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Neuro-Fuzzy Driven Context-Aware Optimized Topology for IoT - Nucot

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Abstract*: *Due to technological evolution, the interaction between the user with local ambiance, the user with remote ambiance, and the user with machines become achievable as well as required reality. Also, process automation in manufacturing, as well as service industries, become a mandatory requirement. In the past interaction with ambiance was isolated and highly limited. Even the process automation was done secluded ways and was implemented using various independent single-purpose embedded systems. Since every such automation thrives to meet the non-functional requirements like cost, performance, reliability, availability, flexibility, and recoverability, the task of automation must be carried out at all possible levels. Moreover, such automation must be realized in cohesive and collaborated mode. These critical requirements have changed the landscape of interaction among different entities like man, machine, process, and Environment. The emergence of new technology namely "Internet of Things" has opened up several avenues to address as well as to meet above mentioned non-functional requirements. Already embedded system has revolutionized process automation across various industries but true automation or optimal automation requires meaningful interaction among man, machine, process, and environment. Hence, IoT objects along with other traditional systems are required to be interconnected to accomplish the best interaction which leads to smart living spaces as well as workspaces. However, these smart IoT objects are inherently made up of constrained resources such as limited computing ability, less storage capacity, and inadequate communication capability. Therefore, traditional network connectivity such as Ethernet LAN, Wi-Fi, Bluetooth LE, and other networking facilities may not provide customized as well as the optimized interconnection among these resources constrained IoT objects. Hence, an alternate topology is required to interconnect these IoT objects in an adaptable and optimized mode. Hence, this paper proposes a neuro-fuzzy driven context-aware optimized topology (NuCoT) for the interconnection of different IoT objects.

***Keywords* : Ambiance, Automation, Internet of things, Topology.**

I. INTRODUCTION

The objectives of establishing computer networks have undergone enormous changes owing to numerous end-user applications as well as ever-changing business landscapes. In the past, computational correctness was the prime requirement for most of the applications such as payroll, accounting, and any other computational applications. Few applications such as banking, stock trading, multi-media streaming, and any other time-critical applications require timely transactions. Hence, the major objective of any network was just the sharing of computational resources. In simple terms, networks have reduced the capital cost by facilitating the sharing of the hardware such as servers, clients, printer as well as software resources such as office tools, messaging tools, and business tools. They have also transformed the physically isolated information islands into virtual data clouds. Hence, networks have created connectivity and made data transfer possible anywhere, at any time and for anyone.

Due to the merits of seamless connectivity and computation, application designers, as well as user, started to add more value-added services like good decision making, better trading and optimal utilization of resources. The end-user becomes smart and expects smarter services at a lesser cost which has created a tremendous challenge to the industries to bring out smarter services as well as products to meet the end-user demands. To fulfill the newer demands, the information needs to be acquired extensively at the micro level from various locations, must be processed precisely in distributed means, has to be stored sensibly and communicated cautiously. Hence, data acquisition, data preservation, and data transfer are the key strategic functionality required by business analytics to create sufficient business intelligence and then to make any possible business process automation. But, these functionalities completely depend on the physical form of the network and such functionalities are purely defined by the word "Context". Hence, everything whether sensing or/and computing or/and communication mostly depends on the context.

A. *Context and Content Awareness*

The context – a hard word to understand but affects many things in the real world. What does context mean? In conventional term it could be defined as "*the situations that make the background for an incident, announcement, or knowledge, and in terms of which it can be completely interpreted (or) the parts of something transcribed or articulated that instantaneously lead and trail an expression or passage and simplify its significance (or) the condition in which something occurs (or) the collection of circumstances that present wherever and whenever something occurs*"

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From information and communication technology (ICT) point of view, the context means every stakeholder who has involved directly or indirectly assisting in acquiring, processing, sorting, filtering, storing and transmitting information in the real world by doing it alone in standalone context or doing it as a group in a networking context.
Every ICT belongs to a certain context. For example, managing home appliances via IoT is completely different from managing all factory robots. Therefore, the type of environment or situation or background defines the required context. Hence, context-awareness acts as an important factor in any type of automation.

