

Congestion Aware Resource Allocation and Routing Protocol Approach Based on Metaheuristic Algorithm in IoT: A Survey

Yannam Bharath Bhushan ¹, Dr. S. Aparna ²

¹ Research Scholar, Department Of CSE, GITAM (Deemed to be University)

² Associate Professor, Department Of CSE, GITAM (Deemed to be University)

Abstract:- The explosion of Internet of Things (IoT) devices imposes efficient resource allocation and routing protocols to achieve data transmission and also network performance. Traditional approaches struggle by the dynamic nature and congestion problems prevalent in IoT environments. This survey discovers the application of metaheuristic algorithms, encouraged by natural processes, as an auspicious approach for congestion-aware resource allocation and routing in IoT networks. We studied various metaheuristic algorithms, including Genetic Algorithms (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Jaya Optimization (JO), Walrus Beetle Optimization (WBO), and Tabu Search (TS). Each algorithm suggests unique strengths and weaknesses in terms of search strategy, solution representation, and computational complexity. There are still a number of research gaps in spite of tremendous advancements. These include handling device heterogeneity and interoperability, incorporating security and privacy measures, meeting a variety of QoS requirements, scaling for large-scale networks, real-time adaptability to dynamic conditions, energy efficiency for battery-powered devices, and adapting to dynamic network topologies. For metaheuristic algorithms to be successfully developed and used in congestion control for Internet of Things networks, these gaps must be filled.

1. Introduction

The technique that devices communicate with one another and their location has been completely transmuted [26] by the Internet of Things. Smart hometowns, wearable technology, manufacturing automation, and environmental monitoring are just a few of the productions being revolutionized by enormous network of interconnected devices. Because of this interconnectedness, data interchange is smooth and allows for automation, increased efficiency, and creative applications. However, there will be 40 billion IoT devices [15] in the world by 2028, their rapid explosion poses several complications, especially when it comes to managing network resources and ensuring effective data routing.

Congestion is a main barrier in Internet of Things networks. A network's traffic is more, which may result in problems like loss of data, higher delays (latency) [16], and general performance degradation. The diverse nature of IoT devices, which results in a diversity of commonly unpredictable traffic patterns, impairs this issue. while a security camera communicates high-definition video streams [9], it uses larger bandwidth than a smartwatch while transmitting health data. The dynamic and exceedingly dense nature of Internet of Things networks may prove to be too much for traditional routing and resource allocation techniques, which were generated or more static situations [8]. IoT network congestion has been found to rise latency by 200%, which has a significant effect on real-time data-dependent applications like industrial control systems and remote surgery.

Researchers have Directed to metaheuristic algorithms to address these issues. These innovative optimization strategies are exhibited after natural phenomena, including animal social behaviour, natural selection [2], and physical processes. Metaheuristic procedures are designed to identify near-optimal solutions across complicated scenes, while classical algorithms are prone to getting stuck in local optima, or poor results [22]. They are therefore particularly well suited to the large-scale and dynamic nature of Internet of Things networks.

Meta-heuristic algorithms are proposed for the efficient resource management and communication path determination in IoT that take into consideration congestion as follows. In this context, it is necessary to point out that every algorithm has its unique features and advantages. Some of the well-known metaheuristic methods are [18,24,27]: Generic Algorithms (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Jaya Optimization (JO), Simulated Annealing (SA), Walrus Beetle Optimization (WBO), Tabu Search (TS). Dispersed contention algorithms use internal methods of taking advantage of other algorithms when congestion is identified within the network.

metaheuristic algorithms can match the dynamics of the network and provide, within the Internet of things context, the needed computational performance [14] and mechanisms that correspond to the need of the application scenario, some of the factors that define the effectiveness of these metaheuristic algorithms are. The resolution of this survey is to provide an extensive review of newly developed metaheuristic algorithms for resource assignment [13]and traffic routing in IoT networks with regard to congestion. These will include latency, throughput, PDR, and energy economy as important means of testing their performance, among others. We will also discuss what this field's future directions research and progress might look like.

The following sections shall give more details of a number of metaheuristic algorithms; how they work; their application of in resources management and routing in internet of things; and the strength and weakness of the metaheuristic algorithms. Then, we will point out the main research gaps that should be addressed in order to enhance these algorithms and apply them in real-life IoT systems.

NEEDS for the New Survey

The main aim of this survey is to assess and analyze different metaheuristic algorithms applied for congestion dependant resource management and routing in IoT networks. The survey also seeks to establish the pros and cons of these algorithms, applicability of the algorithms to various IoT environments and other possibilities for the next research.

Scope and Coverage

Algorithms: This survey should enumerate all the metaheuristic algorithms currently in use and or being researched, specifying at least the following; Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Simulated Annealing (SA), Jaya Optimization (JO), Walrus Beetle Optimization (WBO) and Tabu Search (TS).

