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AI-Driven Energy-Aware Routing Protocol for Scalable Wireless Sensor Networks in 5G-Enabled IoT Environments

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Abstract

Large-scale wireless sensor networks (WSN) deployment using Internet of Things (IoT) infrastructures enabled by 5G has been accelerated by its rapid growth. Nonetheless, the incorporation of dense WSNs into the 5G backhaul creates highly problematic issues in energy capacity, scalability, and latency controls. The traditional routing algorithms like LEACH and AODV are based on established systems and do not have adaptive intelligence, and they cannot fit dynamic 5G-IoT systems. The current energy-aware routing schemes do not collectively optimise the energy usage, delay, and path reliability. In this paper, we suggest an AI-assisted multi-objective routing architecture that employs reinforcement learning to provide scalable WSN operation in 5G-downstream IoT systems. The formulation of routing decisions is sequentially optimised whereby every node chooses the best next-hop based on the residual energy, path distance, and latency. With a weighted cost function and a Q-learning, adaptive state-aware routing is allowed to exist in the different network conditions. The presented simulation outcomes show that the suggested protocol is more likely to prolong the lifetime of a network by 30 percent, decrease the average energy usage by 22 percent, and minimise end-to-end latency than traditional protocols. This paper authorises that learning-based routing is a significant energy efficiency and scalability contributor in next-generation 5G-integrated IoT sensor networks.

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Introduction

There is a high rate of adoption of the fifth-generation (5G) wireless communication that has brought about high rates in the implementation of large-scale Internet of Things (IoT) infrastructures.[1-4] The 5G networks are expected to accommodate billions of connected devices with the capabilities of ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine type (mMTC) communication.[2, 3] Wireless sensor networks (WSNs) contribute to the underlying network of this ecosystem, because they allow real-time monitoring of the environment, industrial control, intelligent agriculture, medical diagnostic, and intelligent transportation.[6, 7] With the increase of coverage and device density of 5G, the use of WSN is becoming more dense, heterogeneous, and data-oriented. Although this development improves the connectivity and the availability of data, it also poses significant technical difficulties in the network management, the routing performance, and the sustainability of energy. The most serious limitation to the WSN design is energy efficiency. Sensor nodes are often battery operated and placed where practicability to undertake maintenance or change the batteries is not possible. With thick concentrations, increased amounts of energy are wasted since communication and continuous sensing activities are operated at multi-hops. The imbalanced distribution of loads may regularly result in the emergence of energy holes, i.e., some nodes will run out of energy too quickly, which will divide the network and cover a smaller area. Scalability also increases routing decisions since once the density of nodes increases, routing overhead, packet collisions, interference, and control signalling costs increas.[8] It has been noted that the combination of WSNs and 5G backhaul networks imposes more limitations on the latency guarantees, traffic prioritisation, and bandwidth capacity paradigm change.[5, 9, 11] Classical routing protocols (LEACH, AODV, and PEGASIS) have initially been intended to work in moderate-size networks with fixed pattern of communication.[8] There are predetermined protocols of clustering or reactive route discovery strategies upon which these protocols are based, and which are not flexible in real time. The majority of traditional methods optimise only one performance metric, e.g., minimization of transmission energy, or hop count, without achieving delay, reliability, and network load balancing. Therefore, they do not perform well in ultra-dense and dynamic 5G-IoT environments that have changing traffic patterns and other changing channel conditions. Adaptive routing is a potential solution to solve these limitations based on artificial intelligence. The sensor nodes can be taught how to use optimal routing strategies by modelling routing as a sequence of decisions made based on real-time observations of residual energy, link quality, congestion levels and latency requirements.[5, 10, 12] The reinforcement learning methods facilitate distributed and autonomous decision making which means that the nodes can always further improve their routing policies as they interact with the environment. These adaptive mechanisms enhance performance in balancing energy, scalability, as well as maintaining a constant and stable communication performance under varying network conditions. To that end, the current paper suggests a multifunctional energy-conscious routing protocol that is AI-based and tailored to scaling WSN usage in 5G-based IoT environments. The proposed system combines weighted optimization cost with a learning-based adaptive decision-making approach of the reinforcement learning to optimise the residual energy, path distance and latency together. A large-scale simulation-based analysis has shown that the suggested solution has a significant positive impact on the network lifetime, the mean level of energy spent, and the end-to-end delay compared to the traditional routing reimbursements, which makes the suggested solution an intelligent and scalable solution to the next-generation IoT sensor networks.