II. RELATED WORK

Many researchers have contributed to their works related to industrial automation, healthcare monitoring, smart farming, smart city, energy harvesting, smart grid, and energy management. [1],[2],[3]. Due to the pervasive requirement of data acquisition, data processing, and data sharing have made many researchers make a fresh investigation regarding numerous challenges, various open issues and possible state of art techniques so that seamless integration of Internet of things with cloud services [4]. The Internet of Things has slowly converted the entire digital world into a virtual village. Already many such IoT objects are capturing, producing and transferring huge amounts of related or unrelated information from several sources. The majority of such information is raw and unprocessed. So, data aggregation and data dissemination are going to be major challenges induced by IoT objects. Hence, stream-oriented edge processing methods have to be designed and developed. Instead of acquiring raw data from such IoT objects, how to make edge-centric processing, their vision, and other related challenges have been explored [5]. Few researchers explore the possibility of IoT as enabling technology for the inter-operability of cloud computing and fog computing to provide smart healthcare [6], [7]. By interconnecting various aspects of healthcare processes and systems, a smart healthcare system had been implemented using the Internet of Things [8]. Energy optimization is the primary requirement for any modern manufacturing industries. Most of the service sectors, as well as another critical sector such as healthcare, started focusing on technologies that provide optimal utilization of energy-related resources which have made them go for customized as well as intelligent gateway-based IoT solutions [9],[10]. Apart from healthcare, many industrial processes like real-time monitoring of continuous steel casting and other related processes have been automated using IoT systems [11].
A detailed study on several enabling technologies such as traditional networking standards, protocols, and their applications has been done to analyze their suitability for making interconnection among various smart devices. [12]. Alternate design namely wireless sensor networking has been proposed in place of traditional networking [13]. A performance study regarding Bluetooth under a homogeneous environment had been performed [14]. Also, investigation of different types of modulation techniques for Bluetooth-LE module for Internet-of-Things (IoT) applications has been done [15].

III. PROPOSED WORK

A. *Problem Analysis*

Among numerous challenges in the internet of things, the major challenge is how to interconnect various smart "Things" or "Objects" or "Systems" or "Devices". Since these "Things" are designed to execute different tasks to accomplish exclusive objectives and outcomes, they are very difficult to connect. To understand the complexity in interconnecting these "Objects", they need to be explored in detail. The uniqueness in their forms and functions has added more complexity to IoT. The conventional networks are used to interconnect various computing devices such as Servers, Workstations, Desktops, Storage devices, and Printers to enhance overall utilization based on the principle of resource sharing. These systems are either homogeneous with similar hardware with identical capabilities or heterogeneous with similar hardware, identical capabilities, but different capacities such as more CPUs, additional memories, and larger storage devices. Resource utilization is the primary objective of creating a network of these devices.

As a result, computer network designers in the past with limited adaptation have used one size fits all approach. But due to the presence of true heterogeneity among various IoT systems, making them communicate with each other is truly a tough task to implement. Here, the true heterogeneity brings dissimilarity in hardware as well as leads to non-identical capabilities and varied capacities among different IoT systems.
Table I reveals how IoT systems differ with each other within a few samples of IoT devices. It has also classified a few IoT systems with respect to a few criterions such as kind of architecture, nature of I/O interfaces and available resources. Due to multiple functions, compartments, and I/O controls, the smart refrigerator has got high heterogeneity and complex I/O interfaces in comparison with other given IoT systems. It also requires different sensors and actuators to bring in more smartness. Smart washing machines and smart watches are also having complex I/O interfaces but to a lesser level in comparisons with Smart refrigerator. But smart fan and smart light are having the simplest I/O interfaces but are having very minimal computing as well as communication resources.

Table I: Architectural differences in IoT - Things

IoT- Things	Type of Architecture		I/O Interfaces		Resource Constraints
	Homogeneous	Heterogeneous	Simple	Complex	
Smart Refrigerator	×	√ √	×	√ √	×
Smart Washing Machine	×	√	×	√	√
Smart Fan	√	×	√	×	√ √ √

Smart Watch	×	√	×	√	√
Smart Light	√	×	√	×	√ √ √

× - Optional / Less Prominent: √ - Required / Prominent: √ √ - Highly Required / More Prominent

Table II: Contextual differences in IoT - Things

IoT- Things	Type of Tasks			Timeliness		Contents	
	Sensing	Actuating	Reporting	Real time	Non Real time	Static	Dynamic
Smart Refrigerator	√	√ √	√ √	×	√	×	√ √
Smart Washing Machine	√	√ √	×	√	×	×	√
Smart Fan	√	√	×	×	√	√	×
Smart Watch	√	×	√	√	×	×	√ √
Smart Light	√	√	×	×	√	√	×

