data collected by the IoT in most of these applications are sensitive and should be kept secure and private. Sensitive IoT data examples constitute location data collected by mobile phones, energy consumption data collected by smart meters, physiological data collected by (in certain instances, wearable) biomedical sensors, and so on. There may be a probability of criminal activity, which can cause either critical damage or fatality due to the revelation of these data. Hence, from this point of view, IoT poses a critical obstacle for trust, privacy, and security, that are treated to be amongst the IoT application development's residual major hindrances.

The majority of the present solutions for the IoT's privacy-sensitive data protection concentrates on the authorization and security of communication channels. After the sensitive sensor data collection, integration, and storage, not much work has been carried out for the protection of this data. Due to this, both malicious administrators and hackers have the opportunity to steal and conceal privacy-sensitive data that is gathered and drawn out from IoT devices. For the protection of privacy-sensitive data from hacking, an IoT infrastructure /platform must be developed in order to guarantee end-to-end security and privacy.

Multimodal problems refer to those numerous fascinating multi-disciplinary problems which have multiple optimal solutions inside the search space. As a result, researchers attempt to seek new techniques which have the ability to identify the majority or even every multiple solution of the multimodal problems. The basis of these techniques is generally to conserve the diversity of the population of potential solutions to prevent convergence to a particular minimum or maximum of the search space. Over the past few decades, the Evolutionary multimodal optimization [2] field has become quite well-known. Niching [3] is the frequently used method for retaining the solution diversity in these algorithms. Niching is used to refer to those methods which partition the population into distinct niches such that solutions which take up the search space's diverse areas survive during the algorithm's evolution irrespective of their quality. From this perspective, niching techniques hinder the algorithm's convergence towards a single solution that results in adversity in multimodal problems.

The creation of vertical fragments (that are defined by a vertical partitioning scheme), in conventional vertical partitioning, is based on information about query patterns and database scheme that is acquired by the Database Administrator (DBA). This is feasible for applications in which such information does not have the tendency to vary with time. Even so, several users can simultaneously access applications such as geographic information systems, decision support, e-business, and multimedia. Thus, as queries have the tendency to vary with time, their underlying databases' vertical partitioning scheme has to also vary as per the alterations in query patterns and database scheme that is termed dynamic vertical partitioning.

Most of the problems faced in engineering design and scientific computing are multimodal type, that implies the existence of

more than one decision variable setting which can accomplish the value of the optimal objective function. It is generally preferred to identify all the optimal solutions when handling such problems, as the decision-makers can get extra advantages from these solutions. Through the study of the solutions' common structure, certain more insight into the problem can be gained. Also, a more robust system can be constructed by the combination of these solutions. Conventional optimization techniques must be run several times at diverse starting points in order to tackle multimodal problems. At each time, there is no assurance that the techniques will converge towards a different solution. Contrastingly, due to their search mechanism, which is based on population, EC methods are more applicable for multimodal optimization [4]. Multiple solutions can be simultaneously identified if the population's individuals are allocated to diverse sources of attraction. As EC methods were initially developed for global optimization, because of the genetic drift phenomena, they usually converge towards a single solution. Niching refers to recently devised techniques for inducing multiple convergence behaviour. These techniques alter the individual's search behaviour to aid in subpopulation formation. EC methods with niching technique incorporation have demonstrated huge potential in the search for multiple solutions. Information about the neighbourhood is encoded into some form by almost every niching methods.

Optimization methods are employed for the resolution of problems where a real function's maximization or minimization is sought through the analytic selection of the integer or real variable values from inside a permitted set. Numerous kinds of optimization techniques and optimization algorithms are utilized in diverse approach types for problem resolution. Ant Colony Optimization (ACO) is a metaheuristic optimization algorithm [5] in which numerous ants utilize heuristic information and the gathered experiences in order to develop the entire solutions at each iteration. The collected experiences are represented by the pheromone trail that is placed on the solution's constituent elements. Pheromones are placed on the constituents as per the solution to solving the problem. ACO algorithm's fundamental characteristic is the combination of the prior information concerning a promising solution's structure with the posteriori information concerning the earlier acquired good solutions' structure.

