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Hybrid Approaches to Address Various Challenges in Wireless Sensor Network for IoT Applications: Opportunities and Open Problems

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Abstract – Since the last decade, wireless sensor network (WSN) and Internet of Things (IoT) has proved itself a versatile technology in many real-time applications. The scalability, cost-effectiveness, and self-configuring nature of WSN make it the fittest technology for many network designs and scenarios. The traditional WSN algorithms are programmed for fixed parameters without any touch of Artificial Intelligence as well as the optimization technique. So, they suffer from a trade-off between various QoS parameters like network lifetime, energy efficiency, and others. To conquer the limitations of traditional WSN algorithms, machine learning has been introduced in wireless technology. But machine learning approaches also cannot solve all the problems in WSN solely. Some of the applications like target tracking, congestion control, and many more, do not give desired results even after applying the machine learning techniques. So, there is a need to introduce optimization in such cases. The paper gives an extensive survey on various optimization methods employed to solve many WSN issues from 2005 till 2020. It also gives a brief description of the usage of various machine learning techniques in WSNs from 2002 till 2020. The paper discusses the advantages, limitations, effects of these methods on various WSN techniques like topology, coverage, localization, network and node connectivity, routing, clustering, cluster head selection, cross-layer issues, intrusion detection, etc. This paper gives a lucid comparison of many state-of-the-art optimization algorithms and descriptive and statistical analysis for discussed issues and algorithms associated with them. It also elucidates some open issues for WSNs/IoT networks that can be solved using these approaches.

Index Terms – Wireless Sensor Networks, Internet of Things, Quality of Service, Artificial Intelligence, Optimization, Machine Learning.

1. INTRODUCTION

The advancements in communication protocols, ubiquitous computing, application-specific designs have given a nativity to the extension of wireless technology in the form of the Internet of things (IoT) [1]. The advancement in wireless technology first began in 1880 in the form of photophone, electric wireless technology like radio waves. Gradually, wireless technology started making use of microwaves and optical fibers in the 20th century [2]. The major advancement was the introduction of data communication which gave rise to the invention of cellular data service, satellite communication, and wireless sensor networks. Wireless sensor network (WSN) is one of the prominent technologies in wireless communications which has its major impact on real-world applications [3]. WSN came into existence in the early 1950s and was used mainly in surveillance applications in the US military. The WSN is a self-organized group of interconnected sensor devices or nodes which gather information from an area of interest and forward the processed information to a central base station [4]. Although this technology is not the latest and has been used many times in researches and real-world applications, even at present, this technology makes other advanced technologies like IoT dependent on it. IoT which is considered a powerful technology in the field of wireless communication employs various other technologies such as WSN, radio-frequency identification (RFID), cloud computing, etc. The connection of physical objects like chairs, books, tables, shelves, etc. with the internet or other internet-based devices is possible only

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with IoT. It gives a huge coverage of radius for communication of several objects, offices, schools, homes, hospitals, etc. To connect the vast number of devices through the internet or any internet-based technology like fog computing, the system needs to follow several protocols [5]. These protocols work towards the efficiency of the system to make it reliable and withstand its complexity. IoT is classified into four aspects: Transmission, support, perceptive, and applications. Each aspect uses some technologies for its successful working, for instance, WSN, RFID, global positioning system (GPS) are under perceptive. Similarly, the transmission is controlled by technologies like Bluetooth, ZigBee, wireless local area network (WLAN), etc. for support system IoT uses data mining, cloud computing, etc. There are several applications of IoT in real-world scenarios. Despite being well equipped with updated and smart technologies, the IoT and WSN face some critical issues which are inevitable [6]. The paper covers literature centered on various technologies, schemes, and algorithms to address many problems coming in the way of coming-of-age wireless communication technologies for various applications. Some challenges in the way of IoT/WSN systems are discussed below-

- The data transmission in any wireless network plays a very dominant role since the whole network's main focus is to transmit data from one place to another.

- Energy scavenging/ harvesting is another aspect that should be considered before deploying the sensors. The sensors have limited battery power and are often not rechargeable. So, the technologies which can make use of solar energy or scheduling approaches to minimize the consumption of energy in the network should come up.

- Fault node detection or anomaly or intrusion detection is the major challenge for which much researches have been done and still taking place. The faulty/ outlier nodes affect directly the accuracy, energy wastage, throughput degradation, etc., of the network.

- The tracking of any object, event, or target is another challenge coming in the way of WSN/IoT applications. Some applications need nearly zero delays to detect any target or event like in the case of military application, fire detection, etc. Also, the coverage area should be maximum to avoid any left-out areas for tracking.

- Routing means the selection of a path that starts from the source and leads to the destination. The routing faces many issues like energy management, throughput, jitter, end-to-end delay, etc.

1.1. Motivation

The introduction of optimization approaches in sensor networks set a milestone for application-oriented research.

The use of various optimization techniques like gradient-based, approximation-based, heuristic, etc., for an application specific work has to be checked for its suitability. This paper aims to review those papers which utilize various optimization approaches to answer a particular problem in WSN assisted IoT networks. It gives an analysis of all the researches done in this domain till now in the form of tables and statistics.

To find generalized solutions to the issues arising from various challenges, optimization comes out to be a prominent way to apply. Algorithms like Swarm intelligence algorithms, prediction-based algorithms, and many more give an optimal solution to many problems. Optimization is categorized into three sub-branches like Random, deterministic and multi-objective [7, 8, 9]. According to the network conditions and depending on the type and requirements of the challenge to be addressed, the optimization problem is used. For instance, in routing protocols majorly the swarm intelligence algorithms are applied to obtain the optimal solution. The Bio-inspired algorithms are divided into evolution-based, swarm intelligence, and ecology-based. The swarm intelligence algorithms like Particle swarm optimization (PSO) and Ant colony optimization (ACO) were frequently used till the end of the 20th century and after that their use with other techniques was done to introduce the hybrid or modified approaches [10]. The SI algorithms such as Butterfly optimization algorithm (BOA), Bacterial foraging optimization (BFO), etc., are used since 2000 [11, 12, 13, 14, 15]. Also, the research in the field of implementation of computational intelligence approaches and machine learning approaches has been done to a great extent [16, 17]. These algorithms are applied in various WSN assisted IoT applications to answer any issue. Also, these algorithms were frequently modified from time to time to produce better optimal results [18]. The points contributing to this survey are as under:

- This paper covers more than 100 applications in IoT which covers technologies like unmanned aerial vehicle (UAV), WSN, industrial WSN (IWSN), etc. in the last decade.

- The paper gives a survey of 13 WSN assisted IoT network challenges and their implementing technologies.

- We describe the number of surveys covering each issue, the percentage of the applications used for various issues, and the common issues.

- We also find some of the research gaps from the papers in the literature and give a possible solution to fill that gap.

- The paper also discusses some of the open issues regarding WSN assisted IoT networks.

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Figure 1 shows how data passes through various stages in a WSN assisted IoT system. The WSN-IoT network is clustered and the data is collected by the aggregator nodes or cluster heads which is further fused into the base station (BS). For further processing of data, it is transmitted to the cloud by the means of a gateway device. Depending on the type of network whether centralized or distributive, the data can be pre-processed or post-processed. The data in the IoT system is passed to a cloud server where it is stored and transmitted to the end-user. The processing unit consists of hardware that works according to the algorithm instructions saved in it. The algorithm is based on the data aggregation techniques and to optimize the QoS parameters some optimization approaches can also be used in combination.

The paper has been assembled in some sections. Section 2 defines various optimization techniques. Section 3 covers the assorted WSN issues along with the hybrid optimization algorithms used for each. It contains 13 subsections each addressing an issue in WSN assisted IoT networks and the literature of algorithms used to solve that particular issue. Section 4 gives a brief overview and literature on various machine learning (ML) techniques used to solve WSN challenges. Section 5 gives statistical and descriptive analyses of the usage of the mentioned algorithms covered in recent years as well as the percentage of the papers covering these challenges in WSN assisted IoT. It also discusses the limitations of these algorithms and some open issues. It gives a tabular description of the solution given by the hybrid optimization algorithm to solve the problems in each issue. Section 6 talks about the research gaps from some of the researches on the challenges of WSN assisted IoT networks. It also tells the status of the research going on and discusses some efforts which can be made to work ahead in this area. Section 7 culminates the paper with a conclusive note.
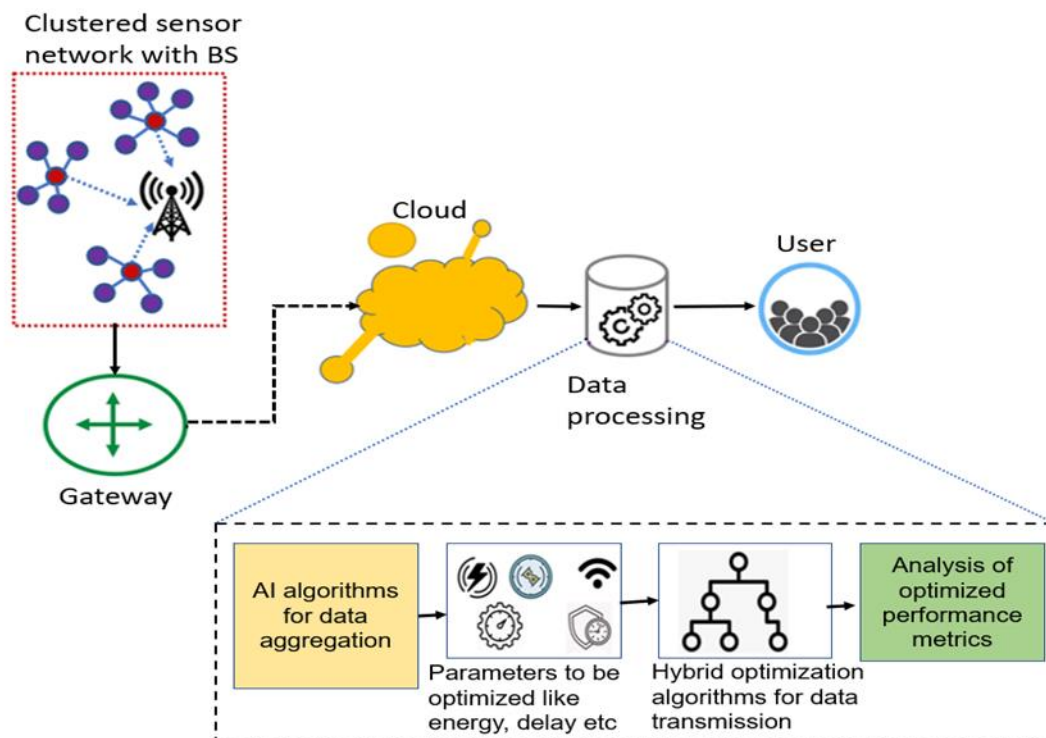

Figure 1 A WSN Assisted IoT Architecture from a Data Aggregation Perspective

2. OPTIMIZATION TECHNIQUES

Optimization or mathematical programming is the improvement (whether maximizing or minimizing) in a function in accordance with a set of constraints that the variables of that function take as their restricted values. The function which has to be minimized/ maximized is called an objective function. The taxonomy of optimization is shown in Figure 2. It is categorized into 3 types: Random, Deterministic and Multi-objective optimization. The detailed definition and their subsequent divisions are described below. Matyas coined the word Random optimization (RO). The method used in random optimization was first proposed by Rastrigin. These optimization methods are direct search based. They are suitable for non-continuous, non-differentiable functions. The gradient of the function is not

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required for random optimization. The other name for random optimization is the Black-box method. In RO the point in the search space moves towards better positions for every iteration. In [19], the constraint nonlinear minimization problem has been studied using modified random optimization. It gives the benefit of finding a global minimum solution. The paper presents the convergence rate and solution for a function with four different constraints applied to it one by one. The commonly used algorithms for random optimization are stochastic optimization algorithms. Stochastic optimization refers to those problems in which there is no certainty of the observed data like noise. Paper [20] explains some stochastic algorithms and future challenges. The stochastic approach makes use of probability distributions ruling over the data are investigated, thereby optimizing the anticipated model performance. It gives a description of single-stage and multistage stochastic algorithms. There are some approaches [21] to solve NP-hard stochastic problems such as computational effort, no free

lunch theorem, hill climbing, random search, simulated annealing, etc. In a Deterministic approach, the data is known accurately for a given problem. The approaches based on deterministic optimization models make use of analytical properties of the problem for generating the series of data points that converge to give a globally optimized solution. The deterministic optimization approaches are categorized into Continuous and Discrete optimization methods. The Continuous optimization methods are further divided into constraint and unconstraint optimization whereas the Discrete methods are classified into the Integer programming method and combinatorial methods of optimization. Paper [22] gives in-depth knowledge on various deterministic approaches to solve the problems of management and engineering. The paper thoroughly explains the signomial programming, mixed-integer non-linear programming. It concludes that though deterministic optimization can address some of the issues in many engineering applications, it is not suitable for nonconvex problems.
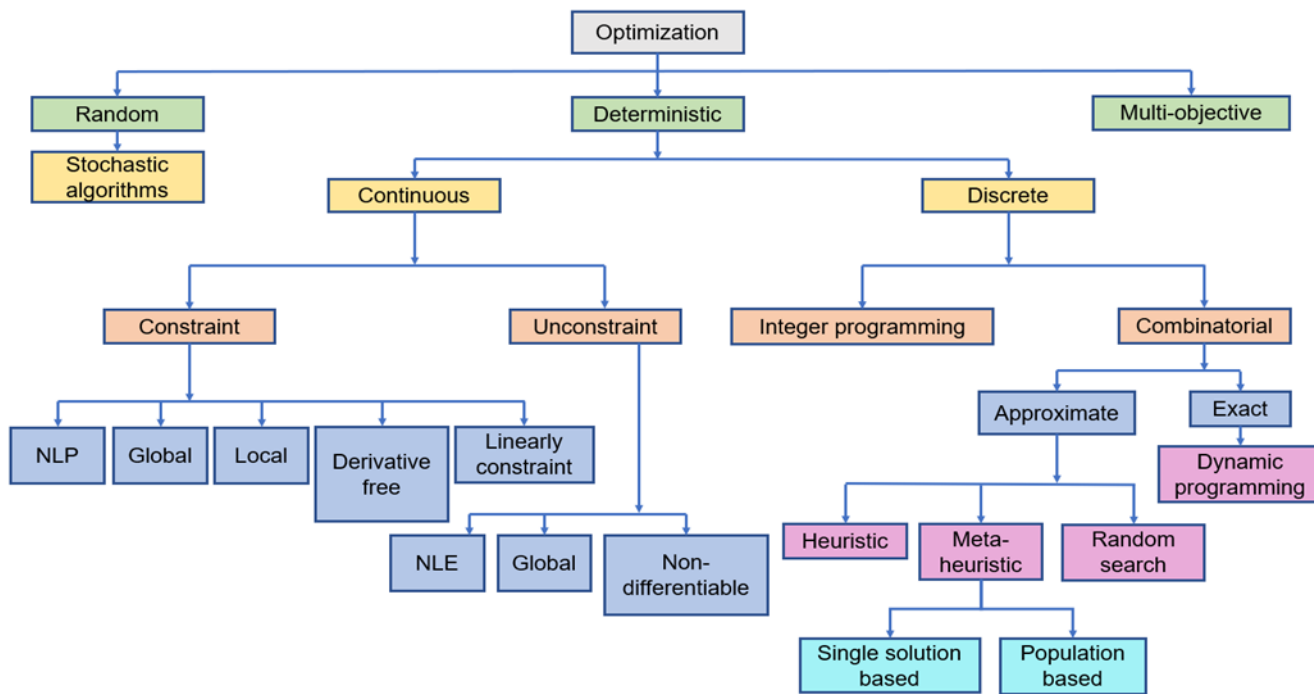

Figure 2 The Taxonomy of Various Optimization Techniques

The paper indicates the pros and cons of the deterministic methods of optimization over heuristic methods. Following are the basic definitions and of continuous and discrete optimization techniques.

