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Research Article

An Intelligent Adaptive Neuro-Fuzzy for Solving the Multipath Congestion in Internet of Things

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ABSTRACT

The Internet of Things (IoT) has recently become a significant focus in research circles. IoT facilitates the integration of numerous physical entities with the Internet. Adhering to a standardized structure is imperative to manage the vast amount of information effectively. Although many researchers in the field of IoT have proposed various layered architectural designs, none have yet fulfilled all the requisite architectural criteria. Network congestion occurs when the volume of data packet traffic surpasses the network's handling capacity. Apart from addressing congestion issues, it is crucial to harmonize network resources like energy, bandwidth, and latency. The Quality of Service (QoS) in IoT applications chiefly depends on proficient congestion management, which is the central subject of this research. The research employs the Adaptive Neuro-Fuzzy Inference System (ANFIS) to regulate congestion, while the Membership Function (MF) undergoes adjustments through the application of the Modified Squirrel Search Algorithm (MSSA). This ANFIS amalgamates the advantages of Fuzzy Logic (FL) and Artificial Neural Networks (ANN) to form a unique framework. Utilizing ANFIS, adaptive analysis services are available to interpret complex patterns and nonlinear interactions, featuring quick learning capabilities. The MSSA aids in tweaking the Membership Function within the ANFIS model, achieving a successful global convergence rate. An adaptive method considering predator presence probability is employed to harmonize the algorithm's exploration and exploitation functionalities, further bolstered by a dimensional search approach. The simulation results demonstrate that the proposed Swarm Intelligence Adaptive Neuro-Fuzzy Inference System (SI-ANFIS) method significantly reduced traffic overhead and attained an impressive accuracy rate of 93.58%.

Keywords: Internet of Things (IoT), Swarm Intelligence, Fuzzy Logic, Congestion, Membership Function.

INTRODUCTION

The Internet of Things (IoT) represents a network of interconnected devices bolstered by advancing technologies that facilitate communication between these devices and larger cloud networks. A growing number of firms across diverse sectors are beginning to leverage IoT for real-time applications. As the business landscape increasingly shifts towards digital platforms, the integration of IoT becomes a necessity for societies and individuals. Deploying numerous IoT devices globally is instrumental in streamlining data collection and automation processes (Majid, 2022). In today's context, IoT serves as a linchpin for fostering and driving numerous innovative breakthroughs. The expansion and accessibility of IoT are fuelled by its affordable data storage solutions and heightened computational abilities. Moreover, with the swift advancements in network bandwidth, the sensors within IoT systems have become more compact, cost-effective, and precise. Nevertheless, the expansion of IoT brings forth considerable challenges, including the need to reduce system complexity, enhance security measures, and address potential communication discrepancies in varied settings (Khan et al., 2022).

Three levels comprise the IoT: the application, network, and perception layers. The perception layer comprises internet-connected devices that can perceive, identify, and share data via wireless links (Tharini & Vijayarani, 2020). Within the constraints of device abilities and network limits, the network layer transmits data from the perception to the application. The application layer eventually processes the information from the network layer. Wireless Sensor Networks (WSNs) serve as "cells" for the IoT to collect and distribute data, allowing intelligent and context-aware applications. As they deploy a type of power source and can sustain them for a long time, these WSN devices are also fundamental IoT enablers in terms of lifespan, energy efficiency reduced cost, and resource interface (Gashi, Luma, & Januzaj, 2022; Sharma, Sharma, Jain, & Kumar, 2022). IoT designs generally include sensors that collect data types and transfer them to the "Base Station (BS)". The BS will upload the data to a cloud server or Internet server. This research will focus on those simulated as sensors inside the selected sensing area (Ramya, Srinivasan, Vasudevan, & Poonguzhali, 2022). Effective processes must be deployed to obtain a competitive edge with higher efficiency and lower operational costs. Consumers or companies must be able to efficiently access the information collected from deployed sensors inside a sensor network as actionable intelligence that enables them to be more responsive (Beishenalieva & Yoo, 2022; Emmanuel et al., 2023).

The sensors are essential for making operations run smoothly and economically. They have more processing power, better memory, and unlimited energy to work all the time (Ahmad, Madonski, Zhang, Huang, & Mujeeb, 2022; Alam, 2023a). The role of BS is to collect, store, display, and analyze sensed data from SNs (Lilhore et al., 2022). In order to interface with user agents or transfer the detected data to a remote server over the Internet, the base station offers a Graphical User Interface (GUI) (Majid et al., 2022). The authorized users will obtain that data from the BS using internet servers. Sensing field data may also be accessed through websites worldwide, which can improve how the data is analyzed and go beyond what a BS can achieve (Ahmad, Wazirali, & Abu-Ain, 2022).

The BS can send periodic "heartbeats" to the cloud servers to let them know the status (either active or inactive) of the sensor network (Ganesh, 2022; Aqeel et al., 2023). In reply, the server can acknowledge the BS commands, push the most up-to-date configuration or software updates to the BS, and support it in system management at the application level. In order to sense and keep track of significant events, WSNs are made up of many small Sensor Nodes (SN) connected (Lăzăroiu et al., 2022). An SN is a tiny device with a sensing unit for collecting data, a processing unit for storing and processing it locally, and a wireless communication unit for sending it (Alawad & Kraemer, 2022; Shuaib et al., 2023). The enhancement in electronics and communications has enabled the building of such inexpensive, tiny, low-power, and multi-functional sensors that operate in the air, underwater, or on the ground (Luo, Wang, Xu, Liu, & Pan, 2022). The nature of the WSN faces diverse issues, namely Energy Consumption (EC), flooding, network traffic, and congestion. WSN cannot afford congestion, which might lead to performance decline and increased resource use. When high data traffic is induced, severe wireless contention and network congestion may occur in the WSN. This results in the convergence of extensive data towards a sink node (Hu, Tang, & Xie, 2022). It creates high reporting rates and leads to a lack of buffer space and bandwidth. It increases Packet Loss Rates (PLR) and degrades the Quality of Service (QoS) performance. Energy in the WSN should be consumed to extend the network's lifetime (Alam, Mohammad, Alfurhood, Mahaveerakannan, & Savitha, 2023). Therefore, packet retransmission represents the consumption of resources, energy, time, and packet forwarding cost regarding the number of hops (Esmaeili, Hakami, Bidgoli, & Shokouhifar, 2022).

