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# Metaheuristic Routing: A Taxonomy and Energy-Efficient Framework for Internet of Things

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**ABSTRACT** The complex and heterogeneous ecosystem of the Internet of Things (IoT) makes it difficult to achieve energy-efficient routing because of the power, memory, and processing constraints of smart motes. Recently, metaheuristic-based routing is preferred by researchers for energy-efficient transmission in IoT. Existing literature divulge their studies to apply metaheuristic directly in IoT by ignoring the principles that account for the overall performance and the global optimum solution. Also, there is no comprehensive study that addresses the issues, principles, and significance of metaheuristic routing in terms of hybridization, objectivity, and applicability in IoT. Being enthused by the aforementioned issues, a detailed taxonomy of metaheuristic-based routing in IoT is presented in this study. A detailed taxonomy is abstracted into an energy-efficient routing framework to provide solutions to the main adversaries encountered during evaluation. The theoretical framework dwells upon two predictive models: i) Metaheuristic-based selection of potential node for energy efficiency in an IoT. ii) Introduction of metaheuristic principles to avoid convergence issues during evaluation. The comprehensive study confers the routing vulnerabilities, energy saving mechanisms, and the pros and cons of metaheuristic in context to IoT. The key research challenges in metaheuristic based routing and future directions to curb with same are thoroughly provided. Further, a smart manufacturing-based case study is demonstrated to generate the fitness criteria for process scheduling problems to gain energy efficiency. The proposed framework provides a benchmarking solution for the ongoing metaheuristic adversaries that have been undercoated in literature to prove the superiority of an algorithm.

**INDEX TERMS** Energy-efficiency, heterogeneity, Internet of Things, interoperability, metaheuristic, route optimisation, routing framework.

## I. INTRODUCTION

In the current realm of technology, IoT emerges at a pace with a pervasive and ubiquitous network of smart devices with potential capabilities. The ubiquitous interconnection among smart objects via wireless communication medium brings energy consumption and heterogeneity challenges [1] in IoT. The complex and constrained ecosystem of IoT makes it difficult to accomplish efficient data transmission [2] while routing. The existing data routing techniques are not energy-efficient to meet the scalable and robust requirement of IoT because of the extra overhead in managing the routing tables. Besides, standard routing techniques like Ad-hoc On-demand Distance Vector (AODV), Link State Routing (LSR), and Open Shortest Path First (OSPF) are based on optimizing a few objectives without consideration for other parameters like traffic flow, residual energy, load, and temperature of a node. Routing protocols require high parameter configuration. The appropriate setting of all network control parameters is complex that is nondeterministic polynomial (NP) -complete in nature. Therefore, the correct setting of quality of service parameters necessitates the heuristic version for the approximate solution to the problem. On the other hand, the miniaturization of smart and portable devices limited the amount of storage power [3] in IoT nodes. IoT nodes store a finite amount of power, and replacing power sources every time in an unattended environment is not a convenient and affordable solution in a scalable and dynamic network. Moreover, the deployment of batteries in an unattended environment becomes a tedious,

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expensive, and time-consuming task. Though, there exist several rechargeable mechanisms that include renewable sources of energy like thermal, solar, and mechanical, and radio energy. Alongside, comes with several challenges in IoT that have been sketched out subsequently:

INTERMITTENT SOURCES: Energy harnessed from solar sources is at its peak when the sun lies 90 degrees to the solar array. The deviation in the angle of incidence also drops the storage capacity of the energy collector. Similarly, mechanical sources offer energy storage as a part of the cycle that includes vibrations, body motion, moving vehicles passing over the energy harvesting device [3]. The mechanical energy source depends upon a high motion footprint.

VOLTAGE RAMP: When the voltage drops below the threshold set, then the batteries will be recharged called low voltage ramp. A voltage ramp is fast when the coin cell is put into the device. Therefore, IoT devices are not always accommodated with voltage fluctuations [4].

RETROFITTING CAPABILITY: Retrofitting is the adaptability towards the incorporation of a new power source in a device that has been dispensed during the manufacturing process. Therefore, plug-and-play-enabled devices must be designed to update and install the third-party drivers to resolve the issue of integration [5].

SINGLE POWER SOURCE: IoT devices are dependent upon a single source of power for the recharging mechanism. This is inefficient due to the intermittency in energy sources. Therefore, energy harvester must be linked with multiple sources of energy to ensure the continuous supply of power [6].

ENERGY CONVERSION EFFICIENCY: The conversion of ambient energy into electrical energy is called energy harvesting. Energy management systems have a low conversion efficiency to produce electrical energy. Highly efficient systems must be developed for harvesting, storage, and maximum usage of energy [7].

Over the last few decades, metaheuristic techniques have attracted a lot of the research community to solve NP-hard problems efficiently. Metaheuristic techniques could serve as an alternative solution due to their stochastic nature, adaptability, flexibility, simplicity, and local minima avoidance for energy-efficient routing in heterogeneous IoT. Metaheuristic techniques are being inspired by the concepts of evolutionary, physical phenomena, and animal behavior [8]. The historical development of some of the standard metaheuristic algorithms used in the state-of-the-art is depicted in Figure 1.

A metaheuristic is the blend of two words: Meta and Heuristic. Earlier, heuristic was used to depict the stochastic nature of algorithms. In advanced algorithms, heuristic means to discover something until the final solution is found by the hit and trial method [9]. Meta means to reach a better higher state. And, metaheuristic is the better version of heuristic to find all the better solutions for a problem beyond finding the local optimum solutions. The performance of metaheuristic is better than general heuristic. Besides, metaheuristic techniques use a kind of trade-off mechanism with randomization and local search. Metaheuristic techniques are trusted to obtain the global optimum solution to the problem in a minimum time [10]. The study assesses the performance of metaheuristic techniques based on three vital factors:

OBJECTIVITY: The configuration of network control parameters in routing protocols is a complex task because of the mismanaged parameter settings. Metaheuristic techniques optimize the network parameters heuristically [9] when nodes are randomly deployed in an IoT network.

HYBRIDIZATION: Routing protocols along with the integration of metaheuristic techniques [11] augmented the potential to perform superior in energy-constrained IoT networks.

APPLICABILITY: Standard routing algorithms are best suited for WSN where the network mobility and the area are limited. In contrast, the stochastic behavior of metaheuristic makes it applicable to be employed in diverse domains of IoT.

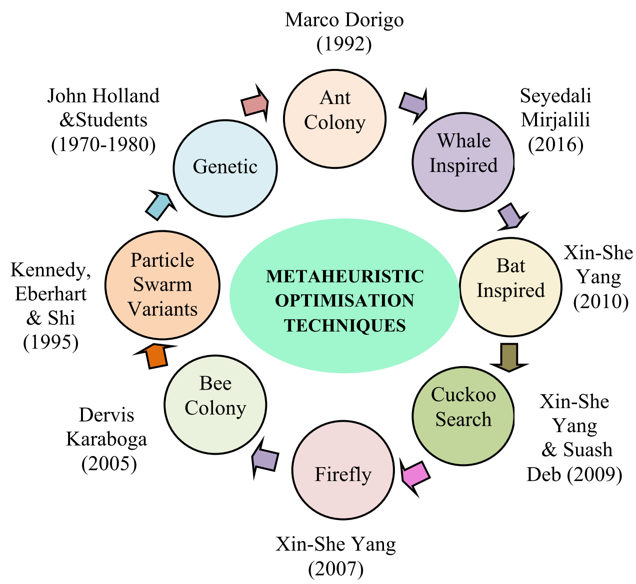


**FIGURE 1.** Historical release of standard metaheuristic techniques [12]–[14].

Metaheuristic techniques are based on the exploitation and exploration of a problem [15]. Exploration bestows multiple solutions to discover the search space globally. On the other side, exploitation searches the local region of the search space if the possibility of a solution to be found in the local region. To achieve the convergence of the problem to a near suboptimal solution, a proper balance is required between exploitation and exploration [16]. A proper balance between the two represents the achievability of the global optimal solution. Therefore, advanced metaheuristic routing techniques must be utilized to improve the overall quality metrics for energy efficiency in heterogeneous IoT networks. Metaheuristic techniques are of utmost importance in the context of IoT because of the fast convergence rate, multiobjective approach, robustness, and adaptability towards topological network changes [17].

A substantial amount of work has been carried out in the field of IoT to deploy viable metaheuristic techniques along with other intelligent techniques. Metaheuristic techniques improve the machine learning techniques like clustering. A few years back, the problem of identifying community patterns in a social network becomes challenging which is an NP-compete problem [12]. The problem was mitigated by using a Genetic algorithm(GA) to categorize community patterns and a set of nodes in a sparse heterogeneous IoT network [12]. Despite Genetic algorithms, other metaheuristic-based techniques like Particle swarm optimization (PSO) and Ant colony optimization (ACO) have contributed a lot in solving clustering problems in Vehicular Adhoc Networks (VANET) [18]. Efficient clustering enhances the data transmission while routing as ACO generates near-optimal solutions in the case of vehicle mobility [13]. The ACO and Simulated Annealing(SA) approach reduce the cluster count and the routing cost in VANET [15]. Similarly, modified ACO is used to address the scheduling problem of the shop floor efficiently on the Internet of Manufacturing Things [14]. The relevance of metaheuristic-based clustering is also seen in bioinformatics. The malicious disease is distinguished from another by gene clustering [19]. Gene clustering incorporates fuzzy c-means clustering and evolutionary based techniques to detect the severity of disease. Moreover, Firefly routing approach (FRA) and intelligent Water Drop routing approach are also used to optimize Quality of Service metrics while routing in IoT-Mobile Adhoc Network (IoT-MANET).

An efficient data clustering framework [20] for data analysis on metaheuristic algorithms is presented in an IoT system. The parallel metaheuristic data clustering framework is implemented on metaheuristic algorithm i.e genetic K-means, Particle Swarm Optimisation, and K-means on a standalone machine and Spark using different languages. The study concludes that the algorithms executed on Spark are much faster than a standalone machine. However, an important pillar of metaheuristics is to determine the performance by implementing the different algorithms on the same machine for the same computational time that has been violated in the framework.

A Multi-start and multi-search (MSMS-S) [21] framework was intended to improve the performance of a single solution-based metaheuristic algorithm for clustering. A multi-search and restart mechanism is used to expand the exploration and exploitation in a search space. However, the MSMS-S framework is meant for lower-level metaheuristic algorithms. Also, the multi-search mechanism is the fundamental property of the metaheuristics such as Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO), Artificial Bee Colony (ABC), and Whale Optimisation Algorithm (WOA) for exhaustive exploitation and exploration of the solution space which does not form the sound criteria for evaluating algorithms.

The Treasure Hunt (TH) framework [22] aims to find the hidden treasure using optimization techniques such as Particle Swarm Optimisation (PSO) and Differential Evolution (DE) in an unknown and complex landscape. The TH is a distributed and scalable framework with TH instances. The TH framework on Cooperatively Coevolving Particle Swarm Optimization 2 (CCPSO2) algorithm depicts the best results on multimodal Rastrigen and multimodal Ackleys functions. On the other hand, DE is effective on Rosenbrock's unimodal function. PSO results are slightly deviated using Ackley's function as compared to CCPSO2.

However, the TH framework does not portray any application in the process of energy-efficient routing and improving the Quality of Service metrics.

In [23], a new software solution for parallelizing Evolutionary Algorithms (EA) by combining the global model with the Coarse-Grained model is presented. The focal point of the hybrid model is the scalability, parallelism, and the determination of communication overhead by varying the number of slaves for Ring, Ladder, Bi-Ring, and complete topologies. An improvement of 9% on average is seen in the execution time in the case of Ring topology. However, hybridization of techniques, parameter configuration, and objectivity has been lacking in the presented model and is considered as a future research study that forms the strong basis for metaheuristics.

Being inspired by the intricacies encountered in the existing frameworks, our research attempts to propose a generic framework for energy-efficient routing in heterogeneous IoT. The root adversaries encountered in the metaheuristic have always been insulated by researchers to prove the superiority or effectiveness of the presented metaheuristic approach. Our research incorporates the concepts of hybridization, elitism, reinforcement, decay, and objectivity so-called metaheuristic principles. The proposed framework in this study counters the challenges for achieving energy-efficient routing in IoT. Moreover, an in-depth analysis of routing vulnerabilities in IoT and future directions, to curb the same, are provided. The proposed framework helps to mitigate the root challenges while solving complex optimization problems as well as the routing problem for energy efficiency.

### A. ENERGY PROSPECTS

The worldwide storage of the energy market expands exponentially as surveyed by IHS Markit [24]. The yearly installation of 6 gigawatts(GW) of energy has been measured in 2017 and would exponentially increase to 40GW by the year 2022. As per the report offered by BP Statistics, the primary energy consumption had an average of 1.7% per year over the last decade. The primary energy-consumption resources include oil [25], Natural gas [4], hydro, nuclear, and renewable sources [5], [26]. The total energy consumption has been spiked to 13511 Million Tonnes of Oil equivalent (Mtoe) in 2017 as compared to 11558 MToe [24] in 2007 as shown in Figure 2. In another statistic [24] published by International Energy Agency((IEA), the total energy consumption has been increased by 2.1 % in 2017 in comparison with 0.9% in 2016. The high power requirements cannot be met when there is an imbalance between

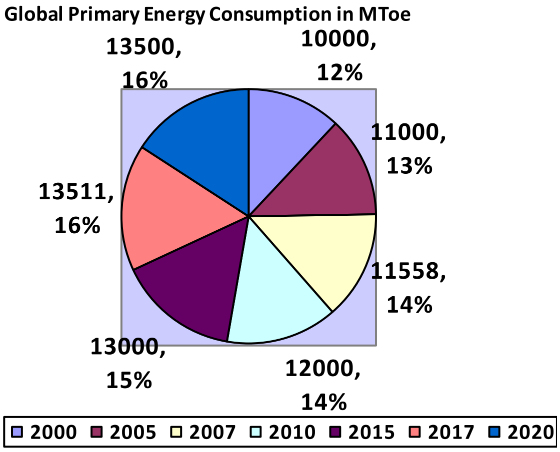


**FIGURE 2.** Global Primary Energy Consumption in Million Tones Oil Equivalent (MToe) [24].

the demand and consumption of energy on a global level.