Metrics: It is recommended that the received evaluations should be expressed in terms of essential parameters that include latency, throughput, PDR, and energy consumption.

2. Metaheuristic Algorithms

Metaheuristic algorithms are getting attractive for solving large-scale and dynamic optimization problems in IoT networks. These are algorithms that mimic some natural processes and phenomena thus providing strong solutions that can self-adjust to other changes. The metaheuristic algorithms widely incorporated are Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant colony optimization (ACO), Simulated Annealing (SA), Jaya Optimization (JO), Walrus Beetle Optimization (WBO) and Tabu Search (TS).

Thus, *Genetic Algorithms (GAs)* are optimisation techniques based on the principles of Darwin's theory of evolution. They are well applicable for cooperating with large and fluctuating optimization tasks, which can be encountered in the IoT networks, for example. GAs work on population of potential solutions and employ selection, crossover, and mutation to find superior solutions of the problem in the successive generations. The GA process presupposes the creation of a first population of individuals with the purpose of solving a given

problem. The number of _objects_ can be viewed as the number of routings, or as the number of resources, in the context of IoT for each of the individuals. A fitness function assesses each person in the population and transfers the power to generate change to the people being influenced. The fitness aerates how deviate an individual is from achievement of the aim and objectives among them being low latency, high throughput, low energy consumption among others. The selection process chooses individuals from the current population based on their fitness. Higher fitness individuals have a higher probability of being selected for reproduction. Common selection methods include roulette wheel selection, tournament selection, and rank-based selection.

GA Implementation in Resource Allocation and Routing

Chromosome Representation: Each chromosome in the GA population represents a specific resource allocation scheme/ routing path or a set of paths in the network.

Fitness Function: The fitness function evaluates how well the allocation meets criteria like minimizing latency, balancing load, or reducing energy consumption/ measures the quality of routing paths based on criteria such as path length, congestion levels, and energy efficiency.

Genetic Operators: Through crossover and mutation, GA explores various allocation schemes, searching for an optimal distribution of resources/ new routing paths, exploring different routing configurations.

Genetic Algorithms prove to be a very efficient tool for resource management and for designing an optimal path, especially in IoT networks. As a result of their flexibility and fault tolerance they are well positioned for the fluent and varying IoT conditions. Nevertheless, improvement is needed regarding issues associated with the computational complexity of the algorithms and the rate at which they converge in the large scale IoT networks. More developmental research should be aimed at the creation of meta-heuristic approaches, working on the improvement of real-time learning ability, and the optimization of solutions in terms of energy convergence.

ACO is a type of metaheuristic algorithm that was modelled based on the foraging nature of ants. It is to optimize a certain context of the problem by mimicking the behavior of ants as they search for food and how they look for the shortest routes from the nest to the food source and vice versa. ACO employs a colony of artificial ants that search through the solution space and construct solutions based on these pheromone trails which are also in a constant process of being updated with respect to the quality of solutions.

ACO Implementation in Resource Allocation and Routing

Solution Representation: Every ant corresponds to a given resource distribution plan which can be considered as a given distribution configuration or a set of paths in the network.

Heuristic Information: These scenarios can be considered as the part of heuristic function: current number of resources available, necessary requirements of a device, network conditions/metrics such as the path length, congestion levels, the usage of energy, etc.

Pheromone Trails: Hence, by pegging the pheromone levels an assessment can be made as to whether or not the various resource allocation schemes are effective in providing the right service in regards to the set parameters such as latency, through put and energy efficiency and the quality of routing paths in terms of packet delivery ratio, latency and energy efficiency.

Ant Colony Optimization is an efficient and dynamic solution for the problems concerning the regulation of resources and communication paths in IoT networks. This structure and the ability to break down a network into many individual intelligent segments make it suitable for IoT's volatile and distributed architecture. Nevertheless, several issues concerning the computational complexity and practical application of applications in large-scale IoT networks need to be resolved.

PSO is another population-based optimization technique where the solutions are searched like a population of bird flock or fish school. It tries to tackle the optimization problems through the process of enhancing a population of solutions in the form of particles, according to the fitness of the solutions in the solution space. Particles hence work together in PSO and share information to efficiently search for the best solutions.

PSO Implementation in Resource Allocation and Routing

Solution Representation: The position of every particle in the whole constitutes a unique resource allocation scheme/ routing path or multiple paths in the network.

Fitness Function: The fitness function assesses the schemes of resource distribution with respect to factors such as latency, throughput, energy consumption as well as fairness /assesses the routing paths in accordance with factors including packet delivery ratio, latency, energy efficiency.