Massive consumption of resources is incurred if packet retransmission involves multiple hop counts. Moreover, an extended buffer wait time in a queue may impact the authenticity and availability of data. Maintaining excellent QoS is essential for real-time applications. Data collection and transmission should be done as soon as possible in order to take direct and necessary action in the impacted region (Hakim et al., 2022). A high PLR and a prolonged processing delay at the receiver end might result in outdated and incorrect information. End-to-end delay (EED), linked to processing, response, and transmission time, is another result of congestion. Due to congestion, WSNs are highly susceptible to PLR, EED, throughput reduction, and increased EC.

The primary objective of this article is to develop and validate an Adaptive Neuro-Fuzzy Inference System (ANFIS), enhanced by a Modified Squirrel Search Algorithm (MSSA), for optimizing congestion control in Internet of Things (IoT) applications, with a focus on improving Quality of Service (QoS). Specific research questions guide this objective:

RQ 1. How does integrating ANFIS and MSSA optimize congestion control in IoT networks?

RQ 2. What improvements in QoS can be realized through the proposed Swarm Intelligence-based ANFIS (SI-ANFIS) method compared to existing methodologies?

RQ 3. How does the MSSA's modification of the Membership function (MF) within the ANFIS model reduce packet loss and end-to-end delay in IoT networks?

While ANFIS brings sophisticated capabilities for congestion control in IoT networks, it also comes with specific limitations, such as complexity in design and implementation, scalability issues, a propensity for overfitting, a slower convergence rate, and limited adaptability to rapidly changing network conditions. These limitations can be effectively addressed through the integration of swarm intelligence. The proposed SI-ANFIS method leverages the strengths of swarm intelligence to enhance the adaptability, scalability, convergence rate, and overall effectiveness of the ANFIS model. By incorporating swarm intelligence principles, specifically through the Modified Squirrel Search Algorithm (MSSA), SI-ANFIS can better manage the complexities and dynamic nature of IoT environments. This integration mitigates the risks of overfitting and scalability challenges. It ensures a faster and more efficient adaptation to changing network conditions, thus significantly improving the congestion control mechanism in IoT networks. In addressing these questions, the ANFIS model, which combines the advantages of Artificial Neural Networks (ANN) and Fuzzy Logic (FL), provides a unique framework for adaptive interpretation and quick learning capabilities, essential for understanding complex patterns and nonlinear relationships in IoT networks. The MSSA is employed to fine-tune the Membership Function of the ANFIS model, aiming to achieve an effective global convergence rate. Further, incorporating an adaptive strategy based on predator existence probability, supplemented by a dimensional search approach, is designed to harmonize the algorithm's capabilities for exploration and exploitation. Through this innovative approach, the study aims to significantly enhance QoS by managing congestion more effectively in IoT environments.

This paper is organized as follows: An overview of IoT in WSN and congestion is detailed in Section 1, the recent literature studies on congestion in IoT-based WSN are given in Section 2, the proposed work of SI-ANFIS is defined in Section 3, the simulation results of SI-ANFIS and existing methodologies are compared in Section 4, and this paper is concluded in Section 5.

LITERATURE REVIEW

Effective communication hinges significantly on the presence of a protocol stack. An ideal characteristic of an IoT stack is its ability to operate with minimal processing power while being lightweight, adaptable, and customizable. The Routing Protocol for Low-Power and Lossy Networks (RPL) is posited as a viable solution for routing in networks characterized by low-power and high loss rates akin to those found in IoT environments (Hkiri, Karmani, & Machhout, 2022). These networks face distinct routing challenges to which RPL can adapt proficiently, offering alternative routes when default paths are not accessible, thereby showcasing a high degree of adaptability to varying network conditions. However, RPL may face scalability and performance consistency challenges in complex and dynamically changing network environments. In terms of the transport layer, the User Datagram Protocol (UDP) emerges as the prevalent choice for IoT applications, attributed to its ease of implementation and unencumbered operation, compared to the more complex Transmission Control Protocol (TCP). While UDP's lightweight nature is beneficial, its limitations in terms of reliability, data sequencing, and integrity checks present challenges in scenarios where data accuracy and completeness are crucial.

At the application layer, the IoT stack encompasses a range of lightweight application protocols, which include the Constrained Application Protocol (CoAP), Message Queue Telemetry Transport (MQTT) (Janani, Jebadurai, Paulraj, & Jebadurai, 2022), Advanced Message Queuing Protocol (AMQP) (Yakupov, 2022), among others.

The development of Congestion Control Algorithms (CCA) for the Constrained Application Protocol (CoAP) has attracted much attention. These protocols are tailored to IoT's requirements, focusing on efficient bandwidth usage and message delivery. However, they differ in aspects such as security, real-time data handling, and overall communication overhead. CoAP, for instance, is designed for simplicity and low overhead but may lack the robust security features necessary for specific IoT applications. MQTT offers efficient message delivery but could be challenged by the increasing need for real-time data processing in IoT networks. AMQP, known for its reliability and interoperability, might introduce more significant overhead compared to CoAP and MQTT. In (Jiang et al., 2022; Makarem et al., 2022), a thorough analysis of the CoAP-specific CCA is recommended. Most solutions include changing the CoAP's default Retransmission Time Out (RTO) calculation method. These techniques boost CoAP/Compute and Control for Adaptive Optics Application (CoCoA) performance but cannot distinguish a clear congestion signal from congested Round-Trip Time (RTT) data. The comprehensive analysis of CCA is summarised in **Table 1**.

Table 1. Comprehensive Analysis of Congestion Control Mechanisms (CCM)

Ref.	Methodologies	Application	Performance Measured
(Quwaider & Shatnawi, 2020)	Neural Network with Immune Hill climbing (NN-IHH) based CCM is developed.	An IoT-based cloud computing system	Link utilization
(Makarem, Diab, Mougharbel, & Malouch, 2022)	Improved CoAP (ICoAP) -CCM	IoT based application	RTO, data transmission, and Root Mean Square Error (RMSE)
(Saleem et al., 2022)	Intelligent Fusion based Congestion Control System (FICCS) for enhancing the performance	Internet of Vehicle (IoV) utilizes FICCS	Accuracy, sensitivity, and specificity
(Suwannapong & Khunboa, 2021)	Enhancement to the CoCo-RED (Congestion Control for Random Early Detection	IoT services through Active Queue Management (AQM)	PLR and response time
(Bansal & Kumar, 2020)	A distance and RTT-based technique to predict network congestion	Client – Server	Packet Delivery Ratio (PDR) and EED
(Demir & Abut, 2020)	A Machine Learning (ML) based adaptive Congestion Control Mechanism (CCM) for CoAP	Client – Server	Throughput
(Swarna & Godhavari, 2021)	A new mechanism to handle the CCM in CoAP	Client – Server	EED, EC, and PLR
(Akpakwu, Hancke, & Abu-Mahfouz, 2020)	A novel CCM for CoAP	Client – Server	Throughput, EC, EED, and PLR
(Suwannapong & Khunboa, 2019)	Modified the Random Early Detection (RED) AQM mechanism and used	IoT services through AQM	Response time and PLR