### B. MOTIVATION

The main motivation to conduct this study is as follows:

- Though metaheuristic techniques are widely employed for the routing process in IoT networks, the generic energy-efficient routing framework in heterogeneous IoT is deficient in the state-of-the-art literature. The prevalent models are specific to the particular metaheuristic technique [22].
- The prominent metaheuristic principles have always been the ignorant part of the actualization in the metaheuristic-based routing. Thus, there is a need for building the routing framework that takes into account the metaheuristic principles for early convergence to the solution [21].
- The challenges encountered in metaheuristic routing degrade the performance and long-term stability of algorithms in scalable and heterogeneous IoT systems [23]. Therefore, a framework to counter the adversaries during the metaheuristic routing would be a great assistance for energy-efficient IoT systems.

### C. CONTRIBUTION

The primary contributions are as follows and depicted in Figure 3.

- We have exhaustively discussed the importance and challenges encountered during the metaheuristic routing and provided countermeasures to cope up with adversaries.
- We comprehend the energy-saving mechanisms and routing vulnerabilities in context to IoT.
- We have proposed a broad taxonomy based on the recent contribution of hybridized metaheuristic routing techniques that have been employed in IoT domains.
- The proposed taxonomy is abstracted into an energy-efficient generic framework with an emphasis on employing metaheuristic principles for the evaluation of QoS metrics during routing based on the fitness function.
- A smart manufacturing based case study is demonstrated for solving the problem of process scheduling problem by generating the fitness criteria using metaheuristic.

### D. RESEARCH ARTICLE ORGANIZATION

The organization of the study is as follows. Section 2 presents the related work and the referred data sources. Section 3 discusses the significance and challenges of metaheuristic routing in IoT. Further the energy conservation techniques in IoT are presented in section 3. Section 4 imparts knowledge about the metaheuristic-based optimization techniques in IoT. Section 5 discusses the metaheuristic routing challenges and future directions in IoT. Section 6 presents the proposed energy-efficient metaheuristic routing framework in IoT. Section 7 illustrates the Smart Manufacturing-based case study. Section 8 and 9 evaluate the performance of the modified fitness function on PSO-EA in the proposed framework. Section 10 concludes the study.

## II. RELATED WORK

In light of the optimization of energy consumption and other related quality of service metrics for increasing the network lifetime in heterogeneous networks in IoT, several researchers

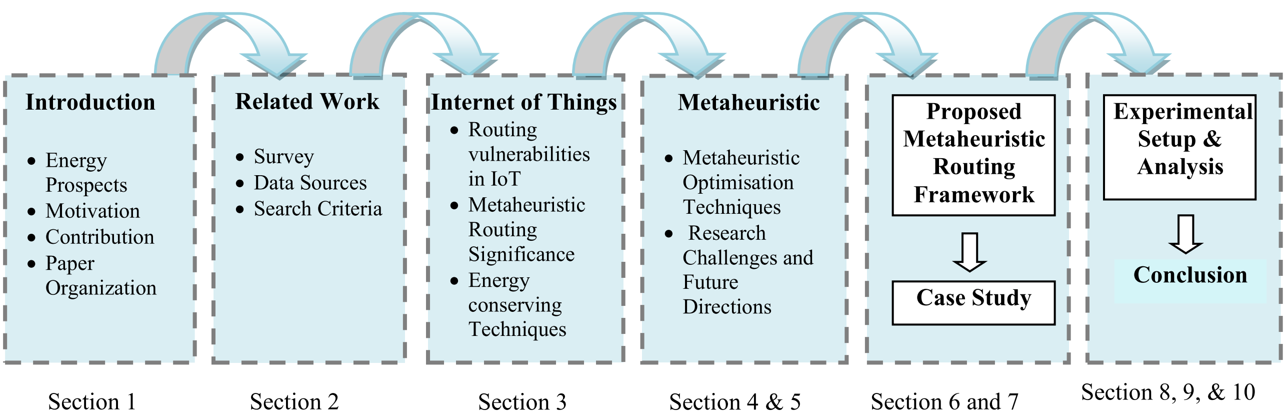


**FIGURE 3.** Research article contribution and organization.

**TABLE 1.** Comparative analysis of the proposed framework with the state-of-the-art frameworks in IoT.

| Author | Year | Framework | Heterogeneity | Approach | Analysis | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|---|---|
| Ahmed E. Khaled *et al.* [28] | 2017 | Atlas framework | Protocol level | IoT Device description language (IoT-DDL) | Supports seamless connectivity between CoAP, REST over HTTP, MOTT w.r.t Eclipse Ponte Framework | ✓ | × | × | × | ✓ |
| Abdulatif Alabdulaf *et al.* [29] | 2018 | Secure Healthcare Surveillance | -Nil- | Fuzzy logic, Fully Homomorphic Encryption (FHE) | The accuracy of datasets varies between 0.29% to 8.90% | × | × | ✓ | ✓ | ✓ |
| Chun-Wei Tsai *et al.* 20] | 2018 | Parallel Metaheuristic Data clustering framework | -Nil- | Clustering and metaheuristic techniques on Hadoop and Spark | Data Clustering algorithms running on Spark are much faster than running on a standalone machine. | ✓ | ✓ | ✓ | × | ✓ |
| Kuljeet Kaur *et al.* [30] | 2019 | Software-defined data centre framework | Infrastructural or System | FFD (First Fit decreasing Algorithm ) | energy saving by 27.9% | ✓ | × | × | ✓ | ✓ |
| Shilin li *et al.* [31] | 2019 | Computation offloading and transmission power allocation framework | Network-level energy consumption | Mixed Integer and linear programming | Solve computation offloading problem | ✓ | × | × | ✓ | ✓ |
| Mustafa Ergen *et al.* [32] | 2020 | Distributed edge-based OMNIBUS solution model | Technological level | OMNIBUS solution | Offers higher storage & processing capacity | ✓ | × | × | ✓ | ✓ |
| Mateo Sanabria-Ardila *et al.* [33] | 2020 | Distributed Reactive Rewriting framework (DRRF) | Semantic, Data level | Reactive programming | Explores semantics of real-time languages | × | × | × | ✓ | ✓ |
| Marc Jayson Baucas et al. [34] | 2020 | IoT based scalable and sensing framework | Data Level | Classification Python library (PySound) | Average power consumption is 1786.86 mW wrt to other techniques | ✓ | × | × | ✓ | ✓ |
| The proposed Framework | 2021 | Metaheuristic based Routing framework in IoT | Data Level, Protocol Level, Device Level. | Metaheuristic Routing techniques in IoT | Addresses the convergence issues and optimal energy efficient cluster head selection in IoT | ✓ | ✓ | ✓ | ✓ | ✓ |

1, Energy-Efficiency; 2: Metaheuristic; 3: Clustering; 4: Challenges; 5: Merits. Notations: -Nil-, Not Defined; ✓, considered; ×, not considered.

have worked on energy-efficient techniques as discussed subsequently. For instance, Chicco and Mazza [27] studied thoroughly the utilization of metaheuristic techniques in the energy sector.

The author envisaged the issues in the applications of energy using metaheuristic techniques to accomplish the global optimal solution. The study included several characteristics to define metaheuristic approaches and covered single objective and multiobjective constraints related to the metaheuristic techniques comprehensively. Olatinwo and Joubert [35] discussed the novel approaches for optimal and energy-efficient resource utilization in water quality monitoring systems.

The Energy-Efficient Particle Swarm Optimisation based model (EEPSOM) in comparison with Ant Colony Optimisation (ACO) and Genetic Algorithm (GA) gives a better convergence rate of 0.33% and 0.37 % in terms of energy efficiency. The sensing IoT nodes are separated into different clusters. Cluster head transfers the sensed data from IoT nodes to the cloud via a fog network. The artificial Neural Network model is applied to cloud data for the classification of data to estimate the severity of a disease. The presented diagnostic model gives the maximum sensitivity of 96.094%, an accuracy of 94.066%, and specificity of 93.492% thereby representing a proficient diagnostic model in healthcare.

In another research, Maddikunta *et al.* in [36] present a hybrid Whale Optimization-Moth Flame metaheuristic Algorithm to select the cluster head in a cluster. The selection of cluster head depends upon the fitness function of residual energy, load, alive nodes, and temperature.

Performance evaluation of hybrid algorithm gives better results in terms of the optimal fitness function, delay, energy consumption, and increases the network lifetime over the existing techniques.

The amount of harvested energy in IoT varies depending upon the non-uniformity of environmental conditions. So, there arises a challenge of accurately predicting the harvested energy. An energy prediction is done by using the concept of the Kalman filter [37]. Also, the energy prediction is done on the access point to regulate the number of bits transmitted and the lost data. In downlink transmission, an orthogonal frequency division multiple access systems is used to mitigate interference. The author considers wind and solar harvesting to power nodes in simulation experiments. The devised algorithm achieves the rate of wasted renewable energy using the prediction algorithm is 25.33%. And, the rate of wasted renewable energy without using a prediction algorithm is 36.95%. Besides, the prediction algorithm enhances the rate of drop bits and the task completion time.

The energy-efficient region–source routing protocol (ER-SR) [38] for energy–efficiency is based on clustering. The region source protocol for energy–efficiency takes into account the residual energy of the nodes that are selected dynamically. The ER-SR technique includes three steps: Region division, information collected by the source node, and data transmission phase. The ER-SR protocol used Ant Colony Optimization (ACO) algorithm for effective distance calculation among the nodes [38].

Though a significant amount of work is done in the field of metaheuristic-based optimization of quality metrics, existing studies still lack a metaheuristic-based routing framework for energy efficiency in an IoT network. The study emphasizes on building a metaheuristic-based routing framework by utilizing the generalized IoT architecture. The proposed framework provides the solution to the proximity between IoT and metaheuristic applicability in diverse application domains for energy efficiency.

Comparative analysis in Table 1 showcases that only a few frameworks of IoT considered the metaheuristic optimization techniques to achieve robustness and energy efficiency in a heterogeneous IoT network. Moreover, heterogeneity and energy-efficiency issue is considered in isolation in the state-of-the-art IoT frameworks. The existing frameworks can be extended by employing metaheuristic techniques to cope up well with the adaptive nature of metaheuristic techniques to solve the computational problems that result in low complexity. To lessen the heterogeneity in IoT networks, standards and frameworks would be consolidated on a global level [39] to achieve interoperability in smart devices.

### A. DATA SOURCES

The study was conducted to broadly analyze the important pillar of IoT i.e energy efficiency in heterogeneous IoT systems. The quality of information is assured before accessing the data from databases. The research articles with good impact factors and citations are targeted to understand the significance of metaheuristic techniques for energy optimization in IoT. To sketch out the recent contribution of metaheuristic techniques in the state-of-art IoT, the high-quality journal and conference articles from IEEEXplore, ACM, Wiley, Springer, and Science Direct databases were referred. Besides, various technical and government reports, tutorial papers, online books, and white papers are also taken into account for the conduct of the same study.

### B. SEARCH CRITERIA

Most appropriate keywords like "Energy-Efficient routing in IoT" ("Traditional routing issues", AND "Mitigation Techniques"), "Energy–Efficient Metaheuristic Techniques in Heterogeneous IoT", "Heterogeneity in IoT", "Energy Optimization in IoT", AND "Quality of Services Metrics optimization in IoT" are searched in context with the title of the study as demonstrated in Figure 4. A manual search is performed if the search string is not matched with the title of the research article.