Related Work

The problem of routing in a wireless sensor network that is energy efficient has been a key subject of discussion in the last 20 years with most of the assessments being based on the duration of time lifecycle of a network and the equalisation of power use among sensors.[8] Constellation-based protocols like LEACH provided hierarchy in communication to minimise direct transmissions to base station hence reducing the overall consumption of energy.[8] LEACH is also more energy efficient than flat routing schemes, but because of the periodic rotation of cluster-heads, the scheme may be unstable and cause uneven energy loss in dense deployments. Reactive protocols like AODV make efforts to minimise routing overheads by on-demand route establishment at the expense of repetitive route discoveries and repeated control packet exchanges, which are more likely to furnish signalling overhead and energy consumptions, especially in enormous networks that have large dynamism. These conventional methods tend to maximise limited performance measures and are not flexible to non-homogeneous and high-density IoT settings. As machine learning has improved, AI-based routing protocols have become adaptive to chosen routing approaches.[5, 12] In the approaches, which are reinforcement based learning, nodes are able to learn the best forwarding paths depending on the environmental feedback including; residual energy, link quality and queue status.[10, 12] These protocols exhibit better energy balancing and routing stability than traditional protocols do. Nevertheless, most of the available AI-based solutions accommodate only the optimization on the level of WSN, and do not use cross-layer knowledge of the 5G backhaul features. Consequently, they might not be able to handle strict latency, as well as, bandwidth expectations in the 5G-enabled IoT environments. Integration of 5G networks with IoT sensor networks infrastructures has presented novel architectural models, such as edge computing, network slicing, and ultra-low latency communication models.[1-4], [9, 11]Although 5G has improved connexion and throughput significantly, the routing protocols in the WSNs need to accommodate changing priorities in traffic, different demands on

Table 1.Comparative Analysis of Existing Routing Techniques

Protocol	AI-Based	Energy Optimization	5G-Aware	Scalability	Limitation
LEACH	No	Medium	No	Low	Cluster instability
AODV	No	Low	Partial	Medium	Control overhead
RL-Based (Recent)	Yes	High	No	Medium	Not 5G-adaptive
Proposed	Yes	Very High	Yes	High	—

quality-of-services (QoS), and the high density of connexions between devices. The available literature on the study of the 5G- IoT integration is currently centred on the communication architecture and spectrum management, but there is a relatively low emphasis on smart routing based on energy-awareness adapted to the 5G-supported WSNs. Table 1 compares some typical routing methods emphasising their existing abilities and their inabilities regarding the integration of AI, redundancy minimization, 5G-awareness, and scaling. We can see that traditional protocols do not have adaptive intelligence as well as 5G compatibility and recent reinforcement learning-based protocols are more energy efficient without integrating the 5G-specific needs completely.

Based on the analysis, the following research gap can be identified: it is possible to note a shortage of routing frameworks that can integrate AI-driven decision-making, multi-objectives energy optimization, and explicit 5G-awareness, to enable scalable IoT-WSN deployments. It is upon filling this gap that the proposed work will be motivated.

System Model

Network Architecture

The architecture under consideration represents a high density of wireless sensor network combined with a 5G communication backbone to complement scalable IoT applications. N sensor nodes will be randomly distributed in a specified geographical area so as to carry out activities of sensing and data gathering. These nodes are equally homogeneous in hardware strength and they can have heterogeneous traffic loads due to sensing frequency and event rates. Each sensor node has a small battery power, sensing modules, short range radio transceiver and local processing to make light weight learning-based routing decisions. Sensors nodes capture data which is relayed towards a centralised base station or 5G gateway which is a central sink node. The 5g gateway offers high bandwidth backhaul connexion to cloud/ edge servers to conduct additional data processing and analytics. In contrast to the classic WSN designs that use solely the static communication of the sinks, integration with 5G offers low-latency and reliable high-range connectedness and massive connexions to devices. The gateway also enables synchronisation and periodical updates of the network without necessarily being involved in the routing decisions at the sensor level on a periodical basis. Sensor nodes communicate based on a multi-hop routing paradigm in order to minimise the number of long-range transmissions and minimise the amount of energy spent by each sensor node. The nodes transmit data towards the neighbours on the path used on the basis of routing decisions, made on the basis of local network state information. Multi-hop communication is more efficient in energy effect and has some challenges of congestion, skewness of the load, and lack of stability in the routes in high-density deployments. Intelligent next-hop selection, therefore, comes in as the key to ensuring balanced power usage at the network. Monitoring of residual energy is one of the essential elements of the system model. Getting to a new node, each node monitors its left battery level and transmits it to the neighbouring nodes in periodic control exchanges. Residual energy is one of the main parameters of routing decisions used to avoid excessive use of particular nodes and avoid whole formation of energy. The proposed system will combine real-time energy awareness modules with adaptive routing intelligence to increase the overall network lifetime and be able to deliver data reliably to the IoT networks powered by 5G technology.