Ref.	Methodologies	Application	Performance Measured
	Fibonacci-based backoff to develop a new CCM for CoAP		
(Ancillotti & Bruno, 2019)	A new rate-CCM for CoAP (BBR + CoAP)	Client – Server	Goodput, Fairness, and Number of retransmissions
(Järvinen, Raitahila, Cao, & Kojo, 2018)	Proposed new backoff techniques for CoAP-based CCM	Client – Server	FCT and number of retransmissions
(Jarvinen, Raitahila, Cao, & Kojo, 2018)	A new adaptive Retransmission Timeout based CCM for IoT	Client – Server	FCT, number of retransmissions, and RTO
(Bolettieri, Tanganelli, Vallati, & Mingozzi, 2018)	An adaptive CCM for CoCoA	Client – Server	RTO, Number of retransmissions, Throughput, and Delay
(Ancillotti, Bruno, Vallati, & Mingozzi, 2018)	Traffic-based congestion control mechanism for CoAP	Client – Server	Data collection delay, Interpacket delivery delay, and Packet Loss Ratio (PLR)

IoT's introduction and integration into general settings has ushered in significant advancements, but not without introducing a set of inherent drawbacks. One of the primary challenges emerging from deploying IoT networks is the limitation in device capabilities, such as minimal memory and slower processing rates. These constraints often lead to network congestion, particularly when numerous devices attempt to connect simultaneously, which is a common scenario in densely networked IoT environments. The small payload sizes of the data packets shared over the network by the IoT system's component devices mean that PLR occurs due to congestion, leading to costly retransmissions that cause further EED and high overheads. The drawbacks identified in the literature are rectified using the proposed SI-ANFIS, which eventually enhances the data transmission performance.

METHODOLOGY

This section introduces the SI-ANFIS, a novel approach designed to manage congestion in IoT networks and enhance QoS. Central to this methodology is the integration of the MSSA for optimizing the Membership Function (MF) of ANFIS. This integration is pivotal in handling the complexity of IoT network environments.

SI-ANFIS combines advanced AI techniques, including Deep Reinforcement Learning (DRL), Deep Neural Network (DNN), and MSSA. The convergence of these techniques enables the system to efficiently process and adapt to the dynamic and nonlinear nature of IoT network traffic. The MSSA's role in refining the ANFIS model further contributes to the system's adaptive decision-making capabilities, essential for effective congestion control. The proposed SI-ANFIS framework aims to create a robust, responsive system for improving network performance and QoS in IoT settings.

Problem Formulation

An agent uses discrete decision epochs to communicate with the system in a traditional Reinforcement Learning (RL) architecture. The agent checks the condition of the system (sy_t) for every epoch (t), then acts in line with its plan (a_t) and receives a reward (r_t). The agent's primary goal is to come up with an approach $\pi(sy)$ for mapping its state to a dispersion of probabilities for actions that maximize discounted cumulative reward. $R_o = \sum_{t=0}^{T} \gamma^t r(s_t, a_t)$, where reward functional is represented by r_t and forthcoming rewards are diminished by the aspect in a range of [0, 1]. The traditional Q-learning is expanded in the DRL to reduce the voids between procedures and sensory inputs in high dimensions. DNN is used as a function approximator in a distinctive feature of the DRL agent. The reciprocal value Q (sy_t, a_t), representing the expected discounted cumulative reward 'R_t', is produced as output by DQN from a pair of state-action (sy_t, a_t) inputs. The cumulative record is given in EQU (1).

$$Q(sy_t, a_t) = E[R_t | sy_t, a_t] \tag{1}$$

Here, $R_{t=} \sum_{k=t}^{T} \gamma^k r(sy_t, a_t)$. The action can be derived using the standard greedy policy in EQU (2).

$$\pi(s_t) = \text{argmax} Q(s_t, a_t) \tag{2}$$

Q-learning describes the state action for each pair, and the Bellman EQU (3) determines the target value during the training phase.

$$y_t = r(sy_t, a_t) + \gamma Q(sy_{t+1}, \pi(sy_{t+1}) | \theta^Q) \tag{3}$$

Where the parameter for Deep Q-Networks (DQN) is indicated by θ^Q. By minimizing the loss in EQU (4), DQN training may be carried out to achieve the desired value.

$$L(\theta^Q) = E[y_t - Q(sy_t, a_t | \theta^Q)] \tag{4}$$

The DRL can only be controlled in discrete steps and has a small range of actions. It is not controlled in a sequence of control extensions. Yet, such as CCM is frequently used in computer and communication networks. Also, a typical CCM is the policy gradient. The acro-critic method focuses on the critic and actor functions that are maintained concurrently. The training process is like the typical DQN, and the action functions incorporation is accomplished via DNN where the state value acts as input, and the finest action value acts as the constant output value. For updating the actor-network, using the chain rule on the projected cumulative reward P concerning the actor parameters EQU (5) and EQU (6) is feasible.

$$\nabla_{\theta^\pi} P \approx E[\nabla_{\theta^\pi} Q(sy, a | \theta^Q) | sy = sy_t, a = \pi(sy_t | \theta^\pi)] \tag{5}$$

$$\nabla_{\theta^\pi} P = E[\nabla_a Q(sy, a | \theta^Q) | sy = sy_t, a = \pi(sy_t) \nabla_{\theta^\pi} \pi(s | \theta^\pi) sy = sy_t \tag{6}$$

Where the critic function is indicated by $Q(sy, a | \theta^Q)$, actor function is indicated by $\pi(sy_t | \theta^\pi)$, and the 'E' indicates the constant.