× - Optional / Less Prominent: √ - Required / Prominent: √ √ - Highly Required / More Prominent

Table II further highlights more differences among IoT systems based on various contexts they do operate on and contents they do produce during their lifetime. Every IoT system is expected to perform at least one or two or all of the functions defined as sensing, actuating, and reporting. Out of these three tasks, sensing is mandatory for all IoTs, and the rest are optional based on the needs of the application. Passive or surveillance-based IoTs will do both sensing and reporting tasks. Active and automation based IoTs will do both actuating and reporting tasks.

Many mono-tasking IoTs will perform both sensing and actuating tasks. Another primary factor that makes each IoT as a unique object is a timeliness. Timeliness, along with content creates various unique contexts in IoTs. Timeliness is not about how fast tasks need to be done with a higher degree of functional correctness, but it's nearly about how accurately computation needs to be done within the accepted time limit or deadline.

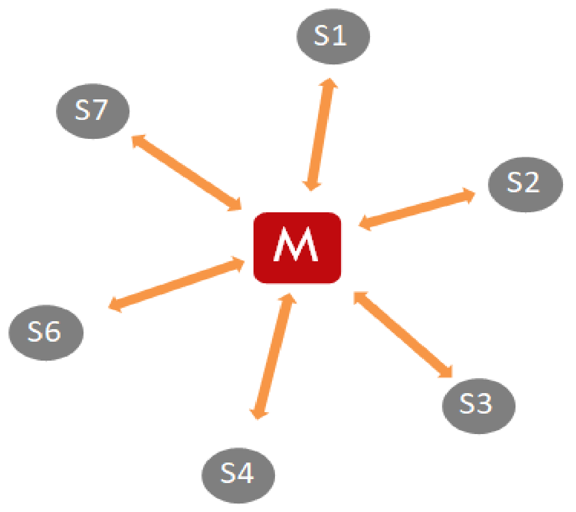
Since every IoT device needs to interact with the ambiance continuously, it will produce enormous content during its operation. These contents are produced by different real-time events and may be static or dynamic. Static content means the same type of data is produced again, and again whereas dynamic content means varied data will be produced. The other challenge faced by IoT devices is how to classify and compute data based on in arrival of events. The events could be classified as periodic which comes at regular intervals of time, aperiodic which arises at irregular intervals of time and finally sporadic which originates at irregular times but with known inter-arrival time.

From Table II, it could be easily interpreted that every IoT requires sensing as must needed functionality. Smart refrigerators and smart washing machines require more prominent actuation functionality in comparison with other given IoTs. Smart watch and smart refrigerator produce more dynamic content than the rest of the given IoT devices. Smart fans and smart lights don't need to meet the hard deadlines, and they do operate on static but repeated data set. Also, they do not require to report prominently.

Based on the analysis of data presented in tables I & II, it is understood that fundamentally IoT systems are unique in their forms and functionalities. A conventional network topology such as Bluetooth LE or Zigbee may not provide an optimal interconnection of these IoT or edge devices or last-mile workers since they are not customized for IoT systems designed using commercially of The Self [COTS] products. Hence, an adaptable and self-learning topology is highly required to interconnect such last-mile workers.

B. *Proposed Adaptive topology*

An alternate topology has been proposed to overcome a few challenges, and issues brought by IoT heterogeneity, and the same has been discussed in this section. Fig 1 gives a snapshot of the piconet formed by the Bluetooth 4.0 LE standard. Here, the piconet consists of seven slave devices, and one master device out of eight possible devices. Any slave in this topology requires a master's assistance to transfer data or to communicate with any other available slaves. Suppose slave s1 wants to share information with slave s2, s1 cannot send information directly to s2 instead, s1 has to wait to be polled by the master. If the master already had started polling slaves from s2, then s1 has to wait for its turn to be polled by the master. The fixed polling policy, as well as the rigid topological structure, increases the delay, thereby adding more stress on slave s1. Since the slaves s1 and s2 are at a single hop distance, if they were allowed to communicate, they would have communicated with less communication cost.