This work has proposed a hybrid ACO-Evolutionary Multimodal utilizing the vertical partitioning approach for data security confirmation in data privacy preservation. The rest of the work has been organized as follows: Section 2 examines the related works. Section 3 outlines the MH-LEACH protocol, TS, and MVO. Section 4 details the results of the simulations conducted. Finally, Section 5 discusses the conclusions.

LITERATURE SURVEY

The issue of IoT privacy preservation was dealt with by Jayaraman et al. [6]. Particularly, innovative techniques were proposed for the IoT data privacy protection, the introduction of IoT Architecture with privacy-preserving capability, and also the description of an effective proof of concept system's implementation, which employs all these measures for guaranteeing the privacy of IoT data. Multiple IoT cloud data stores are employed by these proposed privacy preservation methods for privacy protection of the IoT collected data. An extensively utilized open-source platform for IoT application development is Open IoT. Open IoT's extensions are the basis for the proposed privacy-preserving IoT Architecture and proof of concept implementation. Experimental assessments have also been offered to confirm the proposed privacy-preserving techniques and IoT Architecture's efficacy and performance outcomes.

The development of an adaptive parameter adjustment in Yang et al. [7], initialing, takes into account the differences between niches. Next, for the convergence's acceleration, there is alternate utilization of a differential evolution mutation operator for building the ants' base vectors in order to establish new solutions. Later, for exploitation improvement, a Gaussian distribution-based local search scheme is executed in a self-adaptive manner around the niche's seeds. Overall, a favourable balance between exploration and exploitation is attained by the proposed algorithm. Twenty extensively utilized benchmark multimodal functions are comprehensively experimented on in order to examine each algorithmic component's influence. Comparisons are made with these experimental results against various highly advanced multimodal algorithms and multimodal optimization's competition winners. The proposed algorithm's competitive efficacy and effectiveness are confirmed by these comparisons, specifically when handling complicated problems that have large numbers of local optima.

Influenced by the necessity to safeguard privileged information and also facilitate its utilization for business or various other functions. For the protection of confidential data and critical information in a database, a beneficial technique based on association rule hiding was proposed by Narmadha [8]. Statistical methods, query auditing techniques, and data modification methods are devised and employed for database protection. For database protection, various optimization methods are also utilized with the concept of data mining. This paper employs the Ant Colony Optimization technique, together with association rule mining, for the purpose of concealing sensitive items within large databases.

A routing algorithm is proposed in Said [9] for optimizing the best path's election for data transmission within the IoT system. The ant colony concept utilization in the IoT system is controlled by the algorithm in order to get the best advantage of routing. The IoT environment divided into classified areas, based on the type of networks, by the algorithm. Later on, the algorithm will employ the most feasible ant colony algorithm to the concerned network inside each area. Moreover, it also takes into consideration the routing problem in intersected areas which may emerge in the event of the IoT system. Eventually, the proposed algorithm's performance is assessed with Network Simulator 2. Outcomes of the conducted experiment indicate the proposed routing algorithm's efficiency with regards to the energy consumption ratio, overhead of control bits, throughput, bandwidth consumption, packet loss ratio, and end-to-end delay.

For computing system design, an extensively utilized concept is the locality principle. In Wong et al. [10], incorporation of crowding differential evolution with locality for multimodal optimization is done in order to examine the principle in evolutionary computation. The first proposed method exploits spatial locality for trial vector generation rather than random trial vector generation. The second proposed method makes use of the temporal locality for assistance in the offspring generation. The third proposed method utilizes a combination of spatial and temporal locality. Numerical experiments are carried out for these proposed methods' comparison with highly advanced methods on benchmark functions. The effect of synergy and locality between spatial locality and temporal locality is noted for experimental analysis. Additional experiments are also carried out on two application problems: the protein structure prediction problem and the varied-line-spacing holographic grating design problem. The efficacy of the proposed technique has been proved by the numerical outcomes.

Privacy-Preserving Association Rule Mining (PPARM) technique was proposed by Dani et al. [11] for the privacy-preserving data model's multi-party computation for aggregation, cryptographic security, and the idea of association rule mining. In this

procedure, data is made secure by utilizing cryptographic methods, and random keys generated by the server are utilized to offer a more secure mining method. Data mining in the proposed method is carried out akin to the association rule mining. However, at the client end, the cryptographic method is utilized for securing the sensitivity of the data. Once the data mining is performed, the association rules can be recovered at the client end and also by keys, which are the same as those generated by the server.