The Deep Deterministic Policy Gradient (DDPG) was made with the help of DNNs and the new deterministic policy gradient. It's important to note that DDPG can be used with the target network and experienced replay to maintain learning stability. The representation of learning is associated with the multipath CCM, where every decision is an epoch. The learning values act as an input to the actor-critic scheme that impacts the critic and actor networks. The specific learning rate alters the flow of the congestion window.

Network Architecture

In **Figure 1**, the framework of the proposed SI-ANFIS is displayed. A controller in a Software Defined Network (SDN) serves as the foundation of the SDN, and the switch acts as a gateway to interconnect external systems based on the IoT. By using SDN switches as a gateway, the context of the IoT sends states of the network like the Congestion Window (CWND) and the data transmission frequency of Multipath Transmission Control Protocol (MPTCP) to the SDN controller. The proposed SI-ANFIS agent algorithm has been embedded in the SDN controller to maximize overall utility. It executes at the end node for all the active flows based on SDN-MPTCP. The flows with transmitting host SI-ANFIS are processed, and it is the active SDN-MPTCP. The significant features of SI-ANFIS are given here.

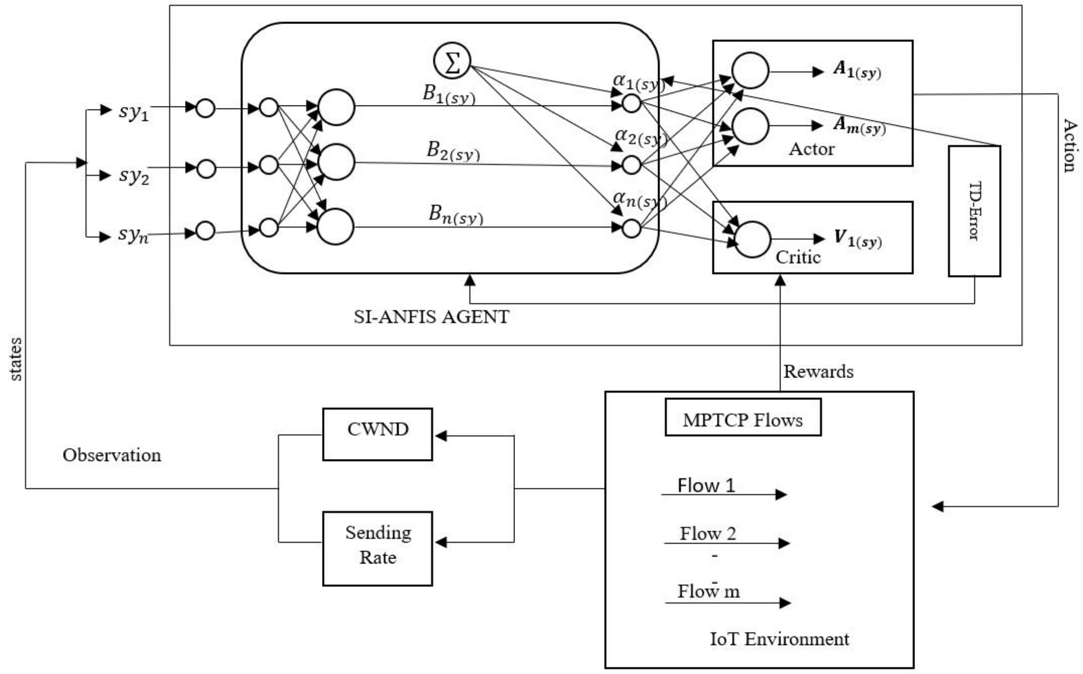

Figure 1. Architecture of SI-ANFIS

Network Representation: In this network, the active state characterization of all active TCP/MPTCP flows is learned using Long Short-Term Memory (LSTM) in a series learning process.

Actor-Critic: Finally, the congestion management action of an SDN-MPTCP flow is determined using the optimum flow state and the learned representation. The representation network uses LSTM and actor networks, and the critic gets training from beginning to end.

Fuzzy Normalized Function (FNF): State-space from the IoT context serves as the actor's and critic's input. The actor and critic networks' projected functions, which aim to estimate the high-dimensional rates of the IoT network, are the output of the FNF.

Swarm Intelligence-Based Adaptive Neuro Fuzzy Inference System

The actor's current method says that the proposed model outputs the state-action inference engine and maps the state to the action to give random policies. In IoT-based wireless services, the SI-ANFIS dynamically changes the size of the congestion windows of the sub-flows to maximize the throughput. The following is a list of the SI-ANFIS specifications. The critic and actor networks receive their input from the environmental state space. The estimated function of the actor networks and the critic is the SI-ANFIS output. The SI-ANFIS learning architecture typically consists of four layers.

Layer 1: Every neuron in Layer 1 indicates the state variable and the state space is passed directly to the subsequent layer's input vector.

Layer 2: Layer 2, which includes the rules, is hidden. In the case of fuzzy rules, each node of the second layer stands for the rule's initial values. The nodes of this hidden layer have the following Gaussian function, EQU (7).

$$v_{ji}\left(sy_t^{j,l}\right) = \exp\left[-\frac{\left(sy_j - u_{ji}\left(sy_t^{j,l}\right)\right)^2}{2\sigma_{ji}^2}\right], i = 1,2\ldots M_h \quad (7)$$

Where the mean and scalar values of the Gaussian function are indicated by and σ_j, respectively. This value relies on the hidden node' j'. The product of the Gaussian function is the fuzzy fitness value, which is for hidden layer j and state $sy_t^{j,l}$. The fuzzy fitness is given in EQU (8).

$$\emptyset_i\left(sy_t^{j,l}\right) = \prod_{j=1}^{M} v_{j,t}\left(s_{yj,t}\right) = \exp\left[-\sum_{j=1}^{M} \frac{\left(sy_{j,t}-u_{j,i}\left(sy_t^{j,l}\right)\right)^2}{2\sigma_{ji}^2}\right] \quad (8)$$

Layer 3: The normalized fitness layer is another name for this layer. This layer's primary goal is to measure every rule's fitness consistently and normalize all rules' fitness. The node's normalized fitness function is given in EQU (9).

$$\psi_i\left(s_t^{j,i}\right) = \frac{\emptyset_i\left(s_t^{j,l}\right)}{\sum_{l=1}^{M_h} \emptyset_l\left(s_t^{j,l}\right)} \quad (9)$$

Layer 4: The critic and the performer make up the SI-ANFIS output. The actor-network comprises action and value functions in EQU (10) and EQU (11). The fourth layer is referred to as the output layer.

$$A_l\left(sy_t^{j,l}\right) = \sum_{i=1}^{M_h} \omega_{ji}\psi_i\left(sy_t^{j,l}\right) \quad (10)$$

$$V\left(sy_t^{j,i}\right) = \sum_{i=1}^{Mh} v_i\psi_i\left(sy_t^{j,l}\right) \quad (11)$$

Where the weight among the output of 'j' in the actor and hidden layer 'i' is indicated as 'w_{ji}', and the weight among the output of 'j' in the critic and hidden layer 'i' is indicated as 'v_{ji}'.