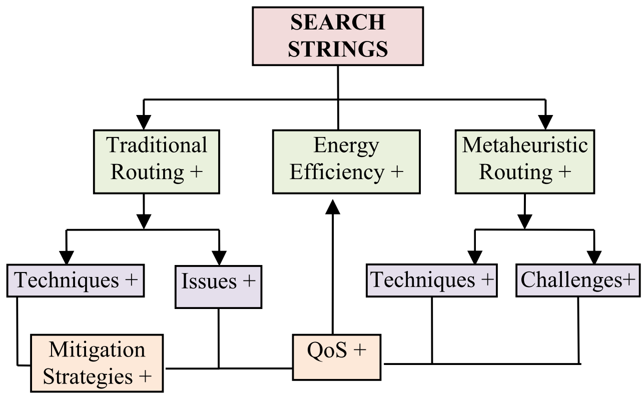


**FIGURE 4.** Search String Criteria.

## III. IoT: ENERGY EFFICIENCY PERSPECTIVE

Industry 4.0 states IoT as an "omnipotent intelligent" collection of smart objects. Smart objects are the essential entities on which the whole IoT network relies. The important components of the smart objects include a microprocessor, sensing element, power element, and radio unit [40] for communication. The radio unit is the most energy-consuming element of sensors. The radio unit includes both transmitter and receiver unit that contributes to the maximum energy consumption. Smart objects make use of radio signals to transmit the data to the base station. In an energy-constrained IoT network, clustering with metaheuristic routing would be a more scalable and energy-efficient solution as compared to other conventional routing techniques. In the sensor-actuator network of IoT, data is transmitted in two ways: transmit data directly to the base station and transmit data to the nearest node to send to the base station [41]. IoT networks are constrained in several resources like energy, memory, processing power, range, and bandwidth [42] that making routing complex. The resource-limited nature of IoT brings

**TABLE 2.** Routing vulnerabilities in context to IoT.

| Routing Vulnerabilities | Discussion | Quality Metrics Affected |
|---|---|---|
| Network Coverage[43] | The range of IoT sensors varies from low to high. In the low range, sensors are not able to transmit to longer distances. | Throughput, Latency, Jitter, Power Consumption, Drift. |
| Collisions [44] | Collisions occur due to the wireless mode of communication, sharing of data in the same time slot. | Throughput, latency, power consumption, Reliability, Jitter. |
| Resource Management**[3]** | Improper resource management cause data linking and data sharing issues among devices. | Throughput, Reliability, Latency, Stability. |
| Unmanaged Traffic[30] | IoT networks continuously face uplink and downlink traffic due to the regular sensing mechanism of sensor nodes. | Throughput, Latency, energy consumption. |
| Mobility[43] | The ability of nodes to freely move from one location to another. | Network connectivity, Geographical coverage, Jitter. |
| Node Deployment[31] | Difficulty in the deployment of nodes in the unattended environment or undiscovered sites. | Network Coverage, Reliability, Drift, Connectivity, Stability. |
| Base Station Position [8] | The position of the base station must be in line with the communication device. | Network coverage, Jitter, Connectivity, Network Lifetime. |

several challenges to the fore while routing as listed and depicted in Table 2.

1) CONSTRAINED NODES: Low range limitation in IoT demands multihop routing so the multiple relay nodes forward data to the desired destination [45]. Also, the low processing power necessitates highly optimized and lightweight routing. The scarcity of memory and bandwidth restricts the size of the data packet to send at a time. Additionally, the limited power capacity (harvested or battery-powered) of IoT nodes makes it hard to determine which nodes would forward the data first as wireless communication takes control over the demolishing of energy by IoT nodes. Due to the energy limitation in an IoT network, IoT devices are usually kept in an idle, working, or sleeping state to minimize energy.
2) HIGH MOBILITY AND DYNAMICITY: Dynamicity in an IoT network is generated because of the on/off radio signal, mobility of IoT nodes, and addition/removal of nodes randomly from the network. Also, node failure in an IoT network occurs due to battery depletion, hardware failure, and external factors. All these factors add to the dynamicity of an IoT network [31]. High mobility of IoT nodes requires reconfiguring the whole network periodically. All these factors escort researchers to move towards metaheuristic routing techniques that can efficiently deal with the dynamicity in IoT.
3) INCOMPATIBLE ROUTING PROTOCOLS: Traditional routing protocols like Destination Sequenced Distance Vector (DSDV), Open Shortest Path First (OSPF), Optimised Link State Routing (OLSR), Adhoc Distance Vector AODV [46], and Dynamic Source Routing (DSR) [45] were unable to meet the growing demands of IoT. Routing protocols in IoT must be designed to support unicast, multicast, and anycast transmission of data. Moreover, routing protocols must support the selection of relay nodes dynamically rather than statically [41]. Only a few parameters were considered by traditional routing protocols while selecting the shortest path which is also a matter of concern. Recently, IETF developed IPV$_6$ enabled RPL routing protocol based on DODAG topology. The RPL protocol aims to handle the scalability, energy, and dynamic requirements of IoT.
4) HETEROGENEITY AND SCALABILITY: The inclusion of more heterogeneous nodes [47] geographically in an IoT network further increases the overall complexity of managing them. The complex decisions deal with the inclusion of new relay nodes, the cost associated with routing, setting up a new path, the extra overhead in managing routing tables, and discovering alternative paths in case of node failure [48]. Hence, the advanced routing protocols must be designed by taking into account the complexities that originated with the increase in scalability.

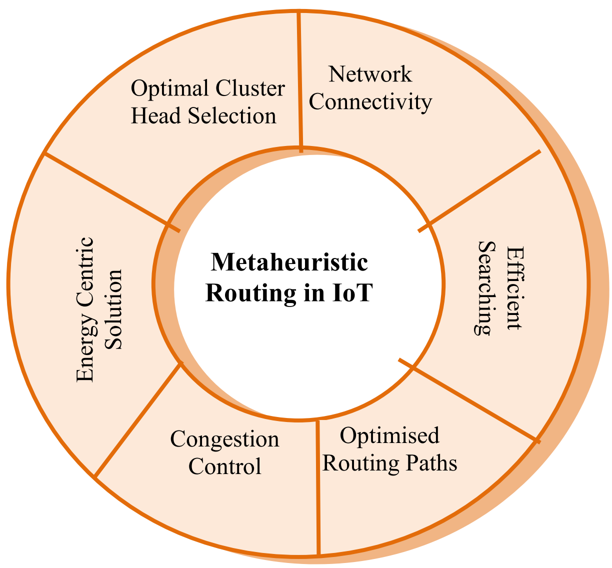


**FIGURE 5.** Significance of Metaheuristic Routing in IoT.

### A. METAHEURISTIC ROUTING: SIGNIFICANCE IN IoT

Recently, metaheuristic routing solutions are adopted over traditional routing in heterogeneous IoT networks because of the following considerations as illustrated in Figure 5.

1) OPTIMAL CLUSTER HEAD SELECTION: Clustering in an IoT network is considered one of the standard techniques for energy management. In clustering, selecting an optimal number of cluster heads in a large-scale IoT network is so challenging and forms an NP-hard problem that cannot be solved by analytical models. Metaheuristic techniques are problem-independent that explore the search space to provide a global solution to the problem. Metaheuristic combines the features of a low-level heuristic to achieve high-level objectives. An electromagnetic force-based metaheuristic algorithm [49] is used to perform inter- cluster routing for energy management in IoT nodes.
2) NETWORK CONNECTIVITY: Metaheuristic algorithms have been used to solve coverage and connectivity problems in heterogeneous industrial IoT by employing heuristic functions for the optimal solution. A multi swarm particle strategy [50] has been adopted to satisfy the demands of Industrial IoT in terms of energy consumption, throughput, and delay. Multi Swarm strategy with canonical and fully informed mechanisms has been incorporated to take benefit of reactive and proactive routing. An objective function is used to trace the values of connected paths.
3) ENERGY CENTRIC SOLUTION: Energy balancing in sensor-enabled IoT networks is a hard combinatorial problem. The energy degradation in the sensor node near the sink results in network collapse. The energy retention in distant sensors is not utilized even if there is sufficient storage of energy. Quantum evolutionary-based algorithm solution is presented in sensor-enabled IoT for improved network lifetime [40].
4) EFFICIENT SEARCHING: Petri nets-Ant Colony optimization (Petri nets-ACO) [51] on the Internet of Manufacturing Things (IoMT) was employed to solve the flexible job Scheduling problem. The energy estimation from four different angles is considered: processing energy, transportation energy, idle energy, and initial energy. Ants in ACO effectively find the best route more efficiently by performing stochastic local search and pheromone updating strategy for setting routes. Premature convergence [51] of search is avoided by setting an upper and lower bound.
5) CONGESTION CONTROL: Congestion detection and congestion avoidance are the major challenges in an IoT network. Congestion detection [52] involves network link monitoring and congestion avoidance inhibits the congestion by employing machine learning and metaheuristic techniques. Particle swarm optimization is applied on a fitness function for accurate delivery of data by considering packet drop ratio and network lifetime as quality metrics [53]. Similarly, multiobjective ant colony optimization with a double Q learning approach has been used to analyze the jamming prediction and energy efficiency [54].
6) OPTIMIZED ROUTING PATH: The significance of quality of service (QoS) metrics like throughput, packet loss ratio, delay, network lifetime, etc., in IoT, directly affects the real-time scenario of a network thereby demanding energy-efficient solutions for the same. Therefore, a study in [14] attempts to optimize routing by using the Firefly routing algorithm and Intelligent water drop routing algorithm in a heterogeneous Mobile Adhoc IoT environment.

### B. IoT: ENERGY CONSERVATION TECHNIQUES

Several energy-conserving techniques are used in state-of-the-art IoT to achieve energy efficiency in an IoT network. The most recent techniques adopted for achieving energy efficiency in an IoT system is Energy Harvesting, Load Balancing, Node Replenishment, and Duty Cycling techniques as mentioned in Figure 6.

#### 1) ENERGY HARVESTING

The process of energy harvesting [37] is the conversion of ambient energy into electrical energy to power IoT nodes. The renewable sources of energy to power IoT nodes are light, thermal, radio, mechanical, wind, and vibration energy [6]. The vibration energy harvests power from the motion of a body, movement, or the vehicles moving on the road. The major limitation in energy harvesting systems is the dependency on the constant availability of energy based on environmental circumstances. For instance, Solar or light-harvesting is only productive when the incident light is 90 degrees aligned to the solar array [3]. Moreover, the energy captured in Piezo mechanical harvesting is based on high vibrations and a maximum traffic footprint. Contrarily, the conditions are not always favorable.

#### 2) LOAD BALANCING

In this process, network load is distributed among the edge nodes, fog nodes, and cloud [55]. Load balancing is categorized into static, dynamic, and initiation. Static load balancing needs prior knowledge of the networking and computing resources [56]. Static load balancing comprises stateless and stateful load balancing. Stateful load balancing takes into account the information of all the sessions based on server load. Stateless load balancing does not require any prior information to select the processing elements. On the other hand, Dynamic load balancing includes distributed and non-distributed load balancing. The load is equally distributed among all the resources in distributed load balancing. In non-distributed, the task of load balancing is performed by each resource [56]. Based on initiation, load balancing is sender initiated and receiver-initiated. In sender initiated, congested nodes find the light nodes to offload the work. In receiver-initiated, lightly loaded nodes search the congested nodes from where the work is offloaded.

#### 3) NODE REPLENISHMENT

Another method for energy efficiency in IoT is Node Replenishment. Node Replenishment is the accusation of energy in

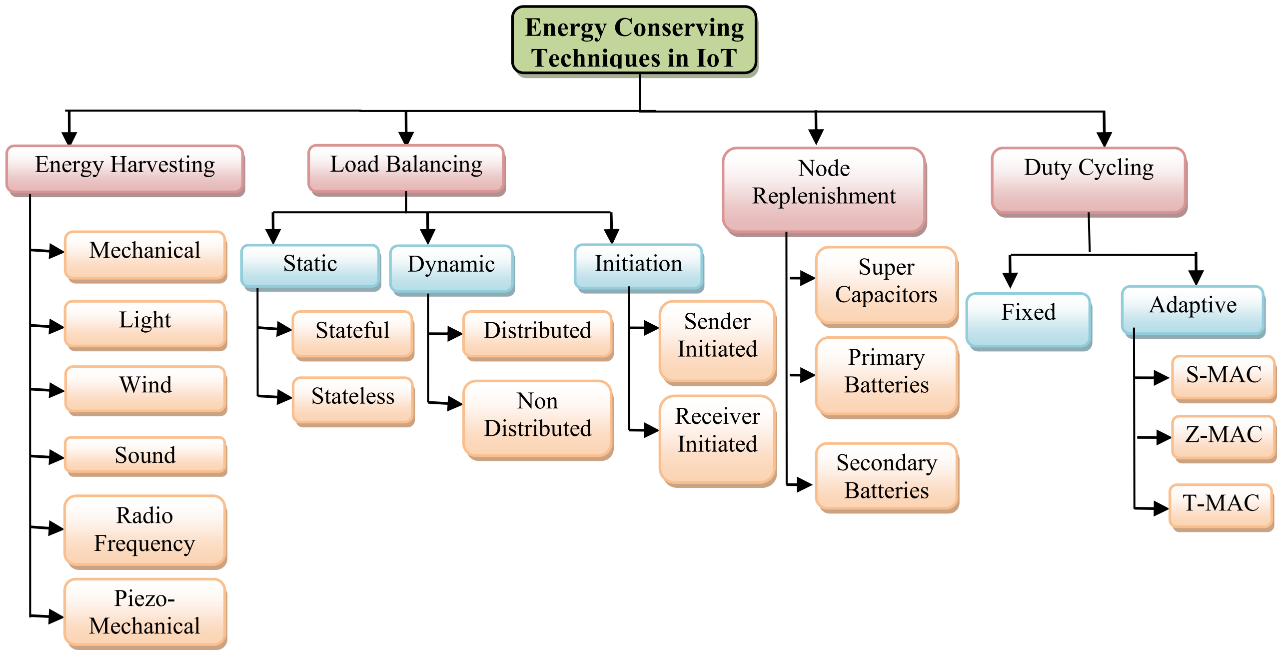


**FIGURE 6. Energy conserving techniques in IoT.**

a node to prevent the nodes from dying when the energy of the node depletes. The different types of storage used in node replenishment are primary batteries, supercapacitors, and rechargeable batteries. Primary batteries [57] are disposable or non-rechargeable batteries.

So, the initial amount of energy determines the node's lifetime. Supercapacitors are low-power storage elements that offer a high power degree and charge-discharge rate. On the other hand, secondary batteries are rechargeable batteries. The design of the primary batteries [57] is much simpler than secondary batteries as one does not have to take into account the rechargeable components to charge or recharge a node. Node Replenishment is based on the size and type of the battery. IoT nodes vary from different sizes to different shapes which in turn varies the size of the node's battery. Mostly, sensors are tiny in size and the energy captured by nodes is also less. Therefore, the lifetime of the nodes ends in a short period. Besides this, replacing batteries is a tedious and expensive task that incurs extra time and cost.