METHODOLOGY

Various data is collected and stored in IoTs, like data related to health, credit data, and so on. These data or records are available for analysis. Each record in the data consists of various features. Some of the features are stored using quasi identifiers. To integrate the privacy-preserving of data to ensure data security, the data is vertically partitioned and stored in different places. Also, the data is encrypted using standard encryption technique like DES.

A broad range of numerical problems can be generally resolved to utilize the Ant Colony Optimization (ACO). By continuous update of the pheromone, the algorithm converges towards the optimal solution. But, as a result of the initial pheromone deficiency, the algorithm has a slow speed of convergence. This section examines in detail the Ant Colony Optimization, the Evolutionary Multimodal Optimization, and the Proposed Ant Colony Optimization-Evolutionary Multimodal for routing.

Ant Colony Optimization (ACO) based routing

The Ant Colony Optimization (ACO) algorithm is a recent nature-inspired technique of evolutionary computation that is initially designed for the discrete problem optimization. The ants deposit a chemical known as pheromone on the soil while moving around. The deposited pheromone's intensity relies on the distance between the ant colony and the source of food. There are bigger pheromone quantities in the shorter paths. As a result, the system's new ants will tend to opt for the path that has the larger pheromone quantity. Every ants will select the shorter path [12] after a time period, with an effect of positive feedback. Diverse problems can be resolving utilizing this structure.

For path construction, pheromone trails are utilized as tool for communication. The accumulated pheromones' higher intensity represents the higher probability of path prioritization as the favoured one, and gradually, in the shortest solution path's generation. The update of the pheromone, τ_{ij} on the edge connecting cities and after iteration is done by utilizing the below equations:

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \quad (1)$$

$$\Delta\tau_{ij}^{k} = \begin{cases} Q / L_k & \text{if ant k uses edge(i,j) in its tour} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

wherein, ρ represents the rate of evaporation between iterations t and t+1, m represents the number of ants, Q is a constant, and L_k is the definition of tour length constructed by the kth ant. An ant k's probability of travelling from city i towards city j is based on the amount of pheromones which are accumulated, and thus, the expression of the probability function which constitutes the pheromone amount is as below:

$$p_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha}.\eta_{ij}^{\beta}}{\sum_{c_{il}\in N(s^p)} \tau_{il}^{\alpha}.\eta_{il}^{\beta}} & \text{if } c_{ij} \in N(s^p) \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

here, $N(s^p)$ represents the available set of cities for the kth ant, l represents a city which was not visited by the kth ant, α and β represents the trail's relative priority over the path information $\eta_{ij} = 1/d_{ij}$,where, d_{ij} represents the distance between city i and city j .

Evolutionary multimodal optimization based routing

Storn and Price [13] initially proposed Differential Evolution. All individual indivi in each generation experiences generation of trial vectors for offspring creation. In this subroutine, three individuals are randomly chosen by the algorithm in order to generate a trial vector. A base vector is formed by one individual. A difference vector is formed by the difference of value between the other two individuals. A trial vector is formed by the sum of these two vectors by the recombination with a parent (indivi) to for man offspring. There is no requirement for manual parameter tuning of crossover and mutation due to the replacement of the conventional crossover and mutation operation with generation of trial vector. It offers differential evolution with an adaptive capability of feasible step size selection. For movement towards optima, a self-organizing capability ability is permitted. As observed in earlier contests, high adaptability is also accomplished for the optimization of diverse non-convex landscapes. For real function optimization, it is treated as one of the most effective evolutionary algorithm by creation of a hotre search field where scholars explore its power in diverse domains such as nuclear reactor core design, multi-sensor fusion, and mechanical engineering design.

For extending differential evolution's ability, Thomsen integrated crowding techniques into differential evolution (CrowdingDE) [10] for multimodal optimization. Each generation's offspring are only capable of replacing those individuals they are most alike to. Even though this is followed by comprehensive computation, it can efficiently convert differential evolution into a specialized algorithm for multimodal optimization. Dissimilarity measurement is employed for determining the dissimilarity (or distance) between two individuals. Euclidean distance is the basis of the distance between two individuals. Smaller the distance between two individuals, the more alike they will be, and vice versa.

$$d(\vec{x}_i, \vec{x}_j) = \sqrt{\sum_{k=1}^{n} (x_{ik}, x_{jk})^2} \quad (4)$$

Here, $\vec{x}_i$ denotes the individual (vector) $[x_{i1}, x_{i2}, \ldots, x_{in}]$ whilst $\vec{x}_j$ denotes the individual (vector) $[x_{j1}, x_{j2}, \ldots, x_{jn}]$.

