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RESEARCH ARTICLE

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Adaptive Intelligence Techniques Integrated Robust and Efficient Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) are crucial for environmental monitoring and industrial automation, but face challenges like crowded transmissions, ad hoc deployment, unattended operation, and limited resources. The Dynamic Packet Congestion Control with Reinforcement Learning (DPCC-RL) and Adaptive Topology Management with Swarm Intelligence (ATM-SI) are proposed that can be integrated to improve network performance in Wireless Sensor Networks (WSNs). DPCC-RL uses reinforcement learning to address crowded packet transmissions, while ATM-SI addresses ad hoc sensor node deployment challenges by optimizing network topology. SAEM-RS, on the other hand, focuses on unattended operation, where sensor nodes must operate autonomously for extended periods. It adjusts sleep-wake schedules based on reinforcement learning decisions and swarm intelligence feedback, optimizing energy consumption during data transmission and ensuring nodes are awake when necessary. These techniques collectively improve network reliability, adaptability, and longevity, making them a robust solution for enhancing WSN performance in complex real-world scenarios. The findings demonstrate that, in comparison to previous techniques, the suggested approach achieved high levels of accuracy, precision, recall, and F1-Score.

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INTRODUCTION:

In the modern era, several industries have seen revolutionary changes as a result of the Internet of Things (IoT) and Wireless Sensor Networks (WSN) merging with one of the most impactful applications being video routing surveillance on roadways.[1] This fusion of technology has empowered cities and transportation authorities to enhance traffic management, improve road safety, and monitor traffic conditions in real-time.[17] However, the effective deployment and operation of such IoT-enabled WSNs for video routing surveillance pose significant challenges, primarily pertaining to energy efficiency and congestion control.[2, 3]

As urbanization continues to grow, the demand for efficient and safe road transportation systems becomes increasingly critical.[18] Video routing surveillance systems have emerged as indispensable tools for monitoring and managing roadways. These systems involve the deployment of numerous sensors and cameras along road networks to capture real-time traffic data, detect accidents, monitor weather conditions, and enforce traffic regulations.[5] The collected data is then processed and transmitted to central control centers, enabling prompt decision-making and timely responses to traffic incidents.[4]

While the benefits of video routing surveillance are undeniable, they come at a cost.[19] The energy consumption of IoT devices and sensor nodes, which are often battery-powered and deployed in remote or challenging environments, presents a significant challenge.[7] Prolonging the battery life of these devices is crucial to ensure the long-term sustainability of the surveillance system, reduce maintenance costs, and minimize environmental impact. Consequently, optimizing energy efficiency is paramount.[6, 20]

Furthermore, as the quantity of IoT-capable devices within WSNs rises, congestion on the network becomes a pressing issue.[8] Congestion can result in data packet loss, delays in information transmission, and compromised system reliability. Effective congestion control mechanisms are essential to ensure that data from surveillance cameras and sensors can be efficiently transmitted to the central control centers without overwhelming the network.[9,21]

This research aims to address these critical challenges by developing advanced techniques for energy-efficient operation and congestion control in IoT-enabled WSNs used for video routing surveillance on roadways. By exploring innovative algorithms, network architectures, and communication protocols, seek to maximise the way that sensor nodes are utilised energy resources and mitigate congestion issues.[10]

The research's later portion will examine the essential elements of energy-efficient and congestion control techniques, review existing literature and technologies, and propose novel solutions tailored to the unique requirements of video routing surveillance on roadways. The ultimate goal is to contribute to the development of sustainable, reliable, and resilient IoT-enabled WSNs that can support the growing demand for enhanced roadway monitoring and traffic management in our urbanized world.[12]

The key contribution of the work is enumerated as follows

- Ad hoc deployment, resource constraints, crowded packet transmissions, and unattended operation are some of the difficulties faced by wireless sensor networks (WSNs). To address these, a novel research approach that combines adaptive techniques and self-management is needed to enhance resource preservation and data packet management.
- The network environment is defined, and an adaptive congestion control system is created using reinforcement learning and Deep Q-Networks, rewarding actions for reduced congestion and improved data delivery.
- Swarm intelligence principles optimize network topology, guide node mobility, and coordinate energy-intensive tasks to minimize overlap and reduce contention, using PSO rules and DPCC-RL technique.