#### 4) DUTY CYCLING

Duty Cycling is one of the most prevalent techniques to gain energy efficiency in an IoT system. Media Access Control (MAC) duty cycling put nodes in an active or inactive state either synchronously or asynchronously to minimize energy consumption [58]. The challenges in conventional duty cycling are overhearing, idle listening, collisions, latency, and over-emitting. The IEEE 802.15.4 communication standard uses an optional Superframe structure to support duty cycling in beaconed enabled networks. The duty cycling that is supported by IEEE 802.15.4 communication standard is fixed [59] in which dynamic network changes are not considered in sensor-actuator networks. Recently, adaptive MAC-based duty cycling protocols are being developed by researchers to reduce idle listening and wake up nodes only on demand. The examples of adaptive duty cycling are Sensor-MAC (S-MAC), Timeout (T-MAC), and Zebra-MAC (Z-MAC) [60].

## IV. IoT: METAHEURISTIC OPTIMIZATION TECHNIQUES

There are innumerable metaheuristic techniques for solving complex mathematical problems with a set of linear and nonlinear constraints as demonstrated in Figue7. The metaheuristic techniques are categorized as Nature-inspired, Evolutionary, Swarm based, and Physics-based. Apart from the basic categorization, the sub-taxonomy of metaheuristic routing in IoT is provided. The main emphasis is to explore the beneficence of metaheuristic-based routing in IoT. Some researchers employed the standard metaheuristic techniques in IoT for energy efficiency. And, some studies evaluate the performance by hybridization of metaheuristic techniques with machine learning or by integrating more than one metaheuristic technique. To date, Particle Swarm Optimisation [61], Ant Colony [35], and Genetic Algorithm [40] in their standard form, as well as hybridization, have shown greater influence in IoT for optimizing energy. Progressively, Simulated Annealing and Whale optimization are also used for energy optimization in IoT. The merits and demerits of metaheuristic techniques along with their variants are depicted in Table 3. In the subsequent section, we will discuss the standardized as well as the hybridized metaheuristic techniques in context to routing in IoT for the optimal convergence of a solution.

### A. PARTICLE SWARM OPTIMIZATION (PSO)

PSO is a metaheuristic technique to compute the solution of the problem by a mathematical formulation by considering particles in a search space [53]. PSO technique is inspired by the flocking behavior of birds realistically. A particle is defined by its velocity and position. The two characteristics velocity and position determine the mobility factor of a particle to move towards a better optimal solution. Each particle tries to move towards the new solution if it is the best among the former solutions obtained based on the velocity and the position. PSO reiterates the process until a termination criterion is reached [10]. The updating particle's position and velocity towards the best solution are given by equations (1) & (2):

$$\begin{aligned} vel_{i,dm}^{i+1} &= \omega vel_{i,dm}^{t} + c_1 \cdot \varphi_1 (P_{i,dm}^{t} - X_{i,dm}^{t}) \\ &\quad + c_2 \cdot \varphi_2 \cdot (P_{g,dm}^{t} - X_{i,dm}^{t}) \end{aligned} \tag{1}$$

$$X_i \dot{\longleftarrow} X_i + l_{rate} v_i \tag{2}$$

Here, $vel_{i,dm}^{t}$ is the dimensional component of the $i^{th}$ particle's velocity in iteration $t$. $X_{i,dm}^{t}$ is the dimensional component of the $i^{th}$ particle's position in iteration $t$. $P_{i,dm}^{t}$ is the best position discovered by neighbors of particle $i$. $c_1$, $c_2$ are the constant weight factors. $\omega$ is the inertial weight. $\varphi_1$ and $\varphi_2$ are the random factors in the range of 0 and 1. $X_i$ is the particle's position. $l_{rate}$ is the learning rate.

LIMITATION: PSO is unable to maintain a trade-off between exploration and exploitation. Exploration restricts the swarm convergence whereas exploitation causes the particles to move impulsively outside the feasible search space that leads to early convergence. A canonical particle multi swarm (CMSPO) optimization algorithm [50] is employed to reduce the speed of particle convergence concerning velocity parameters and avoid local convergence optimal solutions.

HYBRIDIZED APPROACH: Energy Efficient Particle Swarm Optimization (EEPSOC) technique is used to select optimal cluster heads from a set of IoT devices. The elected cluster head forwards the sensed data to the cloud. Then, Artificial Neural Network (ANN) classification model is applied to determine the severity of the disease. The EEPSOC-ANN [14] emits better results when compared with standard ACO and Bee Colony metaheuristic techniques.

### B. ANT COLONY OPTIMISATION (ACO)

Over the last few years, a routing approach that attracted the attention of researchers is Ant Colony Optimisation. The authors in [16] presented the Efficient IoT communication based on Ant Colony by integrating more performance metrics in the discovery of the route selection process. An ant colony [40] approach is inspired by the behavior of ants during their search for food by releasing the chemical-like substance called pheromone. Ants randomly walk to different paths and deposit an amount of pheromone on each path. Other ants follow the path that emanates the highest intensity of pheromone. The highest intensity of pheromone represents the optimized path followed by ants. If ants face any barrier in between the path then the ants follow the alternative path based on the pheromone intensity. Ant colony provides better results in case of performance degradation of IoT network during routing. Ant colony approach has great potential towards efficient communication, scalability, and adaptability concerning network changes. The probability of moving $k^{th}$ ant from node $i$ to $j$ is given in equation (3) [62]:

$$\left\{ \begin{array}{l} P_{ij}^{k}(t) = \frac{[\eta_{ij}]^{\beta} * [\tau_{ij}(t)]^{\alpha}}{\sum\limits_{h \in allowed} [\eta_{ih}]^{\beta} * [\tau_{ih}(t)]^{\alpha}} \\ 0, \; otherwise \end{array} \right\} \tag{3}$$

$\eta_{ij}$ is the desirability of node transition from node $i$ to node $j$ and is inversely proportional to the distance. $\alpha$ and $\beta$ are the constants to regulate the relative pheromone and desirability on the selected path by the ant. $\tau_{ij}$ is the deposited pheromone on the path. The total pheromone update on the path $i$ to $j$ can be calculated as [62]:

$$\tau_{ij}(t+n) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij}(t, t+n) \tag{4}$$

LIMITATION: ACO suffers from the problem of stagnation, premature convergence to the infeasible solution, and local optimum trap [63]. Conventional ACO takes more running time to solve a problem when the size of the problem becomes large [64].

HYBRIDIZED APPROACH: Ant colony Optimisation with clustering algorithm (ACOCA) is employed for optimized searching and faster big data pre-processing [65]. ACOCA minimizes the pre-processing time of big data and increases accuracy and efficiency. ACOCA is preferred over conventional K-means clustering for handling large data sets and global convergence of a solution. Similarly, Ant Colony Optimization-Key Management Technology (ACO-KMT) [62] routing scheme is devised for efficient transmission of packets from source to destination. KMT is used for securing the IoT nodes from being getting traced. Moreover, some studies combine ACO with tabu search [64] to reduce the running time and to find the most optimal routes instead of using only the ACO algorithm in the travelling salesman problem.

### C. FIREFLY ALGORITHM (FA)

The firefly optimization is inspired by the flashing nature of the fireflies. The fireflies are attracted to each other due to their unisex feature. The fireflies are attracted to the brightness [66]. The attractiveness is directly proportional to the brightness. Brightness and attractiveness get decrease with the increase in distance. The brighter fly is attracted to the less bright fly. Fireflies move randomly if none of the fireflies is brighter. The objective function determines the brightness of a firefly. The attractiveness [67] of a firefly $i$ towards other firefly $j$ is given by equation (5):

$$x_i^{t+1} = x_i^t + \beta_0 e^{\gamma r_{ij}^2}(x_j^t - x_i^t) + \alpha \varepsilon_i^t \tag{5}$$

Here, $\beta_0$ represents the attractiveness at distance $r_{ij} = 0$. $\alpha$ is the randomization factor and $\gamma$ is a visibility factor. $\varepsilon_i^t$ is the

**TABLE 3.** Merits and demerits of metaheuristic techniques with their variants and real-time applicability in IoT.

| Metaheuristic Techniques | Merits | Demerits | Variants | Applicability |
|---|---|---|---|---|
| Particle Swarm Optimisation (PSO) | • Parallel computation<br>• Robustness<br>• Efficiency in obtaining global optima<br>• Fast Convergence<br>• Reduced computational time<br>• Solves mathematical complex problems | • Parameter tuning.<br>• Premature Convergence<br>• Incapable to solve problems of scattering<br>• Trapped in a local minimum in case of complex problems. | Canonical Particle Multiple Swarm Optimisation (CPMSO)[50], PSO[53] | Air Pollution Monitoring [69], Smart Energy Management [70], Smart Cities[53] |
| Ant Colony Optimisation (ACO) | • Parallel Searching mechanism<br>• Rapid discovery of good solutions<br>• Adaptability<br>• Convergence guaranteed | • Change in probability distribution with each iteration.<br>• Theoretical analysis is difficult<br>• Uncertainty in convergence | Efficient IoT Communications based on AntSystem(EICAnts)[16], ACO clustering algorithm [66], Multiagent Pathfinding ACO [71], ACO Key Management Technology [63] | Optimal Path identification [71], Security [63] |
| Genetic Algorithm (GA) | • No need for derivatives<br>• Works with continuous and discrete parameters<br>• Solves complex problems<br>• Greater success in achieving a global optimum solution for a variety of functions. | • Repetitive evaluation of fitness function is time-consuming<br>• Results in bad solutions in case of local minima trap<br>• Sometimes inaccurate | Dynamic clustered(GA) [72], GA based cluster Selection[13] | Smart Agriculture [73], Smart Healthcare [74] , Supply Chain Management[75] |
| Tabu Search | • Solves complex problems<br>• Require explicit memory<br>• works with continuous and discrete variables<br>• Can be used for large problems | • Can depend on the strategy for Tabu list manipulation<br>• Trapped in local minima<br>• Less number of parameters determined<br>• Excessive iterations<br>• Parameter Tuning | Improved Tabu search [76], Hybrid Tabu search with ACO [65], Immune Tabu search algorithm [77] | Stochastic vehicle routing problem [76], Travelling Salesman Problem [65], Agricultural machine schedule [77] |
| Harmony Search | • Works with continuous and discrete variables<br>• Initial value settings are not required.<br>• Come out of local optima | • Weak local exploration of search space<br>• The higher number of iterations<br>• Dimensional multimodal problem | Hybrid Cultural Harmony Search [78], Differential based harmony search[79] | Job Scheduling[79], Diesel Blending[78] |
| Simulated Annealing(SA) | • Robustness<br>• Easy implementation<br>• Good for combinatorial problems | • Local minimum termination<br>• Results into more computational time<br>• No upper bound for computation time<br>• Local minimum depends upon initial configuration | Whale optimization with Simulated Annealing[13] Ant colony with Simulated Annealing [80] | Data Analysis of IoT nodes[81], Bus System Design in smart City [80] |
| Bee Colony Optimisation | • Easy to implement<br>• Few controlling parameters<br>• Robust<br>• Handle objective cost | • Slow Convergence<br>• Improper exploitation<br>• No strategy to select population size | Artificial Bee Colony based clustering[82], Modified Artificial Bee Colony[83], Hybrid Artificial Bee colony[84] | Digital Filter Design [83], Clustering [83] |
| Firefly Algorithm (FA) | • Parallel Computation<br>• Simple implementation<br>• Meant for continuous optimization problems | • Trapped in local optimum for multimodal problems<br>• High computational Time<br>• Slow convergence<br>• Memory is not used for previous best solutions | Adaptive Logarithmic spiral–Levy FA[68], Hybrid Firefly clustered Algorithm [85], Randomly Guided Firefly Algorithm [67] | Stock forecasting, Big data management [85], Disease Diagnosis [67] |

random number vector generated from Gaussian distribution. A random walk is depicted among the fireflies if $\beta_0 = 0$.