In Continuous optimization models which accept the real-valued continuous variables use the continuous optimization methods. They are easy to implement and can be used to gather information about neighboring points of a point 'a' at which the objective function is constrained. The continuous

optimization problems are used in discrete functions also because the function may generate a series of continuous data/problems. The approaches used in continuous optimization are the Constraint approach and the Unconstraint approach.

In the constraint approach, some conditions are imposed on the variables of the objective function. The constraints may be simple bounds or some equalities or inequalities that form complex relationships in variables. The nature of the

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constraints decides whether the problem falls in linear, nonlinear on convex function domains. The smoothness of the equation decides whether it is a differentiable or non-differentiable function. Some of the methods used in constraint approaches are nonlinear programming, local and global optimization methods, derivative-free equations, and linear constraint equations. The display of constraints by the contours in Figure 3 gives the picturization of the constraint optimization problem. X and Y are the arrays of numbers ranging from -5 to 5. The contours shown in Figure 3 are plotted by using the equation below:

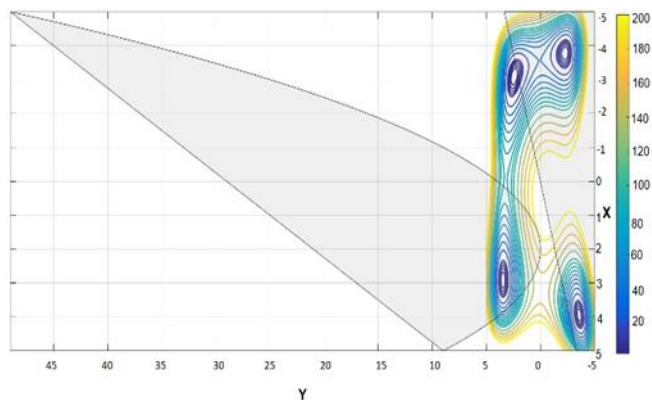$$F = (X^2 + Y - 12)^2 + (X + Y^2 - 9)^2$$

Figure 3 Contours for a Non-Linear Optimization Function

Local optimization approaches to search for the optimum values within the nearest set of solutions of a problem. It is a heuristic approach to solve tougher optimization problems. It moves from one solution to another in a candidate solution set until the optimal values is found. Its area of usage includes operations research, artificial intelligence, bioinformatics, engineering, etc. Some of the example algorithms for local search optimization are the traveling salesman problem (2-opt algorithm), Metropolis-Hastings's algorithm. They can solve functions which have gradient and also which are without gradient.

In Non-Linear programming optimization process first some 'm' decision values $Y_1, Y_2, \ldots Y_m$ is selected from a feasible region. It has a goal to optimize the objective function provided in the problem. The objective function is given by:

$$\text{Maximize } f(Y_1, Y_2, \ldots, Y_m),$$

Subject to the constraints:

$$X_1(Y_1, Y_2, \ldots, Y_m) \leq a_1$$
$$.$$
$$.$$
$$X_m(Y_1, Y_2, \ldots, Y_m) \leq a_m$$

The best example to explain non-linear programming in optimization is mixed integer programming.

The Figure 4 gives an example of a sensor placement problem by using optimization[23]. The deployment is done taking cost as one of the constraints. The cost (X) has to be minimized considering the maximum energy of nodes (Z) and minimum distance between the nodes (Y). It shows a non-linear function with local and global maxima.
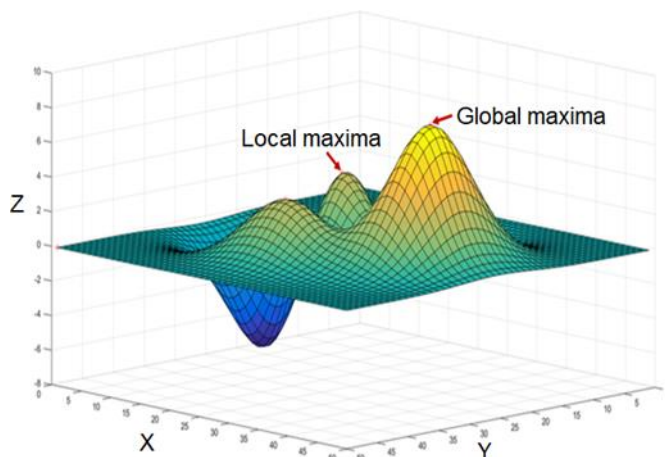

Figure 4 A Non-Linear Optimization Function with its Global and Local Maxima

Unconstrained approach aims at optimizing an objective function that consists of real-valued variables without any restrictions. The variables are constraint-free or there are no conditions imposed on the variables of a function. Let $y \in P^r$ where $r \geq 1$. P is a vector of real numbers. Let $f: P^n \to P$ be a smooth and simple function. The unconstrained problem can be framed as:

$$\min_y f(y) .$$

Some of the algorithms are Newton's method, non-linear conjugate gradient methods, nonlinear Simplex method. The nonlinear least square problem, etc. Unconstrained optimization includes the class of functions which are non-differentiable, and also some global optimization approaches. The unconstrained optimization, in general, follows the below steps:

1. Selecting a starting value y_0.

2. Starting at y_0, produce an iterating sequence with (f) which is a non-increasing value function until the appreciable accuracy is reached. The sequence is given by $\{y_m\}_{m=0}^{\infty}$.

3. The next iteration y_m is generated.

Discrete optimization belongs to the class of optimization which aims at minimizing an objective function with the set

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of discrete data and variables. These problems are universal NP-hard and to solve them an efficient mathematical model has to be designed. It is seen that there exists a trade-off between inaccuracies in coefficient values and the dimension of the problem in the discrete optimization framework. These methods can be categorized into Exact optimization and approximate optimization approaches. Generally, the discrete problems give approximate solutions due to their complexity and high dimension requirements, but some applications relating to exact optimization can be solved by successive analysis of alternatives methods, branch-and-cut method, etc. The approximate solutions for the discrete optimization problem can be obtained by the usage of greedy algorithms. Integer programming is basically the linear programming in which the variables used are strictly integers. There is a close relationship between Integer programming and combinatorial optimization. Both combinatorial and ILP problems are interweaved with the graph theory concepts. Combinatorial problems seek the best subset of the dataset which satisfies a particular criterion like determining the minimum set of links in a connected graph $G = (V, E)$ covering all nodes. The basic framework of ILP is to maximize or minimize a set of linear combination of integers Y_1, Y_2, …Y_N subject to the linear constraints in the form: $b_1Y_1 + b_2Y_2 + \cdots + b_NY_N \leq a$

In ILP, for instance, the transportation problem is referred to as the "bipartite graph", in which source and destination are the "nodes" and the route between source and destination pair is the "arc". Many real-world problems can be solved by ILP such as investment problems, scheduling problems, transportation problems, assignment problems, route selection problems, etc. The greedy algorithms are the most easily solvable one constraint problems in LP whereas the Knapsack problems are NP-complete, some nonlinear problems like piecewise approximation are not suitable to be solved by ILP. For the convex functions with a criterion of minimization/ maximization, ILP is not a suitable choice.

In combinatorial problems the search space is discrete and the algorithm searches for maxima/ minima of the objective function. For example, the Bin packing, traveling salesman problem (TSP) problems, Integer linear programming, etc. can be solved by the combinatorial approach. It is classified into approximate and exact optimization problems. There are two variants defines for a combinatorial problem:

1. The search variant- which searches for the minimal or maximal value of the given objective function. This is the most frequently used method in the combinatorial approach.

2. The evaluation variant- It is used to find an optimal value for an objective function in a given problem.

Every combinatorial problem has some logical conditions along with a well-defined objective function. The set of

solutions that satisfy these conditions are come out to be feasible solutions. Some are optimal solutions also depend on the value of the objective function. The feasible solutions in a combinatorial problem, corresponding to the associated decision (bounded solution) problems.

Approximate algorithms are well known for finding the approximate solutions to NP-hard problems. The optimal solution for such methods is determined by an approximation factor (or ratio). There are cases when the optimization problems could not give a solution in a fixed polynomial time. So, to obtain the solution in polynomial time, approximation algorithms attempt to determine the approximate optimum solution to a given problem. Some of the approximate algorithm techniques include greedy algorithm, convex programming, primal-dual technique, etc.
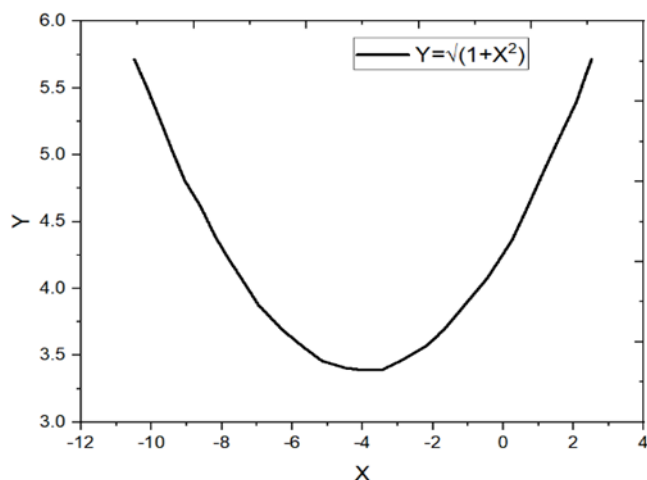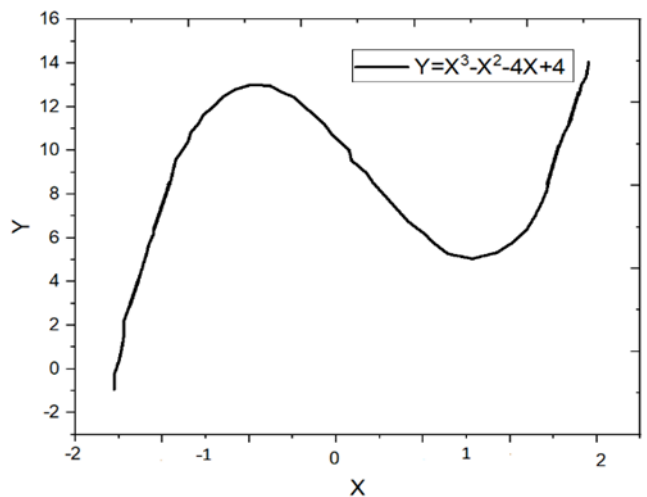

Figure 5 An Example of a Convex Function

Figure 6 An Example of a Non-Convex Function

The reason behind using the global optimization approaches is that many biological systems are nonlinear which turn out to

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be nonconvex problems in nature. The solution for these problems leads to many local optimum values and inaccuracy in the output. So, to avoid this, the global algorithms for optimization are used which determine the global optimum solution for non-convex functions. Figure 5 shows a convex function and Figure 6 shows a non-convex function.

Global optimization approaches are both stochastic as well as deterministic. As the number of iterations increases, there exists an assurance of convergence to a global optimal value. They are divided into 3 optimization techniques namely: heuristic, metaheuristic, and random search. The heuristic approaches are computational approaches that attempt to ameliorate the candidate solution by iteratively executing the algorithm in a given quality measure. Some of the examples include swarm intelligence algorithms, TSP, Genetic algorithms (GA), etc. Metaheuristic approaches are based on the behavior of organisms. They aim to solve the nonlinearity and constraint complexity, multivariate and multimodal function problems of the real-world scenario. Mostly the optimization can be determined by finding the first or second derivatives of the function. But in this case, when the function is complex, there is a need to adopt some methods which are nature-inspired. "Metaheuristic" was suggested by Fred Glover in 1986. Some examples of this approach are Simulated annealing, Differential evolution, Ant colony optimization, Tabu search, particle swarm optimization, and many more. These approaches have two major elements: diversification (or exploration) and intensification (or exploitation). Diversification is the process of exploring search space globally by producing diverse solutions whereas intensification is to find the best solutions in a local search space. Good coordination between these two processes makes the convergence rate of the algorithm fast. The metaheuristic optimization approaches can be a single solution or population-based. Single solution-based algorithms include simulated annealing, variable neighborhood search, etc. population-based algorithms are: PSO, ACO, GA, etc. In [24], authors have given a very lucid review on various metaheuristic optimization methods like invasive weed optimization(IWO), photosynthetic algorithm, paddy field algorithm etc., which are based on the notion of various aspects used in the growth of plants.