The remaining portions of the article are structured as follows: Section 1 describes the introduction; Section 2 summarises the previous research; and Section 3 outlines the suggested methodology. The results of the suggested work are shown in section 4, and the article ends in section 5.

Literature Survey

Uzma Majeed et al.[11] described an energy-efficient distributed congestion control protocol (DCCP) for improving network performance and lowering end-to-end latency. The protocol detects congestion, aggregates information, using two congestion indicators, and creates a map of traffic congestion. This map finds the best route by balancing traffic on several routes and lowering end-to-end delay. Congestion is avoided by delivering warnings to source nodes and altering transmission rates accordingly. The suggested DCCP protocol outperforms existing modern congestion control techniques in experiments.

Daniyal Alghazzawi et al.[22] used MATLAB to demonstrate a model that divides relationships based on evapotranspiration and humidity under various settings. The model's ability to produce comparable variants from the same source value shows its effectiveness and fairness. In ideal zones, the model also depicts increased throughput and lower delay rates. 1.24 is the propagation rate, which exceeds the link capacity value. The additive increase and multiplicative decline conditions are outperformed by the congestion control, among other characteristics.

S. M. Aghdam et al.[13] have suggested in order to reduce packet loss in WMSNs, a novel content-aware cross-layer protocol (WCCP) was suggested. This protocol takes into account the characteristics of traffic, the packet inter-arrival pattern, and the video packet priority. Comprehensive simulations proved the accuracy of the GOP size forecast approach, the congestion method, and the queuing method.

Meera S. et al.[14] suggested Prioritized Interface Queue introduced dual queue in wireless sensor networks to reduce congestion by employing a multi-layer strategy. The utilisation of an intermediate node suggests a congestion control technique to enhance network efficiency by slowing down the data transfer rate to downstream nodes.

According to Naimah Yaakob et al.[15] massive data loads can quickly generate network congestion due to dynamic changes in routing patterns. Congestion has caused considerable delays on the network. As a result, congestion increases the likelihood that data packets may be lost, and the energy used to forward packets to the gateway node is high. To improve performance, a great deal of research has been done. To avoid congestion in the wireless body sensor network, Relaxation Theory with Max-Min Fairness (RT-MMF) is used.

Hasan Ali Khattak et al.[16] discussed various cross-layer design techniques are applied in wireless multimedia sensor networks. Modern cross-layer optimisation techniques are explained using various architectural techniques, as well as important obstacles and issues, as well as future directions.

Self-Adaptive Energy Management with Reinforcement Learning and Swarm Intelligence (SAEM-RS)

From industrial automation to environmental monitoring, WSNs are essential to many applications. WSNs face numerous challenges, including crowded packet transmissions, ad hoc deployment, unattended operation, and limited resources. Crowded packet transmissions result from a large number of sensor nodes simultaneously transmitting data packets, leading to congestion, potential packet collisions, and degraded networks. Ad hoc deployment creates irregular and unpredictable node distribution, causing difficulties in establishing efficient communication routes. Unattended operation, where sensor nodes operate autonomously without human intervention, leads to limited access for battery replacement or reconfiguration. These challenges highlight the complexity of managing data packets in WSNs. Addressing these constraints is crucial for ensuring the reliability, energy efficiency, and effectiveness of WSNs in real-world applications. To address the issue of crowded packet transmissions in WSNs and mitigate the associated challenges, a novel Dynamic Packet Congestion Control with Reinforcement Learning (DPCC-RL) technique is proposed. Initially the network environment is defined, including sensor nodes, communication channels, and congestion factors. It uses reinforcement learning with Deep Q-Networks (DQN) to create an adaptive congestion control system that reduces congestion, improves data delivery, and enhances energy efficiency. This dynamic approach to congestion control can potentially outperform static methods. Adaptive Topology Management with Swarm Intelligence (ATM-SI), is proposed to overcome challenges posed by ad hoc deployment of sensor nodes in WSNs. It uses swarm intelligence principles to dynamically adapt and optimize network topology, ensuring efficient communication routes even without a pre-established infrastructure. The fitness function is defined by factors like node density, proximity, and communication quality. “Self-Adaptive Energy Management with Reinforcement Learning and Swarm Intelligence (SAEM-RS),” is proposed to address challenges in unattended operation. It allows nodes to autonomously adjust their sleep-wake schedules based on reinforcement learning decisions and swarm intelligence feedback. This optimizes energy consumption and ensures nodes are awake when necessary, enhancing the sustainability of unattended WSNs. The integration of the novel techniques offers a comprehensive solution for WSNs, optimizing data transmission in crowded environments, addressing ad hoc deployment challenges, and ensuring efficient energy management for unattended operation.