LIMITATION: The firefly approach [67] does not always converge at the global optimal solution because of the weak

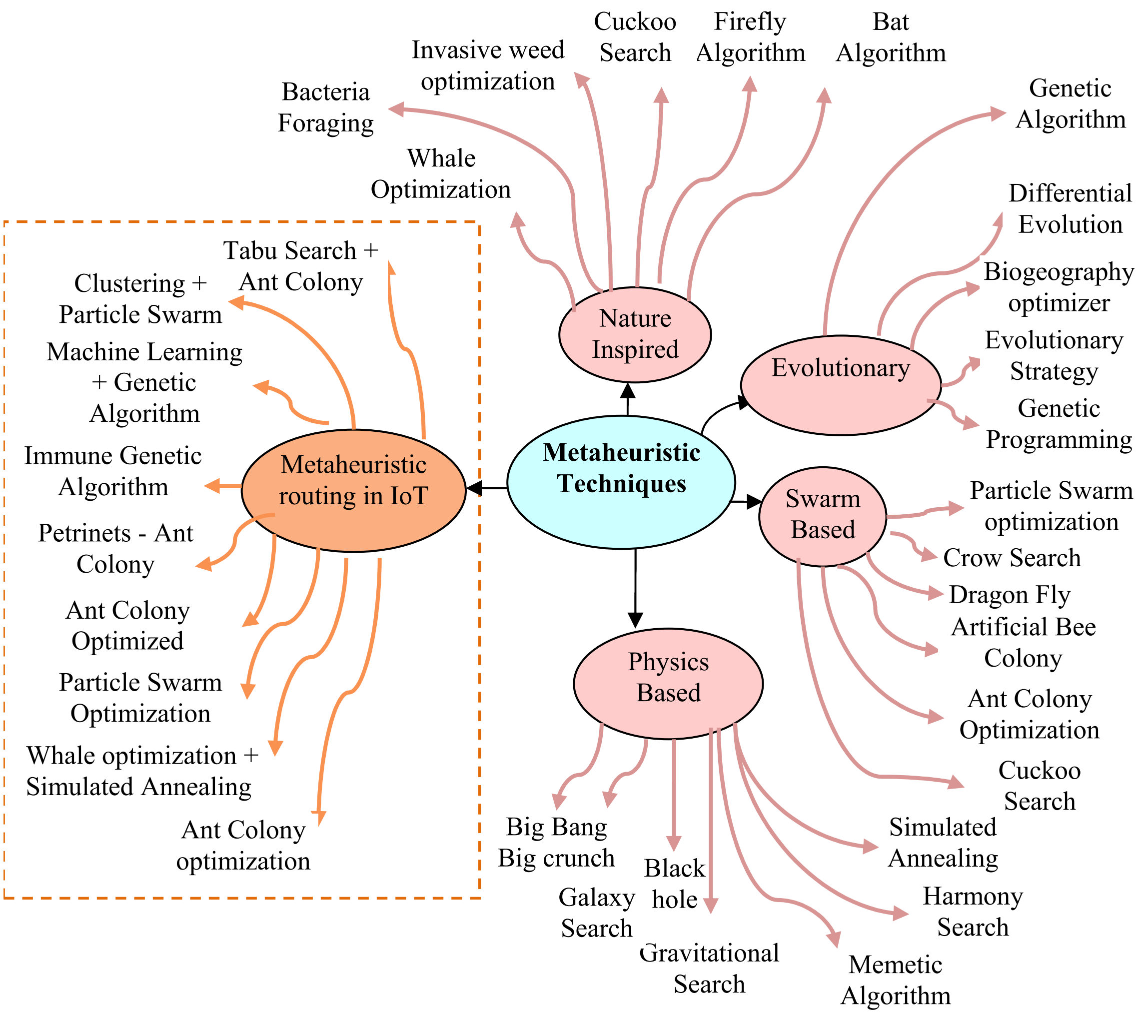


**FIGURE 7.** Broad taxonomy of metaheuristic techniques in relevance to routing in IoT [3].

exploitation in the local search solution space. The FA also results in high computational complexity [66].

HYBRIDIZED APPROACH: To mitigate the problem of global optimization, adaptive logarithmic spiral-Levy FA (AD-IFA) [67] is presented to strengthen local exploitation for fast convergence and stable optimal outcomes. In another study, FA with differential evolution (DE) [85] is employed to achieve global optimization by avoiding the local minima [85]. FA-DE combines the merits of both techniques for faster searching efficiency. Elitist firefly guides each firefly to improve the time complexity and the rate of convergence in the FA-DE approach. An operation similar to mutation has been performed to improve the local searching ability.

### *D. EVOLUTIONARY APPROACH*

An evolutionary technique such as genetic algorithm (GA) is based on genetics and hereditary. Genetic algorithms are used to solve search-based optimization problems. Optimization aims to either minimize or maximize the objective function by altering the input values. Genetic algorithms are further categorized into single objective or multiobjective. Single objective takes into account to optimize only one quality parameter i.e maximize the overall throughput of a network. Multiobjective tries to optimize the multiple quality parameters i.e maximize the throughput as well as energy efficiency [18]. The fitness value of a standard genetic algorithm is based on mainly three steps namely selection, mutation, and crossover. Individuals having the highest fitness value are selected to generate new progeny of individuals called "survival of the fittest" [71]. In the context of IoT, fitness value depends upon several metrics like energy consumption, residual energy, load, temperature, and delay, etc. as mathematically formulated in equation (6):

$$F = \sum_{i} W_i * f_i \forall f_i \varepsilon (C, DD, SD, E, T) \tag{6}$$

where $F$ represents the fitness function, $W_i$ is the weighted parameter, $T$ represents the number of transmissions. $E$ represents the transfer energy, $DD$ represents the direct distance from the sensing node to the base station, $C$ is the cluster distance from the cluster head to the base station $SD$ is the cluster standard deviation distance. Here the transfer energy is equivalent to the total energy consumed to send data from the sender node to the cluster head and from the cluster head to the base station.

LIMITATION: Maintaining diversity is significant in genetic algorithms to yield new candidate solutions. Diversity in GA can be improved by performing hypermutation when the quality of the solution drops. The applicability of genetic algorithms depends upon the in-depth knowledge of the problem. Another limitation with GA [18] is the initial selection of the chromosomes. If there are many solutions then more time is needed to find the fittest optimization. If there are fewer solutions, then the GA may struggle to find the fittest optimization.

HYBRIDIZED APPROACH: Genetic Algorithm with a machine learning regression model [18] is employed in smart traffic lighting to predict the traffic distribution for the next intersection. The GA algorithm is used for selecting the optimized variation in the timing plan of the traffic light. The GA algorithm with a Convolutional neural network (CNN) [72] is used for agro-industry and satellite image processing. The objective functions namely economic profit, land degradation, and $Co_2$ emission is optimized using the GA technique for sustainable land usage.

### E. WHALE OPTIMISATION (WO)

The whale optimization technique is inspired by the hunting pattern of humpback whales. The attacking mechanism of the whales is called the bubble net feeding mechanism [8]. In this mechanism, whales form bubbles around the prey. The attack is attempted in two steps. The first is encircling prey and the second is attacking prey. In the first step, the whale identifies the position to encircle the prey. Initially, the best solution is considered as the targeted prey and the other whales are indicated to update their position in the direction of the prey. The encircling around prey [13] is mathematically depicted in equation (7):

$$\begin{aligned} L &= \left|y.s^*(i) - s(i)\right| \\ s(i+1) &= s*(i) - x \end{aligned} \tag{7}$$

where $i$ stands for the current iteration, $x$ and $y$ are the coefficient vector, $s$ is the position of the vector, and $\boldsymbol{s}^*$ is the position vector of the best solutions. Secondly, the attacking phase includes the shrinking encircling phase and the spiral updating phase known as the exploitation phase. And, in the exploration phase, the whale searches for the global best solution randomly and keeps changing the position concerning other whales.

LIMITATION: The standard version of WO suffers from the problem of low convergence and local minimum trap [8]. Due to the random process of searching, WO usually fails to provide high-precision solutions. The performance of the WO degrades under high-dimensional problems [86].

HYBRIDIZED APPROACH: WO with Grey wolf optimization along with Imperialist Competitive Algorithm is used for optimal cluster head selection in heterogeneous IoT systems [8]. The hybrid approach merges the benefits of three algorithms to solve the problem of buffer overflow [8] in heterogeneous sensors. The grey wolves and hunting behavior of whales are imitated to form the clusters intelligently and autonomously. In [86], a joint search whale optimization algorithm is used to solve the challenge of low convergence, local minimum trap, and high dimensional problems. A similar approach in [13] WO with simulated Annealing(SA) is used to select the cluster head efficiently in an IoT network.

## V. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

The challenges encountered in metaheuristic routing cannot be ignored even if there are manifold benefits. Evaluation of metaheuristic techniques for a set of problems arise a level of perplexity under different testing conditions. The metaheuristic routing challenges are shown in Figure 8.

1) PROBLEM SOLVING POTENTIAL [9]: The efficiency of metaheuristic techniques lies in the problem-solving capability in a wide range of applications. It is not evident in the literature whether a small-scale problem solved by an algorithm can be scaled up to solve the complex problem with the same efficiency. This is at par with the ‘‘no lunch theorem’’ which states any two algorithms are equal when the average performance results for a set of possible problems. So, the open challenge is how to scale up the algorithms for handling parallel and high computational tasks.
   FUTURE DIRECTION: The more robust and intelligent techniques must be developed in the future by testing on the small, moderate, and large-scale problem domains with nonlinear constraints. Proper benchmark functions in the future must be tested on algorithms to check the applicability in scalable applications like routing problems.
2) PARAMETER TUNING [61]: All algorithms have problem-dependent parameters to be evaluated. Here, the open challenge is how to set the parameter tuning of more than one algorithm in comparison. Parameter tuning may depend upon the algorithm as well as on the problem to gain the maximum output of it. Also, Brute force tuning is only applicable if the number of parameters is small. There is no surety that a tuned algorithm that exhibits good results for one problem may be as good as for another problem also. In some cases, adaptive or variants in parameters proved to give better results.
   FUTURE DIRECTION: Setting parameter configuration or parameter tuning is an indispensable and time-consuming task. Therefore, the process of automating the parameter tuning [87] is of great relevance in metaheuristics. Setting appropriate parameters by users requires extensive knowledge of how parameters affect performance. But, the automatic parameter tuning eradicates the problem of prior knowledge of

parameters by users and improves the performance of algorithms.

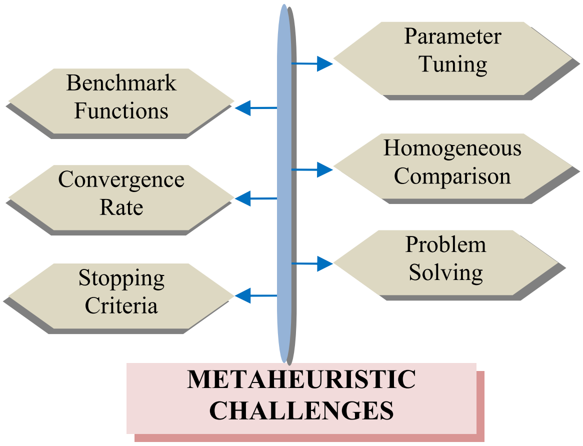


**FIGURE 8.** Evaluation Challenges in Metaheuristic-based Routing.

3) HOMOGENEOUS COMPARISON [9]: A common approach that is followed in literature to evaluate the performance of algorithms by comparing with the same metaheuristic techniques and their variants. Metaheuristic techniques are simpler to implement in their standard form with no initial equality or inequality constraints. Alternative methods along with metaheuristics must be taken into account for fair evaluation that has exhibited better results for a set of problems. The absence of a proper benchmark leaves the situation somehow squandered.
FUTURE DIRECTION: A good practice would always be the use of the combination of metaheuristics with exact methods or with alternative energy-efficient methods for fair comparison among algorithms. Moreover, the comparison among algorithms must be carried out on the same machine for an equal amount of computational time and the same number of instances. While comparing, one must take into account to choose the algorithms that have exhibited the best performance for the number of NP-Hard problems.
4) STOPPING CRITERIA [27]: The stopping time of the metaheuristic algorithm is the most crucial issue. In the existing literature, the maximum number of iteration is considered as the stopping criterion which is an inappropriate way. In case of premature stopping, execution will stop even if the objective function has a chance to offer the best solutions further. In case of late stopping, execution will stop when there is mild or no change in the solution. Thus, results in many constant values that is a problematic issue. Sound choice of a stopping criterion is mandatory for metaheuristic algorithms.
FUTURE DIRECTION: The stagnation criteria are the most appropriate for the above-mentioned issue. When no change occurred in the objective function, the algorithm terminates. This is the definition of adaptive stop criteria or stagnation criteria. Stagnation criteria discard the early or late stopping of an algorithm. Also, the algorithm must run for more than 100 iterations for the fair performance of the algorithm and its comparative analysis.
5) CONVERGENCE RATE [61]: Convergence rate or the computation time is determined by considering the number of iterations executed for evaluating metaheuristic techniques. The convergence rate of any two algorithms can be different or the same. Early convergence can be achieved by setting up good initial choices in single update methods. If the initial choice of individuals contains the global optimum then achieving convergence is immediate. Therefore, the statements claiming that "the convergence rate of one algorithm is better than another" do not always mean that one algorithm is better than another.
FUTURE DIRECTION: Preserving the best candidates in each iteration via elitism strategy and executing the algorithm for an infinite number of iterations ensures the global convergence to the optimal solution. Moreover, it necessitates the design and development of a unified mathematical model to be applied on all metaheuristic algorithms for an in-depth understanding of the convergence rate, stability, effectiveness, and robustness of the employed technique. Therefore, the future research trend will be the design of the unified framework that requires the integration of multidisciplinary approaches like numerical, stochastic, and mathematical to study and analyze the algorithms from different perspectives.
6) BENCHMARK FUNCTIONS [27]: Benchmark functions play an important role to check the performance of the new algorithm with other algorithms. Benchmark functions use test conditions that allow researchers to better understand the algorithm behavior in terms of convergence, stability, pros, and cons. The challenge is what type of benchmark functions could be applied to evaluate the performance. The presence of a benchmark may serve some purpose because of the smooth and regular constraints but they are not always fit according to the problem.
FUTURE DIRECTION: The existing benchmark functions are unconstrained and smooth for regular domains but the real-world problems have many nonlinear complex constraints. For the proper validation and testing of an algorithm, test functions for irregular constraints must be considered. The existing benchmarks are not sufficient for the evaluation of metaheuristic techniques in power and energy domains. Therefore, designing precise benchmarks for energy problems will be a research trend in future research.