The random search optimization is a non-gradient-based approach. They are numerical optimization techniques that can optimize non-continuous and non-differentiable functions. In this approach, the next iteration is independent of the previous iteration's solution. Some examples include Luus and Jaacola method, the black-box method, etc.

Exact optimization approaches give an exact optimal solution to an optimization problem. The Dynamic programming and Branch & Bound algorithm are the two most commonly used algorithms in the exact optimization method. Dynamic

programming uses the notion of establishing an optimized solution. The dynamic programming is applied to a small set of optimization problems. It aims to get an optimal set of solutions of a problem let say Q_{x0} through its sub-problems let's say $Q_{xi} = \{Q_{xi1}, Q_{xi2}, ..., Q_{xin}\}$ and $Q_{xj} = \{Q_{xj1}, Q_{xj2}, ..., Q_{xjm}\}$. Both subproblems are not independent of each other i.e., $Q_{xi} = \{Q_{xi1}, Q_{xi2}, ..., Q_{xin}\} \cap Q_{xj} = \{Q_{xj1}, Q_{xj2}, ..., Q_{xjm}\} \neq \emptyset$

The optimization problem in dynamic programming has 2 properties-

There is an optimal substructure of Q_{x0} which means that the main problem is devised from its subproblem.

Q_{x0} can be broken into non-independent subsets, which is very beneficial in dynamic programming. Each subprogram is solved one at a time and is saved in a table.

The dynamic programming follows some steps written below:

1. First, it checks whether Q_{x0} has optimal substructure or not.

2. To from a structure of Q_{x0} that can be split into some finite non-independent sub-problems.

3. To define the value of an objective function for Q_{x0} repeatedly in the combination of values of an optimum function for its substructure.

4. To solve the objective function of Q_{x0} optimally by bottom-up method, i.e., starting from elementary sub sub-problems and reach to the main problem.

5. To build an optimum solution of Q_{x0} problem by using information from the above steps.
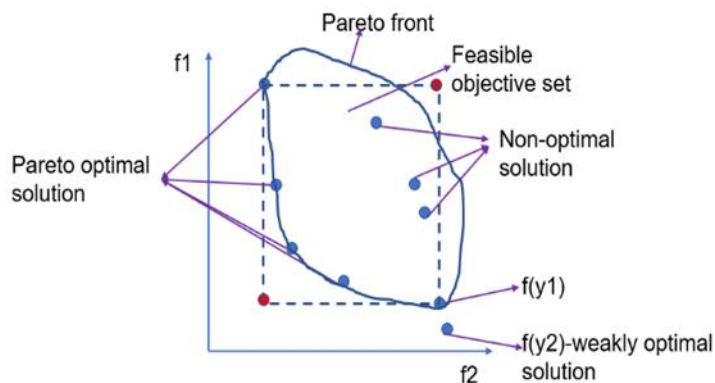

Figure 7 A Pareto Optimal Solution for a Multi-Objective Optimization Problem

Multi-objective optimization can be known as Pareto optimization, vector optimization, multicriteria or multi-attribute optimization. It optimizes more than one objective function simultaneously by a multi-constraint decision-

making approach. It has many applications in the domain of engineering and science where there is a trade-off between more than two objectives in dispute. For instance, in maximizing the performance of a machine while mitigating its friction and other losses and delay, this optimization approach is performed to obtain multiple solutions for the conflicting objective functions. In case of trade-offs between more than two clashing objectives, the optimized solution can be obtained by using multi-objective optimization techniques. For instance, in the WSN assisted IoT networks, developing a new model may involve maximizing the throughput and reliability while minimizing the energy consumption and transmission delay. So, such problems with multiple objective functions can be solved by the multi-objective optimization approach. In Figure 7, f1 represents energy consumption and f2 is the total cost of sensor nodes in a WSN, which has to be minimized. The pareto optimal solution is also called non-dominated solution and the points inside feasible regions are dominated solutions [25].

Apart from the above optimization approaches, there are some problems in optimization which do not need any objective function to optimize. The goal of these problems is to evaluate the variables used in the constraint equations. Such problems are called feasibility problems.

3. HYBRID APPROACHES FOR WSN AND IOT NETWORKS

The various challenges faced while building a sensor network and IoT networks are discussed below. The 13 subsequent sections give brief literature on the usage of various hybrid techniques to address the issues that emerged from each challenge.

3.1. Optimization in Data Transmission Methods

Data transmission is an assemblage of data dissemination, data collection, and data aggregation. Every wireless network follows some sequence to transmit data to the destination. In a data transmission process, initially all the nodes in the network sense the information, then they send this information to their immediate neighbors or data aggregators this process is called dissemination of data. Once the data is collected to all high energy nodes, they start transmitting their collected information to a central node or gateway node which is termed as data collection. The aggregation or conditioning of data can be done at gateway node or at aggregator nodes as

well depending on the nature of the network and the application it is used for. Finally, the aggregated/final data is fused at base station which is called data fusion. This section gives a review of some of the research articles dealing with the optimization of the performance of data transmission systems in wireless/IoT networks. Implementation of the Markov approximation in tree construction and scheduling problem [26] to construct a near-optimal aggregation tree design for deadline constraint aggregation in WSN. It uses the quality of aggregation parameter which is given by the equation below:

$$QoA(\emptyset, \vec{T}^{\emptyset}, t) = |S_{sel-src}^{\emptyset}| = \sum_{i \in S} F_i \prod_{j \in X^{\emptyset}(i)} n_j^{\emptyset}$$

Where S is the set of sensor nodes, $S_{sel-src}^{\emptyset}$ is the set of source nodes selected for aggregation, $X^{\emptyset}(i) \subseteq S$ is the set consisting the node 'i' and its predecessors but not sink in an aggregation tree $'\emptyset'$. 'i' and 'j' are the nodes adjacent to each other. $n_j^{\emptyset}$ is the deciding parameter that a node participates in the aggregation. $\vec{T}^{\emptyset} = [T_i^{\emptyset}, i \in S]$ is the waiting time assigned to each participant node where $0 \leq T_i^{\emptyset} \leq t$ is the time slot for each participant? Article [27] provides a secure way of clustering by implementing a genetic algorithm based on biological organisms processes and an encryption technique based on the RC5 approach which makes use of node residual energy for generating the key. A wireless communication model called cluster based Vehicular Ad-hoc network (CBVANET) is proposed in [28] which focuses on cluster head selection and cluster formation time for the highway oriented application. A new data fusion model is corroborated in [29] with an optimally pruned extreme learning machine along with the grey model to predict the data in the data transmission process from source nodes to sink nodes in a WSN. To maximize network life the authors in [30] have applied joint optimization for both the routing as well as data aggregation using a smooth approximation approach. The optimized energy in data aggregation is achieved in IoT and WSN networks for different topology scenarios in [31] using mixed integer programming (MIP). A nature motivated optimization technique called intelligent water drops algorithm for building the data aggregation tree has been employed in [32] . A brief comparison of above optimization methods used in solving data aggregation related issues are given in Table 1.

Optimization Technique	Literature	WSN Challenge	Comparison With	Remarks
Combinatorial	[26], [108]	Data aggregation	Approximation algorithms, Markov approximation approach	quality of aggregation (QoA) and deadline as the measuring quantities
Genetically derived secure	[27]	Cluster based data	fuzzy-based secure data aggregation (FBSDA)	Uses RC5 approach, performance measures energy, delay, packet

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Cluster-based data aggregation (GDSDA)		aggregation		transmission, and overhead are taken.
Op-ELM+ Grey model+ SLFN	[29]	Data transmission	Grey model (GM) based data fusion and Grey model with least squares support vector machine (GM-LSSVM).	Fast approximation of predicted values by single layer hidden feed-forward network (SLFN), extended network life, minimized data redundancy
Maximum lifetime routing (MLR) for centralized and distributed frameworks	[30]	Routing and Data aggregation	Minimum energy gathering algorithm (MEGA) and Minimum energy routing (MER)	Approximation approach using distributed gradient, superiority based on lifetime and aggregation data rate.
Mixed integer programming	[31]	Data aggregation	With simple data transmission.	Achieve optimality in energy consumption and maximizing throughput in 10 to 40 nodes scenario
Improved intelligent water drops algorithm	[32]	Data aggregation	ACO and Intelligent water drop algorithm	Water drops flow in the presence of obstacles (constraints), optimal path from source to destination.
PSO and gauss newton algorithm (GNA)	[33]	Localization	Gauss-newton algorithm and PSO	localization error, the objective function value with respect to iteration gives robustness in the system
HHO	[34]	Localization	Multi-verse optimizer (MVO), flower pollination algorithm (FPA), whale optimization algorithm (WOA), sine cosine algorithm (SCA), PSO, and GWO.	-
PSO + modified DV-hop	[35]	Localization	Distance vector hop (DV-hop) and Improved DV-hop (IDV-hop)	Range-free localization and positioning error optimization, accuracy, coverage, localization error and variance
Multi-objective optimization	[36]	Localization	-	Evaluation for both isotropic and anisotropic network topologies, minimizes both the number of transmissions and errors produced in localization.
Multi-objective Grey wolf optimization	[37]	Localization	General regression neural network (GRNN), decision theory-based localization algorithm (DTBLA), PSO for node localization (PSONL)	Localization error reduces by 17%.

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Hybrid elephant herding algorithm+ improved tree growth algorithm	[39]	Localization	PSO, butterfly optimization (BOA), firefly optimization algorithm (FFA)	For enhanced localization accuracies.

Table 1 Comparison Chart of Various Data Aggregation Techniques and WSN Node Localization Methods Using Optimization

3.2. Optimization Based Localization Techniques

The localization of nodes can be done in two ways- range-based localization and range-free localization. The range-based localization depends on the measurements of distance and time and requires hardware. The range-free methods albeit suffering from localization errors are frequently considered in the research. Primarily, the measurement for localization is based on three parameters which are distance, received signal strength, and angle of arrival. The performance metrics for localization problems are cost, accuracy, coverage, etc. some of the optimization algorithms that can be used to solve problems in finding the exact location of nodes are genetic algorithm, ACO, harmony search, fruit fly, bat, firework, tree growth optimization, ABC, tabu search, elephant herding. A brief comparison of the optimization methods used in solving localization related issues are given in Table 1. The authors in [7], give a brief description from the year 2009 to 2017 of various metaheuristic optimization algorithms used to solve localization problems in WSN. In [33], the usage of two algorithms, one for localization of nodes and the other to optimize the location of the nodes is done efficiently in the regions where the connectivity is not good. Paper [34] introduces the use of Harris' hawk's optimization algorithm to estimate the location of the sink node which is responsible to control the whole network. In [35], the authors have applied a range-free localization approach using the combination of modified distance-vector hop (DV-hop) method and PSO for positioning error optimization. To find the best solution for the final estimated position of an unknown node the following fitness function is implemented in the paper which is shown below:

$$fit(y,z) = \sum_{i=1}^{n} \left(\frac{1}{hop_i}\right)^2 f(y,z)$$

where n is the number of unknown nodes, hop_i is the minimum hop count between an unknown node and anchor nodes and $f(y,z)$ is the minimized function [35] for distance between an unknown node and each anchor node, which is the localization problem in DV-hop method. In [36] a multi-objective approach to optimize both energy efficiency and the convergence time is employed using the DV-maxHop technique. Paper [37] gives an idea to optimally position the IoT-enabled sensors in the parking area in order to reduce the cost of the system. Paper [38] gives an analysis of metaheuristic optimization approaches like PSO, GA, GWO, Firefly algorithm (FA), and Brain Storm optimization (BSO) based on convergence time and accuracy, network localization error with respect to population size and the number of iterations. A hybridized elephant herding optimization algorithm along with an improved tree growth algorithm has been put forward for achieving high precision and robustness in the unknown target localization in wireless networks [39].

3.3. Optimization Based Connectivity and Coverage Algorithms

Deploying the sensor nodes in WSN is done keeping two factors in mind which are connectivity of the network and the coverage of sensing as well as communication between two nodes. Here, some papers are reviewed which utilized optimization or hybrid optimization approach in solving this issue. Paper [40] aims to optimize the coverage rate of heterogeneous WSN by using an improved and advanced version of two flower pollination algorithms named as non-dominated sorting multi-objective flower pollination algorithm (NSMOFPA). A novel algorithm based on immune optimization for coverage issues has been suggested in [41] that maximizes the coverage area by relocating the mobile nodes. An approach to finding an optimal point in a large coverage with the least active nodes and energy consumption has been proposed using the NSGA-II algorithm [42].

In [43], the authors proposed a novel algorithm called complex alliance strategy with multi-objective optimization of coverage (CASMOC) for node coverage issues arising due to congestion, energy consumption, etc. An attempt to place the sensor nodes optimally while taking connectivity as a high priority is achieved in using three algorithms namely approximation algorithm, greedy algorithm and genetic algorithm [44]. A multi-objective approach with the constraints like coverage, connectivity, and cost of the network is demonstrated in [45]. Paper [46] presents an improved artificial bee colony optimization to improve the coverage rate and to get better connectivity in a WSN. A Gravitational search algorithm with social ski-driver (GSA-SSD) algorithm that focuses on m-connectivity and k-coverage strategy is proposed in[47] which gives better outcome in contrast with PSO, gravitational search algorithm (GSA), ABC, etc.

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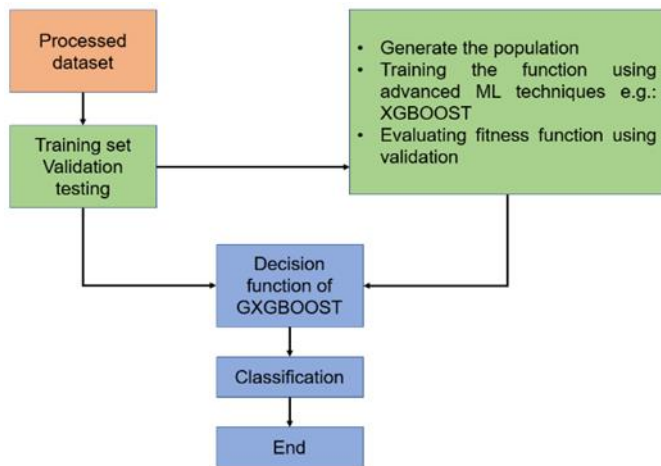Table 2 gives various coverage and connectivity methods using optimization.