Figure 1 shows that the Temporal Difference (TD) is the difference between the approximate and actual values. It is shown mathematically as EQU (12).

$$\delta_t = r_t + \gamma V_v(s_{t+1}) - V_v(s_t) \quad (12)$$

The acquired parameter values are applied when updating the centre, and the width of the hidden layer is given in EQU (13).

$$\mu_i(t+1) = \mu_i(t) + \alpha_u\delta_t \frac{\emptyset_i(1-\emptyset_i)\omega_{ji}(s_t-\mu_i(t)}{\sigma_i^2} \quad (13)$$

$$\sigma_i(t+1) = \sigma_i(t) + \alpha_\sigma\delta_t \frac{\emptyset_i(1-\omega_i)\sigma_{ji}(s_t-\mu_i(t))}{\sigma_i^2} \quad (14)$$

Where the learning rates are indicated by width and center.

In the following steps, the current class of action and policy may impact the critic's present and future rewards. Consequently, the TD error is updated using the value' v' and the Eligibility Trace Approach (ETA). The ETA helps enhance the learning process. In the SI-ANFIS model, the ETA is mathematically represented in EQU (15) and EQU (16).

$$E_t = \sum j^{t-1}\left(\left(\gamma^\lambda\right)^{t-j}\nabla_{v\quad i}V_j(s_t)\right) \quad (15)$$

$$v_i(t+1) = v_i(t) + \alpha_c\delta_t z_t \quad (16)$$

Where the eligibility is indicated 'e_t', and the updated values are shown in the above equations.

The actor's policy is enhanced by the TD error at the end of time 't' in EQU (17).

$$A_l(s_{t+1}) = A_l(s_t) + \alpha_\sigma\delta_t \quad (17)$$

Where the positive parameter is indicated by 'α_σ'. The critic component generates the value function that assesses the action's excellence. Similarly, the actor component computes the action-value function to identify the best course of action. The process of SI-ANFIS is given in **Algorithm 1**.

Algorithm 1. For Congestion control in IoT using SI-ANFIS

Step 1. **Input:** Initialize decay factor λ, discount factor γ, learning rates and α_u

Step 2. The initial state set is 'sy_o', and eligibility traces 'z_o' $v_i(0)$ and $w_{ji}(0)$ are initialized.

Step 3. **For** t=1,2,3,4,…..T **Do**

Step 4. Observe the state of the system 'sy_t'

Step 5. The reward' r_t' from the feedback system

Step 6. Compute the action function in the actor $A_l\left(sy_t^{j,l}\right) = \sum_{i=1}^{M_h} \omega_{ji}\psi_i\left(sy_t^{j,l}\right)$

Step 7. Computed the value function in critic $V\left(sy_t^{j,i}\right) = \sum_{i=1}^{Mh} v_i\psi_i\left(sy_t^{j,l}\right)$

Step 8. Compute the error in TD $\delta_t = r_t + \gamma V_v(s_{t+1}) - V_v(s_t)$

Step 9. Update center and width

Step 10. $\mu_i(t+1) = \mu_i(t) + \alpha_u\delta_t \frac{\emptyset_i(1-\emptyset_i)\omega_{ji}(s_t-\mu_i(t)}{\sigma_i^2}$

Step 11. $\sigma_i(t+1) = \sigma_i(t) + \alpha_\sigma\delta_t \frac{\emptyset_i(1-\omega_i)\sigma_{ji}(s_t-\mu_i(t))}{\sigma_i^2}$

Step 12. Update eligibility trace using $E_t = \sum j^{t-1}\left(\left(\gamma^\lambda\right)^{t-j}\nabla_{v\quad i}V_j(s_t)\right)$

Step 13. Update weigh using $v_i(t+1) = v_i(t) + \alpha_c\delta_t z_t$

The Improved Squirrel Search Algorithm (ISSA) is used to change the MF of the ANFIS model to improve how well the ANFIS model works as a whole. At first, the ISSA tries to make a population at a random rate that matches the squirrel's location. A d-dimension vector in the ISSA describes the locations of each squirrel. This method considers the following for the location of 'n' squirrels in a 2D matrix given in EQU (18).

$$FS = \begin{matrix} s_{11} & \dots & s_{1d} \\ \dots & \dots & \dots \\ s_{n1} & \dots & s_{nd} \end{matrix} \quad (18)$$

Where the flying squirrel in the ith position is indicated by 's_i', and the squirrel in the jth dimension is indicated by s_{ij}. The squirrel in the dimension is found at EQU (19).

$$s_{ij} = s_l + \mathrm{Rand}(0,1) * (s_u - s_j) \quad (19)$$

Where the upper limit is indicated as 's_u', the lower limit is indicated as 's_l', and the random outputs are generated in the range of 0 and 1. Every 's_i' fitness value is determined in EQU (20).

$$F = \begin{bmatrix} F(s_{11}) & \dots & s_{1d} \\ \dots & \dots & \dots \\ F(s_{n1}) & \dots & s_{nd} \end{bmatrix}, \begin{bmatrix} F(s_{11}) & \dots & s_{1d} \\ \dots & \dots & \dots \\ F(s_{n1}) & \dots & s_{nd} \end{bmatrix} \quad (20)$$

Where 'F' displays the fitness function. Every 'S_i' is given a fitness value and then grouped in ascending order. The squirrel is divided into three main classes, according to the ISSA. Depending on predators, some squirrels randomly choose the hickory nut tree, whereas others will go to the acorn nut tree to meet their energy needs. The following EQU (21) calculates how the flying squirrel will move from the acorn nut tree to the hickory tree.

$$s_{at}^{t+1} = \begin{cases} s_{at}^{t+1} + dg * Gc(s_{ht}^{t} - s_{at}^{t}) & R_1 \geq P_{dp} \\ s_{at}^{t+1}, Ent, Hye & Otherwise \end{cases} \quad (21)$$