## VI. METAHEURISTIC ROUTING: PROPOSED ENERGY-EFFICIENT FRAMEWORK IN IoT

To the best of knowledge, there is no metaheuristic-based energy-efficient routing framework in the state-of-the-art heterogeneous IoT that addresses the root challenges of metaheuristic-based routing. The proposed framework attempts to contextualize the issues and solutions that would result in major adversaries while evaluation of metaheuristic algorithms in IoT. Existing studies are continuously utilizing metaheuristics lacking proper benchmarks. The proposed framework provides a benchmark to take into account the principles that have been excluded by researchers while utilizing metaheuristics. Thus, helps researchers to prevent misleading information about the performance and superiority of algorithms. The basis of the three-layer proposed framework is IoT architecture [88]. The components and working of the proposed energy-efficient metaheuristic routing framework are discussed subsequently as shown in Figure 9.

### A. PHYSICAL CONNECTIVITY

In the physical connectivity layer, heterogeneous nodes are randomly distributed over the geographical area. The intelligent devices operating over the bottom layer are uniquely identified. Smart nodes in the bottom layer are characterized by a sensing unit, a processing unit, a communication unit, and a valid power source [48]. Different manufacturers are developing different types of smart products [8] that vary in specification, standards, and technologies. The inconsistency in standards bolsters large players to develop proprietary standards. The data sensed and aggregated by smart nodes in the physical layer are in the form of structured, unstructured, and semi-structured [3] results in unlabelled data. The unlabelled data is processed at the network layer to convert into labeled data by using machine learning techniques for the reliable transmission of data.

Diverse technologies to enable communication among IoT nodes are local communication technologies, cellular technologies, LPWAN technologies, and point-to-point network technologies. Local communication technologies are Zigbee, LoWPAN [89], Z-WAVE, and Bluetooth. Cellular technologies include 2G, 3G, 4G, and 5G/LTE. Point to Point technology is a short-range technology like

NFC (Near Field Communication) and RFID (Radio Frequency Identification) [90]. Heterogeneity among communication technologies, data generated, and hardware specifications necessitate the interoperability among IoT products to ensure consistent communication. The overall notion of ubiquitous connectivity in IoT can only be realized through cooperation and adaption between heterogeneous technologies [91] for scalable and robust IoT.

### B. NETWORK CONNECTIVITY

In the network connectivity layer, reliable transmission of data is only possible if the sub-components of the IoT ecosystem are interoperable with each other. Interoperability in IoT is considered at three levels: Device-level, Data level, and Protocol level. The interoperable levels help to accomplish various types of interoperability that comprise semantic [92], syntactic, technical [93], organizational, platform, system [94], and service.

Amidst all, semantic, syntactic [95], and technical interoperability is the most common. Semantic Interoperability contextualizes the data to extract meaning out of data. Syntactic interoperability must support protocols and standards for the conversion of data. Technical interoperability ensures the connection among physical objects to transmit bytes of data. Organizational interoperability [1] is the compatibility among organizations to manage the clients in a cogent manner. Similarly, dynamic interoperability makes sure to have coordination when dynamic changes occur. Service interoperability coherently exchanges the services among IoT systems. System interoperability collaborates among several software/ hardware devices and technologies. Platform interoperability guarantees compatibility between various IoT platforms.

#### 1) INTELLIGENT SERVICES

The network connectivity layer enables communication among the physical layer devices with the higher processing layers [96]. The data sensed by the sensor nodes in the physical connectivity layer are transmitted to the network layer for further processing like data filtering, data mining, and data storage for enhanced decision making. Data processing in an IoT network is either processed on edge/fog or in the cloud. The time-sensitive data is sent to the nearest nodes for edge computation. On the other mode, the less time-sensitive data is stored and processed on the cloud. Intelligent techniques encompass machine learning, swarm intelligence, computer vision, deep learning, and reinforcement learning [89]. Machine learning algorithms Such as classification, clustering, and decision making drive IoT technology to cluster and analyzes data for better decision-making and imminent predictions. Rapid utilization of intelligent techniques, in turn, provides edge/fog and cloud services on demand. The merits of assimilating intelligent techniques with IoT aid in language translation, data translation, protocol conversion, storage, data analysis and visualization to accomplish interoperability [99]. The intelligent services on the edge of the IoT network improve the quality of service metrics such as reduced delay and energy consumption, increased throughput, and network lifetime.

##### *a: METAHEURISTIC BASED CLUSTER HEAD SELECTION*

The network connectivity layer is partitioned into two sections:

- Cluster formation of sensor nodes.
- Cluster head selection using metaheuristic technique for energy efficiency.

The purpose of forming clusters in IoT is to minimize the transmission distance among IoT nodes as the nodes are geographically distributed. Energy conservation and distance minimization is considered as the primary objective of clustering. The other secondary objectives associated with clustering are evaluated on account of performance parameters like scalability, packet reception ratio, network longevity,

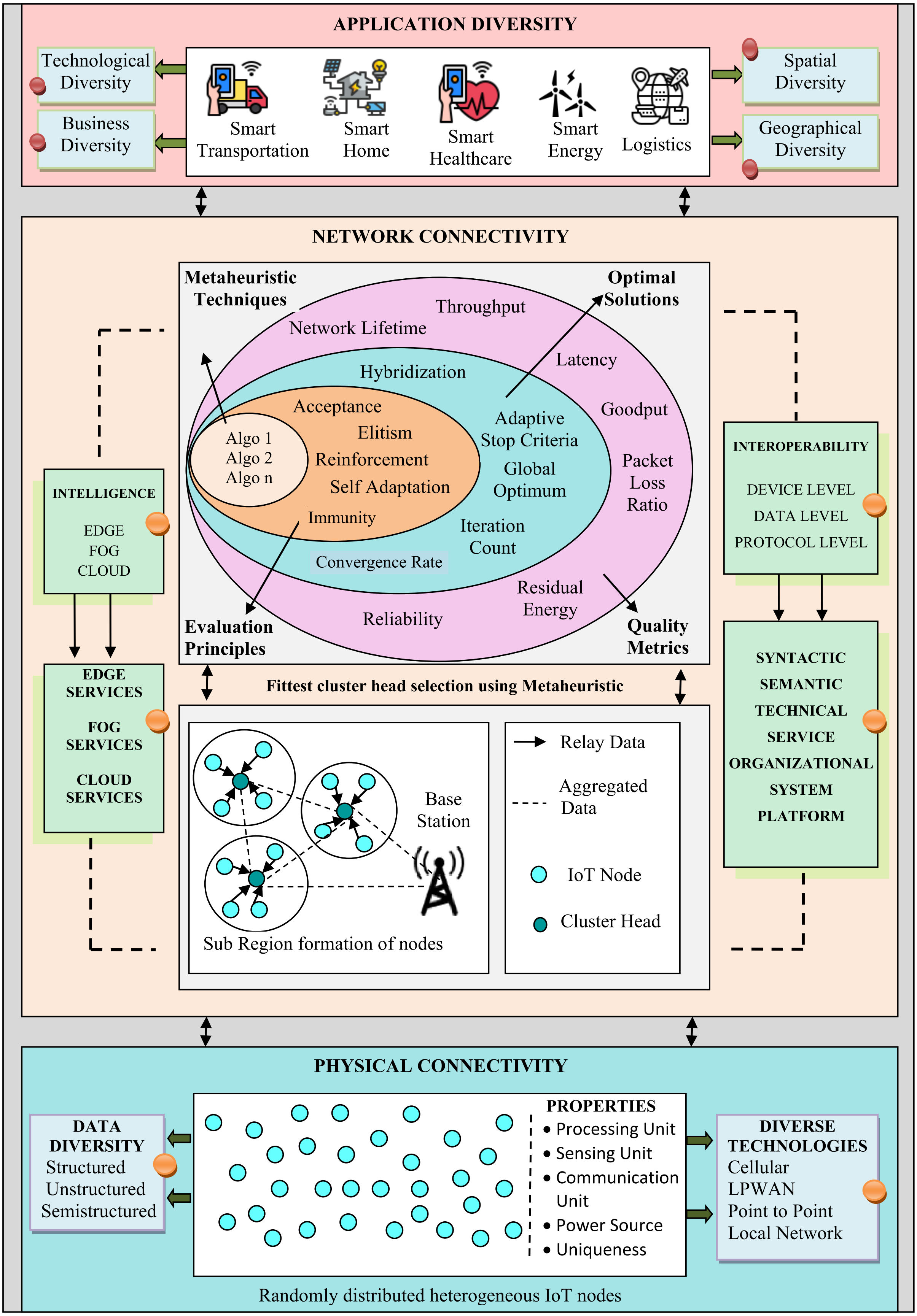


**FIGURE 9.** **Proposed Metaheuristic-based energy-efficient routing framework in heterogeneous IoT [3].**

robustness, reliability, and network throughput. Clusters in an IoT network are formed either statically [71] or dynamically [100]. Cluster head selection using metaheuristic techniques depends upon the fitness function or the objective function. The more the value of a fitness function the more is the chance of a sensor node to get selected as a cluster head. Metaheuristic techniques update the optimized local and global routes within and outside the clustered IoT network dynamically. The fitness criteria take into account the various features depending upon the optimization problem to be solved. Thus, optimizes the QoS parameters that contribute to the overall maintenance and performance of an IoT network. The comparative analysis of performance metrics among various metaheuristic routing techniques is depicted in Table 4.

#### b: FITNESS ASSESSMENT OF CLUSTER HEAD AND QUALITY METRICS

Say, $CL_i$ represents the number of clusters where $i = 1, 2, 3 \ldots, N$. Total number of nodes in each cluster is denoted as $TN_i$ where $i = 1, 2, 3, 4 \ldots, M$. And the total cluster heads are denoted as $T_{Ch}$ that communicate with the base station.

##### FITNESS FUNCTION

The stability of the IoT network depends upon the maximization of the fitness function [13]. In the traditional clustering technique, the distance metric is taken into consideration. Nevertheless, load and temperature metrics must also be considered in an IoT network as these are the major factors contributing to energy consumption. The value of the fitness function depends upon the important quality metrics in IoT as depicted in equation (8):

$$F_i = \alpha * F_{temp} + \beta * F_{load} + \gamma * F_{energy} + \phi(1 - F_{dist}) + \omega(1 - F_{delay}) \quad (8)$$

Here $\alpha, \beta, \gamma, \varphi, \omega$ are the weighted parameters and $F_{temp}$, $F_{load}$, $F_{energy}$, $F_{dist}$, $F_{delay}$ are the fitness function for temperature, load, energy, distance, and delay. The values of temperature and load can be downloaded from the Xively IoT platform. The mathematical evaluation of the parameters taken in the fitness function is illustrated subsequently:

##### FITNESS FUNCTION FOR ENERGY

Nodes in an IoT network have a transmitter and receiver hardware unit. Transmitter dissipates energy while transmitting data by power amplifiers. Similarly, the receiver unit dissipates energy in the form of radio signals. Therefore, the total energy consumed is equivalent to the energy consumed by the receiver, transmitter, and other circuit components. In a clustered network of nodes, the energy is consumed to transmit the packets from nodes to the main central node. Also, loss of energy takes place while receiving data from nodes by a main central node. The energy consumed to send $M$ data bytes from the normal node to the central node in a cluster is given in (9):

$$E(D_a^N) = (E_e * M) + (E_{fe} * M) * \left\| D_N^a - D_{ch}^n \right\| \quad (9)$$

where, $E_e$ is the energy in the form of voltage, $E_{fe}$ is the idle energy, and $D_N^a - D_{ch}^n$ is the distance from the node to the central node in each cluster.

The energy consumed by a central node in a cluster to receive $M$ bytes is given in (10):

$$E(D_{ch}^n) = E_e * M \quad (10)$$

The fitness function for energy consumption is calculated by using (11).

$$F_{energy} = \frac{1}{X}\left\{\sum_{a=1}^{X} E(D_N^a)\right\} + \frac{1}{T_{Ch}}\left\{\sum_{a=1}^{ch} E(D_{ch}^n)\right\} \quad (11)$$

##### FITNESS FUNCTION FOR DISTANCE

The estimation of distance is measured from nodes to the cluster head and from the cluster head to the base station. The minimum distance between the nodes and the cluster head ensures the best cluster head selection as depicted in (12).

$$F_{dist} = \sum_{a=1}^{X}\sum_{n=1}^{T_{Ch}} \frac{\left\|Dist_N^a - Dist_{Ch}^n\right\| + \left\|Dist_{ch}^n - Dist_{Bs}\right\|}{U * V} \quad (12)$$

where $\left\|Dist_N^a - Dist_{Ch}^n\right\|$ indicates the distance of $a^{th}$ node from $n^{th}$ cluster head and $\left\|Dist_{ch}^n - Dist_{Bs}\right\|$ indicates the distance from $n^{th}$ cluster head to the base station. The denominator represents the dimensions of the area in meters.

##### FITNESS FUNCTION FOR DELAY

The delay computation depends upon the placement of the nodes to the cluster head. The minimum number of nodes in a cluster minimizes the delay also [13]. The delay depends upon the maximum transmissions that take place from the cluster head to the base station. The mathematical formulation for the delay computation is shown in (13).

$$F_{Delay} = \frac{Max \sum_{n=1}^{T_{Ch}} Ch_n}{W} \quad (13)$$

### 2) EVALUATION: METAHEURISTIC PRINCIPLES AND GLOBAL CONVERGENCE

To prevent the fallacies claimed in the literature about the superiority of the metaheuristic techniques, one must ensure to follow the principles while evaluating the performance. The empirical points are showcased and adopted for comparative performance and tangible analysis of metaheuristic techniques that have been omitted by most of the researchers while evaluating. Acceptance, Elitism, Reinforcement, Immunity, and self-adaptation form the common basis for metaheuristic algorithms that induce the structural differences among them [27]. Figure 10 provides the countermeasures to cope up with the emerging challenges in metaheuristic routing.