Figure 8 The Flow of An Intrusion Detection System Using GXGBOOST Technique

3.4. Optimization based Intrusion detection techniques

The unpredictable observations appearing from the data of a node is called an anomaly. The intrusion in WSN or IoT networks is considered either at the node level or at the data level. The traffic in the WSN also is a major cause of intrusion since some nodes may contribute to misbehaving thereby affecting the network's efficiency. The communication overhead and the loss in data transmission can be overcome by using intrusion detection schemes in WSN assisted IoT networks. Figure 8 shows the flow of an intrusion detection system using the GXGBOOST technique [48]. A survey on intrusion detection systems in [49, 50] give the information about the technologies and methods used in the intrusion detection systems in a wireless sensor node. Paper [51] proposes a hybrid optimization algorithm based on a Spatio-temporal correlation within clusters and sequential minimal optimization with support vector machines (SMO-SVM) along with optimally-pruned extreme learning machine (OP-ELM) to identify the anomalous behavior of nodes. Gavel et al. [52] Proposed a method called log sum inequality (LSI-D) for determining the density of kernel using Pearson's distributed approach. In [53], the authors have proposed a safe data transmission model for detecting intrusions like Denial of Service (DoS), User to root attack (U2R), Remote to user (R2L), etc. An attempt to implement the multi-objective evolutionary algorithms for intrusion detection in WSN is done in [54]. [55] Proposed a hybrid model using combined approach of Graywolf optimization along with SVM classification for detecting intrusion in wireless sensor networks. An optimized collaborative intrusion detection system utilizing improved artificial bee to optimize weighted SVM approach to mitigate the false alarm rate has been proposed in [56] and is validated for the whole NSL-KDD dataset which is available online. Table 2 shows IDS challenge using various optimization approaches.

Optimization Technique	Literature	WSN Challenge	Comparison With	Remarks
Non-dominated sorting multi-objective flower pollination algorithm (NSMOFPA)	[40]	Coverage	NSGA II, Multi-objective PSO (MOPSO), Multi-objective FPA (MOFPA), GA, PSO, Differential evolution algorithm (DEA), flower pollination algorithm (FPA)	It maximizes coverage rate, minimizes node radiation overflow rate and WSN energy consumption rate by using multi-objective optimization for deployment problems, convergence performance.
Immune optimization	[41]	Coverage	PSO, Biogeography based optimization (BBO) and virtual force BBO (VF-BBO), and clonal selection with artificial physics optimization (CSAPO) algorithms.	It improves the connectivity among sensor nodes. For total trace distance of mobile nodes and ratio of coverage area.
NSGA-II	[42]	Coverage	Optimal geographical density control algorithm.	The results for coverage rate and energy consumption for the proposed scheme have been compared with the
Complex alliance strategy with multi-objective optimization of	[43]	Coverage	Event Probability Driven Mechanism (EPDM), Optimization Strategy Coverage Control (OSCC),	The function for energy conversion is used to schedule the low energy nodes. Performance measures like data received, throughput, coverage rate.

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coverage (CASMOC)			delay constraint success ratio (DCSR), stationary and random network protocols.	
Approximation + greedy + genetic algorithm	[44]	Coverage and connectivity	GA and ACO	The hybrid approach uses approximation algorithms and greedy algorithms to position the sensors and removing the redundancies in the coverage area respectively thereby achieving a high coverage rate and genetic algorithm to link the path between nodes for better connectivity.
Multi-objective optimization	[45]	Coverage and connectivity	GA and NSGA-II.	An evolutionary strategy is adopted to construct a network model and then to optimize the deployment. The results for the number of packets sent, fitness value, and the number of dead nodes.
Improved artificial Bee colony optimization	[46]	Coverage and connectivity	GA and Random distribution algorithm.	Performance metrices- average network connectivity, network coverage, network lifetime
GSA-SSD	[47]		PSO, gravitational search algorithm (GSA), ABC, Social ski-driver algorithm (SSD), GA	It is proved to be computationally methodical compared on the basis of a lifetime of network, power and energy consumption, computation time, and connectivity with respect to the number of nodes.
GXGBOOST	[48]	Intrusion detection system (IDS)	AdaBoost, Gradient boost (GB), XGBoost for various attacks like blackhole, grayhole scheduling, flooding	Uses a genetic model with a machine learning-based advanced technique called XGBOOST to detect intrusion in WSNs, guarantees very high accuracies and a high rate of detection for various attacks. It uses 10-fold cross-validation in experimentation.
SVM-SMO	[51]	ADS	SMO-SVM + OP-ELM, NHC, GA, multiclass SVM, SVM+ACO, multi-layer perceptron (MLP+ J48), K-Means	Uses sequential minimal optimization (SMO) along with support vector machines (SVM) for binary classification and optimally-pruned extreme learning machine (OP-ELM) for multiclass classification of anomalies in the IWSN, uses k-medoid clustering for making clusters and the results are also compared with k-means clustering in terms of accuracy.
LSI-D + Pearson's divergence	[52]	IDS	Pearson's divergence using Naïve's method (NM-D), divergence using Renyi's	High accuracy low false positive rate, high true positive rate, high precision,

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			entropy-based method (R-D)	
Chicken swarm optimization + adaptive SVM	[53]	IDS	PSO, ABC, and GA	High accuracy, high throughput, low energy consumption, low delay, high packet delivery is evaluated for the attacks.
Multi-objective evolutionary algorithm	[54]	IDS	NSGA-II and Strength pareto evolutionary algorithm (SPEA2)	It examines for evaluating the speed of convergence, near-optimal solutions of the intrusion problem in WSNs
Graywolf optimization (GWO) + SVM	[55]	IDS	3,4, and 5 wolves GWO+SVM-IDS and PSO-IDS	The results for false alarm rate, detection rate, number of features, accuracy, and execution time are evaluated.
Improved artificial bee colony optimization (IABC) + weighted SVM	[56]	Optimized collaborative intrusion detection system (OCIDS)	ACO, Backpropagation, J48, MLP, Bagging, AdaBoost, Random forest (RF), SOMET+RF	Mitigates the false alarm rate and enhance the system accuracy. Various attack scenarios are taken into consideration to evaluate the robustness.

Table 2 Optimization Approaches Used in Various Coverage and Connectivity Problems and Intrusion Detection Problems in WSN and IoT Applications
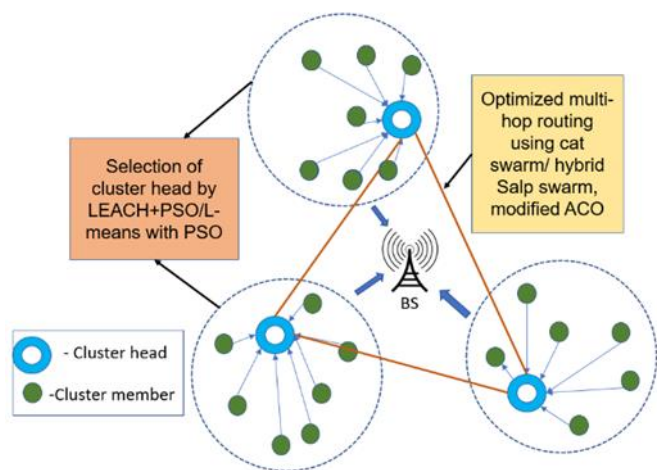

Figure 9 Optimization in Clustering and Route Path Selection in a WSN

3.5.   Optimization Based Routing Algorithms

Routing plays a chief role in the WSN and IoT networks. Every node in a network collects data and transfers it to the base station via a path called route. The path selected must be such that it should contribute to minimum energy wastage and less bandwidth utilization because the nodes have limited battery power. So, this section gives literature on the usage of various network protocols and optimization approaches to obtain an optimal routing. Figure 9 gives a picturization of

clusters in WSN and shows where optimization algorithms are used. Paper [57] proposes an improved artificial bee colony optimization algorithm to optimize the clusters made by Fuzzy C-Means algorithm. A survey on ACO-based routing methods has been performed in [12]. In [11] an optimized clustering protocol called PSO-based uneven dynamic clustering routing protocol (PUDCRP) has been proposed for maintaining the balance in energy consumption in high-density networks. The proposed fitness function used in the paper for G_{best} is given by:

$$Fit = \beta * r_{cov} + \frac{1-\beta}{IoU}$$

And the fitness function for P_{besti} for a single circular area 'i' is:

$$Fit_i = \left| n_{cir_i} - n_{ideal_i} \right|, 0 < i < cir$$

Where $r_{cov} = \frac{n_{cir}}{n}$ and $U = \frac{n_{ov}}{n}$, n_{cir} is the number of nodes in circular areas, n_{ov} indicates number of nodes in overlapping circular sections, 'm' is the total circular areas, n_{ideal_i} ideal number of nodes in the ith circular area and n is the total nodes in a network. In [58], the data-centric routing is applied and the path between the nodes which are participating in the routing is optimized using the ACO approach. An ant colony conveyance approach for multi-objective routing is employed in [59]. Akila et al. [60] demonstrated a cluster-based routing which uses a fuzzy approach for clustering and a coding based statistical

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approach for establishing route path between nodes which is further optimized by PSO. In [61], the authors have attempted an approach called dynamic layered with dual-cluster head-based routing with krill herd optimization technique to choose first and second optimal cluster heads in UWSN application. In [62] an adaptive routing method based on Cuckoo search optimization is incorporated in VANET networks. In table 3 above routing and clustering approaches are overviewed briefly and compared on the basis of various optimization approaches.

3.6. Optimization Based MAC Design

Medium access control (MAC) plays a principal role in conserving energy and enhancing the lifetime of the WSN and IoT networks. The data link layer is the second layer after the physical layer in the OSI model of a WSN. The data link layer has two sub-layers: Logical link control (LLC) and MAC. The protocols designed for MAC layers are called MAC protocols. These protocols generally focus on the scheduling and contention in the transmission of packets. The ML and optimization techniques are employed in MAC protocols to circumvent the network latency and to regulate energy utilization. The following survey of some of the MAC layer-centered optimization approaches shows the efficient usage of optimization in MAC layer design for IoT and WSN

networks. Paper [63] introduces a novel MAC scheduling protocol called Ring partitioned based MAC (RP-MAC) in the clustered WSN. A multilevel integrated Medium access protocol has been proposed in [64] to optimize the performance in large-scale wireless sensor networks by adopting two algorithms for collision avoidance and a back-off technique. Paper [65] uses the Carrier-sense multiple access with collision avoidance (CSMA/CA) technique to enhance system throughput and a modified Markov method as a statistical measure for calculating the probability of communication time limit of the UAVs collecting the data from IoT devices on the ground. In [66], the author has proposed a MAC protocol with dynamic channel coding which uses a low radiated ultra wideband technique to minimize the effects of interference in E-health IoT applications. The hybrid MAC approaches that are history-based and priority-based with Markov chain modeling are proposed in [67], and are compared with traditional MAC techniques for end-to end delay versus cumulative distribution function (CDF) and probability density function (PDF). [68] Proposes Time-out MAC (T-MAC) implementing the model with optimization using Markov chain for unsaturated traffic environments of WSN. In Table 3 various optimization techniques for MAC are overviewed briefly.

Optimization Technique	Literature	WSN Challenge	Comparison With	Remarks
Artificial bee colony + Fuzzy C-Means + improved ACO	[57]	Routing	Centralized Low-Energy Adaptive Clustering Hierarchy (LEACH-C), Fitness value based improved GWO (FIGWO), PSO, and ABC-SD.	Performance metrics taken are network lifetime, throughput, total energy, and network stabilization time.
PUDCRP	[11]	Clustering + routing	PSO semi-distributed method (PSO-SD), PSO based Energy efficient Cluster Head Selection algorithm (PSO-ECHS), Unequal Clustering and Connected Graph Routing Algorithm (UCCGRA), Cluster Aided Multi-Path (CAMP), Energy Efficient and Balanced Cluster-based Data Aggregation algorithm (EEBCDA), Energy-Efficient Multi-hop Routing Protocol (EEMRP), Cluster aided multipath routing (CAMP)	Uses the PSO concept to search the areas which are not affected by hotspots and dynamically allocates the cluster over that coverage area when there is a node failure. A line-aided route method is also used to find the next hop in the network. The simulation results for network life and energy variations have been recorded.