Where current iteration is shown by 't', distance of gliding in a random movement is indicated as 'd_g', probability of predator existence is specified as P_{dp}, the flying squirrel reaches the hickory tree is indicated as 's_{ht}', the arbitrary values R_1, R_2, and R_3 lie in the range of [0, 1]. The gliding constant (G_c) in the statical model is written in the following EQU (22) to achieve the balance between exploration and exploitation.

$$s_{at}^{t+1} = \begin{cases} s_{nt}^{t+1} + dg * Gc(s_{at}^{t} - s_{nt}^{t}) & R_2 \geq P_{dp} \\ s_{nt}^{t+1}, Ent, Hye & Otherwise \end{cases} \quad (22)$$

Squirrels of a smaller size that live in regular trees may periodically move to hickory nut trees in order to store their nuts there. The following EQU (23) can be used to describe the process.

$$s_{at}^{t+1} = \begin{cases} s_{at}^{t+1} + dg * Gc(s_{ht}^{t} - s_{at}^{t}) & R_3 \geq P_{dp} \\ s_{at}^{t+1}, Ent, Hye & Otherwise \end{cases} \quad (23)$$

Where the measurement in the uncertainty is specified by Ent, where the search radius is presented, and Hye indicates the uncertainty value of hyper entropy. The value of Hye is given as 0.1, and the search stability is shown with the assistance of Ent. During the final generation, the location of the population is nearer to the optimized value. Ent is appropriate for tuning the outcome and the search dynamically altered. In the fuzzification layer, every neuron in the adaptive layer is modified with the crisp input. The fuzzified node output value is estimated as:

$$OP_i^l = \begin{cases} R_1(s_{at}^{t+1}), & \forall_i = 1,2, \\ R_2(s_{at}^{t+1}), & \forall_i = 1,2, \\ R_3(s_{at}^{t+1}), & \forall_i = 1,2, \end{cases} \quad (24)$$

The MF of the fuzzy sets used in this research is bell-shaped, and the value is optimized using the ISSA. The optimized Gaussian function is given as:

$$f(s_{at}^{t+1}) = a.\exp\left\{-\frac{(s_{at}^{t+1}-b)^2}{2c^2}\right\} \quad (25)$$

If s_{at}^{t+1}<0, Then congestion can be minimized.

If s_{at}^{t+1}>0, Then congestion can be maximized.

Where the values of a, b, and c are premise parameters of MF of ANFIS (Chopra et al., 2021). The predator probability is assigned the values 0 and 1. The fuzzy rules are formulated based on the above condition, and the rules are determined as huge negative, medium negative, small negative, zero, huge positive, medium positive, and small positive. The following rules are generated from the fine-tuned MF.

Rule 1: If is a huge negative, then congestion is a huge negative.

Rule 2: If is medium negative, then congestion is medium negative.

Rule 3: If is a small negative, then congestion is a small negative.

Rule 4: If is zero, then congestion is zero.

Rule 5: If is a huge positive, then congestion is a huge positive.

Rule 6: If is medium positive, then congestion is medium positive.

Rule 7: If is small positive, then congestion is small positive.

Based on the context of the simulation environment, the MF value will be tuned using the ISSA, and diverse rules will be generated.

LIMITATIONS AND ETHICAL CONSIDERATIONS

In developing the SI-ANFIS methodology, there are some limitations inherent. Integrating Deep Reinforcement Learning (DRL) and Deep Neural Networks (DNNs) within SI-ANFIS presents a complex computational challenge. This complexity may impact the practicality of deploying our system in real-time across large-scale network environments, especially where computational resources are limited. Additionally, while our model demonstrates encouraging results in simulated SDN environments, its ability to generalize effectively in diverse real-world IoT scenarios remains to be rigorously tested.

From an ethical standpoint, a significant emphasis on the responsible implementation of our AI-driven system has been made to ensure the utmost privacy and security of data traversing through IoT networks. The model implements robust data protection measures to safeguard sensitive information. Furthermore, maintaining algorithmic transparency in the decisions made by SI-ANFIS is another critical aspect we have considered.

RESULT AND DISCUSSION

The entire SDN is set up on an Intel i7 processor platform with Windows 10 operating system and a virtual box of Oracle VM with NVidia GeForce 940MX. The memory allocation is 4 GB of RAM to the host version of 2.2.1 Minimet in 1.3 OpenFlow. The effectiveness of the proposed method is known from its performance metrics, namely Round-Trip Time (RTT), Accuracy, Bandwidth Overhead (BO), Data Flow Rate, and Control Traffic Overhead (CTO). The performance measures of the proposed SI-ANFIS are compared with existing methods, namely NN-IHH, ICoAP, and FICCS. The simulation setup is given in **Table 2**.

Table 2. Simulation Setup

Parameter	Value
Area of Monitoring	200*200 m^2
Node Count	500
Queueing Method	RED/Fuzzy
MAC Type	IEEE 802.11
Data rate	0-200 *kbps*
Simulation Time	30 *Sec.*
Maximum Packet in Queue Buffer	70

Round Trip Time (RTT)

The RTT measured in milliseconds (ms) how long a network requests to move from one location to another and return the same. Network managers typically use RTT to assess their networks' reliability and transmission rate to diagnose connectivity issues on local networks and the wider Internet. In the proposed SI-ANFIS, the RTT is highly minimized compared to the existing method. The obtained RTT for different packet counts of NN-IHH, ICOAP, FICCS, and SI-ANFIS is given in **Table 3** and **Figure 2**.

Table 3. The Comparative Analysis of RTT vs. Packet Count

Packet Count	NN-IHH	ICOAP	FICCS	SI-ANFIS
100	0.63	0.59	0.56	0.441
200	0.67	0.62	0.59	0.471
300	0.69	0.64	0.62	0.492
400	0.73	0.65	0.63	0.51
500	0.75	0.67	0.65	0.516

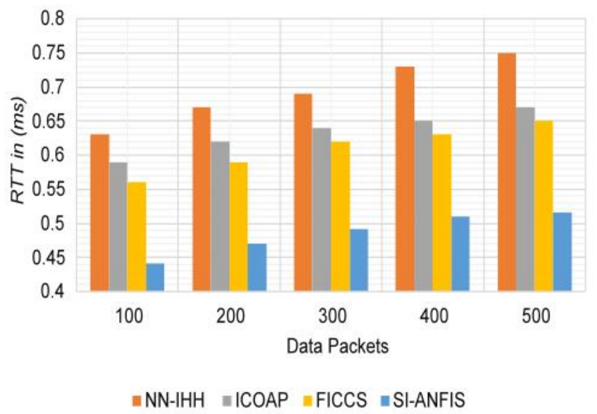

Figure 2. Comparison of RTT vs. Packet Count

Figure 2 shows that the RTT is the minimum for SI-ANFIS compared to the existing methods, namely NN-IHH, ICOAP, and FICCS. A minimal RTT shows the success of the proposed method and reaches PDR in a minimal amount of time.