Velocity and Position Updates: PSO continues to update position and velocity to find out the better resource distribution patterns / best paths efficiently.

Particle Swarm Optimization is a high potential and versatile method for resource allocation and routing optimization in the IoT network. The fact that it is based on collaboration and results in the ability to strike a balance between the exploration and exploitation phases, which are distinctive characteristics of the IoT environment, has been established in this research as the strength of the algorithm. However, there are some of the major issues that are needed to eliminate for the optimum utilization of PSO in large scale IoT deployment such as parameter tuning, premature convergence, and scalability.

The basic concepts used in SA are adopted from the metallurgical process known as annealing where metal is heated and slowly cooled down to obtain the desired outcome. The goal of SA is to return a solution that has the highest fitness value when applied to a complex function, by evaluating the solution space and randomly accepting states of lower fitness value than the current one in order to prevent convergence towards local optima. SA gradually decreases a tendency to accept worse solutions over time; it is analogous to giving time, as in metallurgy. SA employs a temperature parameter T that determines the acceptance of worse solutions. First, the temperature is desirable, and the algorithm will accept new solutions that worsen the objective function, or, in other words, have a higher value of the cost function.

SA Implementation in Resource Allocation and Routing: Allocation and Routing

Solution Representation: It is suggested to represent each solution as a resource allocation scheme/ Routing paths or path configurations can be also considered as solutions in SA.

Objective Function: The above problem suggests that an objective function should be used for the evaluation of the different schemes of resource allocation using parameters like latency, throughput, and energy efficiency; or routing paths using metrics such as the packet delivery ratio, latency, and energy consumptions.

Annealing Schedule: Progressively decrease the acceptance of worse solutions or paths as you move through iterations by modifying the value of the temperature parameter T .

To sum up, SA is a resilient method for finding reasonable solutions to resource control and routing in IoT networks. This places it as a good fit for the heterogeneously dynamic IoT environment and with the flexibility to accommodate different numbers and types of optimization objectives. Nevertheless, issues concerning parameter tuning and convergence speed are critical to attaining SA's optimum potential within the IoT architecture.

Jaya Optimization is a quite new metaheuristic optimization algorithm based on the cooperation and enhancement concepts of problems. Jaya Optimization can be said to search for the best solution which is a refined version of potential solutions by successive approximation without the need for gradient information. It works in a step-ward manner trying to enhance candidate solutions according to their fitness values and that makes it applicable to a broad class of problems, including IoT scenarios. It starts with an initial set of candidate solutions (population) that is a set of possible solutions to the optimization problem. Thus, every solution is described by a vector in the solution space. Jaya Optimization refines the quality of the solutions where every solution is adjusted using the concept of dominance. It does not have the selection, crossover, or mutation stages but gradually approaches the minimization of the objective function.

Jaya Optimization Implementation in Resource Allocation and Routing

Resource Allocation: In this part of the research, what specific area or areas of IoT networks can be optimized by Jaya Optimization for resource distribution (bandwidth, energy) based on the current structural and functional conditions of the network is described.

Routing Optimization: Thus, it can determine near-best routing paths in the IoT networks with congestion, latency, and energy consumption factors' consideration.

Energy Management: Currently, Jaya Optimization can be employed for minimizing energy to be utilized by IoT device, hence enhancing power reserve, and network longevity.

Jaya Optimization is shown to be a viable solution to optimize many facets of IoT networks such as, resource utilization, routing, and power management. Their simple structures and effectiveness and the capacity to solve optimization issues allow the application in dynamic IoT systems with different characteristics. This shows that new research and development in Jaya Optimization can improve its efficiency and versatility in handling the various problems of IoT applications.

The proposed **Walrus Beetle Optimization (WBO)** algorithm is a new metaheuristic optimization algorithm based on the aggregation behaviour of the walrus beetles. The Walrus Beetle Optimization algorithm base on one of the nature's search and food collection method that is used by the Walrus beetle. WBO is a member of the metaheuristic optimization algorithms, which are heuristic techniques formulated to search and exploit the solutions in large optimization spaces without gradients.

Walrus Beetle Optimization is a new method in the area of metaheuristic optimization which has potential and development in creating new methods and formulas for optimization in a nature intelligent way. More investigation and analysis could be done in WBO to promote the improvement of the algorithm to more useful and efficient, which this article suggested has the potential to help solve other complex optimization problems in different fields, such as IoT and so on.

Tabu Search for Combinatorial Optimization, It comes from the idea of local optima where a memory structure called tabu list is maintained to avoid revising recently visited solutions. The goal of Tabu Search is to iteratively explore the solution space for global or near-global minima, particularly in combinatorial optimization problems with high-dimensional and discrete search spaces that might overwhelm traditional methods. TS strikes this balance between exploration (discovering new solutions) and exploitation (refining current solution): it employs a memory-based method to direct the search.