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Data centric protocols + ACO	[58]	Routing	Directed diffusion routing, Gradient based routing, energy aware routing,	Remaining energy and bandwidth required are evaluated for four routing protocols with ACO application
MO-ACO	[59]	Clustering + routing	Multi-objective evolutionary algorithm (MOEA) and Energy efficient clustering and routing (EECR).	Performance metrics are packet delivery (PDR) rate loss, energy consumption, routing load, throughput, and latency.
PSO +Fuzzy clustering approach (FPCA)	[60]	Routing + clustering	Cluster Head Cooperative Trustworthy Energy Efficient MIMO (CH-C-TEEM), systematic energy balanced cooperative transmission scheme (SEBC)	Maximize the signal to interference plus noise ratio (SINR) of the network and minimize the energy expenses and load at the same time.
Dynamic layered dual cluster head-based routing with krill herd optimization	[61]	Routing +clustering	Dual-cluster head-based routing using PSO (DC-PSO).	UWSN application
Adaptive routing with cuckoo search optimization	[62]	Routing	Ad-hoc on-demand distance vector routing (AODV) and general packet radio service (GPRS).	For VANET, packet delivery ratio, overhead load and end-to-end delay.
Ring partitioned based MAC (RP-MAC)	[63]	MAC	Energy efficient and reliable routing (E2R2), multi-hop routing, and Time division multiple access-based MAC (TDMA-MAC) protocols	Weighted Voronoi diagram (WVD) algorithm to make clusters, a Two-fold data aggregation (TFDA) scheme to reduce the number of transmissions, hybrid chicken swarm optimization algorithm (intra-cluster communication), and position-based routing (PRT) tree algorithm (inter-cluster routing) Performs good for energy consumption, network lifetime, dead nodes, and throughput.
Multilevel integrated MAC	[64]	MAC	QoS MAC (Q-MAC), frequency division and frequency division combine protocol (FT-MAC), Sensor MAC (S-MAC), Pattern MAC (P-MAC), data gathering MAC (D-MAC), spatial-temporal MAC (ST-MAC), near optimal duty	It adopts two algorithms one uses the back-off technique and the other utilizes a scheme to avoid the collision in data frames. Performs good for throughput, delay, energy consumption

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			cycle scheduling (O-MAC)	
TMAC with optimization using Markov chain	[68]	MAC	Asynchronous Duty cycle-based MAC(X-MAC), traditional T-MAC, S-MAC.	To optimize the delay, energy consumption, power requirements, and throughput
Firefly optimization algorithm	[69]	Synchronization	firefly organization which follows pulse-coupled oscillators (PCO)guidelines to outflow the light used for mating purposes	The time synchronization issue gives rise to some problems like packet collision, deafness among the nodes, data gathering challenges, and many more.
Cramer rao lower bound+ maximum likelihood estimation	[71]	Synchronization	Quantum Annealing (QA), integer linear programming (ILP), simulated annealing (SA)	Global optimal solution thereby enhancing the performance of the system.
Generous transformational optimization (GTOA)	[74]	Synchronization	PSO, multi-objective genetic algorithm (MGA), and ABFA.	The work has been validated on some real-world datasets and is transmitted to the cloud interface of the IoT power system.
PSOGSA	[77]	Congestion control	Cuckoo search (CS) and adaptive CS (ACS) algorithms	The novel algorithm employs an objective function that considers the energy level of nodes and then controls the arrival rate of the packets based on priority. Performance metrics are congestion level, energy, throughput, sending rate, etc.
CCCLA	[81]	Congestion control	Constrained Application Protocol (CoAP), Advanced congestion control protocol over CoAP (CoCoA), simple IoT, transmission control protocol for congestion control (TCP-Siam)	Affects some parameters to control the congestion in the system and influences the performance like a utility, loss ratio, power requirements.
A-DP	[88]	Target tracking	Compared with other algorithms which use the greedy approach and generalized Breiman, Friedman, Olshen, and Stone (GBFOS) scheme.	The number of sensors and the small number of bits is the prerequisite for such a combinatorial approach. Fit for large WSNs
EKF+ adaptive dynamic	[89]	Target tracking in energy	Simulated-annealing based multi-sensor scheduling scheme, ADP-based	The challenge of sensor scheduling over an infinite horizon has been overcome in this paper, achieves more accuracy and energy

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programming-based multi-sensor scheduling algorithm (ADP-MSS)		harvesting WSN	single-sensor scheduling scheme.	efficiency.
PSO + Mixed gaussian sensing model	[90]	Target sensing	Mixed gaussian sensing model without optimization	The performance metrics based on accuracy and energy competence are evaluated.
A Multi-ALgorithm Genetically Adaptive Multi-objective (AMAL-GAM)	[93]	Target tracking	Updated unscented Kalman filter + various sensor sorting techniques like sigma points, target trajectory, mutual information, fisher information	Updated unscented Kalman filter method for effective tracking of the target in a highly unpredictable environment where the motion of the target is very uncertain.
Multi-objective optimized mutual information with upper bound based sensor selection (MOP-MIUB)	[94]	Target tracking	Multi-objective MI, FI, for knee point and compromised solutions.	Minimum number of selected sensors and low mean square error is achieved.

Table 3 Usage of Various Optimization Techniques in Routing, Clustering, MAC, Synchronization, Congestion Control and Target Tracking Related Problems in WSN/ IoT Applications

3.7. Optimization Based Synchronization Techniques

The structure of the WSN/IoT network is such that it can organize and constitute a topology based on the application. Apart from the energy efficiency, anomaly nodes detection, etc., issues, there exists another issue called synchronization in time, space, packet delivery, etc. Paper[69] gives a survey on the usage of the firefly optimization algorithm in solving time synchronization problems in WSN. A scheduling algorithm called Optimal Synchronization Scheduling Algorithm (OSSA) is proposed which designs a clock model and a stochastic approach for optimization to minimize the average age error and the average cost of the system[70]. The issue of joint synchronization and localization has been addressed in [71] by deriving Cramer-Rao lower bound and Maximum likelihood estimator (MLE) and developing a model which employs the proposed semidefinite programming for converting the MLE non-convex optimization problem into convex. In [72], the authors have focused to reduce the number of controllers and distance between the sensors by implementing the cuckoo optimization approach. One of the applications in underground mining in which industrial IoT (IIoT) is employed is discussed in [73] which uses a hybrid approach constituting the traditional synchronization schemes like Reference broadcast synchronization (RBS) and Timing-sync protocol (TPSN) for sensor network and is applied with improved clock synchronization based dynamic superframe design ensuring robustness. The energy synchronization along with mitigation in power losses in IoT systems has been achieved by the introduction of generous transformational optimization (GTOA) algorithm [74]. For the distributed IoT applications employing a multiantenna fusion center, a hybrid Linear minimum mean square (LMMSE) method is considered for two synchronization schemes which are alternate direction method of multipliers (ADMM) (centralized) and asynchronous distributed (AD-ADMM) (distributed approach) in [75]. The precision in the agricultural application of WSN is achieved by deploying the sensor nodes and properly synchronizing them with respect to the sink node's

clock is demonstrated in [76]. In Table 3 above mentioned synchronization methods are briefly discussed and compared on the basis of utilization of optimization methods in them.

3.8.   Optimization Based Congestion Control Strategies

Whenever a node or channel tackles a large amount of data above its scope, congestion comes in the way of WSN and IoT. The main reasons for congestion to occur are many-to-one transmission, overflow in the channel, the collision of packets, effectual variation in time, etc. Figure 10 gives an overview of various congestion control approaches used in WSN assisted IoT networks. In this subsection, a survey of some papers concentrating on this challenge is done which uses an optimization strategy to obtain a contention-free model and better QoS parameters. In order to regulate the retransmission of the data due to the congestion in WSN/ IoT networks a novel optimization approach called Particle swarm optimization and gravitational search algorithm (PSOGSA) is presented in [77]. Figure 11 shows the PSOGSA scheme to control the congestion. The position and velocity updates for GSA is aggregated with that of velocity and position equations of PSO and the fitness function used for the hybrid approach is:

$$fit \rightarrow \max(f^{arate} + f^{bw} + f^{txrate} + f^{cong} + f^{qlength} + f^{ene})$$

where f^{arate} is the arrival rate function, f^{bw} is the function for available bandwidth of child node, f^{txrate} indicates the function for evaluation of transmission rate, f^{cong} denotes function regarding congestion, $f^{qlength}$ denotes the function for queue length, f^{ene} gives the consumption of energy in a cluster, these functions are presented in the equations 15,16,17,18,19 and 25 respectively in [77]. The work in [78], focuses on the bidirectional congestion regulation on the Internet of Drones networks by using a near optimal shortest path technique called technique for order of preference by similarity to ideal solution (TOPSIS) based on preference order. An approach to regulating the congestion by optimizing the cross-layer and resource allocation by network utility maximization is studied in [79]. A very lucid and elaborative review on all congestion control techniques using optimization, machine learning, and classical approach has been done in [80]. In [81] the authors introduces an intelligent system in IoT network to overcome congestion and bandwidth problem by proposing a cognitive game learning automata approach called Cognitive Congestion Control in IoT using a game of Learning Automata (CCCLA). The congestion control approaches implementing the optimization techniques like Adaptive cuckoo search, PSO, ACO, flock based congestion control (Flock-CC), GWO, etc., are incorporated in [82, 83, 84, 85, 86, 87]. In Table 3 the usage of optimization in congestion control techniques are reviewed briefly and compared.
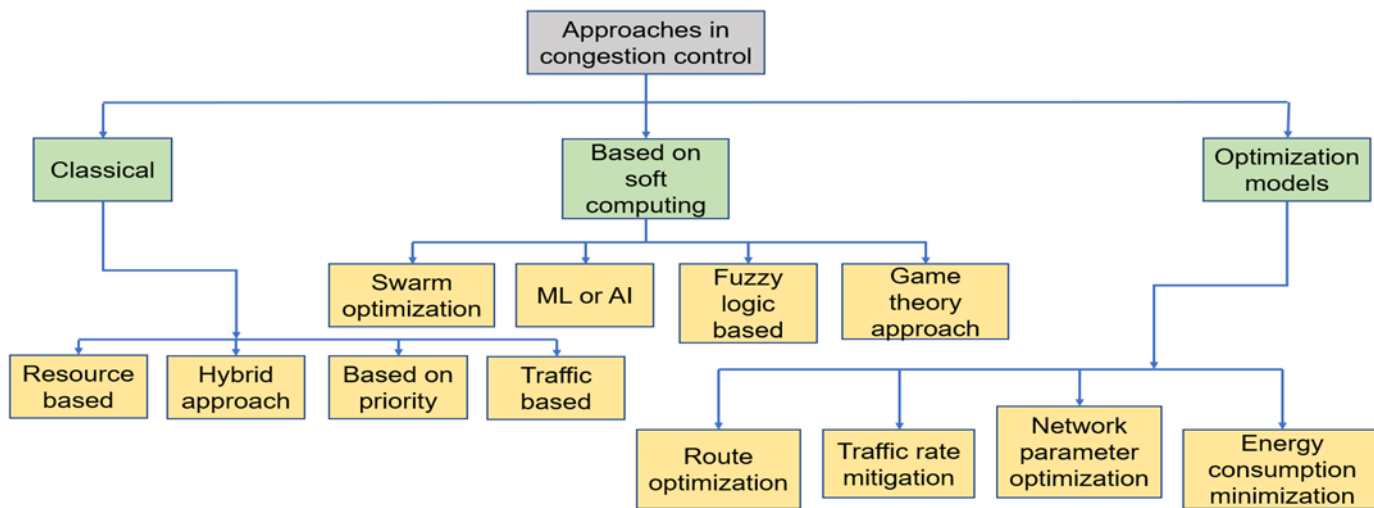

Figure 10 A Flow Schema Showing Various Congestion Control Approaches

Optimization Technique	Literature	WSN Challenge	Comparison With	Remarks
QoS based on greedy path selection (QoS-G), QoS based on optimization-based	[95]	Event detection	Multipath routing (MP), single path routing (SP), multi-constraint multipath	Minimum energy requirement and efficient data retransmission with a low delay for event perception application of wireless networks. High network lifetime, average

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path selection (QoS-O) and enhanced QoS (QoS-E) using Multi-constraint optimization			routing (MCMP)	success rate, average energy consumption, delay, and reliability.
Destination-oriented directed acyclic graph (DODAG) implementation in QoI aware routing protocol for low power and lossy networks (RPL)	[96]	Event detection	Standard RPL	Less energy consumption even in a noisy situation. The reduced data transmission along with the optimization in energy and topology construction is achieved by improving RPL.
Spatio-temporal correlation-based fault tolerant event detection scheme (STFTED)	[97]	Event monitoring	Optimal threshold decision schemes (OTDS)	Weighted voting framework (low level stage) which is location-based, the Bayesian fusion algorithm (high level stage).
Convex function optimization + SVM	[98]	Event driven application	Minimizing the Maximum of Energy consumption (MME), TS-based (Tabu search) approaches, Minimizing the Sum of Energy consumption (MSE), Maximizing the Minimum of Residual energy (MMR),	Determines the path trajectory of the sink node and by means of it enhances the life of the network.
Compression sensing	[100]	Event detection	Consensus algorithm at various iterations	It evaluates the log-likelihood ratio (LLR) for the events locally. Iteratively the process is executed to optimize the LLR based on a consensus algorithm and a global solution is found till the convergence of the algorithm.
Closed loop power manager with predictive transmission power controller (CLPM-PTPC)	[102]	Energy harvesting	CLPM-fixed, and CLPM adaptive transmission power control (CLPM-ATPC) approach.	It records a 15% reduction in energy consumption as compared to the fixed transmission model, packet reception ratio and the energy consumption for CLPM-PTPC is more energy-efficient than CLPM-ATPC and CLPM-fixed.
Two phase life time enhancing method (TLM)	[103]	Energy harvesting	Maximum Energy First (MEF), Maximum target First (MTF), priority-based greedy scheduling algorithm (PGS), Priority-based random selection (PRAN), multi-objective	A multi-objective PSO to localize the rechargeable mobile nodes (first phase), non-dominated sorting and bidirectional local search method with a modified binary multi-objective evolutionary (MBNSBLS) (second phase), results for network lifetime vs energy threshold, the number of sensor nodes, sensing range, the number of targets prove supremacy of TLM.