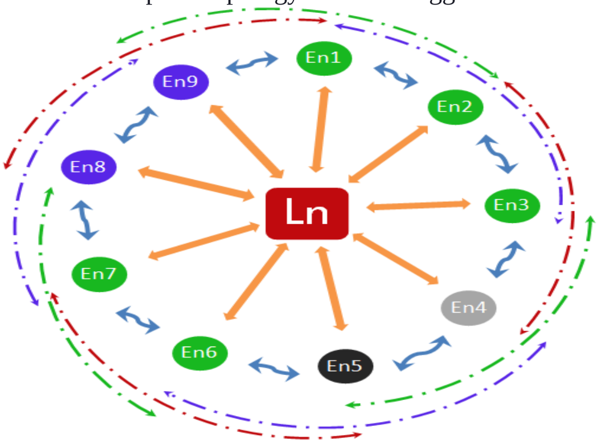
M-Master node & s1:s7 - Slave node
Solid Arrows – Single hop

Fig 1: Bluetooth 4.0 LE topology for Piconet

But again due to inflexible topology as depicted in figure a, Slave s1 and s2 require four hops for sharing data among themselves.

Here the first hop is required for master polling slave s1, the second hop for s1 to send data to the master, the third hop for the master to poll slave s2 and final fourth hop for sending data from the master to s2. If more piconets are connected through scatternet, then overall delay, as well as the cost of communication, will also be increased linearly.
If the master device fails, then the entire network will become nonfunctional. Therefore, the network has an inherent issue of single-point failure which makes it vulnerable and unreliable. If s1 wants an acknowledgment from s2 to ensure reliable data transfer, then again the slave to master, master to slave sequences are repeated which further enhances both delays as well as the communication cost. Hence, the conventional topology may not be optimal to connect functionally non-uniform and structurally non-identical IoT objects.

To overcome a few issues and challenges such as increased communication delay as well as overall communication cost, an alternate adaptive topology has been suggested.



Ln-Link node & En1:En9 - Edge node
Solid Arrows – Single hop: Dotted Arrows – Double hop
Fig 2: Adaptive topology for Edgenet

Fig 2 shows the formation of Edgenet using an adaptive neuro-fuzzy controller. Here the roles of individual nodes are redefined and their responsibilities are also refined. The role of the Edgenet is to make a last-mile network by interconnecting all available last-mile workers or IoT edge devices. These edge devices will observe the environment continuously, might control the ambiance selectively or actuate any other relevant edge devices such as home appliances, industrial controls, autonomous controls, and automation interfaces. They might send information to larger networks such as the internet or to other computing domains such as data centers or data clouds. Here there is no master/slave hierarchy but all devices are considered equally. They could be configured for limited any to any connection but the unlimited connection among single hop and double hop neighbors.

In the proposed topology node named Ln acts as a link node that helps any edge node to transfer data to any other edge node separated by greater than two-hop distances. It also helps the edge node to communicate to those edge nodes separated by two hops, but only when the intermediate neighbor fails. Edge nodes En1, En2, En3, En6, and En7 are identical in their functionalities and resources. Edge nodes En8 and En9 are identical in their functionalities and resources. Edge nodes En5 and En6 are partially identical in their functionalities and resources.
The primary advantage of this topology is within the Edgenet finer clusters such as (En1, En2, En3, En6 & En7), (En8 & En9) and (En5 & En6) could be formed by a neuro-fuzzy classifier. Self – configuring ability of this topology could be used to make virtualization among these nodes in their respective clusters. All edge nodes can assume the dual roles in the proposed topology. They either can perform the role of sender-receiver or can act as a relay node just to dispatch the data between its immediate neighbors.
All edge nodes can assume the dual roles in the proposed topology. They either can perform the role of sender-receiver or can act as a relay node just to dispatch the data between its immediate neighbors.
Due to this multi-role topology, both single point node failure, as well as a link failure, is eliminated. If the transit node fails, the network will not be shut down completely, instead, communication is restored with the active participation of relay nodes. If any single link between edge nodes or between an edge node and transit node fails, any particular edge node will not be isolated as well as denied any connectivity completely, instead communication is restored with the active participation of relay nodes. In a worst-case scenario, any two edge nodes can communicate with the maximum of two hops. In the best-case scenario, any two edge nodes can communicate with a maximum of a single hop.