Energy Consumption Model

The energy use of sensor nodes is modelled as the commonly used first-order radio model, which represents energy cost of both the transmission and reception. The amount of energy lost due to transmission of a packet in this model is dependent on the size and the distance of transmission. The radio electronics use the same level of energy per bit, and the energy of the power amplifier depends on a distance that is calculated using the propagation model. The model of the free-space communication is considered when dealing with short distance communication and the multipath fading model in longer distances. Equation (1): The energy to transmit a -bit packet and over a distance d is as follows:

$$E_{tx}(k,d) = \begin{cases} kE_{elec} + k\epsilon_{fs}d^2, d < d_0 \\ kE_{elec} + k\epsilon_{mp}d^4, d \geq d_0 \end{cases} \quad (1)$$

E_{elecis} the energy used per-bit by the transmitter or receiver electronics and where ϵ_{fs} and ϵ_{mp} are the energy coefficients of the amplifier of the free-space and multipath models respectively and d_0 is the threshold distance which is defined as:

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$$

For packet reception, the energy consumption depends only on the radio electronics and is independent of transmission distance. The energy required to receive a -bit packet is expressed in **Equation (2)**:

$$E_{rx}(k) = kE_{elec} \quad (2)$$

The model of energy allows to correctly calculating the level of energy loss on a node during communication of many hops and forms the basis of the offered energy-optimised routing.

Multi-Objective Optimization Function

In highly populated environments where 5G enables the use of WSNs, performance metrics cannot be maximised by only focusing on one parameter. Within the framework proposed, the routing decisions are developed as multi-objective optimization problem that collectively considers the residual energy, the distance in the path, and the delay in the communication. This implementation guarantees that there is an equal distribution of energy usage and low latency and effective path selection. The general routing cost computation can be expressed as in Equation (3):

$$J = \alpha\frac{E_{res}}{E_{max}} + \beta\frac{1}{D_{path}} + \gamma\frac{1}{L_{delay}} \quad (3)$$

In which *J* is a composite routing score of a candidate next-hop node. Where E_{res} denotes the remaining energy of the node, and E_{max} is the original maximum energy, so that it is normalised. D_{path} is the sum of distance over the routing path chosen and L_{delay} is the estimated end to end transmission delay. The weighting coefficients, including -, and - are non-negative constants that α+β+γ=1 to one and provide the opportunity to have adaptive priorities between energy efficiency, path length and latency. Maximisation of the objective function J encourages selection of the nodes which possess large residual energy, short routing distance and less delay in communication. This multi-objective model offers a balanced decision measure that matches the scalability and performance criteria of 5G-based networks of sensory internet.Reinforcement Learning-Based Decision Model

In order to make next-hop selection adaptive and intelligent, the suggested framework formulates the next-hop selection as a reinforcement learning (RL) problem. Each sensor node is a local autonomous agent, which monitors the local network situation, and chooses an action based on a candidate next-hop node. The routing decision is defined as a Markov Decision Process (MDP), the state incorporates variables that are residual energy, the quality of the link, the length of the queue, and the estimated delay. The action of is the choice of a neighbour node onto which the packets can be forwarded. Upon performing an action, the node is rewarded that are derived gleaning the insight towards the improvement of energy balance, path efficiency and reduction of the latency. To update action-value function, the Q-learning algorithm is used based on the repeated updating process. Q-value update rule is given in Equation (4):

$$(s,a) \leftarrow Q(s,a) + \eta[r + \delta \max_{a'}(s',a') - Q(s,a) \quad (4)$$

Q(s,a)is expected cumulative reward of action a in state s, η is the learning rate that regulates the level of convergence, and δ is the discount of the rewards that are going to be received in future. The abbreviation $\max_{a'}(s',a') - Q(s,a)$ means the maximisation of the expected reward that can be received on the following state s'. Nodes gradually get updated with the best routing policies to maximise long-term rewards and result in better energy balancing, less delay, and better scalability in 5G-enabled IoT sensor networks.