**TABLE 4.** Comparative analysis of performance metrics among various metaheuristic routing algorithms.

| Author & Year | Architecture/Framework/ Model | Method Type | Algorithm | Key Feature Added | Quality Metrics | Analysis |
|---|---|---|---|---|---|---|
| Shamim Yousefi et al. & 2020[82] | Standardized network and energy model | Metaheuristic | Artificial Bee colony_Device Clustering(ABC_DC) | Optimal cluster head selection using ABC | Energy consumption, Alive nodes, Delay | ABC_DC improves the network lifetime, transmission delay w.r.t Huris-C, Fizzy-C, and ELeach-C |
| S. Vimal et al. & 2020[54] | Jammed cognitive network model and energy aggregation model | Metaheuristic | Multiobjective Ant Colony with double Q-learning (MONACO) | Deep Reinforcement learning and double Q learning | PDR, Network Lifetime, and Energy Consumption | MOACO improves the quality metrics in comparison with GA and ABC. |
| Jianpeng Zhang & 2020[98] | M2M network architecture | Metaheuristic | Intelligent Chaos ACO | Adaptive perturbation strategy | Residual energy, delay, invalid node ratio, energy surplus rate | Intelligent chaos ACO saves energy consumption by 7.3% w.r.t Long-range (LR), Short range (SR), and Balanced Multipath Routing (BMR). |
| Mukhdeep Singh et al. & 2018[53] | Not applicable | Metaheuristic | Particle Swarm Optimisation | Standard comparison b/w ACO, PSO, and ABC | Residual energy, PDR, and Network Lifetime | PSO improves the network lifetime and packet delivery ratio in comparison with ACO and ABC |
| Hassan Daryanavard et al. & 2019[81] | Not applicable | Metaheuristic | ACO and Simulated Annealing(SA) | Standard comparison for sensor size less than or equal to 50. | Execution time & speed | ACO take less execution time for less than 50 number of nodes in comparison with SA with increasing number of sensor nodes. |
| Mingchuan Zhan et al. & 2017[99] | Bio-inspired hybrid trusted routing protocol (B-iHTRP) Architecture | Metaheuristic | B-iHTR (ACO + physarum autonomic optimization (PAO) | Trust Assessment , Multiple Zones | Delay, Overhead, Zone radius | B- iHTR performs better in selecting optimal routes w.r.t AntHocNet, AODV, and HOPNET |
| Celestine Iwendi et al. & 2020 [13] | Hybrid WOA-SA model | Metaheuristic | WOA-SA | Hybridization | Normalised network energy, load, temperature, alive nodes. | WOA-SA shows good results in comparison with ABC, GA, and WOA. |
| Chuan Xu et al. & 2019[38] | ER-SR Routing model | Metaheuristic | ER-SR Routing Protocol | Region division is based on a range | Packet delivery ratio(PDR), Network lifetime, delay, energy consumption | ER-SR depicts higher energy efficiency and moderate performance w.r.t ER-RPL, MSGR, and PRO. |
| Celestine Iwendi et al. & 2018[63] | Not applicable | Metaheuristic | ACO_Key Management Technology (ACO_KMT) i.e Energy-efficient routing algorithm(EERA) | Cooperative Routing, Key Management technology | Area Throughput, Delay, Packet transmission efficiency | EERA showcased the best performance in energy efficiency and packet transmission rate when compared with EESR, and LHSA |

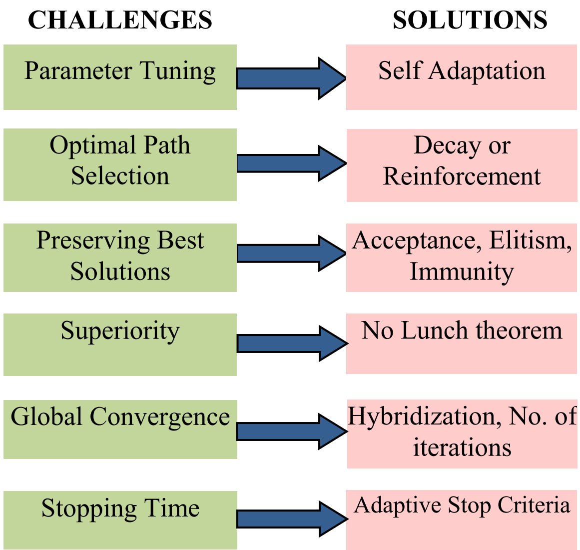


**FIGURE 10.** **Countermeasures to avoid critical challenges in metaheuristic routing.**

- **Acceptance:** The principle of acceptance is based on accepting or rejecting the solutions in the solution space. Three conditions might appear in acceptance. Firstly, solutions are accepted temporarily in the quest to expand the search space. Secondly, solutions are accepted if no constraint violation occurs defined in the objective function and vice-versa. Lastly, solutions are accepted at least below or equal to the value of the threshold to attain the current best solution.
- **Elitism:** The standard metaheuristic techniques do not have a provision to retain the best solutions in population-based methods. To evade the issue, the Elitism principle must be considered to preserve the individuals with the best objective function. Elitism passes the set of best solutions to the next iteration. With the assistance of elitism, it has been possible to converge at the global optimum to some extent.
- **Reinforcement:** The reinforcement principle is essential to discard the inconvenient paths and reinforce the convenient paths as happens in the case of the Ant Colony algorithm. The reinforcement principle is applied similarly to the decay principle by using a multiplicative factor greater than unity. And, decay uses a multiplicative factor less than unity that is applied at different iterations. An example of decay is the cooling rate parameter used in the simulated annealing algorithm.
- **Self Adaptation and Immunity:** The challenge of parameter tuning could be mitigated by the self-adaptation of parameters automatically. Also, the Immunity principle prioritizes the solutions based on the identification of properties to pass on to the next iteration. Thus, helps to pass only the best candidate solutions to the next iteration.
- **Number of Iterations and Adaptive Stop Criteria:** The number of iterations must be taken into account while utilizing any metaheuristic approach for statistical significance. The number of iterations must be kept as high to solve the problem in a reasonable time. In some cases, proficient code and fast programming would be a more relevant solution when the number of iterations determines the computation time. An adaptive Stop criterion is the most appropriate solution to avoid the early stopping and late stopping of an algorithm. Adaptive stop criteria prefer to stop the algorithm when no changes are found in the objective function.
- **Hybridization and Convergence:** To improve the performance of an algorithm, the hybridization of metaheuristic techniques is done either by combining exact methods or with the combination of different heuristics. The formulation of a hybrid metaheuristic must aim at global search and the exact methods that can be used for the local search. Hybridization prevents the local trap and improves global convergence. Many metaheuristic algorithms lack proof of convergence that could be accomplished by elitism and the Immunity principle.

### C. APPLICATION DIVERSITY

Applications provide services to mobile users, enterprises, and large organizations. Different applications have different operating requirements to employ different types of data delivery models. In periodic data delivery [101], data sensed is transmitted in periodic intervals. In the case of event-driven data is transmitted on the generation of events. And in query-driven data delivery, data is delivered upon getting query by the data collector [101].

The demand for IoT is flourishing in every sector with increasing diversity. The various diverse IoT applications are categorized as spatial, geographical, technological, and business applications. Spatial applications offer services in aerial, terrestrial, and underwater locations. Geographical applications are distinguished on account of rural, urban, city, and forest. Business applications [102] operate in different sectors like smart city [103], smart transportation, agriculture, logistics, and military. Technological diversity [104] encompasses diverse technologies for example machine learning, artificial intelligence, deep learning, embedded technologies, sensor technologies, and data analytic technologies.

The proposed framework acts as the first line of defense against metaheuristic adversaries and bridges the landscape between evaluation and energy efficiency in IoT during routing. The emergent intersects targeted by the proposed framework is as follows:

- Selection of cluster head by using metaheuristic technique for energy-efficiency in heterogeneous IoT.
- Precise selection and analysis of the initial generation of solutions for optimization of routing path and energy.
- Introducing Elitism and Immunity principle for preserving the best solutions.
- Self-adapting stopping criteria and parameter tuning for preventing early convergence and parameter setting.

- Hybridization and Reinforcement for improving the performance of metaheuristic algorithms for selecting or discarding the routing paths.
- The metaheuristic principles and solutions discussed in the proposed framework would provide a roadmap for the incorporation and implementation by using the right strategy. Thus, opens a door for producing authentic information that contributes to the research community by preventing fallacies.

## VII. CASESTUDY: ENERGY-EFFICIENT METAHEURISTIC BASED SMART MANUFACTURING

The immense progression of Information technology (IT) brings technological advancement by integration and collaboration of smart devices known as "Smart manufacturing". Smart manufacturing produces goods in bulk to maintain the balance between demand and supply. Smart manufacturing uses IoT infrastructure to trace the

streamline production, supply chain, and distributed product shipment. IoT-based Smart manufacturing [105] cyclically performs repairing in faulty components by tracing the subunits. Diverse types of sensors and data processing elements are integrated to automate the whole process of the streamline. As the manufacturing process is becoming complex and dynamic, efficient and scalable metaheuristic with machine learning techniques would assist to portray rapid manufacturing services. As per the statistical report provided by IoT Analytics, it has been predicted that the number of IoT products and services would increase to $310B by the year 2023 [106] as shown in Figure 11. The global statistical report is based on the adoption of industry 4.0 services and supporting technologies among various manufacturing verticals.

### A. WORKFLOW OF SMART MANUFACTURING

As depicted in Figure 13, two scenarios are considered: Fog based data transmission and the role of metaheuristic techniques. The fog layer incorporates a network of fog nodes (routers, switches, gateways, and servers). The fog nodes perform several operations like data uploading, data integration, data filtering, data storage, and compression on receiving the data from edge nodes. The fog management node assigns service requests to different fog nodes to perform the task in a coordinated manner. Data from edge devices is further translated into unified data formats and protocols for reliable communication and interoperability. Fog computing mitigates latency, energy consumption, and data-related issues by offloading some data to the cloud. The key issues and supporting technologies [107] in Smart manufacturing are demonstrated in Figure 12.

In smart manufacturing, big data is generated by the activities of internal manufacturing subunits and collaboration among enterprises. The data aggregated by fog management nodes and edge devices is transmitted to the Cloud [105]. Big data [108] often contain erroneous, redundant, and duplicate data. The processing of big data includes data collection, preprocessing, storage, analysis, and visualization of data [109]. The most common techniques used for data processing are Hadoop, MongoDB, Apache Hive, and Map Reduce [110]. Data processing models or prototypes are created in the cloud to get valuable insights about data, complexity levels, energy analysis, and resource management, proactive and reactive maintenance [111]. The prototype build-in cloud layer is updated continuously based on information gathered and new data generated. Big data analysis provides business insights to know about market statistics, risk assessment, and production management [112].

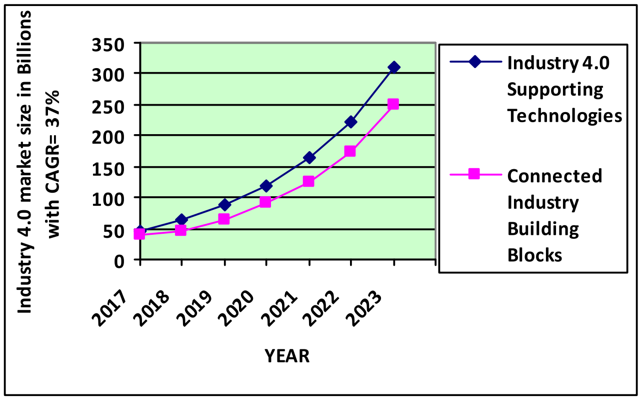


FIGURE 11. Smart manufacturing global market size (2017–2023) [106].

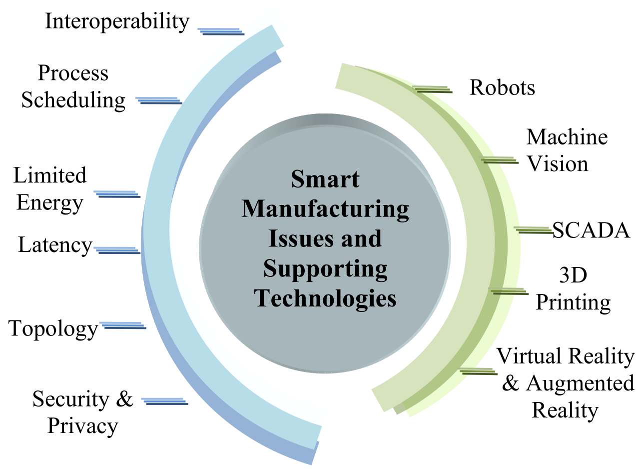


FIGURE 12. Key issues and supporting technologies in smart manufacturing.

### B. SMART MANUFACTURING: FITNESS FUNCTION DESIGN FOR PROCESS SCHEDULING PROBLEM

In smart manufacturing, a product has to undergo several phases to convert from its raw form into a ready-to-use complete product. Proper process scheduling plays a vital role in the efficient management of products. Each raw product is assigned to a machine to perform multiple tasks for the final finishing of a product. Here, the scheduling problem is which product will be assigned to which machine first [113]? Efficient process scheduling of a product in smart manufacturing depends upon the duration of the complete product design. The complete duration of product design includes the processing time, inspection time, move time, and waiting time. If the process scheduling results in less total completion time, more is the priority of a machine to get assigned the other product. Therefore, fitness function design in smart manufacturing would be calculated as the weighted sum of processing time, inspection time, move time, and wait time. The greater value of the fitness score represents the high priority of a machine to get assigned the next product for scheduling as formulated in equation (14).

$$Fitness = (\alpha * f_{pt} + \beta * f_{It} + \delta * f_{Mt} + \theta * f_{wt}) \quad (14)$$

where, $f_{pt}$ is the fitness function for processing time, $f_{It}$ is the fitness function for an inspection time, $f_{Mt}$ is the fitness function for move time, and $f_{wt}$ is the fitness function for waiting time.