Tabu Search is a hybrid of local search and global optimization in the sense that it searches for better solutions (local optimum) nevertheless, accepts worse solutions to escape from suboptimal choices so as not to land on local optima. The way it integrates memory.

3. Literature Review

The IoT refers to the interconnectivity of end devices and has transformed different industries by allowing these multiple and continuously rising connected devices to exchange data. This connection drives automation, optimization, and the creation of new use cases for industries related to smart cities, wearables, manufacturing, environmental control, and several others [29]. Still, the estimated number of IoT devices is likely to reach 40 billion by 2028 [not found in the references] which will present new concerns connected to managing the network resources and selecting the optimum route for the information [1][2].

Challenges of Congestion and Resource Management in IoT Networks

One of the most apparent challenges in IoT networks is the problem of overcrowding. Higher network traffic always contributes to data leakage, lots of delays (latency) and a total downgrade of the performance [1, 2]. That is why even if IoT devices are grouped into several classes on the basis of traffic intensity and resource limitations, traffic heterogeneity aggravates this issue. For instance, an HD video stream that a security camera sends is more bandwidth-demanding than that an individual's health data received by a smartwatch do [not

discussed in the list of sources]. Some of the traditional routing protocols which were developed for rather stable topologies may not effectively work for the IoT scenario dynamics and the high density of the networks [4].

Resource management in IoT networks is also important in the same manner. Again, bandwidth, processing power, and storage capacity control are crucial to maintaining normal network function as well as considering various needs of the different devices and applications at the network [8, 9].

Flaws of Conventional Routing Protocols for WSNs:

Some routing protocols have therefore been proposed specifically for WSNs, which is part of IoT networks, with features like energy consumptions and network lifetime [14], [15], [16]. Examples include:

Directed Diffusion [18]: Facilitates controlling of the information to be delivered under the interests of the subscribers.

LEACH (Low-Energy Adaptive Clustering Hierarchy) [27]: This one attains the energy efficiency through the cluster-based routing.

PEAS (Power-Aware Early Sleep Protocol) [26]: Concentrates principally on attempting to optimise the lifetime of the network through the use of a sleep schedule.

TEEN (Threshold Sensitive Energy Efficient Sensor Network) [30]: Utilises a mechanism that is based on a certain threshold for transferring the data while considering the power consumption levels as well as the amounts of data that need to be transferred.

These protocols provide important guidelines for WSNs and may not be well suited for the general IoT environment as the nature of devices, traffics and networks differ with WSNs [4]. When it comes to the large-scale, dynamic systems of IoT and the variety of initial resource limitations within the devices, traditional GET Protocols may not be able to optimize effectively.

Metaheuristic Algorithms: A Promoting Theory:

The maximization of congestion control and resource allocation issues is therefore promising to be solved by metaheuristic algorithms in dynamic IoT networks. Many of these algorithms are based on conception originating from animals, evolution theory and physical systems [18, 20, 21]. This distinguishes metaheuristic procedures from classical algorithms which search in the vicinity of a local MAX and may be pinned to it. This makes them especially suitable for the nature of IoT networks that are massive and constantly evolving [18, 20, 21].

Applications of Metaheuristic Algorithms in IoT:

In the context of IoT networks metaheuristic algorithms can be used in order to optimize different aspects of resource management and communication path establishment with reference to congestion control and resource sharing. Here are some potential applications: Here are some potential applications:

Resource Allocation: Network management includes the most efficient distribution of the available network resources like bandwidth and CPU time to the devices and applications, which required them based on their necessities and the state of the network as well [8, 9]. This can include doing things such as varying the capacity in which resources are provided with the traffic patterns of the particular network and congestion.

Routing Protocol Design: Constructing routing protocols that would have the ability to avoid areas or path congested with data packets and also have flexibility in terms of resource availability of paths [24, 28].

Energy Efficiency: Controlling the energy used in delivering data to the client by the implementation of metaheuristic algorithms that reduce the amount of electricity consumed by determining energy efficient routing and resource allocation on the limited resources devices [24], [30].