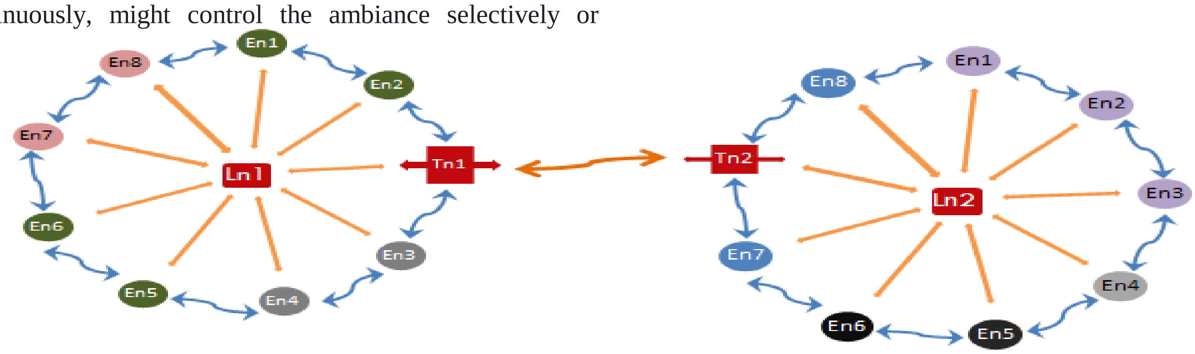


Fig 3: Formation of LinkNet using two EdgeNets

Fig 3 shows how EdgeNets could be extended to cover more edge nodes by interconnecting more EdgeNets. A transit node is selected in an EdgeNET and the same node is used to link with transit node from another EdgeNet. As shown in Fig 3, transit nodes Tn1 and Tn2 are used to connect EdgeNet-1 and EdgeNet-2.

The selection of transit node is based on number of hops, degree of heterogeneity, number of I/O interfaces, type of energy source, processing ability, storage capacity, communication capability, type of tasks such as sensing, actuating as well as reporting between the two potential transit nodes available among any two EdgeNets required to be connected.

The neuro-fuzzy classifier is used to elect the transit node in each EdgeNet. Apart from making connectivity among various EdgeNets, the transit nodes also acts as a message broker by aggregating all reporting messages from the centralized link node in each EdgeNet to the other link node in another EdgeNet. This topology facilitates effective data acquisition and also simplifies in-network optimal data processing.

C. *Topology Construction Using Neuro-Fuzzy Classifier*

After the investigation based on the information in Table I & Table II, it is unambiguous that IoT systems are unique due to various contexts which require flexible, re-configurable and adaptable topology to connect such a pure heterogeneous device. Due to the characteristics of fuzziness and learning ability, Neuro-fuzzy Classifier is best suited to fulfill the requirements such as flexibility, re-configurability, and adaptability to create an optimal topology for interconnecting various IoT systems.

Table III shows various context-based inputs are mapped with different linguistic variables. Here, six contextual inputs have been identified. Sensing context defines different physical phenomena such as temperature, pressure, humidity, moisture, light intensity, wind speed, wind direction, vibration, movement, velocity, viscosity, radiation, flow, smoke as well as sound and actuating context outlines many controlling aspects such as electric relay, mechanical switch, hydraulic control, and pneumatic trigger. A node type context summarizes the presence of different types of hardware and the number of nodes identifies available one-hop neighbors. Action type context reveals how the selected IoT device will respond to any event employing a proactive context or reactive context. Finally, the number of hops gives available links.

Table III: Context mappings of inputs with linguistic variables

Inputs	Sensing	Actuating	Node Type	Number of neighbors	Action Types	Number of hops
Linguistic Types	High	High	Medium	Low	Medium	Low
	Medium	Low	Low	Medium	High	High
	Low	Medium	High	High	Low	Medium

Table IV shows mapping of input variables and output classes with various identifiers. It also explains about various identifier notations used to frame several fuzzy rules and in making of Neuro-fuzzy classifier system.