Proposed Ant Colony Optimization - Evolutionary Multimodal Routing

Majority of the Evolutionary Algorithms may experience early convergence and get trapped within the local optimum if there is no application of diversity maintenance methods. For coping with this issue, these algorithms have their own local operations

to maintain the diversity. In CrowdingDE, the crowding method will be the local operation itself where, every offspring can only take the place of the individual that is most like itself. Upon closer examination of this method, the individual replacement scheme is proposed with a constraint such that replacement of an individual occurs only when another individual is produced and assessed to be fitter than the former in the same niche. Thus, for suitable replacements, this algorithm is made to wait passively for trial vector generations.

Without any prompts, ants are capable of identifying the path which is the shortest from their colony to the food source. According to the topography, ants are able to properly circumvent hindrances and also be flexible to seek alternative new paths. This phenomenon's nature is such that the ant releases pheromone, which is a specific type of secretion. As time passes, the pheromone also gradually vanishes. The path's distance is represented by the pheromone deposits. Depending on the concentration of the residual pheromone deposits, the paths can be modified by the ants. More ants will select a certain path if there is a high probability of electing that path. More pheromone gets released by the ants. A path will have more pheromone when more ants choose that path. Hence, a positive feedback mechanism is produced. Ultimately, the shortest paths from the colony to the source of food can be identified by the ants with this positive feedback mechanism. Especially when there are obstacles between the food source and the ants, the ants are able to circumvent the obstacles and also identify the shortest path after a time period of the positive feedback by pheromone changes in the diverse paths.

RESULTS AND DISCUSSION

For experiment, number of nodes 500 to 1500 are considered. Table 1 to 4 shows the Number of clusters formed, Average End to End Delay (sec), Average Packet loss rate (%), and Lifetime computation- Percentage of nodes alive respectively for ACO, Evolutionary multimodal optimization and proposed ACO-Evolutionary Multimodal.

Table 1 Number of clusters formed for ACO-Evolutionary Multimodal

Number of Nodes	ACO	Evolutionary multimodal optimization	ACO-Evolutionary Multimodal
500	18	19	23
750	29	30	31
1000	49	50	50
1250	55	58	58
1500	55	56	57

Table 1 shows that the Number of clusters formed for ACO-Evolutionary Multimodal performs better by 24.4% and by 19% than ACO and Evolutionary multimodal optimization respectively for number of nodes 500. The Number of clusters formed for ACO-Evolutionary Multimodal performs better by 2% and no change than ACO and Evolutionary multimodal optimization respectively for number of nodes 1000 and the Number of clusters formed for ACO-Evolutionary Multimodal performs better by 3.6% and by 1.8% than ACO and Evolutionary multimodal optimization respectively for number of nodes 1500.

Table 2 Average End to End Delay (sec) for ACO-Evolutionary Multimodal

Number of nodes	ACO	Evolutionary multimodal optimization	ACO-Evolutionary Multimodal
300	0.0044	0.0043	0.0042
600	0.0057	0.0055	0.0052
900	0.0509	0.0483	0.0465
1200	0.085	0.0806	0.0783
1500	0.168	0.1615	0.1568

Table 2 shows that the Average End to End Delay (sec) for ACO-Evolutionary Multimodal performs better by 4.7% and by 2.4% than ACO and Evolutionary multimodal optimization respectively for number of nodes 500. The Average End to End Delay (sec) for ACO-Evolutionary Multimodal performs better by 9% and by 3.8% than ACO and Evolutionary multimodal optimization respectively for number of nodes 1000 and the Average End to End Delay (sec) for ACO-Evolutionary Multimodal performs better by 6.9% and by 2.9% than ACO and Evolutionary multimodal optimization respectively for number of nodes 1500.