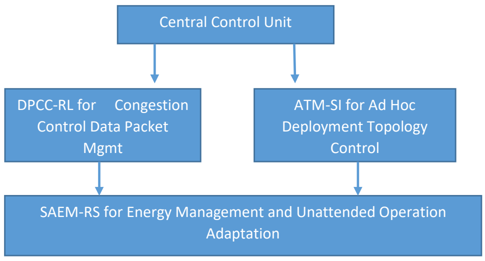

Fig. 1: Block diagram for the proposed method

Adaptive Topology Management with Swarm Intelligence (ATM-SI)

Problems in many domains, particularly computer science and engineering, are resolved by the approach known as particle swarm optimisation was first introduced with reference to social and intellectual behaviour. The individuals—henceforth known as particles—move across the multi-dimensional space of searching, each of them standing in for a potential fix for the multidimensional optimisation issue. The fitness of each solution is determined by a performance function associated with the optimisation problem that has to be solved. Two factors which employ data from particle to particle and iteration to iteration affect the movement of the particles. Because iteration-to-iteration data is used, the particle stores the best solution it has visited thus far, called pbest, in its memory. While traversing the solution search area, it is drawn to this solution. Particle-to-particle interaction causes the particle that retains the best possible outcome that it has ever visited and to become established to this remedy, also known as gbest. The terms “cognitive” and “social” components refer to the first and second factors, respectively. The pbest and gbest for each particle are updated if, over the course of an iteration, a better or more dominant solution (in terms of fitness) is discovered. Iteratively, this process goes on until the desired outcome is reached or it is concluded that no workable solution can be found within the computational constraints. The ith particle of the swarm is represented by an n-dimensional vector for an n-dimensional search space is given by $A_i = (a_{i1}, a_{i2}, ..., a_{in}$ $V_i = (v_{i1}, v_{i2}, ..., v_{in})T$ is another n-dimensional vector that represents the particle's velocity. $p_i = (p_{i1} + p_{i2})...., p_{in})T$ represents the ith particle's previously best visited position. In the swarm, the best particle is indicated by the index *'g'*. The formula for updating velocity (1) is used to update the ith particle's velocity is provided by

$$\upsilon_{id} = \upsilon_{id} + c_1 r_1 (p_{id} - a_{id}) + c_2 r_2 (p_{gd} - a_{id}) \tag{1}$$

and the position has been revised utilising

$$a_{id} = a_{id} + v_{id} \tag{2}$$

where c_1 and c_2 are constants, also known as parameters for social and intellectual scaling, correspondingly (typically, $c_1 = c_2$; r_1 and r_2 are uniformly distributed random numbers in the interval [0, 1]); and d = 1, 2....n ; i = 1; 2....S, where S is the swarm's size. The original PSO algorithm is represented by equations (1) and (2). The search resolution is increased by arbitrarily limiting the particle velocities with a constant called Vmax. To further enhance the management of exploration and extraction, the notion of an inertia weight was developed. The desire to eliminate the requirement for Vmax served as the driving force. The particle swarm optimisation algorithm was first described by adding an inertia weight (w) to the calculations and the velocity update equation (3) that results is as follows:

$$V_{id} = w * v_{id} + c_1 r_1 (p_{id} - a_{id}) + c_2 r_2 (p_{gd} - a_{id}) \tag{3}$$

The best course of action aims to reduce w linearly to 0.4 starting with a value of 0.9. This allows for preliminary exploration and then acceleration in the direction of a better global optimum.