Accuracy: A master clock is used to broadcast a constant stream of data bits. The number of start bits, stop bits, or gaps is needed because the data transmitter and receiver employ a synchronized clock frequency. Data moves faster, and timing errors are less prevalent since the transmitter and receiver are synchronized. Conversely, accurate device timing synchronization is crucial for data accuracy. In the proposed SI-ANFIS, the accuracy is high compared to existing methods. The obtained accuracy for entire routing across switches with NN-IHH, ICOAP, FICCS, and SI-ANFIS methods is given in **Table 4** and **Figure 3**.

Table 4. The Comparative Analysis of Accuracy

Algorithms	Accuracy (%)
NN-IHH	82.18
ICOAP	83.27
FICCS	86.54
Proposed SI-ANFIS	93.58

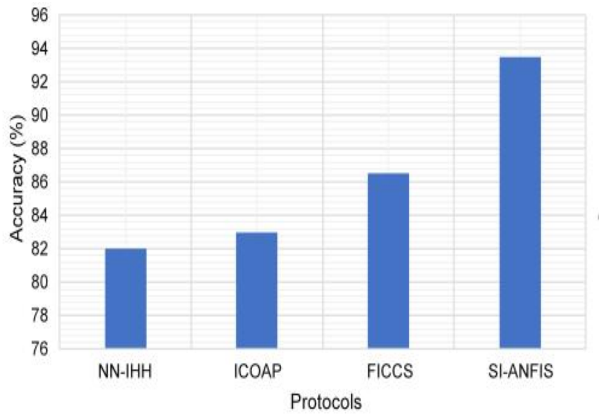

Figure 3. Comparison of Accuracy

Figure 3 shows that the accuracy is highest for SI-ANFIS compared to the existing methods, namely NN-IHH, ICOAP, and FICCS. High transmission accuracy shows the effectiveness of the proposed method and achieves PDR without any loss.

Bandwidth Overhead (BO)

The absolute number of bits introduced along the route corresponds to the BO. Encoding forwarding ports with the prescribed number of bits can dramatically reduce the bandwidth penalty. In the proposed SI-ANFIS, the BO is minimal compared to existing methods. The obtained BO for entire routing across switches with NN-IHH, ICOAP, FICCS, and SI-ANFIS methods is given in **Table 5** and **Figure 4**.

Table 5. The Comparative Analysis of BO vs Flow Arrival Rate (FAR)

FAR	NN-IHH	ICOAP	FICCS	SI-ANFIS
0.2	0.41	0.26	0.27	0.19
0.4	0.632	0.46	0.53	0.41
0.6	0.721	0.74	0.9	0.63
0.8	0.991	0.83	1.2	0.62
1	1.2	1.1	1.5	0.76
1.2	1.25	1.12	1.6	0.83
1.4	1.42	1.42	1.7	0.9
1.6	1.8	1.51	1.91	0.98
1.8	2	1.751	2.2	1.11
2	2.1	1.9	2.5	1.1

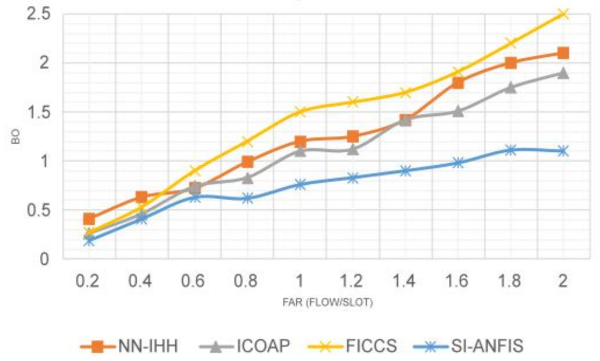

Figure 4. Comparison of BO vs. FAR

Figure 4 shows that SI-ANFIS does not use much more bandwidth than the current methods, such as NN-IHH, ICOAP, and FICCS. Minimal bandwidth overhead shows the proposed method's effectiveness and effectively reaches PDR.

Control Traffic Overhead (CTO)

A packet is a unit of data that is sent through a network. Every transmission encompasses overhead data, which is necessary to route the data to the correct location. The CTO is the entire bit count of control traffic generated by specifying a flow. It is finding a collection of contact switches that balances bandwidth usage, controls traffic usage, and maximums flow table utilization. In the proposed SI-ANFIS, the CTO is minimal compared to existing methods. The obtained CTO for the entire routing across switches with NN-IHH, ICOAP, FICCS, and SI-ANFIS methods is given in **Table 6** and **Figure 5**.

Table 6. The Comparative Analysis of Control Traffic vs. FAR

FAR	NN-IHH	ICOAP	FICCS	SI-ANFIS
0.2	1.25	1.12	1	0.94
0.4	1.44	1.91	1.72	1.55
0.6	2.69	2.41	2.11	1.9
0.8	3.76	2.81	2.32	2.2
1	4.71	4.6	2.71	2.22
1.2	4.81	5.2	4.31	3.11
1.4	6.96	6.3	5.1	3.91
1.6	7.3	7.1	6.12	4.11
1.8	8.3	8.2	7.22	4.91
2	9.3	8.91	7.92	5

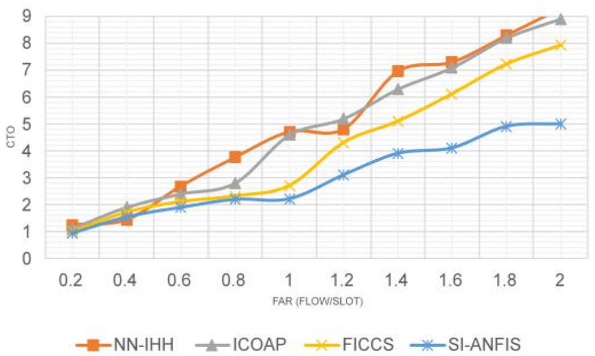

Figure 5. Comparison of CTO vs. FAR

Figure 5 shows that the CTO is the minimum for SI-ANFIS compared to the existing methods, namely NN-IHH, ICOAP, and FICCS. Minimal CTO shows the effectiveness of the proposed method and reaches PDR effectively.