Table IV: Fuzzy identifier mappings

Input identifier	Inputs	Output identifier	Output Classes
i_1	Sensing	Link node	d_1
i_2	Actuating		
i_3	Node type	Transit node	d_2
i_4	Number of neighbors		
i_5	Action types	Data caching	d_3
i_6	Number of hops		

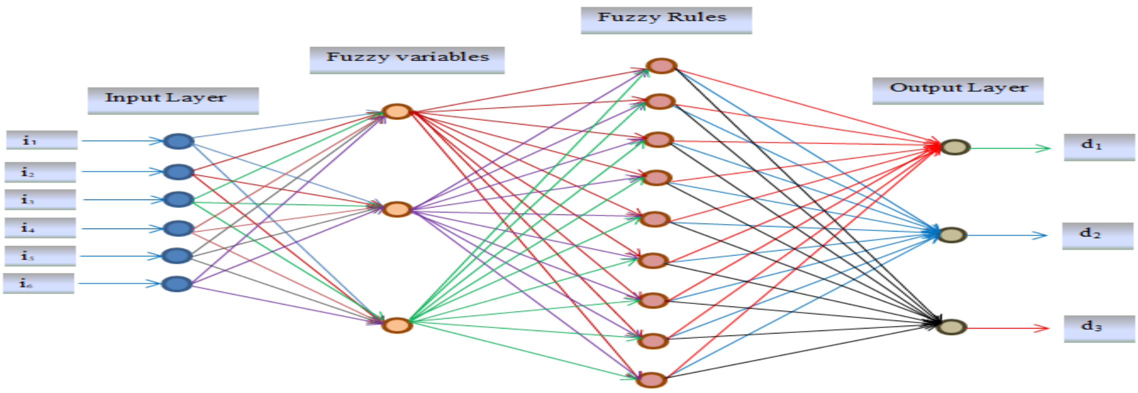


Fig 4: Neuro-fuzzy topology classifier

Based on various contexts and input/output identifiers as mentioned in Tables III & IV, the following Fuzzy rules are defined for the neuro-fuzzy classifier as given below:-

$Rule_s$ = ***If*** i_1 ***is*** c_1 ***&&*** i_2 ***is*** c_2 ***&&*** i_3 ***is*** c_3 ***&& . . . &&*** i_m ***is*** c_n***, then output relates with class*** d_1 ***or*** d_2 ***or*** d_3***.***

where m = 1,2,3,4. . . 9 belong to nine rules, n = 1, 2, 3 denotes various fuzzy variables, the' i' refers to the input variables and 'd' is defined as relevant output class.

Few sample fuzzy rules have been given below:

1. If i_1 is high and i_2 is high and i_3 is low and i_4 is high and i_5 is high and i_6 is medium, then output relates with class d_1
2. If i_1 is medium and i_2 is high and i_3 is low and i_4 is medium and i_5 is high and i_6 is medium, then output links to class d_1
3. If i_1 is low and i_2 is low and i_3 is low and i_4 is high and i_5 is high and i_6 is low, then output associates with class d_2
4. If i_1 is low and i_2 is low and i_3 is medium and i_4 is medium and i_5 is medium and i_6 is low, then output relates to class d_2
5. If i_1 is high and i_2 is low and i_3 is medium and i_4 is high and i_5 is medium and i_6 is medium, then output associates with class d_3.

Fig 4 shows the detailed representation neuro-fuzzy based topology classifier. It uses multiple layers to predict various output classes. The input layer takes six variables from i1 to i6 described in the table. The next layer introduces a fuzzy set with three linguistic variables. In the third layer, numerous fuzzy rules are applied. Finally, the result of the output layer is mapped with a few output classes. The proposed NuCoT method uses the Mamdani-type fuzzy model in the form of nine fuzzy rules, six input variables, and three fuzzy variables [16]. The defuzzification has been done using the weighted average method to derive output classes.

$$d_m = \frac{\mu_1 \sum_{k=1}^{9} i_k}{\mu_1 \sum_{k=1}^{9} i_k} \quad \text{----------eqn1.}$$

In eqn1,d_m is defined as the required output class, 'i' is relevant input variables and µ1 is the first fuzzy variable in the given set of fuzzy variables {µ1, µ2, µ3}. Here, nine fuzzy rules are applied and are represented as k = {1, 2, 3, 4, 5, 6, 7, 8, 9}.