Particle swarm optimisation is primarily an algorithmic approach that seeks to iteratively enhance a potential solution with respect to a given quality metric. Any optimisation problem must first be formulated in accordance with the optimisation problem in order to be solved. Based on fitness value, which is established by the shortest path a data must take to reach the base node, the best path must be chosen in this proposed algorithm. Since working with energy-efficient routing, the longer the data must travel, the more energy will be lost during data transmission. Therefore, using PSO to calculate fitness value and creating an optimal path that takes into account all sensor nodes. Finding each path's fitness value is necessary to determine the optimal plan of action utilising PSO. The local and global best for PSO will be chosen using this fitness value. The optimal path is the one with the lowest fitness value.

$$(fitness\ value = d(i,j)+d(j,b) \tag{4}$$

Where i and j are the node.

Since the PSO equations shown in equations (1) and (2) above operate on real number values, it can generate paths more easily by using the natural number system. To do this, use the shortest positioning index, which sorts values from minimum to maximum value and assigns positions correspondingly. The algorithm is given below

Step 1	Phase of Initialization
	for(s=0 through no.of populations or solutions)
	for(d=0 to the sensor node count)
	Solutions are chosen at random
	Use the solution to compute a new route.
	End for
Step 2	Phase of Update
	while the criteria are not compatible
	for(s=1 to no .of solutions or populations)
	for(d=1 to number of sensor nodes)
	PSO update equation is used to update the solution.
	Create a new path by utilising the updated solution.
	End for
	Calculate the updated route's fitness value.
	Determine the local and global best.
	End for
	Note the global best
	End while

PSO has been used to find the most efficient route that uses the least amount of energy. To create an initial solution, select a random number of solutions from the set of a! Solutions; a is the total number of solutions. Determine the fitness value of each solution using equation (4) after obtaining the initial random solutions. Next, determine which solution overall is best, and designate it was the first best both locally and globally. Utilising the PSO update formula, calculate the nodes of new solutions and update old ones. Every solution's fitness value is then determined using these solutions and their nodes. Until the specified iteration is satisfied, the procedure will be repeated. The solution that performs better than the others is substituted depending on the fitness value and continuous iteration. Thus the shortest path was found in the WSN. After that to avoid congestion Dynamic packet congestion control with RL.

Dynamic Packet Congestion Control with Reinforcement Learning (DPCC-RL)

Establish the congestion control's control objective and use a Markov decision process (MDP), which is a tuple (S, A, P, R, γ), before implementing DPCC-RL. Where P represents the probability matrix of state transition, R denotes the reward function, γ signifies the discount factor, S comprises a collection of states, and A comprises a set of measures. Reinforcement learning is used because obtaining the P in this intricate setting is not possible. Conventional Congestion control systems similar to TCP usually treat all flows equally and use the same approach to each one. This means that during a network's bandwidth is shared by various flows during the congestion avoidance phase when data is sent at the same speed. However, in WSN, the best possible control can attained through collaborative optimization and full utilization of the new features. Different strategies can be used for different types of content through fusing the features of the content with the demands and specifications of the user.

When different contents share a link, content-based fairness, which is more reasonable for WSN, can be realised (a distinct speeds of transmission can be used for different contents to better meet various needs). WSN networks are able to offer users improved service in this way. Therefore, delivering the best service to users while preserving network stability is the main goal of congestion control in WSN. To be more precise, content-based bandwidth allocation aims to equitably distribute available bandwidth among different types of content while avoiding overburdening the network with requests.

A scheduling program that uses the window mechanism based on DPCC-RL should be introduced in order to accomplish the aforementioned goal. Finding the best cwnd (which stands for the total consumer throughput) decision policy is the aim of the DPCCRL-based window mechanism model. To fill the pipeline, the scheduler schedules multiple Interests based on different needs. The user's requirements for various contents (including priority), the request's specifications, network performance, fairness, and other aspects can all be taken into account by the scheduling strategy. The utility function defined later affects both the scheduler and the window mechanism.