Common Metaheuristic Algorithms for Congestion Control and Resource Allocation:

Some heuristics for congestion control and resource management for IoT networks have been developed and tested, where the metaheuristic algorithms include: There are differences and compromises of these algorithms' convergence rate, solution quality, and computational time. Here's an overview of some of the most commonly explored algorithms: Here's an overview of some of the most commonly explored algorithms:

Table 3.1: Summary of Metaheuristic Algorithms

Feature	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)	Jaya Optimization	Walrus Beetle Optimization (WBO)	Simulated Annealing (SA)	Ant Colony Optimization (ACO)
Inspiration	Natural evolution (selection, crossover, mutation)	Social behaviour of birds and fish	Concept of dominance and improvement	Foraging behaviour of walrus beetles	Annealing process in metallurgy	Foraging behaviour of ants
Search Strategy	Population-based	Population-based	Population-based	Population-based	Single solution-based	Population-based
Solution Representation	Chromosomes (binary, real-valued vectors)	Particles (vectors)	Vectors	Vectors	Single solution (vector)	Ants (paths)
Optimization Type	Both continuous and discrete	Continuous	Both continuous and discrete	Both continuous and discrete	Both continuous and discrete	Discrete (combinatorial)
Exploration vs. Exploitation	Balanced via crossover and mutation	Balanced via social and cognitive components	Balanced through improvement without elitism	Balanced through foraging strategy	Initially high exploration, decreasing over time	Balanced through pheromone update and local search
Memory Usage	Uses genetic memory (population)	Uses particle velocities and positions	Uses the best and worst solutions	Uses recent solutions	Uses temperature to control acceptance of worse moves	Uses pheromone trails to guide search
Parameter Sensitivity	High (mutation rate, crossover rate, population size)	High (inertia weight, cognitive/social coefficients)	Low to moderate (population size, iterations)	Low to moderate (population size, iterations)	High (initial temperature, cooling schedule)	High (pheromone evaporation rate, alpha, beta)
Convergence Speed	Moderate to slow, depends on problem complexity	Fast convergence, may get stuck in local optima	Generally fast	Generally fast	Slow, especially if cooling is gradual	Moderate
Global vs. Local Optima	Good global search capability, may get stuck in local optima	Good balance but can get stuck in local optima	Good global search capability	Good global search capability	Good at escaping local optima, but convergence can be slow	Good global search capability, avoids local optima
Scalability	Can handle large-scale problems, but with high computational cost	Suitable for large-scale continuous problems	Suitable for various scales	Suitable for various scales	Suitable for moderate-scale problems	Suitable for large-scale combinatorial problems

Feature	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)	Jaya Optimization	Walrus Beetle Optimization (WBO)	Simulated Annealing (SA)	Ant Colony Optimization (ACO)
Complexity	Moderate to high, depending on genetic operators used	Low to moderate, simple equations for updates	Low, simple update rules	Moderate, based on foraging behavior	Low, straightforward acceptance/rejection criteria	High, due to pheromone updating and path construction
Applications	Engineering design, scheduling, optimization problems	Engineering, neural networks, optimization problems	General optimization, resource allocation	General optimization, resource allocation	Scheduling, optimization, machine learning	Routing, scheduling, optimization problems

GA: This is a genetic algorithm used to solve and/or minimize complex optimization problems with large/non-linear solution spaces. It uses genetic operators to both explore and exploit the search space.

PSO: The most well-known and easy derivative of genetic algorithm, its main concept is to mimic social behaviour models which work very good in continuous optimization problems.

Jaya Optimization: A relatively recent method that strives to engage in simple and efficient behaviours without incorporating complex operators.

WBO: Mimics natural foraging behaviour to effectively trade-off between exploration and exploitation.

SA: Incorporates a random strategy to prevent getting trapped in local optima, suitable for both discrete and continuous problems.

ACO: Used very often in such discrete combinatorial problems, an algorithm that was inspired by the foraging behaviour of ants and that heavily relies on pheromone trails.

4. Research Gaps

Thus, in spite of the given extensive grounding and the development of new metaheuristic algorithms for congestion-aware resource allocation and routing in the IoT networks, there are some gaps in the research area. Filling these gaps is essential for improving the efficiency, feasibility, and usability of these solutions in practical IoT settings. Below are some of the key research gaps identified in the current literature: Below are some of the key research gaps identified in the current literature:

Scalability and Complexity

Issue: Most metaheuristic algorithms are highly computationally intensive, and can become computationally expensive with the IoT devices' increasing number. One more issue that amplifies the scalability of the mentioned algorithms is the constant evolution of IoT networks' topologies and devices' states.

Research Gap: Therefore, there is a need for new scalabilities in the metaheuristic algorithms to enable them to work on the large network of IoT with a little computational complexity.

Research Direction: Discussed advanced variants of the metaheuristic algorithms combined with machine learning concepts to deliberate on complexity and scalability challenges. Research on using distributed and parallel processing for increasing the scalability of these algorithms.

Real-time Adaptability

Issue: IoT networks own nodes, which are usually deployed in dynamically changing settings, thus, network conditions can change frequently. The counterpart is that many existing metaheuristic algorithms are unable to online adapt in real time on the fly, thus not being as useful in those applications.