Data Flow Rate

The pace at which data enters a network is called the arrival rate. The arrival rate measure indicates how many packets are controlled or placed on hold in a certain period. The obtained data flow rate for entire routing across different switch comparisons is attained for the NN-IHH, ICOAP, FICCS, and SI-ANFIS methods in **Table 7** and **Figure 6**.

Table 7. The Comparative Analysis of Flow Rejection Rate (FRR) vs. FAR

FAR	NN-IHH	ICOAP	FICCS	SI-ANFIS
0	0	0	0	0
0.5	0.12	0.11	0	0
1	0.36	0.81	0	0
1.5	0.72	1.11	0	0
2	0.791	1.22	0	0
2.5	0.82	1.31	0.11	0.12
3	0.86	1.31	0.11	0.12
3.5	0.89	1.31	0.22	0.12
4	0.891	1.42	0.32	0.12
4.5	0.91	1.42	0.52	0.23

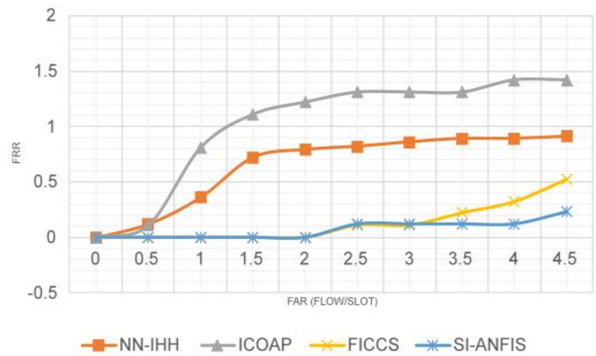

Figure 6. Comparison of FRR vs. FAR

For different FAR, **Figure 6** illustrates the FRR of four forwarding methods. The FRR of a HOMA-Greedy forwarding method increases dramatically as a higher proportion of flows are added to the network. This is because flow entries must be added to each switch along the forwarding routing paths. This phenomenon is commonly referred to as flow-table overflow.

The comprehensive evaluation of the SI-ANFIS system within a Software-Defined Network (SDN) environment has demonstrated its superiority over existing methods like NN-IHH, ICOAP, and FICCS across key performance metrics. The system has achieved significantly lower Round-Trip Time (RTT), indicating enhanced network responsiveness, critical for real-time IoT applications. Additionally, its accuracy, exceeding 93%, suggests exceptional precision in data transmission, which is vital for IoT system reliability. The SI-ANFIS system's efficiency in resource utilization is evident through its lower BO and CTO, showcasing its capability to optimize network performance while also reducing operational costs. Moreover, its ability to maintain a low FRR across varying data flow rates underlines its robustness in handling high volumes of data, an essential attribute for large-scale IoT networks.

These results validate the effectiveness of the SI-ANFIS approach in managing network congestion and enhancing QoS in IoT environments. Integrating the Adaptive Neuro-Fuzzy Inference System with the Modified Squirrel Search Algorithm within the SI-ANFIS framework has proven to be a formidable combination, adept at addressing the complexities of modern network systems. The lower RTT, improved accuracy, and efficient management of network resources collectively contribute to a more reliable, efficient, and scalable IoT ecosystem.

The implementation results of the SI-ANFIS system solve the primary objective of enhancing congestion control and QoS in IoT applications. The integration of ANFIS with MSSA, leading to significantly lower RTT and higher accuracy rates, directly addresses how this integration optimizes congestion control. The reduced RTT and enhanced accuracy support a more efficient and reliable network, meeting the dynamic demands of IoT systems. The findings indicate that SI-ANFIS effectively minimizes BO and CTO while maintaining a lower FRR across different data flow rates. This performance enhancement reflects the system's enhanced capability in resource management, thereby improving the overall QoS. The minimal BO and CTO, coupled with the low FRR, ensure the network's capability to handle large data volumes efficiently. The results demonstrate a high global convergence rate and adaptability to network changes.

In conclusion, the SI-ANFIS provide a highly effective solution for congestion management in IoT networks, highlighting the potential of integrating advanced AI techniques, such as neuro-fuzzy inference systems, with swarm intelligence algorithms to address the evolving challenges in IoT network management. The success of SI-ANFIS paves the way for further research and development in this domain, potentially leading to more resilient, efficient, and intelligent IoT.

CONCLUSION AND FUTURE WORK

Managing congestion remains a pivotal challenge in communication networks, an issue that has gained renewed focus recently, particularly concerning the IoT to foster resource efficiency and enhance network performance. Network congestion transpires when the influx of data packet traffic exceeds the network's processing capacity. Alongside addressing congestion, achieving a harmonious balance of network resources, including energy, bandwidth, and latency, is equally crucial. The study primarily revolves around the QoS pertaining to IoT applications, given their substantial reliance on adept congestion control mechanisms. ANFIS is employed to oversee congestion, with modifications to the MF being carried out through the utilization of the MSSA. In this framework, ANFIS amalgamates the strengths of ANN and FL.

Based on simulation findings, the proposed SI-ANFIS exhibited promising results, reducing traffic overhead and realizing a notable accuracy rate of 93.58%. This study concludes that the SI-ANFIS system presents a promising advancement in congestion control and network management strategies for the evolving needs of the Internet of Things. This study employed conventional traffic scenarios for evaluation, where sensors transmit data to the gateway either periodically or incessantly. A potential avenue for enhancing this research could be the extensive testing of the proposed algorithms under various real-world traffic conditions, including wave-like traffic patterns. It would indeed be intriguing to analyze the performance of these algorithms across diverse traffic scenarios. Secondly, testing the system's performance in different IoT environments, such as smart cities, healthcare systems, and industrial IoT, where each presents unique traffic challenges. Thirdly, it focuses on scaling SI-ANFIS for larger IoT networks, enhancing its efficiency and computational feasibility for widespread application. Lastly, exploring the integration of SI-ANFIS with emerging IoT technologies like 5G, edge computing, and blockchain (Alam, 2023b) could open new possibilities for improving data processing speeds, security, and decentralization in IoT networks. These future directions are pivotal in advancing SI-ANFIS as a robust and versatile solution for intelligent network management in the IoT domain.

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