Although not only would a high-dimensional state space increase the computational load but also slow down convergence, DPCC-RL is capable of handling continuous, high-dimensional state spaces. Therefore, simply selecting the state variables makes sense that are appropriate for representing the network states and recording action execution. As explained below, consider a ten-dimensional variable to be the state space in this instance. Additionally to avoid interference between successive monitor intervals and meet the Markov property, separate the monitor interval from the decision-making interval, and discard the mixed portion of any two monitor intervals. *i_prefix* the content request's prefix and *i_prioritise* the content request's priority parameter (introduced later). The monitor interval comprises of the following: *i_cwnd* the window in which packets of interest can be sent immediately; *i_count* the total amount of interest packets that were sent; *d_count* the total amount of packets of data received; *l_count* the total number of packets retransmitted; *d_size* the size of the received data packets on average; *d_rtt* the average RTT of the data packets received, *m_time* interval time between the monitors, *d_time* the decision interval time.

By using the actions of previous congestion control algorithms, such as ICP, BBR, and others, to adjust the size of cwnd in response to changes in the network environments, the sending rate of interest packets is primarily controlled. In order to make the DPCC-RL-based model's action space simpler, seven actions have been selected here, taking into account the rate of convergence and the computational complexity. These actions directly impact the size of the window for Interest packets are sent; the window remain in place until a different action is decided upon and the current monitor interval is completed. Ultimately, discover that these values can provide acceptable performance in a variety of WSN network scenarios.

DPCC-RL depends on the definition of reward. It is unreasonable that the majority of current WSN congestion control works treat all contents equally. Designing the utility function of a single piece of content in this way will address different content characteristics and multiple user requirements:

$$Utility(t) = \alpha_i . \log\left(throughput_i(t)\right) - \beta_i . RTT_i(t) - \gamma_i . loss_i(t) - \delta_i . reordering_i(t) \quad (5)$$

where p_{pi} various content types and monitor intervals are represented by t > 0 and $i \in \{1, 2, \ldots, N\}$. The parameters α_i, β_i, γ_i, and regulate the relative importance or weight of throughput, loss rate, average RTT, and packet reordering (as indicated by the occupancy rate of the sort buffer), which stores contents that cannot arrive in the serial number order and have not yet been written to file) within the current interval. These parameters are pertinent to use. To put it another way, In order to minimize packet reordering, delay, and loss rate, the control objective of a single content request is to maximize throughput. The utility function of a single piece of content informs the scheduling strategy as well as the overall utility function that is shown below. When multiple contents share a bottleneck link, the log function of throughput guarantees that the contents will converge. Next, define the following as a consumer's total utility function across various applications:

$$\widehat{Utility}(t) = \frac{1}{N}\sum_{i=1}^{N} P_{pi}.Utility_i(t) \qquad (6)$$

where P_{pi} is the priority parameter supply to help the scheduler distinguish between various material with different specifications. A proportionate allocation factor can also be applied to it. The ultimate goal of congestion control in WSN is to maximise the consumer's maximum utilisation of bandwidth resources to satisfy user demands without causing congestion, guarantee that high priority applications are always served first but low priority applications are never left out, and calculate the long-term total utility value. This is specified by the total utility function. Because the action in DPCCRL is assessed using a numerical reward, Setting the reward to match the overall utility value for every monitor interval and utilising the training algorithm is feasible to determine the best course of action for maximising the long-term reward.

It is generally possible to select a particular model-free DPCC-RL training algorithm and build neural network architectures based on the computational power of the host devices. When computing power is limited, the standard Deep Q-Network (DQN) model ought to be utilised. Although the former is suitable for discrete low-dimensional actions, the latter can output action values in a continuous space. Deep Q-Networks (DQN) is utilized to train the congestion control agent. This combines reinforcement learning with congestion control in WSNs, providing adaptability to dynamic network conditions and addresses the specific issue of crowded packet transmissions, which is critical for enhancing data delivery reliability and energy efficiency in WSNs by offering a dynamic approach to congestion control that learns and adapts over time, potentially outperforming static congestion control methods. Specifically, discrete actions can be chosen based on the continuous output model's training results. To demonstrate the effectiveness of the suggested mechanism, primarily present the traditional DQN-based approach while taking the computing complexity and convergence speed into account. In this case, the state set and action set are represented by S and A. Every state-action pair that exists (s, a) has a Q-value, or , that represents the quality of carrying out action *a* in the state *s* of the environment. Each time an activity *a* is carried out in a state *s*, the Q-values are updated, producing a reward and a new state (Equation 7). Hence, in this scenario, the reward in each monitor interval can be made to equal . The best window control plan will be identified as the Q-value updates in the path of maximizing the overall utility value over the long term.