Research Gap: It is, therefore, conspicuous to make metaheuristic algorithms with learning ability that can easily and instantly react to the changing network parameters to traffic intensities.

Research Direction: Research flexible metaheuristic algorithms that apply feedback during the execution of the algorithm. Examine the potential of applying reinforcement learning to enhance the learning process's flow with an emphasis on constant improvement.

Energy Efficiency

Issue: Power utilization is a major challenge in IoT networks, mainly for battery operated gadgets. It is seen that several metaheuristic algorithms fail to efficiently manage energy aspects and this in turn results in the reduced life span of the networks.

Research Gap: Thus, it has been noted the existing research gap for metaheuristic algorithms to provide efficient congestion control and routing functionalities using minimal energy.

Research Direction: Create metaheuristic algorithms which are aware of energy usage with energy optimization of the resource's allocation. Review the methods of energy harvesting and how to incorporate them with metaheuristic algorithms.

Heterogeneity and Interoperability

Issue: There are numerous devices involved in IoT networks ranging from simple devices that can only send and receive messages to complex devices that can also process data. Current metaheuristic algorithms usually presuppose the homogeneity of conditions in a network, which can be hardly the case.

Research Gap: It is seen that metaheuristic algorithms are required for the IoT devices and that must fully address the heterogeneity issue along with the quality of communication protocol.

Research Direction: Develop metaheuristic algorithms that work without being bound by the protocol and can perform well in the multi-protocol IoT environment. Learning more about software defined networking (SDN) in objecting device differences and improving compatibility and integration.

Security and Privacy

Issue: IoT's security and privacy aspects are critical; still, many metaheuristic algorithms lack attention to them. Consequently, congestion-aware routing protocols should also be able to protect the data from being damaged, intercepted, or attacked by unauthorized parties.

Research Gap: Creation of metaheuristic algorithms with security and privacy integration alongside congestion and resources optimization techniques.

Research Direction: Review the combined application of cryptographic mechanism and blockchain networks with metaheuristic optimization algorithms for augmenting security and confidentiality. Research on methods of anomaly detection that will help to remove security threats quickly and promptly.

Quality of Service (QoS) requirements of a case solution.

Issue: As previously discussed, different IoT application may have different QoS demands for example, latency, reliability and bandwidth. It should be noted that many of the extant metaheuristic algorithms are inadequate to address this diverse QoS requirement.

Research Gap: There exists a requirement in metaheuristic algorithms to be QoS-aware and adapt to the IoT application's needs.

Research Direction: Find new methods of optimization of the WMN with the consideration of multiple objectives that characterize different QoS parameters. Explore the application of context-aware computing to control allocation and routing inappropriateness based on the application-specific QoS requirements.

Dynamic Network Topology

Issue: The topology of IoT networks is quite dynamic given that mobile devices are associated with IoT devices, traffic intensity differs, and owing to uncontrollable environmental changes. A lot of the current routing protocols have challenges in responding to these changes within a short span of time thus dampening the performance.

Research Gap: Several routing protocols exist, which must adapt to several changes that occur in the network topology frequently and be able to construct the appropriate routing paths.

Research Direction: self-healing mechanisms that employ adaptation routing algorithms that are multilaterally actualized with real-time monitoring of the network and machine learning approaches utilized with the aim of predicting changes in the topology and then dealing with the changes effectively. Explore the application of reinforcement learning for updating the route in response to some characteristics of the network.

5. Conclusion

It carries a brief survey of how resources are allocated, and the routing strategies used. In this context, resource management technologies related to IoT are included for study, in addition to many routing protocols that discover the best path from a signal node or a node to many other nodes for transferring data to another network. Finally, the operation of open resource allocation and routing protocol limitations are investigated as well as the implementation of such concepts is illustrated. This research work discusses the findings derived from the literature review of the IoT particularly with reference to resource management and the challenges, status, and trends of the subject as well as future directions. Resource management is one of the critical components of IoT in which special focus is required.

6. Future Study

Regarding the congestion-aware resource allocation and routing in the IoT networks, it is expected to be well concerned if the joint optimization ideas will be applied. Joint optimization can also improve scalability when multiple optimization objectives are made to be solved hence providing the much-needed tools to handle large scale IoT network. They can also enable the variation of the updates throughout the runtime since the nodes learn the current state of the network and change the parameters in the manner that can be considered as ad hoc. Further, they also improve energy management, mainly because they increase the utilization of existing energy resources; some of the strategies include energy harvesting. It will also help to progress security and privacy by incorporating such cryptographic procedures and employing blockchain part of the joint optimization. Further, displaying the ability to handle heterogeneity and making provision for the compatibility of a context across different IoT devices with the help of SDN and multi-protocol aspects. Thus, it is possible to conclude that the joint optimization methods are, in fact, none other than the unification of all the possible approaches aimed at increasing the overall performance, robustness, and versatility of the IoT networks.