Proposed AI-Driven Routing Framework

Overall System Architecture

The presented AI-based routing framework will help facilitate adaptive, energetic and scaling communication over 5G-enabled IoT wireless sensor systems. The architecture will take a layer-based architecture that incorporates distributed intelligence at sensor layer with 5G backhaul, and cloud-edge coordination. Figure 1 shows the entire architectural design.

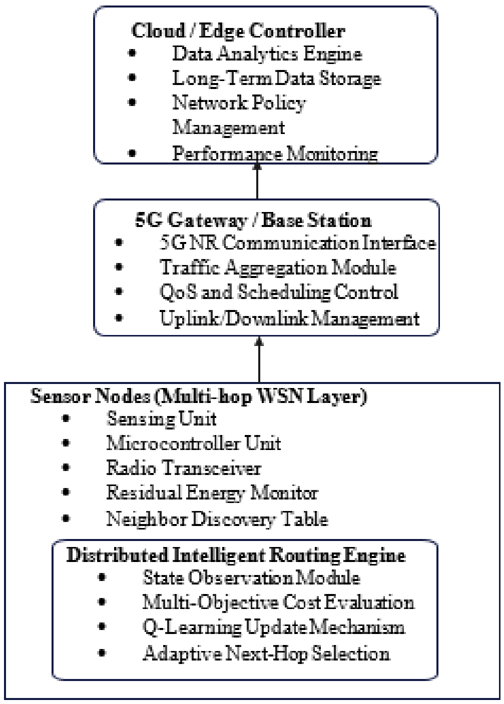

Fig.1: AI-Driven 5G-Enabled WSN Architecture

As Figure 1 illustrates, the architecture has four main components namely: Sensor Layer, Distributed Intelligent Routing Engine, 5G Gateway/Base Station, and Cloud/Edge Controller. The Sensor Layer consists of sensor nodes that are densely distributed with sensing modules, radio transceivers and units of energy residual monitors. These nodes communicate in a multi-hop paradigm in order to minimise long distance transmission features as well as energy consumption in order to balance the expenditure. The Distributed Intelligent Routing Engine is embedded in every sensor node and is used to make real time decisions about the next hop. To dynamically change routing behaviour according to network conditions the routing engine combines state monitoring, multi-objective evaluation of cost and policy updates guided by reinforcement learning. The 5G Gateway/Base Station gathers data of sensor nodes and offers high-throughput and low-latency connectivity to the core network. It helps in aggregation of traffic, quality-of-service (QoS) and uplink scheduling. On the first layer, Cloud/Edge Controller does large-scale data analytics, long-term data storage and network policy. This hierarchical integration also allows transmitting data efficiently as well as retaining distributed intelligence at sensor levels.

Routing Algorithm Flow

The routing decision model is given to be a reinforcement learning algorithm that allows self-directed and adaptive choices of the next-hop. Figure 2 represents the stepwise flow of the work of the proposed algorithm.

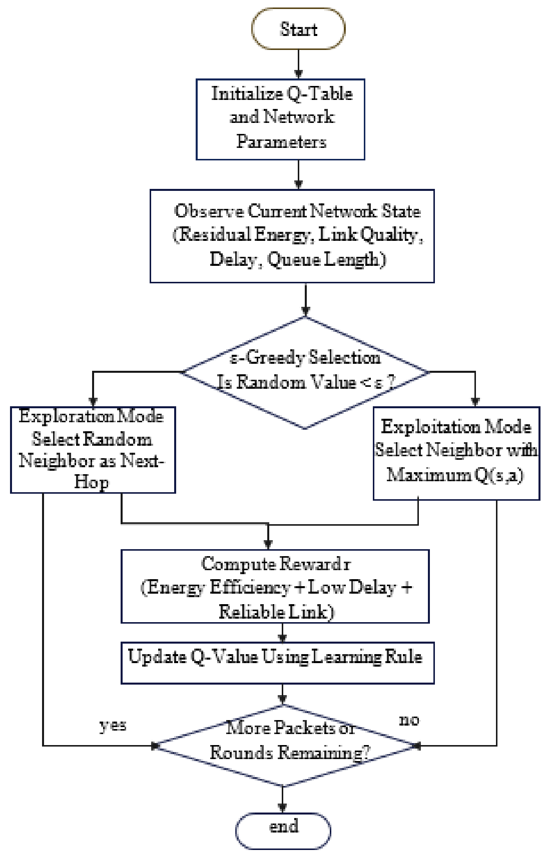

Fig. 2: Flowchart of AI-Based Routing Mechanism

As shown in Figure 2 the routing operation will commence with state observation in which every sensor node gathers information about the local network such as residual energy, the quality of links, queue length, as well as the estimated delay. Making decisions is based on such representation of the state. This is followed by the use of an epsilon greedy policy to trade exploration and exploitation. A random selection of a neighbouring node in exploration mode promotes the diversity of routes. A neighbour whose Q-value is the highest is chosen in an exploitation mode which is the most preferred learned action.