$$Q(s,a) = (1-\alpha)Q(s,a) + \alpha[r + \gamma max_{a'} Q(s',a')] \qquad (7)$$

Thus, the integration of the novel techniques, namely "Dynamic Packet Congestion Control with Reinforcement Learning (DPCC-RL)," "Adaptive Topology Management with Swarm Intelligence (ATM-SI)," and "Self-Adaptive Energy Management with Reinforcement Learning and Swarm Intelligence (SAEM-RS)," offers a comprehensive solution for Wireless Sensor Networks (WSNs). DPCC-RL optimizes data transmission in crowded environments, ATM-SI addresses ad hoc deployment challenges, and SAEM-RS ensures efficient energy management for unattended operation thereby enhancing the network reliability, adaptability, and longevity, making them a robust suite of tools for improving WSN performance in complex real-world scenarios. The following section will address the results of the suggested approach.

Result and Discussion

This section presents the statistical analysis that was performed to evaluate the suitability and effectiveness of the proposed SAEM-RL algorithm-based congestion management. The performance evaluation, comparative assessments, and parameter criteria used to assess the system's efficacy are shown in the section that follows. The analysis was carried out by Python with tensor flow based on keras package. Consider the number of nodes as 150, Adam optimizer is used with learning rate as 0.001. The loss considered as binary cross entropy.

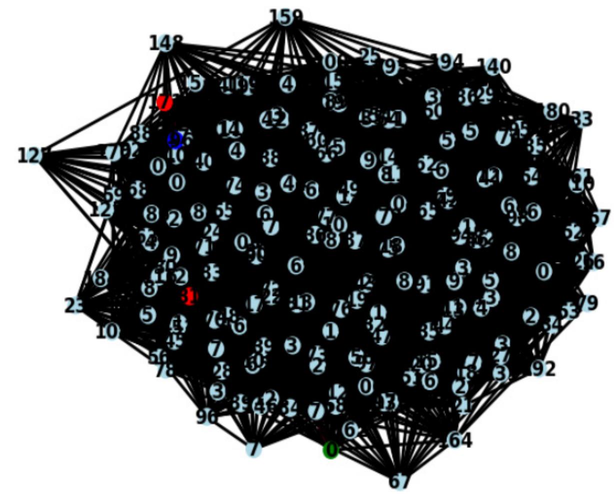

Fig. 2: Shortest path estimation

Figure 2 depicts the shortest path estimation of the proposed method. Since it can adjust to changing network conditions, ATM-SI-based shortest path estimation is especially useful in WSNs. It provides a strong solution for communication path optimisation in sensor networks by accounting for variables such as energy consumption, node connectivity, and overall network efficiency.

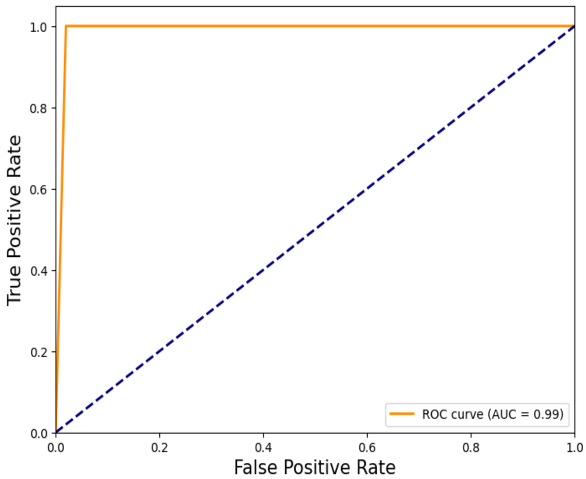

Fig. 3: ROC curve for WSN

Figure 3 depicts the ROC curve for WSN. Balance between False Positive Rate (FPR) and True Positive Rate (TPR) in Wireless Sensor Networks (WSNs) is represented graphically by the ROC curve. It shows the rate at which the system incorrectly classifies typical behaviour as malicious and the capacity of the Deep Q Network (DQN) to detect congestion. The ROC curve rises towards the upper-left corner from its starting point of (0,0) as the DQN's discriminatory capacity increases and attained 0.99. The overall effectiveness of the DQN-based intrusion detection system is measured by the ROC curve's Area under the Curve (AUC). In wireless sensor network environments that are dynamic and resource-constrained, the ROC curve analysis aids in optimising the DQN for best performance.