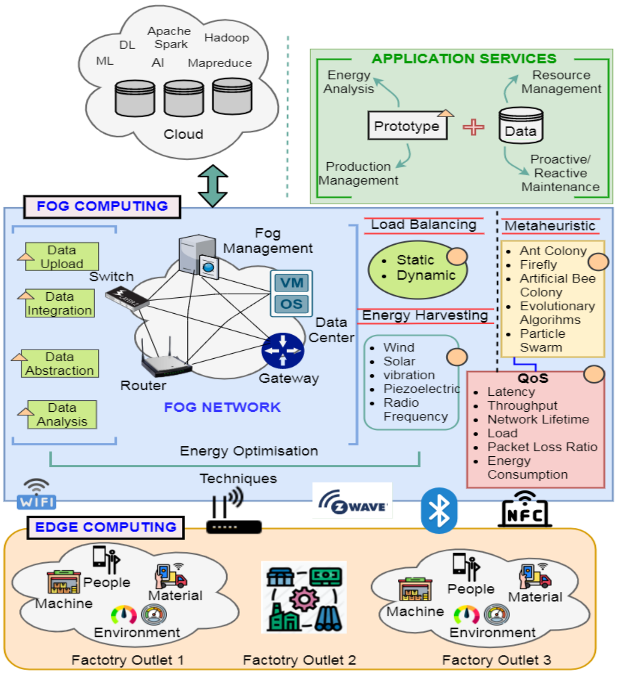


**FIGURE 13.** Metaheuristic-based smart manufacturing for sustainable IoT.

### C. OTHER METAHEURISTIC BASED USE CASES

The optimization of demand and supply of products in smart manufacturing can be done by using the genetic algorithm [113] which in turn maximizes the economic profit of a firm instead of using a traditional model like the Lewis model. Genetic Algorithm (GA) assists customers to understand the product preferences depending upon the various features. In addition, a genetic algorithm can be a good solution for collecting manufacturing waste by optimization [114]. Waste loaders are traced for dumping the waste. For this, a real-time location of dumping areas is required. This issue is resolved by using a genetic algorithm that can identify the geo-locations and the fitness condition is set by the Govt. of India, Urban Development Ministry in the state of Coimbatore.

The ventilation conditions in smart manufacturing are managed through low-cost energy-efficient sensors and a hierarchical-based genetic algorithm [18]. Lighting conditions in smart manufacturing are adjusted via a control algorithm based on the GA technique. Lighting patterns could be considered as chromosomes that contain genes [18]. Fitness criteria determine to preserve or eliminate the light pattern after performing the crossover and mutation operation. Other metaheuristic techniques such as particle swarm optimization with the ZigBee network also contributed to minimum energy consumption and path cost [115]. GA along with Zigbee network and particle swarm optimization searches the route metaheuristically when the network complexity increases.

## VIII. EXPERIMENTAL SETUP

The fitness criteria for quality of service metrics in the proposed framework are implemented on the hybridization of the metaheuristic approaches i.e PSO and adaptive EA called PSO-EA. Adaptive EA controls the mutation and selection rate adaptively with the size of the population. The combined approach of both the algorithms is taken into account to overcome the convergence and search capability issues. The selection, crossover, and mutation, are the main characteristics of an adaptive evolutionary algorithm to generate the fittest population in each round. The detailed working of PSO and the evolutionary approach have been discussed in section IV. The evolutionary algorithm depicts the low convergence speed whereas PSO converges at a faster speed. The flowchart of the PSO-EA hybridized approach is shown in Figure 14. The simulation experiment was performed in MATLAB 2016b. The selection of the potential node in a region to transfer the data packet to the sink node depends upon the fitness values of the performance metrics. The fitness values of the performance metrics such as load, temperature, distance, energy consumption, and delay are calculated from equations (9) to (12) formulated in the proposed framework. The sensor nodes are randomly distributed in a 500m X 500m network area at X,Y coordinate locations. The initial energy of sensor nodes is kept as 1Joule. The experiment uses the elitism strategy that ensures only the elitist candidates are passed on to the next generation by sorting the solutions based on the fitness rank. The second metaheuristic principle followed is the adaptive stop criteria when no change occurred in the objective function. The introduction of the elitism principle subsequently prioritizes the solutions to ensure immunity. Some solutions are discarded in each round that corresponds to the decay principle. The simulation parameters used in the experiment are listed in Table 5.

## IX. RESULTS AND ANALYSIS

Figure 15 demonstrates the comparison of energy consumption of EICAnts [16], PSO [53], ABC-DC [81], and the proposed (PSO-EA) with the varying number of nodes. The total energy consumed is the energy dissipated to send a packet from the normal node to the potential node and from the potential node to the sink node as depicted in equation 11

**TABLE 5.** Simulation parameters.

| SIMULATION PARAMETERS | VALUES |
|---|---|
| Initial population size | 500~500 |
| Network area | 500 $m^2$ |
| Number of nodes | 100 ~ 200 |
| Selection ratio | 0.9 |
| Mutation ratio | 0.5 |
| Amplifier energy | 0.0014$pj/bit/m^2$ |
| Voltage energy ($E_e$) | 50$nJ/bit$ |
| Packet size | 50 *bits* |
| Initial energy | 1$J$ |

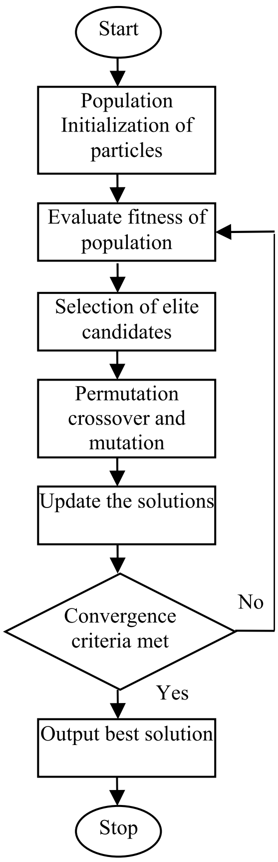


**FIGURE 14.** Flowchart of the PSO and adaptive EA.

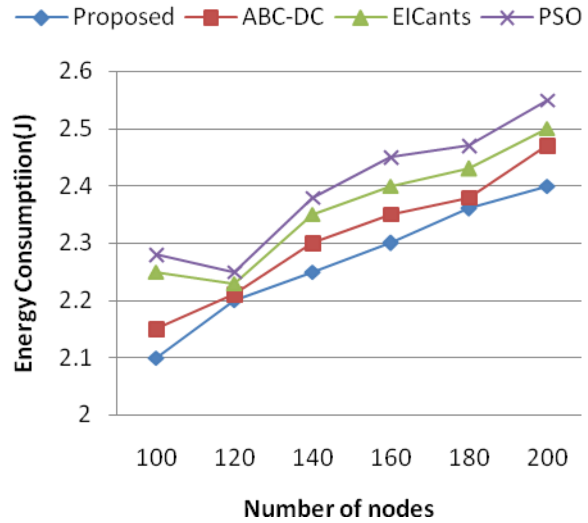


**FIGURE 15.** Energy consumption comparison.

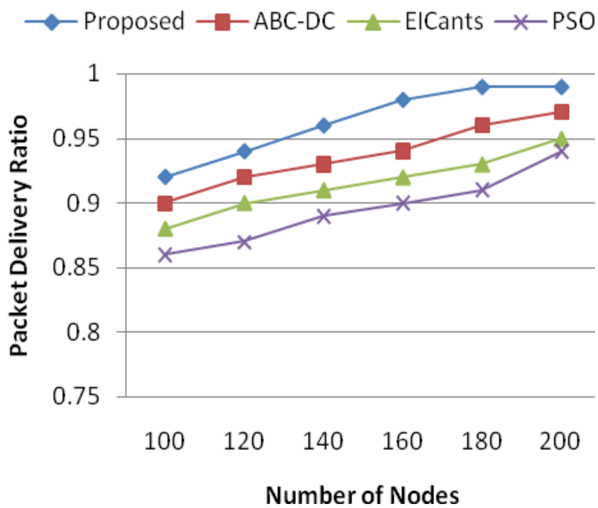


**FIGURE 16.** Packet Delivery Ratio comparison.

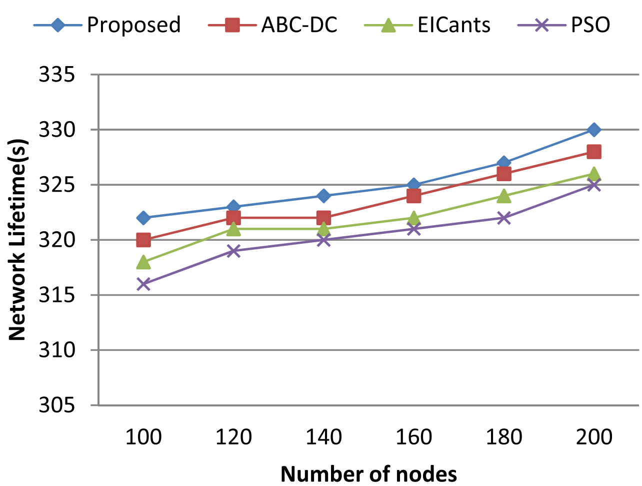


**FIGURE 17.** Network Lifetime comparison.

in the proposed framework. The energy consumed by the proposed technique is significantly low because of the low-cost potential node and optimal route selection in each round by following the elitism strategy that allows the elitist solutions to pass onto the next generation.

Figure 16 shows the comparison of the packet delivery ratio with the increase in the number of nodes. Packet delivery ratio (PDR) is the fraction of packets received by the receiver node and the total packets send by the sender nodes. PDR increases with the increase in the number of nodes by prioritizing the optimal routes to send packets to the sink node by introducing the immunity principle. The delivery of packets via optimal routes reduces the delay as shown in Figure 18.

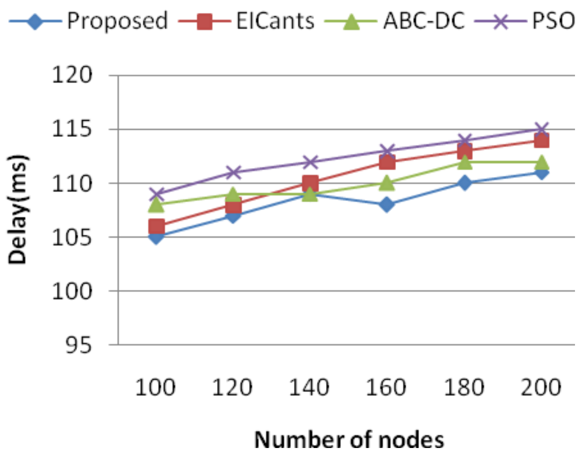


**FIGURE 18.** Delay comparison.

This is because the routes incurring maximum costs are discarded via fitness value. Delay computation is calculated as the maximum transmissions that took place from the normal node to the sink node as shown in equation 13.

Figure 17 depicts the comparison of the network lifetime of the proposed with the EICAnts [16], PSO [53], and ABC-DC [81], with the varying number of nodes. In general, network lifetime is the time of the first node dies in a network. In the experiment, the network lifetime is decided by the 5 percent of nodes that die in the network. The proposed method shows a significant increase in the network lifetime as the increase in the number of nodes increases the probability to choose the optimal path out of the multiple paths.

## X. CONCLUSION

The comprehensive study draws the attention of readers to the intricacies encountered in the metaheuristic-based routing in heterogeneous IoT. The importance of metaheuristic-based routing and the challenges are unleashed that hinder the optimal use of energy in IoT for data transmission. The proposed metaheuristic-based routing taxonomy reveals the fitness evaluation in standardized techniques, its shortcomings, and its hybridized versions in IoT. The comparative analysis of recent metaheuristic techniques along with clustering is performed to determine the beneficence in the current realm of IoT technology. In addition, the merits and demerits of metaheuristic approaches have been portrayed to determine the real-time applicability in smart domains of IoT. The proposed framework provides the countermeasure solutions under different evaluation conditions and the optimal selection of potential nodes for energy efficiency using metaheuristics. In addition, the fitness functions for essential routing metrics are designed to select the potential node to forward the data packets. Also, the proposed framework highlights the main metaheuristic principles by ignorance of which leads to a major bottleneck for the global convergence to the optimal solution. A smart manufacturing-based case study demonstrates the fitness criteria to solve the process scheduling problem. The fitness criteria formulated in the proposed framework is evaluated on the hybridized PSO-EA by employing the elitism, immunity, reinforcement, and adaptive stop criteria principle. The proposed framework shows a significant improvement in energy reduction, delay, network lifetime, and packet loss ratio. Therefore, the performance of the metaheuristic techniques could be effectively determined by employing the metaheuristic principles. The upcoming research must prefer the metaheuristic techniques for self adaptability, configurability property, and better-searching capability by taking into account the metaheuristic principles for energy efficiency in IoT. A novel three-layer framework expands the new area of metaheuristic-based research practices and would address the emerging challenges in the field of IoT. In the future, the proposed framework will be applied to evaluate the performance of metaheuristic techniques with other energy conservation techniques like duty cycling and energy harvesting for energy optimization in IoT.

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