Table 3 Average Packet loss rate (%) for ACO-Evolutionary Multimodal

Number of nodes	ACO	Evolutionary multimodal optimization	ACO-Evolutionary Multimodal
300	11.93	11.31	11.01
600	18.88	18.34	18.36
900	19.73	18.89	18.36
1200	20.61	19.91	19.46
1500	30.76	31.06	29.26

Table 3 shows that the Average Packet loss rate (%) for ACO-Evolutionary Multimodal performs better by 8% and by 2.7% than ACO and Evolutionary multimodal optimization respectively for number of nodes 500. The Average Packet loss rate (%) for ACO-Evolutionary Multimodal performs better by 7.2% and by 2.8% than ACO and Evolutionary multimodal optimization respectively for number of nodes 1000 and the Average Packet loss rate (%) for ACO-Evolutionary Multimodal performs better by 4.9% and by 5.9% than ACO and Evolutionary multimodal optimization respectively for number of nodes 1500.

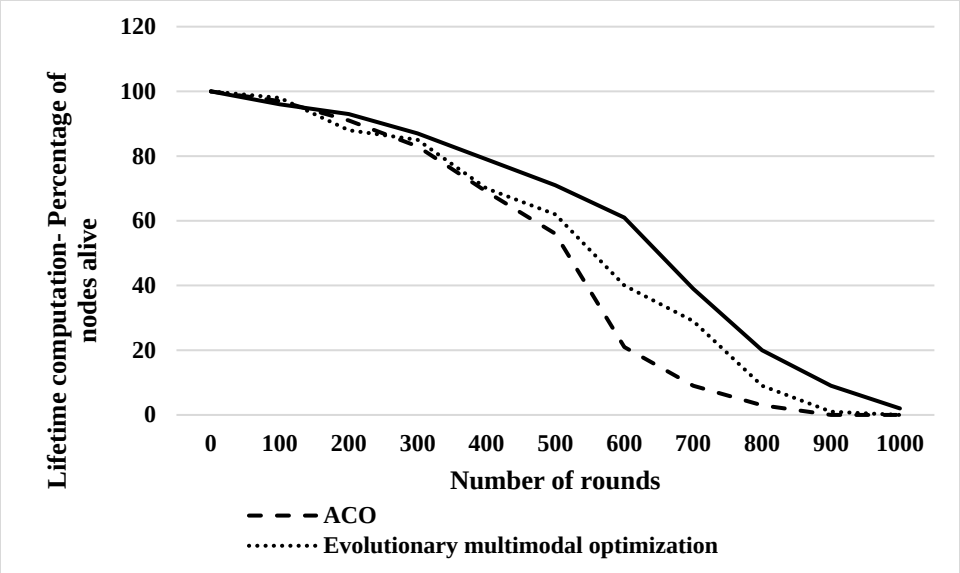

Figure ` Lifetime computation- Percentage of nodes alive for ACO-Evolutionary Multimodal

Figure 1 shows that the Lifetime computation- Percentage of nodes alive for ACO-Evolutionary Multimodal performs better by 1.04% and by 2.1% than ACO and Evolutionary multimodal optimization respectively for number of nodes 100. The Lifetime computation- Percentage of nodes alive for ACO-Evolutionary Multimodal performs better by 4.7% and by 2.3% than ACO and Evolutionary multimodal optimization respectively for number of nodes 300 and the Lifetime computation- Percentage of nodes alive for ACO-Evolutionary Multimodal performs better by 97.6% and by 41.6% than ACO and Evolutionary multimodal optimization respectively for number of nodes 600.

CONCLUSION

A robust method for metaheuristic algorithm design for the resolution of combinatorial optimization problems is the Ant Colony Optimization (ACO). Simulation results demonstrate that, for number of nodes 500, the ACO-Evolutionary Multimodal's Number of clusters formed works better by 24.4% compared to the ACO, and by 19% compared to the Evolutionary Multimodal Optimization. For number of nodes 1000, the ACO-Evolutionary Multimodal's Number of clusters formed works better by 2% compared to the ACO, and no change for the Evolutionary Multimodal Optimization. For number of nodes 1500, the ACO-Evolutionary Multimodal's Number of clusters formed works better by 3.6% compared to the ACO, and by 1.8% compared to the Evolutionary Multimodal Optimization.

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