To evaluate the performance metrics such as accuracy, precision, recall and F1-score of the suggested technique. The definition of the following metrics are stated as below.

Accuracy: Through the computation of the proportion of cases that were accurately predicted to all instances, accuracy evaluates the overall correctness of the model.

Precision: Precision focuses on the accuracy of positive predictions by computing the ratio of correctly forecast positive instances to all forecasted positive instances.

Recall: Recall measures the ability of the model to capture every positive instance by dividing the total number of correctly predicted positive instances by the total number of actual positive instances.

F1-score: The F1-Score, which achieves equilibrium between recall and precision, is derived from the harmonic mean of these two metrics.

To compare the proposed method performances metrics such as accuracy, precision, recall and F1-score with existing algorithm such as Logistic regression (LR), Support vector machine (SVM), Multi-Layer Perceptron (MLP), Extreme Gradient Boost (XG Boost).

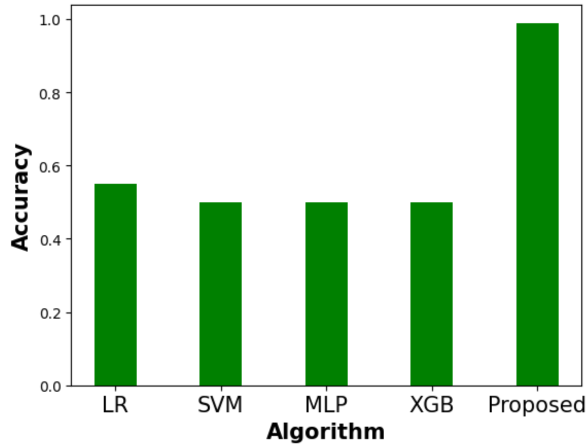

Fig. 4: Comparison for Accuracy

Figure 4 portrays the comparison for accuracy of the suggested method with existing algorithm. The proposed method utilized the DQN which attained accuracy as 0.99 when compared to existing algorithm such as accuracy attained 0.59 for LR, 0.58 for SVM, 0.57 for MLP and 0.56 for XGB.

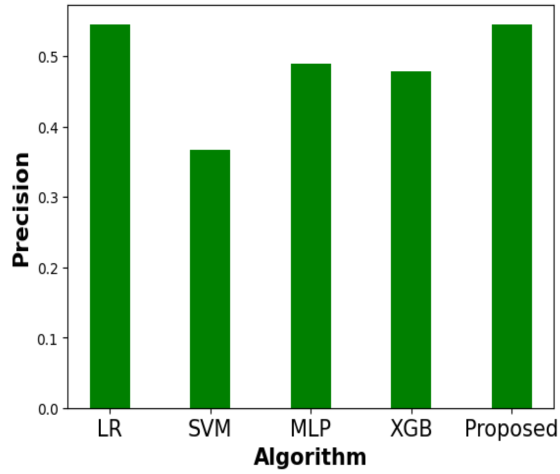

Fig 5: Comparison for Precision

The comparison of the suggested method's precision with the prevailing algorithm is shown in Figure 5. The proposed method attained precision as 0.58 when compared to existing algorithm such as precision attained 0.56 for LR, 0.38 for SVM, 0.47 for MLP and 0.45 for XGB.

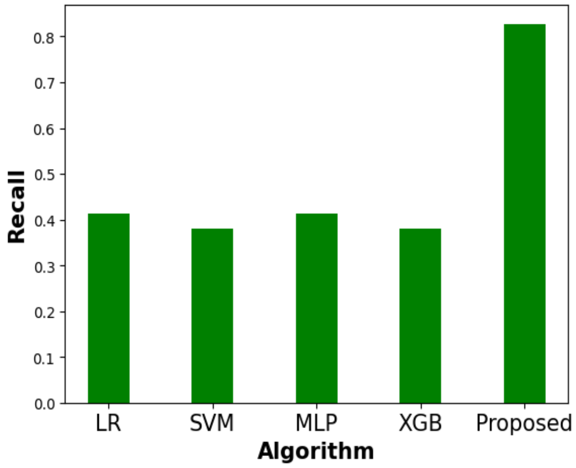

Fig. 6: Comparison for recall

Figure 6 depicts the comparison for recall of the suggested method with prevailing algorithm. The suggested method attained recall as 0.89 when compared to existing algorithm such as recall attained 0.41 for LR, 0.38 for SVM, 0.43 for MLP and 0.4 for XGB.