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			evolutionary algorithm based on decomposition (MOEA/D), GA	
Adjustment based allocation	[104]	Energy harvesting	Generalized assignment problem based, C-schedule.	It works on the theory of adjusting the distance of the mobile node depending on the time slots. It becomes an NP-hard problem that is known to be complex in nature, so to reduce its complexity, a less complex online centralized approach is implemented. It gives high throughput, minimum delay, and maximum collected data.
Energy optimization	[105]	Solar-based Energy harvesting	Avrora network simulation.	The results are validated for 10 and 20 node WSN scenarios at 3%, 10% duty cycles. It also analyses the operation for an energy-neutral model for 40%, 46%, and 50% duty cycles.
Software defined energy harvesting WSN (SD-EHWSN)	[106]	Energy harvesting	Weightless swarm algorithm (WSA), model-based best response (MBR), model free Q-learning (MFQL), cross entropy optimization (CEO)	The sensor nodes are powered by solar energy which is stochastic in nature, so the game approach is modeled along with a stationary Markovian model for optimizing the collaborative beam forming approach which results in enhancement of SNR
Best node scheduling using jammer based EHWSN	[107]	Energy harvesting	Conventional Round robin scheduling	The work derives two probability measures namely probability of the secrecy capacity (PCS) and secrecy outage probability (SOP) to ensure the best secrecy for the proposed model. The monte Carlo method of simulation is adopted.
MILP based task schedular(offline)+ heuristic approach(online)	[109]	QoS	QoS adaptive scheme with genetic algorithm (GEN), gradient curve shifting (GCS), random algorithm for network QoS (RAN), critical task first scheduler (CTF), PSO, hybrid worst fit genetic algorithm (HWS)	Proposed method guarantees about 170% enhancement in the lifespan.
Lyapunov drift plus penalty + Block coordinate descent	[110]	Cross layer	Block coordinate descent method (BCD)	Uses Lyapunov drift with coordinate descent technique to address the energy issues in multi-energy requirement scenarios like

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method				transmission, stochastic behavior of energy scavenging and channel state, sensing, reception of data, etc.
Hidden terminal problem +neighbor cooperative technique	[111]	Cross-layer	IEEE802.15.4 non-slotted CSMA/CA (D-CSMA-CA)	Enhances the range of communication, adaptive and directive phased arrays are employed at the physical layer and cross-layer optimization for the super-frame of IEEE 802.15.4 is used. The complexity and overhead minimization and efficiency in throughput and scalability are achieved by the use of directive antennas asymmetrically.
Reducing delay and maximizing lifetime (RDML)+optimization for changing the duty cycle+ optimization for network deployment	[112]	Cross-layer	Equal distance scheme, optimal duty cycle scheme	Proposed scheme for large duty cycle values guarantees a 19-30% reduction in delay and 43% enhancement in the life of the network.

Table 4 Overview of Optimization Techniques Used in Event Detection, Energy Harvesting, QoS and Cross Layer Challenges of WSN Based IoT Applications

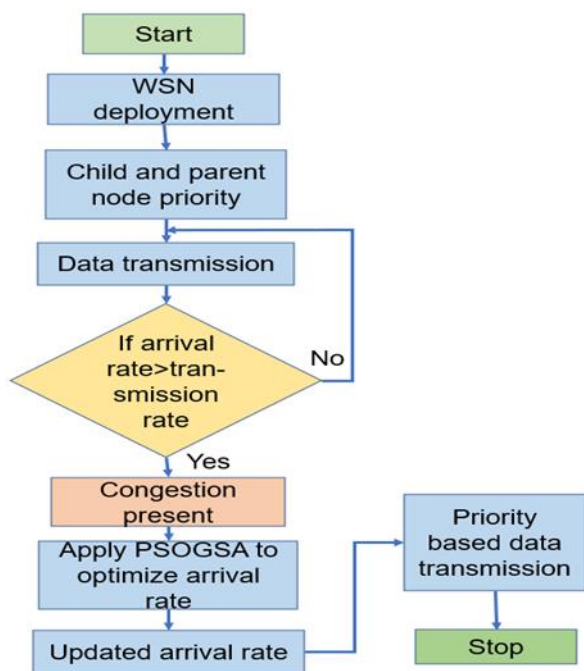Figure 11 The PSOGSA Algorithm[77] Regulates the Congestion in a WSN

3.9. Optimization Based Target Tracking Methods

The tracking of an object in a WSN is an important task in some applications like surveillance. The tracking method depends majorly on the transmission and allocation of bits.

There are four fundamental approaches to accomplish tracing of target or objects either moving or stationary. These methods are cluster-based, mobicast base, a prediction based and tree-based tracking. Among the centralized and distributed target tracking methods, the most utilized are distributed ones. A target tracking scenario in Figure 12 shows how the target can be tracked by the nodes in its proximity on the basis of its trajectory. Paper [88] uses bit allocation based on approximate dynamic programming (A-DP) and convex optimization techniques. A multi-sensor scheduling and Adaptive dynamic programming-based target tracking scheme which uses an extended Kalman filter method is proposed in [89]. A node reputation scheme-based local voting approach is demonstrated along with the application of PSO for obtaining the target position is proposed in [90]. A distributed tracking scheme which uses an auction-based adaptive sensor activation approach for improving tracking quality, energy regulation, and network life is proposed in [91] which uses the prediction region concept for tracking the object in WSN. An attempt to ameliorate the tracking precision, accuracy and reliability of the WSN is done by proposing a method based on a dynamic selection of cluster nodes called dynamic multilateral scheme with cooperative sensing based on the distance of it from target and base station [92]. A practice of selecting the sensor nodes without knowing their number is done by using a multi-objective genetically adaptive algorithm called Multi-Algorithm Genetically Adaptive Multi-objective (AMAL-GAM) [93]. To handle the uncertainties in the path of choosing the sensors for target detection, a novel mutual

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information-based upper bound method is proposed in [94]. In Table 3 the implementation of optimization in various target tracking based applications are overviewed briefly.
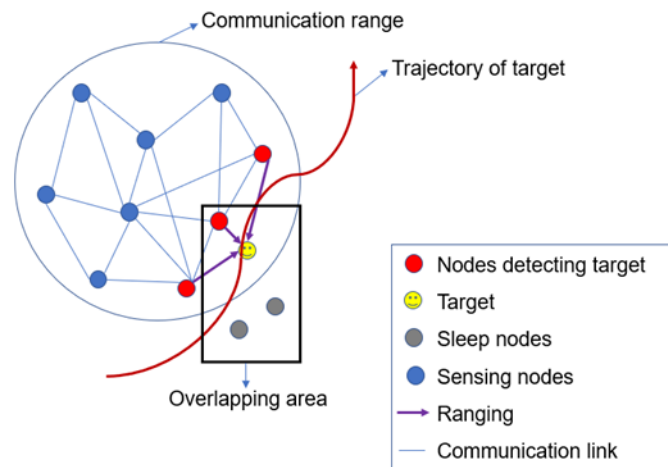

Figure 12 Target Tracking in WSN Assisted IoT Networks

3.10. Optimization Based Event Detection Methods

The task of WSN is to monitor an area of interest in which the deployment of sensors is done. This monitoring is for many purposes like monitoring some environmental conditions continuously in a region, monitoring an industrial plant parameter, detecting an event, etc. The event detection needs continuous updating of data observed with nearly zero latency. In order to achieve low false rates of alarm, perfect

3.11. Optimization Based Energy Harvesting Techniques

synchronization elevated true rate of detection, various optimization, and hybrid optimization algorithms are proposed. The table 4 discusses various optimization-based event detection applications and the survey of the same is done in this section. A multi-constraint optimized QoS provisioning technique for an event perception application of wireless networks has been proposed in [95]. Quality of information aware routing with low power (QoI- aware RPL) method is employed in noisy WSN environment to reduce the energy consumption in event detection [96]. A fault-tolerant event detection based on spatiotemporal correlation is proposed in [97] which gives an effective and better event tracking. Paper [98] uses the combination of non-deterministic finite automation and directed acyclic graph concepts to address the issue of an event searching in a multi-probability RFID system of an event stream. The event detection gives rise to an open issue called a mobile sink. So, in order to regulate the mobility of the sink thereby bounding it in terms of time for the purpose of gathering data from an event-driven scenario, an optimization model based on a convex function solution that uses the regression technique (SVM) is suggested in [99]. A compression sensing technique that takes consensus problems into account is used to investigate the event tracking issue in the cyber-physical systems (CPS) [100]. A robust system [101] to monitor the event and reporting it to the sink optimally thereby maximizing the lifetime by optimizing the convex constraints for multiple event detection by the means of distributed dual decomposition technique is performed using ultra-wideband (UWB) signaling phenomena in WSN.
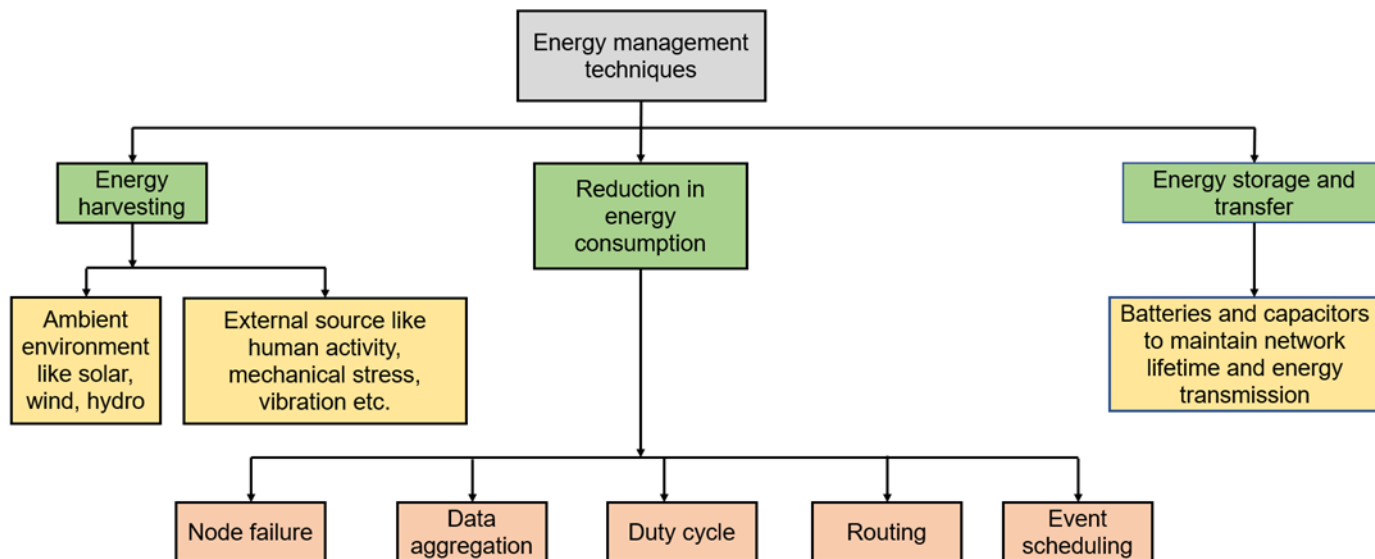

Figure 13 Taxonomy of Various Techniques Used in Energy Harvesting

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Many applications in IoT and WSN need a longer life with good management of energy. Since the energy of nodes depends on the battery, measures have to be taken to save this precious energy. Various Energy harvesting (EH) methods are suggested to date. The use of optimization in energy harvesting WSN and IoT makes the network very efficient and resistant against the energy drain. Figure 13 depicts various techniques used in energy harvesting. This section discusses some important and latest methodologies implementing the optimization in Energy harvesting WSN (EHWSN) and IoT. Paper [102] uses both transmission power curtailment as well as optimization in duty cycle jointly in the experiment performed on hardware. Paper [103] talks about enhancing the span of network life by covering maximum coverage of sensor nodes. A paper that uses mobile sink [104], gives excellent research about the use of time slots of the sensor node data transmission in deciding the path for the mobile sink. Paper [105] focuses on optimizing energy consumption using different duty cycles in solar-powered sensor nodes in EHWSN. In [106], the authors use a collaborative beam forming method for reducing the network overhead and energy consumption in software-defined EHWSN. There is another approach for enhancing the secrecy at the physical layer of EHWSN by using jammers to generate jamming signals [107]. In Table 4, the above-mentioned energy harvesting applications along with the usage of optimization in them is presented.

3.12. Optimization Based QoS Methods

The Quality-of-service aware techniques have been used in WSN/ IoT networks to achieve reliability, delay mitigation, reduction energy balancing, scalability, limited resources, dynamic nature of network, security, heterogeneous traffic, etc. The below-mentioned survey gives the use of QoS methods based on optimization techniques to address these challenges. In [113], the authors proposed a heuristic approach i.e., a differentially guided krill herd algorithm to find an optimal path for quality of service routing to increase the performance of the mobile ad-hoc networks. The paper [114] gives an extensive survey on cognitive radio sensor networks using multi-objective non-linear programming to optimize many parameters like QoS assertion, hand-off reduction, energy efficiency, throughput, etc. An attempt to optimize various QoS parameters in a cloud service of IoT along with maintaining the privacy of the system is made by using a hybrid algorithm called Shuffled frog leap algorithm with genetic algorithm (SFLA-GA) [115] which combines the concepts of genetic as well as shuffled frog leaping optimization framework. A real-time scenario using various IoT modules and RPL based routing is used in [116] to optimize the QoS by considering the pulsed sensor data, Received Signal Strength (RSS), and path loss as the factors to solve the power consumption problem. A mobility-aware QoS parameter optimization method is suggested in [109]

which is able to compute the real-time approximate values for network life and energy requirement. Even though a rapid transmission system due to high mobility in the vehicle-to-vehicle (V2V) network of an intelligent transport system makes the system fast but it has some side-effects also like demeaning QoS performance. So, to define such problems an algorithm called QoS-aware, green, sustainable, reliable, and available (QGRSA) [117] is proposed and applied to the real data and it reveals the improvement in the QoS parameters in the future edge computing of IoT-driven networks. A mathematical model [118] for the mixed-integer NL programming along with the outer approximation scheme is framed to optimize the sum rate in the IoT networks and to maximize the inclusion of the IoT devices.
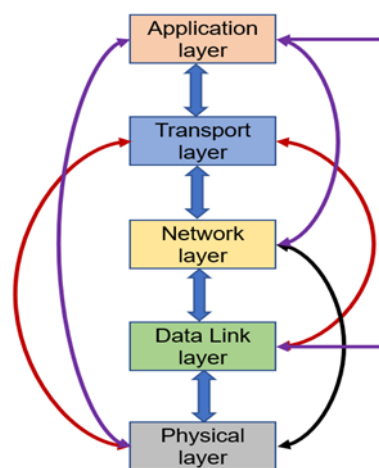

Figure 14 Cross-Layer Connections in an OSI Model of a Wireless Network

3.13. Optimization based cross-layer issues

The management of tasks between every layer of the OSI model of a wireless network is called cross-layer optimization. Some of the tasks include multipath routing, congestion control, error recovery with retransmission, etc. These issues arising from cross-layer management can be mitigated by implementing a suitable optimization approach. Figure 14 gives Cross-layer connections in an OSI model of a wireless network. A survey on various cross-layer issues and their solutions has been presented in [119] in visual sensor network (VSN). The paper [120], gives an elaborative survey from the year 2000 to 2013 on the various cross-layer issues faced by WSN and IoT networks and has explained the solution to each problem by QoS techniques. [110] gives a heterogeneous energy guidance model by optimizing two parameters that are energy and lifetime on a cross-layer platform. An approach to address the hidden-terminal problem based on the neighbor-cooperative technique for accessing channels is suggested in [111]. A novel design based on Delta diagram [121] along with the modified version

of grey wolf optimization is proposed to answer the challenges raised due to the high level of heterogeneity, reliability, and end-to-end transmission in the cross-layer optimization approach of IoT systems. Reducing delay and maximizing lifetime (RDML) scheme is proposed in [112] to optimize multiple layers in an industrial WSN system. A multilevel decomposition method [122] (primal and dual) based on binary search method is proposed to solve non-convex MIP for achieving optimization in cross-layer issues, better QoS metrics and topology design in the wireless body sensor networks. The paper [123] poses challenges in the way of cross-layer designing through an elaborated tabular description of the optimization methods to solve such issues in multimedia sensor network (WMSN) applications. The paper [124] proposes an optimization in cross-layer for opportunistic routing to dwindle the delay and losses in WSN and enhancement in the network reliability by approx. 36-87%. In Table 4 the above mentioned QoS and cross layer optimization techniques are briefly reviewed.