IV. RESULT AND DISCUSSION

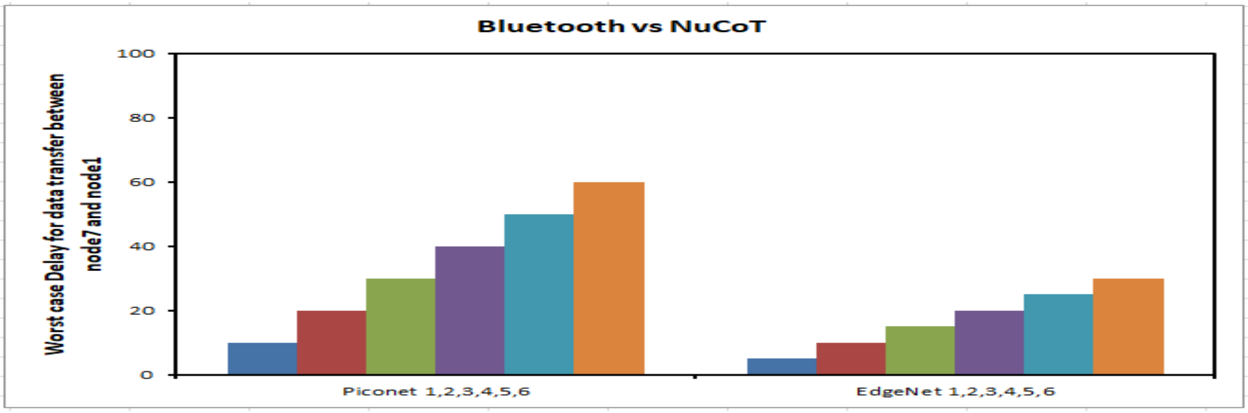


Fig 5: Worst case analysis for data transmission delay between node7 and node1 in Piconets for Bluetooth and EdgeNets in NuCoT

Fig 5 provides a snapshot regarding worst-case delay analysis for data transmission between node7 and node1 in Piconets for Bluetooth and EdgeNets in NuCoT. Since Bluetooth piconet supports only seven slaves, comparative analysis has been carried for edge nodes in NuCoT driven EdgeNet.

- Let d_p be the polling delay induced by a master in enquiring every slave for data transmission.
- Let d_{ts} be the transmission delay for any slave to transfer data to master in Bluetooth and
- Let d_{te} be the transmission delay for any edge device to transfer data to any other edge device in NuCoT
- Let d_{tm} be the transmission delay for any master to transfer data to slave

Hence, the cumulative delay for the worst-case scenario in Bluetooth is computed in eqn2.

$$\text{Delay} = \sum_{i,j,k=1}^{k=n,j,k=7} (dp_{ij} + dt_{j\to k}) \quad \text{----- eqn.2.}$$

And the cumulative delay for the worst-case scenario in EdgeNet is computed in eqn3.

$$\text{Delay} = 2d_{te} + \sum_{i,j=1}^{2} dt_{i\to j} \quad \text{------ eqn 3.}$$

Under the worst-case scenario in the Bluetooth environment, total transmission delay for slave7 to transfer data to slave 1 becomes additive across subsequent piconets. The total delay for this scenario is getting increased linearly and the same pattern could be observed from the fig 4. But under the same worst-case scenario in NuCoT based network, the total transmission delay for edge node7 to transfer data to edge node 1 is almost reduced by 50%. Hence, NuCoT based topology outperforms traditional Bluetooth topology.

V. CONCLUSION

For better automation, Smart sensing, Smart processing and Smart controlling are the primary tasks to be performed with possible optimization. Hence, a device to device communication becomes a challenging task. The traditional wired or wireless based network has many challenges and issues in achieving the meet the non-functional requirements like cost, performance, reliability, availability, flexibility, delay-tolerance and recoverability.

Another critical challenge is how to sense as well as interact with the environment under various unique contexts and also to control the same selectively in a given context. Here, the major barrier in realizing these critical requirements is the physical form of the network. Therefore, an alternate topology construction strategy is required.

This paper has proposed a neuro-fuzzy based context classifier to form a flexible, adaptable, self-configurable and scalable topology to provide relevant and optimized interconnection among a variety of IoT objects. Here, two types of node clusters have been proposed. Basic node cluster forms EdgeNet that creates a smaller network of all edge IoT objects and LinkNet creates a larger network by interconnecting EdgeNets.

EdgeNet is formed with the help of the individual context of any given IoT object. The context classification, as well as the selection, has been done by the Neuro-Fuzzy classifier.

Finally, theoretical simulation has been done and the results are analyzed. The simulation result has shown that the proposed neuro-fuzzy driven context-aware optimized topology (NuCoT) for IoT might outperform the traditional networking standard such as Bluetooth LE.

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