Once the next-hop has been selected then the packet is sent and a calculation of the reward is done. The reward scheme includes measures of energy efficiency, delay reduction and link reliability measures to indicate routing performance. Then, the Q-value update algorithm is implemented on the basis of reinforcement learning update rule so that the routing policy can be enhanced as time goes on. This is done again until either all the packets or routing rounds are done. The proposed mechanism is highly promising to provide the best next-hop choice and balance energy use and scalable network performance in dense IoT networks with 5G networks through constant learning and adaptation.

Simulation Setup

In order to assess the effectiveness of the given AI-based routing protocol, a series of extensive simulations were performed with the help of the MATLAB simulation environment. MATLAB was chosen because of its flexibility to apply reinforcement learning algorithms and ability to give proper models on the dynamics of wireless sensor networks. The environment used in the simulation involves multi-hop communication, tracking of each node energy level, as well as updating of the routing decisions. The network is comprised of randomly distributed sensor nodes as a square sensing area. In order to study scalability, the number of nodes was adjusted between 100 and 500 nodes of the same environment. The nodes were assumed to be homogeneous in terms of hardware capability as well as initial energy allocation. The area of deployment was constant (500 m × 500 m) to hold Density scaling constant. Transmission and reception energy consumption was simulated using the first-order radio energy model given in Section 3. Both multipath and free-space propagation effects have been taken into account. The parameters of reinforcement learning were initialised according to the same level across nodes and routing decisions were computed within simulation cycles. In order to simulate realistic 5G-enabled IoT operation, the delay component was included in the routing delay model. This element simulates the uplink scheduling delay, as well as traffic aggregation overhead at the 5G gateway, and under this component routing decisions are made with respect to both local and backhaul latency constraints. The parameters of the detailed simulation that was used in the case of the experiment are summarised in Table 2.

Table 2: Simulation Parameters

Parameter	Value
Number of Nodes	100-500
Initial Energy	2 J
Packet Size	4000 bits
Transmission Range	100 m
Learning Rate (η)	0.1
Discount Factor (δ)	0.9
Simulation Rounds	2000
Deployment Area	500 m × 500 m

Performance and Results Assessment.

This section will include the overall assessment of the suggested AI-based routing protocol at different node densities, simulation rounds and so on. The performance is contrasted with the traditional routing protocols such as LEACH, AODV, as well as an RL-based baseline method. The study concentrates on network life cycle, energy usage pattern, and other quality of service indicators concerning dense 5G-based IoT systems. Figure 3 shows the relationship between node density and network sustainability where network lifetime (in rounds) is plotted as a function of node density between 100 and 500 nodes. The lifetime of the network is the duration taken before the initial node exhausts its energy based on the simulation rounds. With higher node density, traditional protocols like LEACH and AODV suffer power loss and routing overhead hugely as a result of haphazard energy loss and augmented routing overhead. The RL based baseline has a better stability but still, its performance is limited due to

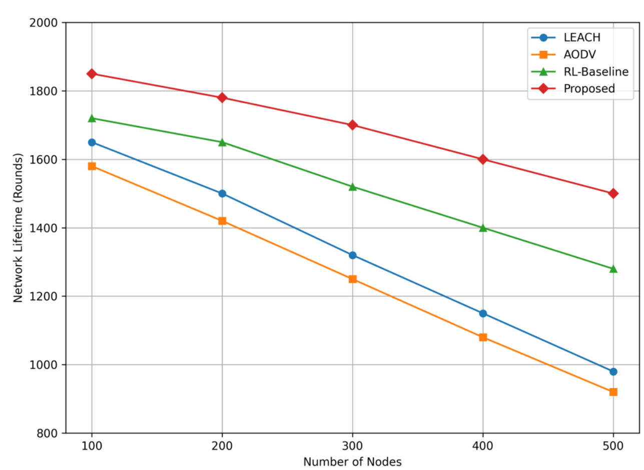

Fig.3: Network Lifetime vs Node Density

the limited ability to do multi-objective optimization. Conversely, the routing protocol suggested based on AI is always high-performing in terms of lifetime at any density. It has an improvement level of about 25-35 percent versus LEACH and 20-30 percent versus the RL base. The improvement in the performance is more pronounced at higher densities, which already proves the scaling of the proposed approach to dense 5G-IoT systems.