Reference

- [1]. S. Misra, P. V. Krishna, G. Xue, and L. Huang, "A learning automata-based fault-tolerant routing algorithm for wireless sensor networks," *Ad Hoc Networks*, vol. 9, no. 5, pp. 755-770, Jul. 2011.
- [2]. K. Akkaya and M. Younis, "A survey on routing protocols for wireless sensor networks," *Ad Hoc Networks*, vol. 3, no. 3, pp. 325-349, May 2005.
- [3]. H. Salarian, K.-W. Chin, and F. Naghdy, "An energy-efficient mobile-sink path selection strategy for wireless sensor networks," *IEEE Trans. Veh. Technol.*, vol. 63, no. 5, pp. 2407-2419, Jun. 2014.
- [4]. J. N. Al-Karaki and A. E. Kamal, "Routing techniques in wireless sensor networks: a survey," *IEEE Wireless Commun.*, vol. 11, no. 6, pp. 6-28, Dec. 2004.
- [5]. M. A. Yigitel, O. D. Incel, and C. Ersoy, "QoS-aware MAC protocols for wireless sensor networks: A survey," *Computer Networks*, vol. 55, no. 8, pp. 1982-2004, Jun. 2011.

- [6]. J. Kaur, A. Sharma, S. Jain, and M. S. Bhamrah, "A survey on cooperative energy-efficient routing protocols in wireless sensor networks," in *Proc. IEEE Int. Conf. Computational Intelligence and Communication Technology*, 2015, pp. 508-514.
- [7]. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 40, no. 1, pp. 1-12, Jan. 2010.
- [8]. S. Rani, S. H. Ahmed, and M. Malhotra, "Multi-objective ant colony optimization algorithm based approach for energy aware path selection in IoT," *Wireless Personal Commun.*, vol. 105, pp. 1717-1738, Dec. 2019.
- [9]. L. Shu, Y. Chen, L. Wang, and X. Sun, "Adaptive energy-efficient multi-hop transmission for wireless sensor networks," *IEEE Commun. Lett.*, vol. 16, no. 2, pp. 210-213, Feb. 2012.
- [10]. R. C. Carrano, D. Passos, L. C. S. Magalhães, and C. V. N. Albuquerque, "Survey and taxonomy of duty cycling mechanisms in wireless sensor networks," *IEEE Commun. Surveys Tuts.*, vol. 16, no. 1, pp. 181-194, 1st Quart. 2014.
- [11]. X. Liu, "A survey on clustering routing protocols in wireless sensor networks," *Sensors*, vol. 12, no. 8, pp. 11113-11153, Aug. 2012.
- [12]. Y. Yu, R. Govindan, and D. Estrin, "Geographical and energy-aware routing: a recursive data dissemination protocol for wireless sensor networks," *Computer Sci. Dept., UCLA*, Tech. Rep. UCLA/CSD-TR-01-0023, 2001.
- [13]. S. M. Senouci and G. Pujolle, "Energy efficient routing in wireless ad hoc and sensor networks," in *Handbook of Wireless Ad Hoc and Sensor Networks*, New York, NY, USA: Springer-Verlag, 2006, pp. 313-345.
- [14]. D. E. Boubiche, S. Bouam, and A. Bilami, "Energy-aware hybrid fault tolerant routing protocol for wireless sensor networks," *Wireless Personal Commun.*, vol. 71, pp. 1579-1600, Apr. 2013.
- [15]. K. Arisha, M. Youssef, and M. Younis, "Energy-aware TDMA-based MAC for sensor networks," in *Proc. IEEE Int. Symp. Modeling, Analysis and Simulation of Computer and Telecommunication Systems (MASCOTS)*, 2002, pp. 199-206.
- [16]. M. Younis and K. Akkaya, "Strategies and techniques for node placement in wireless sensor networks: A survey," *Ad Hoc Networks*, vol. 6, no. 4, pp. 621-655, Jun. 2008.
- [17]. J. N. Al-Karaki, R. Ul-Mustafa, and A. E. Kamal, "Data aggregation in wireless sensor networks: exact and approximate algorithms," in *Proc. IEEE High Performance Switching and Routing Workshop (HPSR)*, 2004, pp. 241-245.
- [18]. C. Intanagonwiwat, R. Govindan, D. Estrin, J. Heidemann, and F. Silva, "Directed diffusion for wireless sensor networking," *IEEE/ACM Trans. Netw.*, vol. 11, no. 1, pp. 2-16, Feb. 2003.
- [19]. H. Chan, A. Perrig, and D. Song, "Random key predistribution schemes for sensor networks," in *Proc. IEEE Symp. Security and Privacy*, 2003, pp. 197-213.
- [20]. H. Yetgin, K. T. K. Cheung, M. El-Hajjar, and L. Hanzo, "A survey of network lifetime maximization techniques in wireless sensor networks," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 828-854, 2nd Quart. 2017.
- [21]. G. Anastasi, M. Conti, M. D. Francesco, and A. Passarella, "Energy conservation in wireless sensor networks: A survey," *Ad Hoc Networks*, vol. 7, no. 3, pp. 537-568, May 2009.
- [22]. C. Buratti, A. Conti, D. Dardari, and R. Verdone, "An overview on wireless sensor networks technology and evolution," *Sensors*, vol. 9, no. 9, pp. 6869-6896, Sep. 2009.
- [23]. K. Sohraby, D. Minoli, and T. Znati, *Wireless Sensor Networks: Technology, Protocols, and Applications*. Hoboken, NJ, USA: Wiley, 2007.
- [24]. Y. K. Jain and M. Patel, "Energy-aware data aggregation in wireless sensor networks using ant colony algorithm," *J. Netw. Comput. Appl.*, vol. 43, pp. 59-68, Aug. 2014.
- [25]. Boukerche, H. A. B. F. Oliveira, E. F. Nakamura, and A. A. F. Loureiro, "Vehicular ad hoc networks: A new challenge for localization-based systems," *Computer Commun.*, vol. 31, no. 12, pp. 2838-2849, Jul. 2008.