4. BRIEF REVIEW ON MACHINE LEARNING TECHNIQUES USED IN WSN/IOT

Machine learning has been identified as a technique that eases the prediction of outcomes by using experiences without being denotatively programmed by the user. Since the time ML has been coined by Arthur Samuel in 1959, it has been widely explored in many applications and researches. The taxonomy of ML is shown in Figure 15 which depicts the types and further classification of each type. Broadly ML is divided into 4 paradigms namely supervised, unsupervised, semi-supervised and reinforcement learning. Based on the nature and complexity of the dataset and the WSN challenge, a specific ML technique should be used to obtain best results. For example, in [125, 126], Bayesian approach is used to address the problem of localization. However, object tracking and clustering and outlier detection problems can also be solved using Bayesian and Naïve Bayesian techniques [127-129]. Regression methods are used to predict some missing data sequence or data gathering in WSN [130-133]. Support vector machine technique is majorly used in intrusion/anomaly detection in WSN and IoT networks [134-139]. Decision trees work best when used in data fusion and intrusion detection systems [140-142]. Random forest classifiers are good at diagnosing the malfunction of devices used in IoT networks and they can also handle the MAC address spoofing problem [143,144]. In [145-149] artificial neural network is employed to solve routing, data aggregation and localization problems. Apart from classification and regression, which use labelled datasets, there are some approaches which can work on unlabeled datasets too like in [150-159] some clustering algorithms like k-means and Fuzzy c-means are used to focus on clustering and faulty node detection related issues. Clustering, data compression and outlier detection can best be solved by principal component analysis technique mentioned in [160-163].
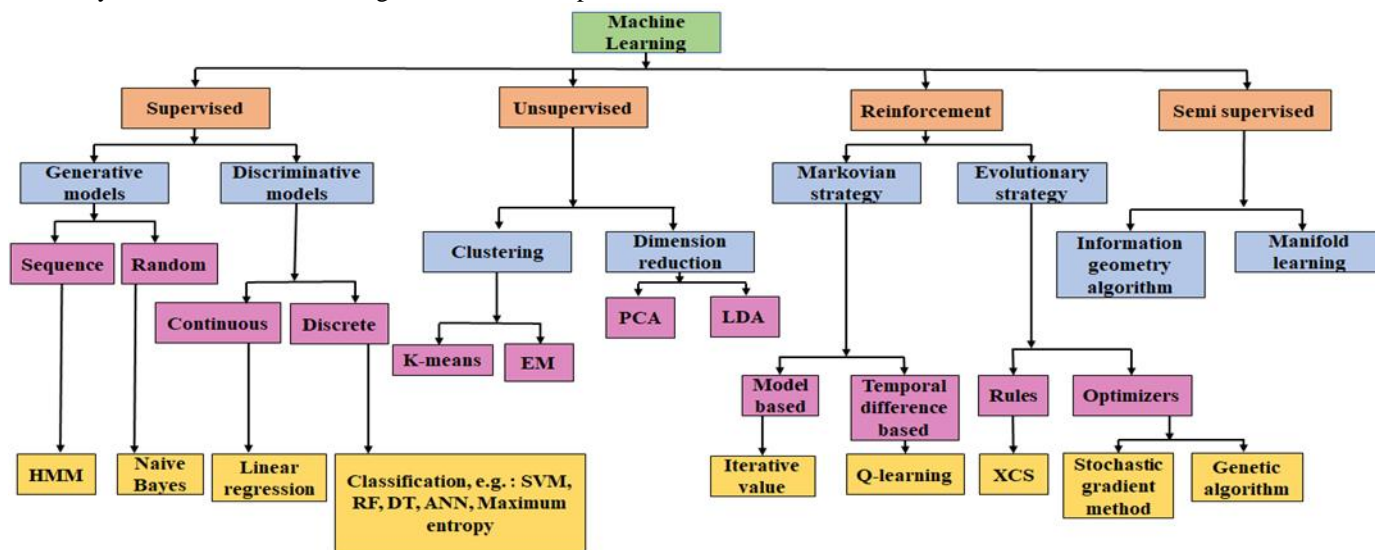

Figure 15 Taxonomy of ML Techniques

The WSN nodes are battery powered so energy is the main constraint for any sensor network. Energy management and harvesting issue can be solved using reinforcement learning technique [164-167]. Its Q-learning works well for MAC layer issues [164]. Deep learning is another artificial intelligence technique which constructs artificial neural network for taking decisions by its own. Unlike machine learning in which the dataset projected has to be structured and then it is trained to test on the new data, deep learning uses artificial neural network with many layers which is capable of taking both structured as well as unstructured datasets and takes intelligent decision on its own after the

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training of the huge complex dataset. In WSN, some challenges like data fusion, routing and query processing can be nicely answered using deep learning techniques [147], [169-171]. In [172-174] semi supervised learning is used for estimation, node tracking and localization problems in WSN. Table 5 shows the applicability of various machine learning methods to solve the particular challenge, it also gives literature associated with each ML technique.

ML Approach	WSN Issues	Literature	Environment	Complexity	Mobility	Performance Metrics
Bayesian	Localization, data aggregation, single target tracking, event detection	[125][126] [127]	Centralized	Moderate	Static/ mobile	Energy efficiency, Increased accuracy
	fault tolerant, outlier detection, Routing	[128] [129]	Distributed	Moderate	Static	Increased accuracy
Regression	Localization, data aggregation	[130][131]	Distributed	Moderate/ low	Static	Increased accuracy
	Connectivity, Anomaly detection, energy harvesting with solar source	[132][133]	Centralized	Moderate /High	Static	Increased accuracy and network lifetime, optimize network quality and reliability
SVM	Anomaly detection, outlier detection, fault detection	[134][135] [136][137] [138][139]	Centralized/ Distributed	High		Throughput, latency, energy consumption
DT	Data aggregation,	[140]	Distributed	Moderate	Static/mo bile	Improved accuracy
	Connectivity, sink hole attack, intrusion detection	[141][142]	Centralized	High/ moderate	Static	Increased accuracy, enhanced network lifetime
RF	Coverage, MAC design contention-based hybrid type	[143][144]	Distributed	Moderate/ low	Static	Increased accuracy
ANN	Routing, Localization faulty sensor node detection, data aggregation, congestion control, QoS	[145][146] [147][148] [149]	Centralized/ Distributed	High/ moderate	Static/mo bile	High accuracy, end to end delay, energy consumption, link quality estimation
K-means	Localization, hybrid anomaly detection	[150] [151]	Centralized	High/ moderate	Static	Average prediction accuracy, high quality with huge datasets, sensitivity of noise data

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	Routing, connectivity, data aggregation	[152][153] [154]	Distributed	Low/ moderate	Static	Decreased work load, efficient redundancy elimination
FCM	Localization, routing	[155][156]	Centralized	High	Static	High accuracy
	Congestion, faulty node detection	[157][158] [159]	Distributed	Low	Static	Low work load
PCA	Localization, outlier detection, hardware faults, data aggregation, single target tracking	[160][161] [162][163]	Distributed	Moderate/ low	Static	Increased accuracy, improved network lifetime
Reinforcement learning	Congestion control, Outlier detection, QoS, Cross-layer communication framework, coverage, schedule and contention-based MAC design with synchronization, DoS attack	[164][165] [166][167]	Distributed	High/ Moderate/ low	Static	Efficient task scheduling, throughput, energy efficiency, improved network lifetime
	Energy harvesting with solar source	[168]	Centralized	Moderate	Static	-
Deep learning	Intrusion detection, faulty data, Routing, energy harvesting with wind source	[169][147] [170][171]	Centralized/ Distributed	High	Static/mobile	High accuracy
Semi supervised	Localization, faulty node detection	[172][173] [174]	Distributed / centralized	Low/ moderate	Mobile	Improved accuracy, optimal time complexity

Table 5 Approaches in ML to Solve the WSN Challenges and Issues[175]

5. STATISTICAL AND DESCRIPTIVE ANALYSIS AND LIMITATIONS

Apart from the study done in the previous sections, still there are lot more papers and researches in the field of implementation of optimization methods in WSN. This section gives a graphical analysis of research carried out using optimization and hybrid optimization techniques to solve many WSN problems. Figure 16 depicts the percentage distribution of various WSN/IoT challenges which uses optimization approaches to solve them. The highest percentage is occupied by routing since there are lot of papers and articles regarding this challenge. Figure 17 shows the

percentage distribution of the research in the field of optimization when two challenges are taken together. The target tracking along with routing takes a major part of the total researches carried out in this domain.

Similarly, Figure 18 shows how much the implementation of an optimization approach weighs, when it is used in the WSN and IoT networks applications. The stochastic or random optimization is the highly and most frequently used technique as revealed in the pie chart. Figure 19 is a bar graph showing the number of papers contributing to various WSN challenges and each challenge using four major types of optimization techniques namely stochastic optimization, genetic

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algorithms, evolutionary algorithms and multi-objective optimization. Here, again the highest number is achieved by clustering and routing. Figure 20 gives the number of WSN and IoT research papers contributing to three different technologies namely machine learning, optimization techniques and hybrid techniques (combination of two or more artificial intelligence and/ or optimization techniques)

since year 2000 till 2020. Here, for every five year the distribution is shown increasing and it is highest in the years 2016 to 2020. The percentage of papers occupied by most frequently researched and discussed WSN challenges implementing the optimization and hybrid optimization techniques are given in the Figure 21. The highest percentage of papers are from routing domain.
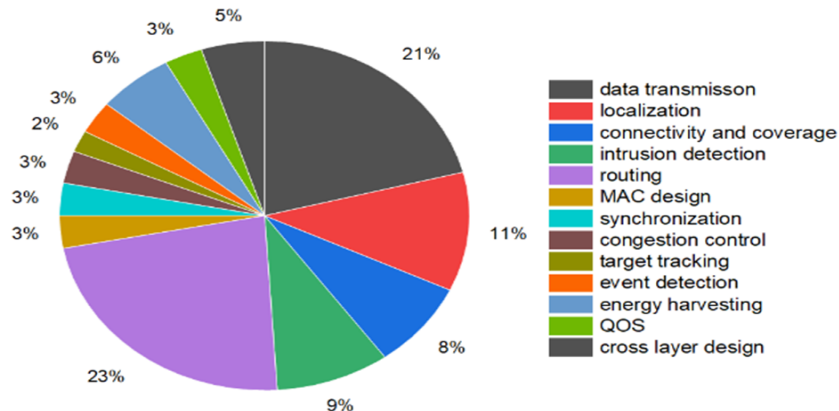

Figure 16 The Percentage Distribution for Research Papers Using Various WSN/IoT Challenges
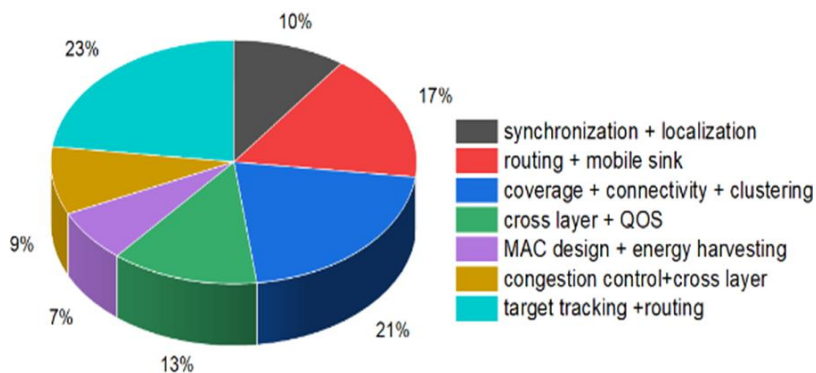

Figure 17 Pie Chart Representation for the Percentage of Papers with Two Challenges Taken at a Time
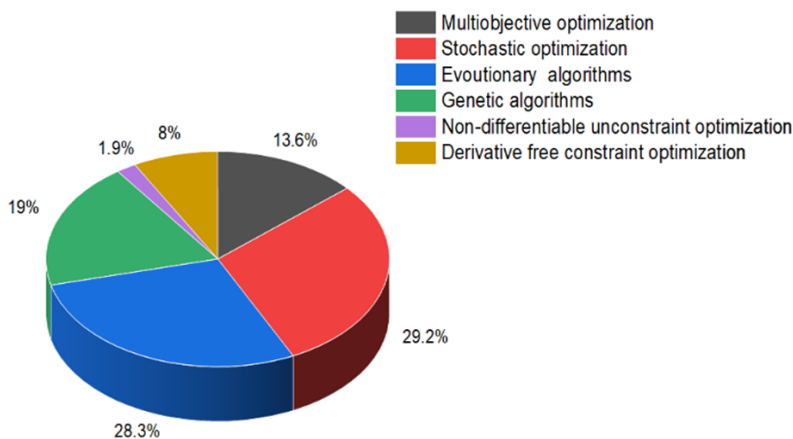