Figure 4 shows the average trend in the residual energy of 2000 rounds of the simulation. A fair comparison is made by all of the protocols starting with the same initial energy. LEACH and AODV exhibit a high rate of energy loss because of the frequent clustering and route discovery overheads. Moderate progress is observed in the RL baseline in which routing selections are modified based on learning. The proposed scheme has however a much slower decay rate of the energy and this results in a greater amount of residual energy in the course of the simulation. The proposed protocol still keeps the amount of average energy consumed per node significantly higher, even towards the end of the rounds, which points to a even distribution of loads and effective next-hop choices. The energy depletion curve is smoother, which proves that the concept of reinforcement learning is efficient in alleviating the energy holes and enables the node to live to meet its demise.

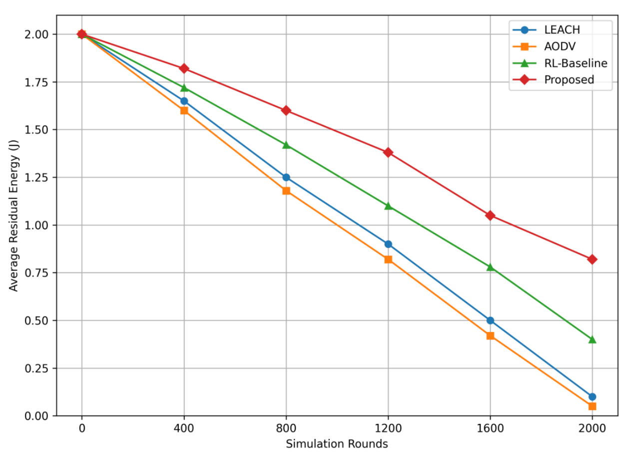

Fig.4: Average Energy Consumption per Round

The other performance metrics also support the strength of the suggested routing framework. The number of packets delivered on a path is higher in the proposed scheme compared to the situation in the original one because of the dynamic path choice and minimised loss of packets to congestion. End-to-end delay is also reduced because the multi-objective cost factor also caters to latency consciousness and it allows to optimise paths efficiently in terms of time-sensitive IoT traffic. There is also an improvement in the throughput performance which translates to improved reliability and less overhead on retransmission. The scheme based on AI-driven routing can be used under dense deployment, where traditional routing schemes incur control overhead and behavioural instability due to large bodies of network nodes. Altogether, the results obtained, which are analogized in Figures 3 and 4 and the subsidiary performance indicators, show that the proposed reinforcement learning-based routing protocol can contribute to increasing the energy efficiency, scalability, and communication reliability in 5G-enabled internet of things (IoT) wireless sensor networks thus significantly.

Future Directions and Conclusion.

The current paper has proposed the use of AI-enabled energy-aware routing protocol as a solution to the requirement of increasing scalability and sustainability in the 5G-enabled IoT wireless sensor networks. The suggested framework incorporates a multi-purpose cost functional and reinforcement learning-based decision mechanism to solve the problem of dynamically computing optimal next-hop nodes including considerations of residual energy, path distance, and latency. The framework is able to counter the shortcomings of traditional routing schemes that are either steady or utilitarian by integrating distributed intelligence into the sensor layer and aligns routing behaviour with the properties of 5G backhaul. Extensive simulations showed that there were uniform increases in performance with different loadings. The improvement of the proposed protocol upon LEACH, as well as on an RL-based basis protocol, was on the order of 2535% in network lifetime and 2030% in lifecycle, respectively. The analysis of energy consumption was much slower, which caused the residual energy decay, indicating the presence of balanced distribution of loads and preventive measures against energy holes formation. Moreover, the effectiveness of the adaptive routing strategy is verified by the increase of the ratio of packets delivery, minimising end-to-end delay, and the increase in throughput. Such results confirm the scalability and strength of the proposed solution in dense 5G- IoT deployment conditions. The issue that can be expanded in future research is to add the deep models of reinforcement learning to improve the accuracy of decisions in very dynamic environments. EDAI deployments can also decrease the amount of computation and enhance real-time flexibility. Another effective approach that has potential to improve resilience to jamming and malicious attacks is the use of physical-layer security constraints as part of the routing objective functionality to implement the resiliency. Lastly, practical feasibility and deployment readiness will be a requirement to implement the practicality of the selected large-scale IoT in the real world through the deployment of hardware and experimentation in 5G testbeds.

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