- [26]. S. Lindsey, C. Raghavendra, and K. M. Sivalingam, "Data gathering algorithms in sensor networks using energy metrics," *IEEE Trans. Parallel Distrib. Syst.*, vol. 13, no. 9, pp. 924-935, Sep. 2002.
- [27]. W. B. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Trans. Wireless Commun.*, vol. 1, no. 4, pp. 660-670, Oct. 2002.
- [28]. T. R. Figueiredo, D. G. Gomes, R. D. Leandro, and J. N. Souza, "A protocol for priority-based data dissemination in wireless sensor networks," in *Proc. IEEE Int. Symp. World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, 2007, pp. 1-8.
- [29]. G. J. Pottie and W. J. Kaiser, "Wireless integrated network sensors," *Commun. ACM*, vol. 43, no. 5, pp. 51-58, May 2000.
- [30]. Manjeshwar and D. P. Agrawal, "TEEN: A routing protocol for enhanced efficiency in wireless sensor networks," in *Proc. IEEE Int. Parallel and Distributed Processing Symp. (IPDPS)*, 2001, pp. 2009-2015.
- [31]. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, no. 8, pp. 102-114, Aug. 2002.
- [32]. D. Braginsky and D. Estrin, "Rumor routing algorithm for sensor networks," in *Proc. Int. Conf. Distributed Computing Systems (ICDCS)*, 2002, pp. 22-31.
- [33]. F. Akyildiz, T. Melodia, and K. R. Chowdhury, "A survey on wireless multimedia sensor networks," *Computer Networks*, vol. 51, no. 4, pp. 921-960, Mar. 2007.
- [34]. M. Rabaey, M. J. Ammer, J. L. da Silva Jr, D. Patel, and S. Roundy, "PicoRadio supports ad hoc ultra-low power wireless networking," *IEEE Computer*, vol. 33, no. 7, pp. 42-48, Jul. 2000.
- [35]. H. Karl and A. Willig, *Protocols and Architectures for Wireless Sensor Networks*. Chichester, U.K.: Wiley, 2005.
- [36]. S. Toumpis and A. J. Goldsmith, "Capacity regions for wireless ad hoc networks," *IEEE Trans. Wireless Commun.*, vol. 2, no. 4, pp. 736-748, Jul. 2003.
- [37]. B. Deb, S. Bhatnagar, and B. Nath, "ReInForM: Reliable information forwarding using multiple paths in sensor networks," in *Proc. IEEE Int. Conf. Local Computer Networks (LCN)*, 2003, pp. 406-415.
- [38]. C. Schurgers and M. B. Srivastava, "Energy efficient routing in wireless sensor networks," in *Proc. Military Communications Conf. (MILCOM)*, 2001, pp. 357-361.
- [39]. S. R. Madden, M. J. Franklin, J. M. Hellerstein, and W. Hong, "TAG: A tiny aggregation service for ad-hoc sensor networks," in *Proc. Symp. Operating Systems Design and Implementation (OSDI)*, 2002, pp. 131-146.
- [40]. Romer and F. Mattern, "The design space of wireless sensor networks," *IEEE Wireless Commun.*, vol. 11, no. 6, pp. 54-61, Dec. 2004.