Figure 18 Weightage of Various Optimization Techniques Used in the Field of WSN and IoT Applications
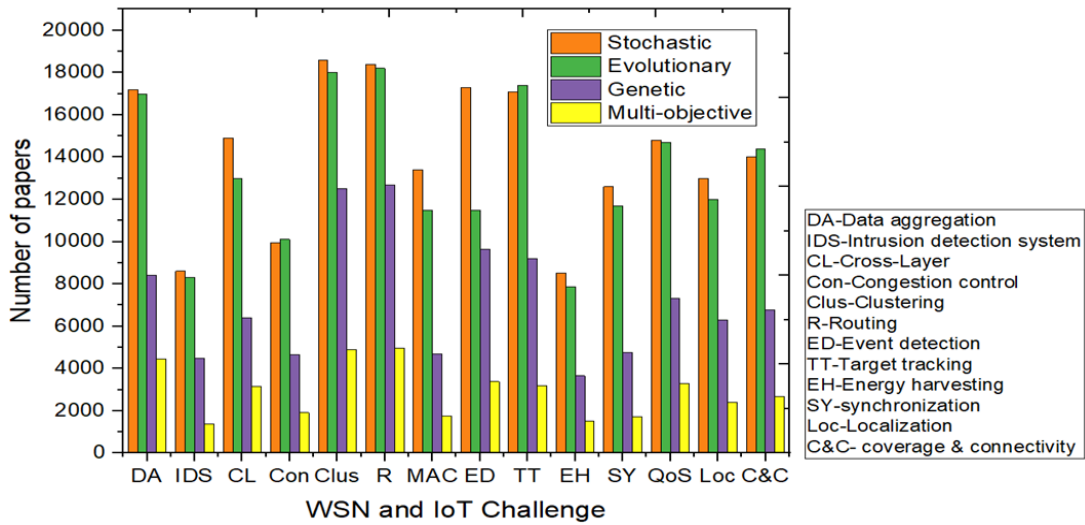
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Figure 19 Number of Papers Contributing to Each Optimization Method for Various Challenges in WSN and IoT Networks
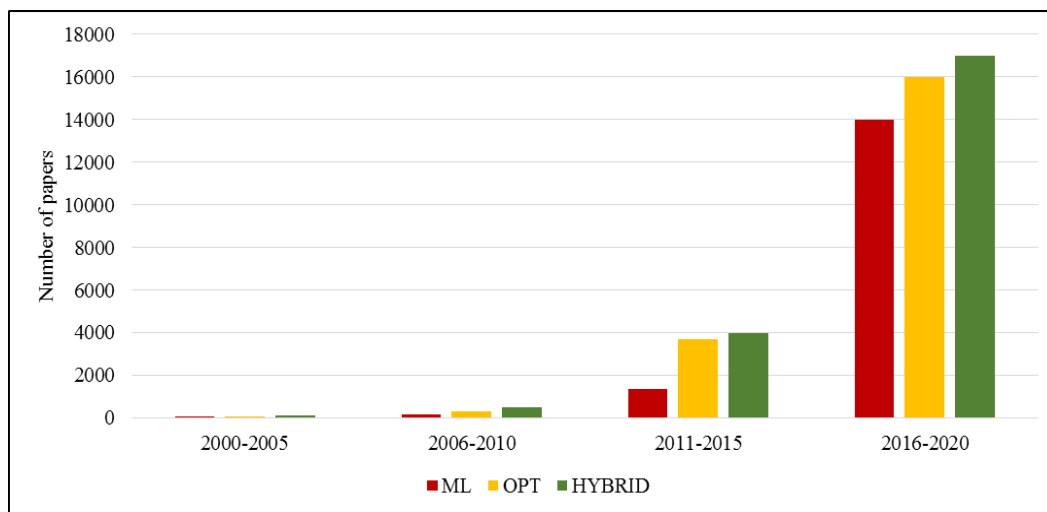

Figure 20 Number of Papers Using ML, Optimization and Hybrid Techniques with Respect to the Range of Years
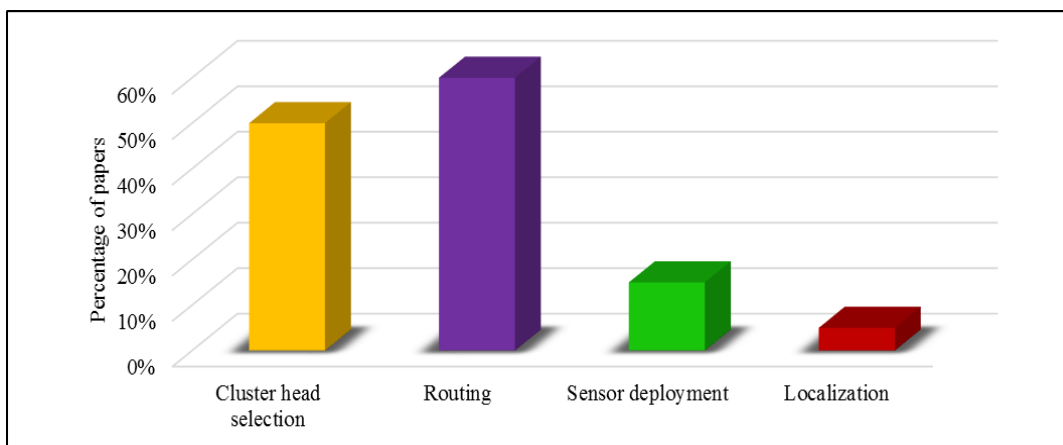

Figure 21 The Percentage of Papers Covering Four Most Frequently Discussed Challenges

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In the present scenario, the researchers have used many optimizations and smart techniques to make the system efficient and robust still there remain some limitations. Table 6 shows the range of accuracy for various techniques. For example, if any problem statement is solved using only the machine learning technique, then it will give the accuracy ranging from 70 to 80%. When optimization is used alone, the accuracy may reach up to 94%. But it is observed that when both optimization and artificial intelligence are used together, they may enhance the accuracy to 97%, and can improve other QoS parameters also. Deep learning technology is also an advanced aspect of artificial intelligence. The model itself learns and takes decisions intelligently on its own in deep learning so, it is considered to be the most intelligent technique. The table 6 shows the percentage of accuracy achieved (98% and above) for the challenges which are addressed by using both deep learning and optimization. But there exists some limitation for such type of researches. Some literature discusses the implementation of unsupervised Deep learning in clustering or prediction of data in the WSN / IoT networks [176, 147] but since the system requirement and cost is too high and it is only effective on a very large number of datasets (especially images), so the notion of the usage of Deep learning is not suitable in the context of WSN. Also, in IoT, few applications may require techniques based on Deep learning based on the nature of datasets. Deep learning makes the system and the training model too complex to handle, so is least referred in the field of wireless communications. The Table 7 below shows the suitability of the optimization and hybrid techniques for a particular challenge to obtain the most efficient result.

Algorithms	Accuracy
Machine learning	70-80%
Optimization	90-94%
Hybrid approaches	94-97%
Deep learning +optimization	98% and above

Table 6 Estimated Accuracy of Various Techniques Used in WSN Assisted IoT Networks

WSN and IoT Challenge	Hybrid Optimization Technique	Literature	Remarks
Network Design, coverage and connectivity	MCDA, GSA-SSD	[177][47]	Optimization in the network design for each OSI layer and topology management
Localization	MP-PSO, Multi-objective optimization functions+DV-maxHop	[178][36]	Enhancing localization accuracy by minimizing the localization errors and by finding optimal path, mobility prediction reduces the amount of energy utilized.
Clustering and Routing	Discrete PSO and Genetic algorithm (DPSO+GA), Fork and join adaptive PSO (FJAPSO)	[179][180]	Optimized selection of cluster head and route/path optimization
Intrusion detection, fault tolerance	SVM-SMO+OP-ELM, BGWO+SVM, NSGA-II+SPEA2	[51] [55] [54]	Enhancing the accuracy of the IoT/WSN model by improving convergence rate, decreasing false alarm rate and enhancing detection rate.
MAC design and	Cross-layer distributed scheduling algorithm	[181][65]	Sleep scheduling optimization, energy conservation of WSN and IoT networks, delay tolerant networks

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scheduling	(CDSA), 3D-MC-modified CSMA/CA		and to enhance throughput
Data transmission	Game theory based mobile RPL (GTM-RPL), ACO, MOPSO	[182][183] [184]	Improving various QoS parameters and performance metrics by introducing optimization in DTS.
QoS	SFLA-GA, Neural networks+fuzzy rule	[115][185]	Focuses on improving the security and communication inside the network to optimize the QoS parameters.
Security	Evolutionary algorithms, Fuzzy logic, Stochastic cost minimization mechanism (SCMM)	[186] [187]	Focuses on trust management to achieve secure data transmission
Congestion control	PSOGSA, Adaptive cuckoo search based optimal rate adjustment (ACSRO)	[77][82]	To predict congestion location and search for optimal alternate paths. For distributer and centralized networks.
Target tracking	Optimization+MILP	[188]	Target tracking by clustering approach for heterogeneous and distributed networks.
Event detection	FS+Priority based optimization	[189]	In smart cities, detecting the occurrence of events in distributed networks.
Synchronization	AD-ADMM, OSSA	[75][70]	Multiantenna communication with distributed approach.
Energy harvesting	Energy optimization using NN model, JOA	[190][191]	To predict the energy required for scavenging in distributed networks.
Cross-layer issue	Optimization between physical and network layers using CMR+ Shortest Path Routing (SPR)	[192]	BBNs, BAN in distributed network

Table 7 Summary of Hybrid Optimization Techniques Which Obtain Best Results in Addressing WSN Based IoT System Challenges

6. RESEARCH GAPS, OPEN CHALLENGES AND FUTURE TRENDS

6.1. Research Gaps

By hybrid algorithms we mean the combination of machine learning and optimization or two or more optimization approaches applied to solve some issues like consumption of energy, network latency, average jitter, accuracy, and many more. While some papers use the benefits of one challenge efficiently to address another issue like in [193] the mobile sink-aided approach is being used to solve problems in data collection in EHWSNs. The research in the application of various optimization schemes to accomplish the task and to answer the challenges in WSN and IoT networks is also performed [14, 18] but to a limited extent. In other words, the use of optimization algorithms for a particular challenge is only investigated so far. This paper gives a detailed description of various issues from the mentioned challenges faced while framing WSN or IoT-based networks for various enactments like surveillance, event monitoring, underwater monitoring, etc.

6.2. Open challenges

Some open challenges are discussed below:

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6.2.1. Localization

The localization challenge is very well answered by the use of optimization approaches like PSO, firefly optimization, etc. Still, there is a need to answer some of the issues arising from this challenge for instance the attacks which occur in a sensor network need to be localized in advance by the beacon nodes or by some efficient approach. Also, it is required to reduce the time complexity of the algorithm because as we begin to use a hybrid algorithm to solve any issue, its time complexity enhances.

6.2.2. Coverage

In the random deployment scenario, the challenge of assigning minimum sensors to cover the whole area of interest is confronting in the way of a successful deployment strategy. The coverage hole caused due to random localization is very hard to predict, so this problem needs to be explored. The 3-D coverage scenario with minimum complexity of computation is also a domain that needs further research.

6.2.3. Anomaly Detection

In the wireless network detecting anomalies is a major challenge that is addressed by many researchers. Some algorithm guarantees the accuracy with less FPR but the complexity goes on increasing. The intrusion creates delay and drops the average throughput of a network. Furthermore, this challenge needs to be answered in the case of WSN assisted IoT networks with high efficiency. Anomaly at the data level is much more critical than at the node level. Once the anomaly is detected, the system must be capable of correcting that anomaly/fault to improve the network's fidelity.

6.2.4. Routing and Data Aggregation

Both routing and aggregation are challenging tasks when it comes to multiple sources and sink nodes. In this case, the topology of the network is very dynamic and may change the node's position. So, there is a need to develop an efficient and optimal route to overcome this problem. Also, the optimal routes should be able to circumvent the traffic coming in its way. In the present scenario, the network with mobile nodes faces the problem of scheduling when abrupt data at the sensor nodes occur. This problem needs special attention.

6.2.5. QoS Optimization

It is another important aspect of WSN assisted IoT networks. For distinct applications, separate QOS standards are needed which is quite challenging. The cross-layer optimization protocols may be the best means to make the QOS parameters efficient and reliable. For instance, to maintain the synchronization between MAC and the physical layer, there is a need to adjust suitable duty cycles. The development of self-charging-discharging periods for dynamic network environments may help to achieve good energy management.

6.3. Future Trends

The practice of using Edge computing and Fog computing along with optimization approach to decrease the latency and to ensure security is the possible future trend. Also, the research must include more hybrid algorithms to address a challenge, since these algorithms are the package of solving problems at various aspects like ML approach in WSN/IoT solves prediction based, error-based problems and optimization solve local minima/maxima-based problems. Any wireless network faces almost similar challenges as discussed in this article. So, the research can be expanded for the extended versions of IoT networks and fog computing in IoT with the same issues and challenges.

7. CONCLUSION

WSNs are entirely distinct from the traditional wireless networks in many aspects, so the need for special tools and protocols arises to overcome the challenges and limitations of the network. As a result, WSN or IoT networks are designed with innovative frameworks for real-time applications and to handle various network constraints like energy, delay, path selection, etc., optimization provides an assembly of approaches to maximize the working potential of wireless sensor networks and IoT networks. Table 7 summarizes the challenges addressed by adopting the suitable optimization methods which give best results. The discussions and analysis done so far has given a clear idea of various network challenges and their solutions by adopting hybrid optimization techniques along with machine learning approaches. The survey covers the research done since year 2005 to 2020. Various challenges like data aggregation, network congestion, QoS parameters, synchronization, etc., along with their solutions have been discussed briefly for the convenience of readers. The key point in this research is to make the researchers aware of the trends and usage of various algorithms in their methodology to achieve a good performance rate. However, many issues are still open and need research efforts for developing resource-constraint and lightweight models to enhance the intelligence and reliability in WSN and IoT applications.

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