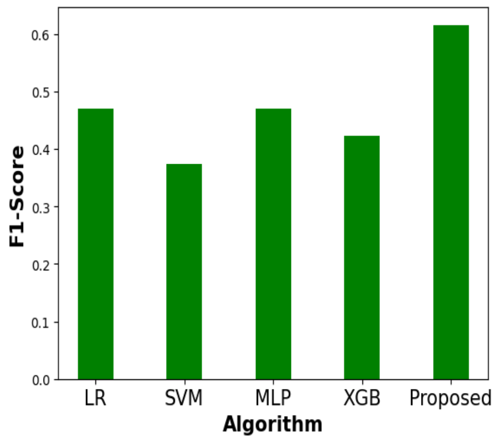

Fig 7: Comparison for F1-score

Figure 7 depicts the comparison for F1-score of the suggested technique with existing algorithm. The suggested method attained F1-score as 0.65 when compared to existing algorithm such as F1-score attained 0.48 for LR, 0.36 for SVM, 0.49 for MLP and 0.45 for XGB.

Table 1: Comparison Performance of the suggested technique with existing algorithm

Existing Algorithm	Accuracy	Precision	Recall	F1-Score
LR	0.59	0.56	0.41	0.48
SVM	0.58	0.38	0.38	0.36
MLP	0.57	0.47	0.43	0.49
XGB	0.56	0.45	0.4	0.45
Proposed	0.99	0.58	0.89	0.65

Table 1 depicts the comparison performance of the proposed method with existing algorithm. In existing algorithm faces issues as complexity in data management and crucial in energy efficiency. To overcome the drawback the proposed SAEM-RS which incorporates the Dynamic packet Congestion control reinforcement learning with adaptive topology management swarm intelligence which optimize the shortest path and detect the congestion in the network. The proposed SAEM-RS attained high value of accuracy as 0.99, precision as 0.58, re-call as 0.89 and F1-Score as 0.65 when compared to existing algorithm. Thus the proposed method outperforms better when compared to existing algorithms to detect the congestion in the WSN.

Conclusion

In this article, the integration of the novel techniques, namely Dynamic Packet Congestion Control with Reinforcement Learning (DPCC-RL), Adaptive Topology Management with Swarm Intelligence (ATM-SI), and Self-Adaptive Energy Management with Reinforcement Learning and Swarm Intelligence (SAEM-RS), presented a comprehensive and synergistic solution for addressing diverse challenges in Wireless Sensor Networks (WSNs). DPCC-RL effectively optimized data transmission in crowded environments, mitigating congestion and enhancing data delivery reliability and energy efficiency. ATM-SI tackles the challenges of ad hoc deployment by dynamically adapting and optimizing network topology through swarm intelligence principles, ensuring efficient communication routes without a pre-established infrastructure. SAEM-RS addresses the issues associated with unattended operation by autonomously managing energy resources, adjusting sleep-wake schedules based on reinforcement learning decisions and swarm intelligence feedback. Collectively, these techniques contribute to the enhancement of network reliability, adaptability, and longevity, offering a robust suite of tools to improve WSN performance in complex real-world scenarios. Especially the performances are achieved high accuracy as 0.99, precision as 0.58, recall as 0.89 and F1-Score as 0.65 when compared to existing algorithms. Thus the proposed method effectively detect the congestion in the WSN.

Conflict Of Interest

They author declare that have no conflict of interest

Ethical Approval

Institutional Review Board approval was not required.

Consent for Participate

All contributors agreed and given consent to participate.

Consent for Publication

All contributors agreed and given consent to Publish.

Data availability

No data, models, or code were generated or used during the study

Competing interests

None

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Author Contribution

The authors confirm contribution to the paper as follows and all authors reviewed the results and approved the final version of the manuscript.

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